WHY HOURS WORKED DECLINE LESS AFTER TECHNOLOGY SHOCKS?*

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Abstract

The contractionary effect of technology shocks on hours gradually vanishes over time in OECD countries. To rationalize the decline in hours and its disappearance, we use a VAR-based decomposition of technology shocks into symmetric and asymmetric technology improvements. While hours decline dramatically when technology improves at the same rate across sectors, hours significantly increase when technology improvements occur at different rates. Because they are primarily driven by symmetric technology improvements, permanent technology shocks drive down total hours. Such a decline progressively vanishes due to the growing importance of asymmetric technology shocks. To reach these two conclusions, we simulate a two-sector model which can reproduce the contractionary effect on hours once the economy is internationally open and we allow for production factors' mobility costs, factor-biased technological change, and home bias. To account for the vanishing decline in hours, we have to let the share of asymmetric technology shocks increase over time.

Keywords: Hours worked; Symmetric and asymmetric technology shocks; Tradables and non-tradables; International openness; Factor-augmenting efficiency; Labor reallocation.
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1 Introduction

Has the response of hours to permanent technology improvements changed over time? What is the main driver behind this change? Our empirical findings reveal that the impact effect on hours of a permanent technology shock hides a large and gradual structural change. More specifically, the contractionary effect of technology improvements on hours has significantly shrunk over the last fifty years in OECD countries. We show that the increasing importance of technology improvements which occur at different rates between (traded and non-traded) sectors is responsible for the gradual disappearance of the negative effect of a permanent technology shock on hours.

The shrinking contractionary effect of technology shocks on hours has been documented by Galí and Gambetti [2009], Barnichon [2010], Nucci and Riggi [2013], Cantore et al. [2017] on U.S. data only. These papers put forward more pro-cyclical monetary policies, a reduction in hiring frictions, an increase in performance-related pay schemes, or a greater substitutability between capital and labor, respectively, to rationalize the vanishing decline of hours. While these interpretations may fit the U.S. experience, we provide evidence showing that none of these explanations can account for the vanishing decline in hours after technology shocks we document for OECD countries.

Indeed, our empirical analysis reveals that the gradual disappearance of the negative impact of technological change on hours is not restricted to the U.S. and is also shared by OECD countries. To be more specific, we find that a 1% permanent increase in utilization-adjusted-total-factor-productivity (TFP) produces a decline in hours by -0.31% on impact in the pre-1992 period while hours remain unresponsive to technology shocks in the post-1992 period. Our structural interpretation of the decline in hours after a technology shock together with its gradual disappearance rests on the international openness aspect and the multi-sector dimension of OECD countries which exert opposite effects on hours.

When the economy is internationally open, households find it optimal to increase imports and borrow from abroad to enjoy more leisure after a permanent technology improvement. While international openness has a contractionary effect on hours, the multi-sector dimension has a positive influence. More specifically, in a multi-sector economy, technology improves at different rates across sectors and this technology dispersion has a strong expansionary effect on hours by fostering labor demand in low productivity growth (non-traded) industries. Therefore, the increasing share of technology improvements driven by asymmetric technology shocks between sectors can potentially rationalize the vanishing decline in hours we document empirically. In line with our hypothesis, our evidence reveals that the share of the forecast error variance of utilization-adjusted-TFP growth attributable to asymmetric technology shocks between sectors has dramatically increased from 7% before 1992 to more than 44% in the post-1992 period.

Besides the fact that our interpretation fits the experience of our sample of OECD countries, our line of explanation also accords well with the evidence documented by Foerster et al. [2011] who find that the share of output fluctuations explained by asymmetric shocks across sectors has dramatically increased since the great moderation. The rising share of asymmetric technology shocks between sectors we document for industrialized countries deserves particular attention as our estimates also show that (only) asymmetric technology improvements are shocks which are associated with innovation (concentrated in traded industries).

By considering a panel of 17 OECD countries over 1970-2017, we find empirically that total hours decline by -0.15% on impact after a 1% permanent technology improvement. Our estimates on rolling windows (with a fixed length of thirty years) reveal that the decline in hours shrink from -0.26% (the first thirty years) to -0.11% (the last thirty years). To rationalize theses findings, we put forward two hypothesis. First, hours decline after permanent technology shocks because they are primarily driven by technology improvements which are symmetric across industries. Second, the decline in hours worked shrinks over time as aggregate technology shocks are increasingly influenced by technology improvements which are asymmetric between sectors.

The first step of our analysis is to perform a VAR-based decomposition of aggregate technology improvements into symmetric and asymmetric technology shocks between sectors, in the same spirit as Garìn et al. [2018] who decompose economic fluctuations into a common (across sectors) and a sector-specific component. Our evidence shows that a technology shock characterized by a technology improvement which is uniformly distributed between (the traded and non-traded) sectors leads to a dramatic decline in hours by -0.47% on impact. By contrast, when the technology shock is concentrated toward specific (i.e., traded) industries, hours significantly increase by 0.31% on impact.

The second step of our analysis is to rationalize the magnitude of the decline in hours and its gradual disappearance we document for OECD countries. We develop an extension of the open economy setup with tradables and non-tradables pioneered by Kehoe and Ruhl [2009] and simulate the model by considering symmetric and asymmetric technology shocks between sectors calibrated to the data. To discipline our exercise, we generate exogenous shocks as measured in the empirical part. We conduct two separate but intertwined quantitative exercises which corroborate our two hypothesis.

First, we show that five elements are essential to generate the contractionary effect of a permanent technology shock on hours we estimate empirically: international openness, barriers to factors' mobility between sectors, home bias in the domestic traded good, factor-biased technological change, and a mix of symmetric and asymmetric technology shocks.[1]

[1] We could also employ the home bias terminology for non-traded goods but because consumption in non-traded goods significantly mitigates the decline in hours after a technology shock only once we allow for

International openness is key to producing a decline in hours after a permanent technology improvement. Because a technology shock stimulates consumption and investment, an economy open to international trade and world capital markets finds it optimal to import goods from abroad and lower labor supply by running a current account deficit.

However, abstracting from factors' mobility costs between sectors and assuming that home- and foreign-traded goods are perfect substitutes leads the model to overstate the reallocation of productive resources toward the non-traded sector and the decline in total hours. Because factors' mobility costs reduce the shift of resources toward the non-traded sector, households must give up a fraction of their higher consumption of leisure to produce additional units of non-traded goods. Households must further give up leisure to meet the demand for domestic (tradable) goods when home- and foreign-produced traded goods are imperfect substitutes because consumers are reluctant to replace domestic with imported goods. While these ingredients mitigate the decline in hours caused by financial (and trade) openness, we also have to let technology improvements be biased toward labor in the traded sector (in line with our estimates) to account for the effects of a technology shock on hours. Intuitively, when traded output turns out to be more labor intensive, higher demand for labor in traded industries neutralizes the incentives to shift labor toward the non-traded sector which further mitigates the decline in hours.

While the four aforementioned ingredients ensure that the model can account for the magnitude of the decline in hours, the performance of the baseline model also implicitly rests on assuming a mix of symmetric and asymmetric technology shocks between sectors. When technology improves at the same rate in both sectors, sectoral goods' prices depreciate (because an excess supply shows up on goods' markets) which puts downward pressure on sectoral wages and causes a dramatic decline in hours (by -0.40% on impact close to -0.47% in the data). In contrast, asymmetric technology shocks have a strong expansionary effect on hours (by 0.28% on impact close to 0.31% in the data). Because asymmetric technology improvements are concentrated within traded industries, non-traded goods' prices appreciate (due to the excess demand on the non-traded goods market) which has an expansionary effect on labor demand in non-traded industries. Firms in this sector thus pay higher wages to attract workers which has a positive impact on labor supply. Since hours significantly increase when technology improvements occur at different rates across sectors or fall dramatically when technology improves at the same rate, none of the shocks taken separately can account for the evidence. We need a mix of the two to ensure that technology improvements are associated with a productivity differential between tradables and non-tradables which provides incentives to shift labor toward non-traded industries and generates upward pressure on wages.

In the second quantitative exercise, we assess the ability of our model to account for

mobility costs between sectors, we find it more relevant to refer to the role of barriers to factors' mobility.

the shrinking decline in hours we document empirically. To conduct this analysis, we let the share of technology improvements driven by asymmetric technology shocks increase over time from 10% to 40% in line with our estimates based on rolling sub-samples. While our open economy setup reproduces well the shrinking contractionary effects on hours of technology shocks we document empirically, we show that factor-biased technological change is a key element to account for the evidence, in particular when we focus on the time-varying responses of sectoral hours. When we impose Hicks-neutral technological change, the restricted model generates a time-decreasing impact response of traded hours worked in contradiction with our evidence because asymmetric technology shocks encourage labor to shift toward non-traded industries. By neutralizing the incentives to shift labor away from traded industries, technological change biased toward labor in the traded sector ensures that traded hours decline less over time as the share of asymmetric technology shocks is increased, in accordance with our estimates.

Importantly, the decomposition of technology shocks into a symmetric and an asymmetric component between sectors also allows us to reconcile two strands of the literature. Shea [1999] and Alexopoulos [2011] find that technology shocks driven by innovation increase labor while the literature pioneered by Galì [1999] finds that technology shocks lower hours worked. Because our evidence reveals that only asymmetric technology shocks give rise to innovation, if we focus on technology improvements driven by asymmetric technology shocks, these shocks will increase significantly labor, in accordance with the first strand of the literature. By contrast, if we focus on aggregate technology shocks, hours worked will fall because symmetric technology shocks are predominant.

The article is structured as follows. In section 2, we propose a VAR-based decomposition of technology shocks into a symmetric and an asymmetric component between sectors to rationalize the time-varying effects on hours we estimate empirically. In section 3, we develop a two-sector open economy model where factor-augmenting technology has a symmetric and an asymmetric component between sectors. In section 4, we calibrate the model to the data and assess its ability to account for the time-varying effects. Finally, section 5 concludes. The Online Appendix contains more empirical results, conducts robustness checks, details the solution method, and shows extensions of the baseline model.

2 Technology and Hours across Time: Evidence

In this section, we document evidence for seventeen OECD countries about the link between technology and hours across time. Below, we denote the percentage deviation from initial steady-state (or the rate of change) with a hat.

2.1 Contribution to Existing Literature

Before going into details about the empirical strategy, it is useful to explain our contribution to the existing literature investigating the effects of a technology shock on hours.

Existing explanations of the time-increasing impact response of hours to a technology shock. The vanishing decline in hours after a technology shock has been documented by Galí and Gambetti [2009], Cantore et al. [2017] on U.S. data only. The first paper puts forward more pro-cyclical monetary policies to rationalize the disappearance of the fall in hours after a productivity increase. Intuitively, while a permanent technology improvement leads firms to reduce hours when prices are sticky and money supply is fixed, the decline in hours is mitigated as monetary policy turns out to be more accommodating with technology shocks. The second paper suggests that technological change biased toward capital (which lowers labor demand) has shrunk over time as a result of the time-increasing value of the elasticity of substitution between capital and labor in production. The third line of explanation explored by Barnichon [2010], Galí and Van Rens [2021], Mitra [2023] assumes that the reduction in labor market frictions has lowered hiring costs which have led firms to adjust employment instead of hours per worker. Nucci and Riggi [2013] have proposed a fourth line of explanation based on the development of performance-related pay scheme in the U.S. from the mid 1980s.

The gradual disappearance of the decline in hours after a technology shock is not limited to the United States. In Fig. 1, we plot the dynamic response of hours worked to a 1% permanent increase in utilization-adjusted-total-factor-productivity (TFP) by considering two sub-periods. We use local projections to estimate the dynamic response of hours to the technology shock whose identification will be detailed later. In line with the literature pioneered by Galí [1999], we focus on the impact response of hours to a technology shock. As shown in the dashed red line, a permanent technology shock produces a decline in hours by -0.31% on impact in the pre-1992 period while hours remain unresponsive to technology shocks in the post-1992 period (see the blue line).[2]

Can existing theories rationalize the vanishing decline in hours after a technology shock in OECD countries? In Online Appendix A, we investigate empirically whether the four existing theories brought to the fore to rationalize the vanishing decline in hours in the U.S. can also accommodate the evidence we document for OECD countries. While we relegate detailed evidence to Online Appendix A for reasons of space, we summarize our main results below. First, the hypothesis proposed by Galí and Gambetti [2009] cannot explain the vanishing decline in hours we document for OECD countries as we do not find that monetary policies are significantly more accommodating with technol-

[2] We choose 1992 as the cutoff year for the whole sample because the Great Moderation occurs in the post-1992 period for European countries which account for three-fourth of our sample, see e.g., Benati [2008] for the U.K. and González Cabanillas and Ruscher [2008] for the euro area.

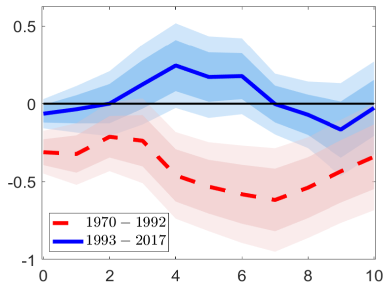


Figure 1: Response of Hours to Technology Shocks: 70-92 vs. 93-17 Notes: The figure shows the response of hours to a 1% permanent increase in utilization-adjusted-TFP before (dashed red line) and after (solid blue line) 1992. Solid and dashed lines represent point estimates and light (dark) shaded areas represent 90 (68) percent confidence intervals. Vertical axis measures deviation from the pre-shock trend/level in percent.

ogy shocks in OECD countries. Second, we find empirically that technology shocks are not biased toward capital in OECD countries and the elasticity of substitution between capital and labor has not increased but instead has remained stable over time (in contrast to the hypothesis by Cantore et al. [2017]). Third, our estimates reveal that the response of employment to a technology shock remains muted on impact which questions the hypothesis based on the reduction of hiring frictions. In addition, on average, in OECD countries, the relative volatility of employment has remained stable which is not surprising since the evidence gathered by Galí and Van Rens in their online appendix indicates that most of the OECD countries did not experience the decline in labor market frictions observed in the United States. Fourth, we find a significant time-declining response of the real wage to technology shocks in OECD countries which is hard to reconcile with the assumption of a rising performance pay put forward by Nucci and Riggi [2013].

Our explanation of the vanishing decline in hours after a technology shock in OECD countries. In contrast to the existing literature, we stress the importance of two key aspects shared by all OECD countries. First, the international openness dimension generates a strong negative link between technology and hours. Intuitively, by increasing imports after a permanent technology shock, the home country can meet a higher demand for traded goods which in turn releases labor resources to produce more units of non-traded goods so that households can work less. As we shall see in the quantitative analysis, frictions into the movement of resources and imperfect substitutability across goods will reduce the negative correlation between hours and technology. The second key aspect we emphasize is the multi-sector dimension of OECD countries. In a multi-sector economy, technology improves at different rates across sectors and the dispersion in technology improvements across sectors appreciates relative prices in low productivity growth industries which makes hiring more profitable (as long as the price-elasticity of demand is low) and leads these industries to pay higher wages, thus putting upward pressure on wages and increasing labor supply.

Our first contribution is to show that hours decline after a technology shock (as long as the economy is internationally open) because technological change is primarily driven by symmetric technology shocks which lower labor supply. In Online Appendix B, we contrast the impact effect on hours of a 1% permanent increase in utilization-adjusted-TFP across variants of our baseline model laid out in section 3. We find that hours decline when the economy is internationally open and increase if the economy is closed. Our second and key contribution is to show that the decline in hours shrinks over time because technological change is increasingly driven by asymmetric technology shocks which have a strong positive impact on labor supply. If our explanation were correct, the share of the forecast error variance of utilization-adjusted-TFP growth attributable to asymmetric technology shocks between sectors should be lower before 1992. Indeed, our estimates reveal that the share of asymmetric technology shocks has dramatically increased from 7% before 1992 to more than 44% in the post-1992 period. While in the empirical part we document evidence which corroborates our hypothesis, we further test our assumption in section 4 by feeding our two-sector open economy model with the increasing share of asymmetric technology shocks we observe in the data.

The decline in hours after a technology shock: Existing vs. our explanation. As shown in Online Appendix B where we contrast numerically the effects of a technology shock in a closed economy model with flexible prices with those in an open economy, international openness is an essential element to rationalize the decline in hours. Differently, the 'standard' explanation of the decline in hours after a technology shock pioneered by Gali [1999] stresses the role of sticky prices. Under the assumption that money supply does not increase and prices are rigid, the excess supply in the goods market caused by higher productivity will be eliminated through a decline in hours. This explanation has been challenged by Chang and Hong [2006] who do not find that a strong correlation between the response of labor and the duration of output prices adjustment. In addition, as shown by Dotsey [1999], Cantore et al. [2017], a closed economy model with sticky prices will produce a rise in hours worked when monetary policy is pro-cyclical (in line with the evidence).

The second line of explanation has been suggested by Cantore et al. [2014] who put forward technological change biased toward capital to explain the decline in hours in the United States. When we consider our sample of seventeen OECD countries detailed later, we do not find that technology shocks are biased toward capital and thus this explanation cannot account for a decline in hours after a permanent technology improvement.

While most of the existing literature investigating the effects of technology shocks on total hours worked considers a closed economy, Collard and Dellas [2007] consider a one-sector RBC model in open economy. The authors must impose an elasticity of substitution between domestic and foreign goods smaller than one to give rise to a decline in hours. We empirically find however that the decline in hours is concentrated in the non-traded sector and the response of traded hours worked remains muted. To generate these findings, we have to consider a two-sector open economy where home- and foreign-produced traded goods are high substitutes, as evidence suggests, see e.g., Bajzik et al. [2020] who report an elasticity larger than one.[3]

2.2 Data Construction

We briefly discuss the dataset we use. We take data from EU KLEMS and OECD STAN to construct time series for tradables (indexed by the superscript $j = H$) and non-tradables (indexed by the superscript $j = N$). Online Appendix H provides a lot of details about the source and the construction of time series. Our sample contains annual observations and consists of a panel of 17 OECD countries. The period runs from 1970 to 2017.

Classification of industries: tradables vs. non-tradables. To classify eleven 1-digit ISIC-rev.3 industries industries as tradables or non-tradables, we use data from the World Input Output Dataset (WIOD) to calculate the openness to international trade of each industry, measured by the ratio of imports plus exports to gross output. We treat industries as tradables when trade openness is equal or larger than 20%. We thus classify "Agriculture, Hunting, Forestry and Fishing", "Mining and Quarrying", "Total Manufacturing","Transport, Storage and Communication", and "Financial Intermediation" in the traded sector. The remaining industries "Electricity, Gas and Water Supply", "Construction", "Wholesale and Retail Trade" and "Community Social and Personal Services", "Hotels and Restaurants" and "Real Estate, Renting and Business Services" are classified as non-tradables. We perform a sensitivity analysis with respect to the classification in Online Appendix L.2 and find that all conclusions hold.

Macroeconomic variables. We construct time series for sectoral hours worked, L^j_{it}, the hours worked share of sector j, $\nu^{L,j}_{it}$, where the subscripts i and t denote the country and the year. To capture the transmission mechanism of a technology shock in a two-sector open economy, we also analyze the movements in the value added share at constant prices, $\nu^{Y,j}_{it}$, in the relative price of non-tradables which is computed as the ratio of the non-traded value added deflator to the traded value added deflator (i.e., $P_{it} = P^N_t/\mathsf{P}^H_{it}$), and in the terms of trade denoted by $P^H_t = \mathsf{P}^H_{it}/\mathsf{P}^{H,\star}_{it}$ where P^H_{it} is the traded value added deflator of the home country i and $\mathsf{P}^{H,\star}_{it}$ captures foreign prices defined as an import share (geometric) weighted average of the traded value added deflator of the sixteen trade partners of country i. Note that the share of imports from the trade partner is averaged over 1970-2017. Because the strict definition of the current account includes items such as unilateral transfers which play no role in our model, we have constructed time series for the current account by

[3]We cannot give justice to the vast literature seeking to rationalize the decline in hours after a technology shock but it is worth mentioning that alternative explanations have been proposed such as factors mitigating the increase in aggregate demand, see Francis and Ramey [2005] who allow for capital adjustment costs and habit formation or by assuming that technology gradually builds up, see Lindé [2009].

calculating the difference between the GNP and the sum of final consumption expenditure by households, gross fixed capital formation, and final consumption expenditure by the government.

Utilization-adjusted sectoral TFPs. Sectoral TFPs are Solow residuals calculated from constant-price (domestic currency) series of value added, Y_{it}^j, capital stock, K_{it}^j, and hours worked, L_{it}^j, i.e., $\hat{\text{TFP}}_{it}^j = \hat{Y}_{it}^j - s_{L,i}^j \hat{L}_{it}^j - \left(1 - s_{L,i}^j\right) \hat{K}_{it}^j$ where $s_{L,i}^j$ is the labor income share (LIS henceforth) in sector j averaged over the period 1970-2017. To construct time series for K_{it}^j, we first construct the aggregate capital stock K_{it} by adopting the perpetual inventory approach and then we use the sectoral valued added shares to split K_{it} into K_{it}^H and K_{it}^N, see Online Appendix L.3. We construct a measure for technological change by adjusting the Solow residual with the capital utilization rate, denoted by $u_{it}^{K,j}$:

$$\hat{Z}_{it}^j = \hat{\text{TFP}}_{it}^j - \left(1 - s_{L,i}^j\right) \hat{u}_{it}^{K,j}, \tag{1}$$

where we follow Imbs [1999] in constructing time series for $u_{it}^{K,j}$, as utilization-adjusted-TFP is not available at a sectoral level for most of the OECD countries of our sample over 1970-2017, see Online Appendix I where we detail the adaptation of Imbs's [1999] method. In Online Appendix M.3, we find that our empirical findings are little sensitive to the use of alternative measures of technology which include i) Basu's [1996] approach which has the advantage of controlling for unobserved changes in both capital utilization and labor effort, ii) and time series for utilization-adjusted-TFP from Huo et al. [2023] and Basu et al. [2006]. Our preferred measure is based on Imbs's [1999] method because it fits our model setup where we consider an endogenous capital utilization rate and the last two measures can only be constructed over a shorter period of time and for a limited number of OECD countries.

2.3 Identification of Asymmetric vs. Symmetric Technology Shocks

Objective and strategy. Our objective is to demonstrate that the gradual disappearance of the negative response of hours to technology shocks is caused by the increasing importance of technology improvements which occur at different rates between sectors. To show this point, we proceed in three steps below. First, we estimate the effects on hours of a permanent technology shock. Second, we contrast the effects on hours after a symmetric technology shock with those caused by asymmetric technology shocks. Third, we estimate the time-varying effects on hours of a permanent technology improvement and quantify the progression in the share of technology improvements driven by asymmetric technology shocks.

To conduct our empirical study, we compute the responses of selected variables by using a two-step estimation procedure. We first identify a permanent technology improvement by adopting the identification pioneered by Gali [1999]. Like Gali, we impose long-run restrictions in the VAR model to identify permanent technology shocks as shocks that increase permanently the level of our measure of technology. Because Erceg et al. [2005] and Chari et al. [2008] have shown that persistent non-technology shocks can disturb the identification of permanent technology shocks, we adjust TFP with the capital utilization rate. Chaudourne et al. [2014] demonstrate that the use of 'purified' TFP to measure technological change ensures the robustness of the identification of technology shocks. In the second step, we trace out the dynamic effects of the identified shock to utilization-adjusted TFP by using Jordà's [2005] single-equation method. This two-step approach is particularly suited to our purpose as we identify technology shocks once and for all and next estimate the dynamic responses of a set of variables to the identified shock and assess empirically its time-varying effects on rolling windows.

VAR identification of symmetric vs. asymmetric technology shocks across sectors. The starting point of the identification of symmetric and asymmetric technology shocks is the sectoral decomposition of the percentage deviation of utilization-adjusted-aggregate-TFP (i.e., $\hat{Z}^A_{it}$) relative to its initial steady-state:

$$\hat{Z}^A_{it} = \nu^{Y,H}_i \hat{Z}^H_{it} + \left(1 - \nu^{Y,H}_i\right) \hat{Z}^N_{it}, \tag{2}$$

where $\hat{Z}^H_{it}$ and $\hat{Z}^N_{it}$ measure technology improvements in the traded and the non-traded sector, respectively, and $\nu^{Y,H}$ is the value added share of tradables. Eq. (2) can be rearranged as follows

$$\hat{Z}^A_{it} = \hat{Z}^N_{it} + \nu^{Y,H}_i \left(\hat{Z}^H_{it} - \hat{Z}^N_{it}\right), \tag{3}$$

which enables us to decompose technological change into technology improvements which are common and asymmetric between sectors. When technology improves at the same rate in the traded and the non-traded sector, i.e., $\hat{Z}^H_{it} = \hat{Z}^N_{it}$, then the second term on the RHS of eq. (3) vanishes and technological change collapses to its symmetric component (indexed by the the subscript S), i.e., $\hat{Z}^A_{S,it} = \hat{Z}^H_{S,it} = \hat{Z}^N_{S,it}$. In contrast, the asymmetric component (indexed by the the subscript D) of aggregate technological change is captured by the second term on the RHS, i.e., $\hat{Z}^A_{D,it} = \nu^{Y,H}_i \left(\hat{Z}^H_{D,it} - \hat{Z}^N_{D,it}\right)$, which reflects the excess of technology improvements in the traded sector over those in the non-traded sector (weighted by $\nu^{Y,H}_i$).

The above discussion implies that technology in sector j is made up of a symmetric and an asymmetric component, i.e., $Z^j_{it} = \left(Z_{S,it}\right)^{\eta_i} \left(Z^j_{D,it}\right)^{1-\eta_i}$ with $\hat{Z}^H_{S,it} = \hat{Z}^N_{S,it} = \hat{Z}_{S,it}$, where we denote by η the share of technological change which is common across sectors. Log-linearizing this expression and plugging the result into eq. (2) leads to the decomposition of aggregate technological change into a symmetric and an asymmetric component:

$$\hat{Z}^A_{it} = \eta_i \hat{Z}^A_{S,it} + \left(1 - \eta_i\right) \hat{Z}^A_{D,it}, \tag{4}$$

where $\hat{Z}^A_{S,it} = \hat{Z}_{S,it}$. To decompose shocks to Z^A_{it} into symmetric and asymmetric technology shocks, we use the fact that an increase in the symmetric and the asymmetric components both raise Z_{it}^A while only a rise in the asymmetric component raises the productivity of tradables relative to non-tradables, see eq. (3).

We consider two versions of the VAR model. In both cases, we estimate a reduced form VAR model in panel format on annual data with two lags and with both country fixed effects and time dummies. The first version includes utilization-adjusted-aggregate-TFP, real GDP, total hours worked and the real consumption wage. All quantities are divided by the working age population which removes the trend caused by population growth and also ensures that each country has the same weight in the empirical analysis; all variables enter the VAR model in rate of growth, see Online Appendix L.1 which documents evidence about the presence of a unit-root process for all variables of interest. We impose long-run restrictions to identify technology shocks as shocks which increase permanently Z_{it}^A, see Online Appendix G which provides more details about the SVAR identification. In the second version, we augment the VAR model with the ratio of traded to non-traded utilization-adjusted-TFP ordered first. We impose long-run restrictions such that both symmetric and asymmetric technology shocks increase permanently Z_{it}^A while only asymmetric technology shocks increase Z_{it}^H/Z_{it}^N in the long-run. Technically the long-run cumulative matrix is lower triangular which implies that only asymmetric technology shocks in the first row increases both the ratio of traded to non-traded technology and aggregate technology while symmetric technology shocks in the second row leave the relative productivity of tradables unaffected.

Estimating dynamic effects. Once we have identified technology shocks from the VAR model's estimation, in the second step, we estimate the dynamic effects on selected variables (detailed later) by using Jordà's [2005] single-equation method. Besides the fact that Pagan [1984] has demonstrated that the coefficient and the standard error on generated regressors are consistent and asymptotically valid, by decoupling the shock identification and the estimate of the dynamic responses, our approach ensures that the variables respond to the same shock. The second advantage of local projections is that this method does not impose any structure to the dynamic adjustment and thus is less restrictive. The local projection method amounts to running a series of regressions of each variable of interest on a structural identified shock for each horizon $h = 0, 1, 2, ...$

$$x_{i,t+h} = \alpha_{i,h} + \alpha_{t,h} + \psi_h (L) y_{i,t-1} + \gamma_h \varepsilon_{i,t}^Z + \eta_{i,t+h}, \tag{5}$$

where x is the logarithm of the variable of interest, y is a vector of control variables (i.e., past values of utilization-adjusted-TFP and of the variable of interest), $\psi_h (L)$ is a polynomial (of order two) in the lag operator; $\alpha_{i,h}$ are country fixed effects which control for time invariant characteristics such as mobility costs between sectors or substitutability between goods, and $\alpha_{t,h}$ are time dummies which control for common macroeconomic shocks. While Online Appendix L.11 shows that estimates are little sensitive to the inclusion of time dummies, it is still important to include them in the regression because in doing this, we can interpret the dynamic responses as deviations relative to the sample average. The coefficient γ_h on the RHS of eq. (5) gives the response of x at time $t+h$ to the identified technology shock $\varepsilon^Z_{i,t}$ at time t for an average OECD economy. We compute heteroskedasticity and autocorrelation robust standard errors based on Newey-West.

Robustness checks w.r.t. SVAR identification. Because the SVAR estimation allows for a limited number of lags, the SVAR critique has formulated some reservations with regard to the ability of the SVAR model to disentangle pure technology shocks from other shocks (which have long-lasting effects on productivity) when capital adjusts sluggishly, see e.g., Erceg et al. [2005], Dupaigne et al. [2007], Chari et al. [2008]. While the use of utilization-adjusted-TFP ensures the robustness of the identification of technology shocks, as demonstrated by Chaudourne et al. [2014], we have also conducted a series of robustness checks related to several aspects of our VAR identification of technology shocks and measures of technology which are detailed in Online Appendices L and M.

First, in Online Appendix M.1, we test whether the identified shocks to technology are correlated with non-technology shocks. Following Francis and Ramey [2005], we run the regression of identified technology shocks based on three measures of technology on (three) shocks to government spending, monetary policy, and taxation. The F-test reveals that none of the demand shocks are correlated with our identified technology shocks only when we use utilization-adjusted-TFP to measure technology. Technology shocks identified on the basis of the Solow residual (unadjusted with factors' utilization) and labor productivity are instead found to be correlated with the demand shocks. Second, following the recommendation by Chari et al. [2008] and De Graeve and Westermark [2013] who find that raising the number of lags may be a viable strategy to achieve identification when long-run restrictions are imposed on the VAR model, in Online Appendix M.2, we increase the lags from two to eight and find that all of our conclusions stand.

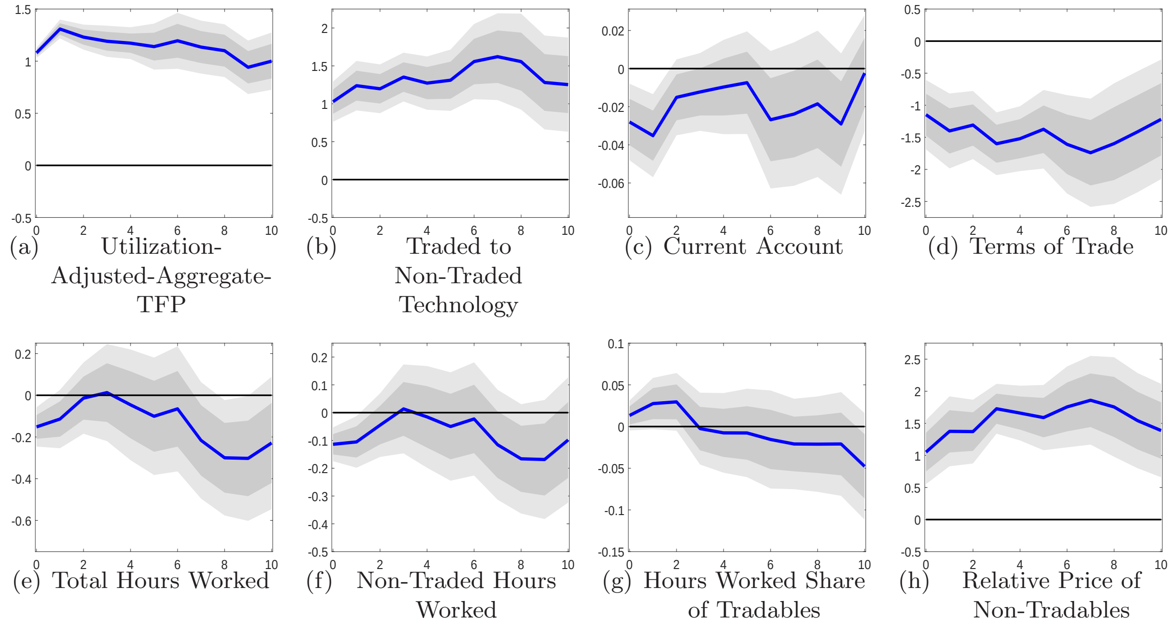
Third, in Online Appendix M.4, we adopt the Maximum Forecast Error Variance (FEV) approach proposed by Francis et al. [2014] which extracts the shock that best explains the FEV at a long but finite horizon of the measure of technology. We find that the response of hours when the technology shock is identified by means of the Maximum FEV is not statistically different from that obtained when imposing long-run restrictions for the median estimate as well as at the individual level (except for three out of seventeen countries). Fourth, following Fève and Guay [2010], in Online Appendix M.5, we estimate in the first step a VAR model by excluding hours and including only the rate of change in utilization-adjusted-TFP and the log ratio of consumption plus net exports to GDP and impose long-run restrictions to identify technology shocks and then in the second step, we estimate the dynamic effects by using local projections. We find no differences between our results and those obtained when we exclude hours from the first step. Fifth, as detailed in Online Appendix M.6, we build on the method proposed by Dupaigne and Fève [2009] and replace the country-level-utilization-adjusted-TFP with the import-share-weighed-average of utilization-adjusted-TFPs of the home country's trade partners which by construction is not influenced by country-specific persistent non-technology shocks. Differences are not statistically significant although hours do not fall below trend on impact because world technology shocks are further driven by asymmetric technology shocks compared with shocks to country-level utilization-adjusted-TFP.

Robustness checks w.r.t. our empirical strategy. The time-varying impact response of hours to a technology shock could potentially suggest that parameters which govern labor demand or labor supply or both have changed over time. This is the route taken by Li [2023]. Instead, we assume that the model's parameters have remained unchanged and our explanation of the vanishing decline in hours is based on the changing nature of technology shocks over time, in the same spirit as Görtz et al. [2024]. While we provide below a set of empirical evidence which supports our assumption of the change in the composition of technological change, we test our hypothesis in the theoretical part. More specifically, we simulate our model by keeping all model's parameters fixed and by assigning values to the share of asymmetric technology shocks in accordance with our empirical estimates. It is worth mentioning that we do not detect any structural breaks in the time series for utilization-adjusted-TFP and hours nor in their relationship, see Online Appendix L.1 and L.13, which is not surprising as the changing composition of technology shocks is a gradual process.

Because in estimating the response of hours to a technology shock, we assume that the coefficient is the same across countries, we have conducted a series of robustness checks in Online Appendix L.9 where we allow for a heterogeneity in responses across countries. All of our robustness checks confirm the validity of the homogeneity assumption. Fourth, we use a two-step approach where we identify the structural technology shocks and quantify empirically their impact on a set of variables by using local projections. Because the shock measure is a generated regressor for which standard errors are asymptotically valid, several papers have adopted this two-step approach, e.g., Coibion and Gorodnichenko [2015]. To further test the robustness of this approach, we alternatively considered the one-step method (see e.g., Ramey and Zubairy [2018]) where we regress the variable of interest on the rate of growth of utilization-adjusted-TFP and find that our results are unchanged (see Online Appendix L.10).

2.4 Effects on Hours of a Technology Shock

We first investigate the effects of a permanent increase in utilization-adjusted-TFP normalized to 1% in the long-run and shown in Fig. 2(a). The dynamic adjustment of variables to



(a) Utilization-Adjusted-Aggregate-TFP (b) Traded to Non-Traded Technology (c) Current Account (d) Terms of Trade

(e) Total Hours Worked (f) Non-Traded Hours Worked (g) Hours Worked Share of Tradables (h) Relative Price of Non-Tradables

Figure 2: Dynamic Effects of a Permanent Technology Shock. Notes: Traded to non-traded technology refers to utilization-adjusted-TFP of tradables relative to non-tradables.

an exogenous increase in Z_{it}^A is estimated by means of local projections. Solid lines in Fig. 2 represent point estimates, light (dark) shaded areas represent 90 (68) percent confidence intervals. The horizontal axis of each panel measures the time after the shock in years and the vertical axis measures deviations from trend. The response of non-traded hours worked is re-scaled by the sample average of labor compensation share of non-tradables to express the variation in L_{it}^N in percentage point of total hours worked.

Effects on hours. Fig. 2(e) reveals that a permanent technology improvement (of 1% in the long-run) significantly lowers hours worked by 0.15% on impact in OECD countries. Since one key element we put forward to rationalize the decline in hours in the quantitative analysis is the international openness dimension of OECD countries, we have estimated the response of the current account to a permanent technology shock in Fig. 2(c). The figure shows that the current account deteriorates significantly in the short-run. This finding suggests that an average OECD country will increase imports and borrow from abroad to enjoy more leisure after a technology shock.

Labor reallocation. Fig. 2(f) shows that the decline in total hours worked is concentrated in the non-traded sector in the short-run while the situation is reversed from $t = 4$ as labor is reallocated toward the non-traded sector as can be seen in Fig. 2(g). The deindustrialization trend movement in the long-run is driven by the productivity growth differential between tradables and non-tradables which averages 1.2% (see Fig. 2(b)).

As technology improvements are concentrated in the traded sector, non-traded industries charge higher prices to compensate for the higher marginal cost, as can be seen in Fig. 2(h) which shows that the relative price of non-tradables appreciates. Because the demand for non-traded relative to traded goods is little sensitive to the relative price of non-tradables (see e.g., Mendoza [1992], Stockman and Tesar [1995]), the non-tradable content of expenditure increases which causes labor to shift toward the non-traded sector. However, labor reallocation toward the non-traded sector materializes only in the long-run. As shown later in section 4.2, there are a number of factors which prevents labor from shifting in the short-run, in particular imperfect substitutability between home- and foreign-produced traded goods. Because productivity growth is concentrated in traded industries, the value added share of tradables at constant prices increases permanently which leads to a depreciation in the terms of trade as shown in Fig. 2(d). Because home- and foreign-produced traded goods are high substitutes, as evidence suggests, see e.g., Bajzik et al. [2020], the terms of trade depreciation has a strong expansionary effect on labor demand in the traded sector by increasing both the domestic and foreign demand components for home-produced traded goods. Besides the terms of trade adjustment, both factors' mobility costs and technological change biased toward labor also play a key role as shown later in the quantitative analysis.

Skilled vs unskilled. In Online Appendix R, we differentiate between skilled and unskilled workers by considering eleven (out of seventeen) OECD countries. Our evidence reveals that the decline in total hours after a technology shock is mostly driven by the fall in skilled workers' hours. According to our estimates and in line with the model's predictions, the dramatic decline in skilled workers' hours is caused by an increase in unskilled-labor-augmenting productivity together with a high substitutability between skilled and unskilled labor, see Online Appendix J.7 where we estimate the elasticity of substitution between the two groups of workers.

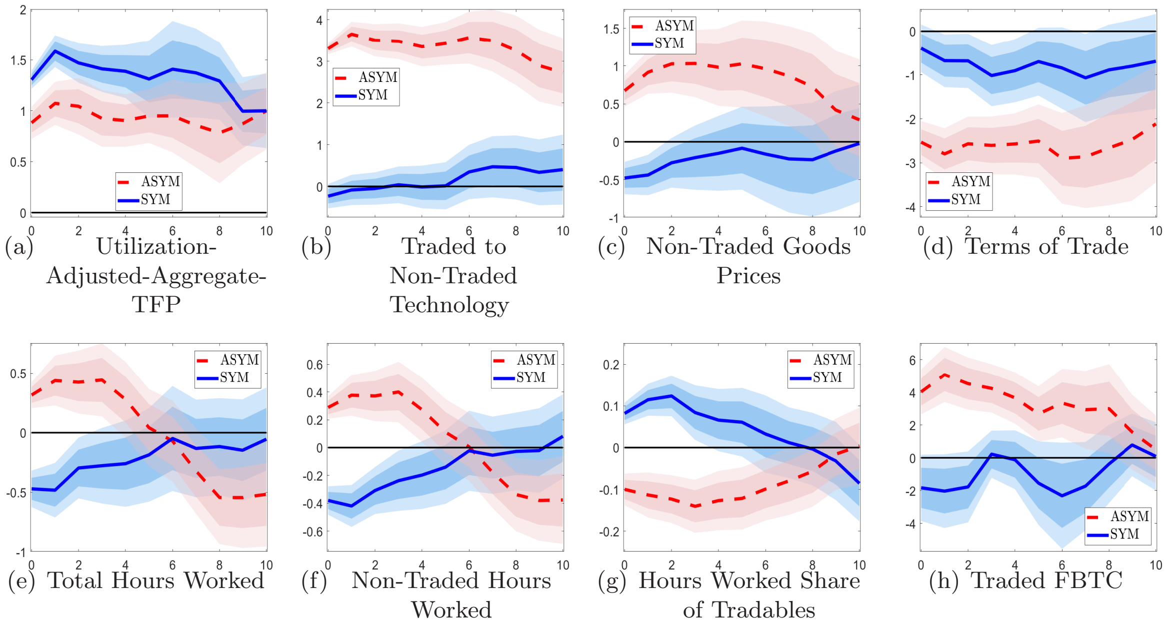
Cross-country dispersion. While after a permanent technology improvement, an average OECD economy works less and runs a current account deficit, our estimates mask a wide cross-country dispersion, as documented in Online Appendix L.14. According to our model's predictions, such a dispersion is driven by international differences in mobility costs between sectors, in the share of asymmetric technology shocks or the degree of substitutability between home- and foreign-produced traded goods. In this regard, hours are expected to decline more in large than in small countries because the latter economies display larger mobility costs, a smaller substitutability between domestic and foreign goods and a greater share of asymmetric technology shocks. Indeed, we find that hours decline dramatically in large countries and remain muted in small countries after a permanent technology shock. It is worth mentioning that the validity of our conclusions does not require that the seventeen countries' current account balances add up to zero after a technology shock because current account deficits can be financed by countries which are not included in the sample.

2.5 Symmetric vs. Asymmetric Technology Shocks across Sectors

So far, we have considered a shock to utilization-adjusted-TFP (i.e., to Z_{it}^A). According to eq. (4), a technology shock can be decomposed into a symmetric and an asymmetric technology shock between sectors. In this subsection, building on our discussion in section 2.3, we identify symmetric and asymmetric technology shocks between sectors (i.e., shocks to $Z_{S,it}^A$ and to $Z_{D,it}^A$, respectively) and we contrast the dynamic effects driven by symmetric (shown in blue lines) with those driven by asymmetric (shown in dashed red lines) technology shocks in Fig. 3. Light (dark) shaded areas represent 90 (68) percent confidence intervals. While both shocks lead to a technology improvement by 1% in the long-run (i.e., $\hat{Z}_{i,S}^A = \hat{Z}_{i,D}^A = 1\%$), see Fig. 3(a), the behavior of technology at a sectoral level is different. As can be seen in Fig. 3(b), asymmetric technology shocks generate a significant increase (by 2.9% on average) in utilization-adjusted-TFP of tradables relative to non-tradables while productivity growth is uniformly distributed across sectors after a symmetric technology shock since the ratio Z^H/Z^N remains unchanged at all horizons. It is worth mentioning that the effects shown in Fig. 2 are a linear combination of the effects driven by symmetric and asymmetric technology shocks displayed by Fig. 3.

Effects of symmetric technology shocks. Fig. 3(e) reveals that symmetric and asymmetric technology shocks produce distinct effects on labor as hours worked decline dramatically (by -0.47% on impact) after symmetric technology shocks while hours increase (by 0.31% on impact) after asymmetric technology shocks. These opposite effects are the result of the impact of productivity on sectoral prices. As shown in the blue line in Fig. 3(c) and Fig. 3(d), both non-traded and traded goods' prices depreciate after symmetric technology shocks which in turn put downward pressure on wages and exert a negative impact on labor supply. This negative impact is amplified by the fact that technological change is biased toward capital in the traded sector as captured by a decline in our measure of factor-biased technological change, see Fig. 3(h). As detailed in Online Appendix F, we adapt the methodology pioneered by Caselli and Coleman [2006] and Caselli [2016] to construct time series for utilization-adjusted-factor-biased-technological change at a sectoral level by using the ratio of labor demand to capital demand and plugging our estimates for the elasticity of substitution between capital and labor together with time series for the labor incomes share, the capital labor ratio and the capital utilization rate.

As can be seen in Fig. 3(f), the decline in total hours worked is mostly driven by the fall in hours worked in the non-traded sector. Because the elasticity of substitution between traded and non-traded goods is low (i.e., less than one), the fall in non-traded prices drives down the share of expenditure spent on non-traded goods which reduces labor demand in the non-traded sector. By contrast, because home- and foreign-produced traded goods are high substitutes, the terms of trade depreciation raises the share of home-produced traded



(a) Utilization-Adjusted-Aggregate-TFP (b) Traded to Non-Traded Technology (c) Non-Traded Goods Prices (d) Terms of Trade

(e) Total Hours Worked (f) Non-Traded Hours Worked (g) Hours Worked Share of Tradables (h) Traded FBTC

Figure 3: Dynamic Effects on Hours of Asymmetric vs. Symmetric Permanent Technology Shocks. Notes: Traded to non-traded technology refers to utilization-adjusted-TFP of tradables relative to non-tradables; 'FBTC' means factor-biased technological change.

goods and thus further increases the share of tradables. This has an expansionary effect on labor demand in the traded sector which leads to a shift of labor toward traded industries as reflected into an increase in the hours worked share of tradables displayed by the blue line in Fig. 3(g).

Effects of asymmetric technology shocks. Asymmetric technology shocks produce very distinct effects on labor. Because technology improvements are concentrated in traded industries, see the red line in Fig. 3(b), asymmetric technology shocks give rise to an excess supply for home-produced traded goods and an excess demand for non-traded goods. As shown in Fig. 3(c) (see the dashed red line), the excess demand puts upward pressure on non-traded goods prices. Because traded and non-traded goods are gross complements, the appreciation in non-traded prices increases the share of non-tradables which has a positive impact on non-traded hours worked, as displayed by Fig. 3(f).

The rise in L^N is amplified by the shift of labor toward the non-traded sector. As shown in the red line of Fig. 3(g), the hours worked share of tradables declines dramatically on impact by 0.1 ppt of total hours worked before recovering gradually. The first four years, the reallocation of labor toward the non-traded sector accounts for one-third of the rise in non-traded hours worked. To encourage workers to shift, non-traded firms must pay higher wages which puts upward pressure on non-traded wages and thus on the aggregate wage which has a strong expansionary effect on labor supply as shown in Fig. 3(e) (see the red line). On impact, the rise in total hours worked mostly originates from non-traded industries and is amplified by the fact that asymmetric technology improvements are significantly biased toward labor (in the traded sector), as displayed by Fig. 3(h) (see the red line). The combined effect of the terms of trade depreciation displayed by Fig. 3(d) and the rise in the labor intensity of traded production prevents traded hours worked from decreasing at time $t = 0$.

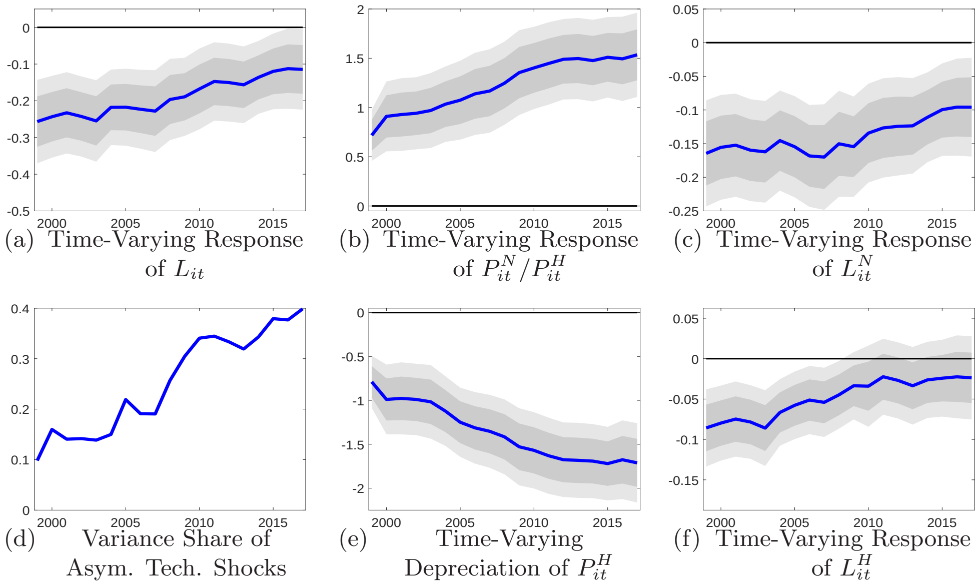
Do symmetric or asymmetric technology shocks or both increase innovation? One important question is whether symmetric or asymmetric technology shocks stimulate innovation in the traded and the non-traded sector. Using data from Stehrer et al. [2019] (EU KLEMS database) we construct time series for the capital stock in R&D in the traded and non-traded sectors. Data are available for thirteen countries over 1995-2017. Our evidence relegated to Online Appendix L.5 reveals that symmetric technology shocks do not significantly increase the stock of R&D and thus these shocks should capture better management practices and improvements in firm's organization. In contrast, our estimates show that asymmetric technology improvements are shocks which are associated with a significant and positive increase in the stock of R&D (concentrated in traded industries). Innovation will take place if the rise in the stock of R&D gives rise to a higher utilization-adjusted-TFP. While we find an elasticity of traded technology w.r.t. the stock of R&D in the traded sector of 0.238, the elasticity is virtually zero in the non-traded sector. These evidence thus underlines that (asymmetric) technology improvements which are concentrated within traded industries capture technological innovation.

2.6 The Time-Varying Response of Hours

Our evidence reveals that a permanent technology improvement has a contractionary effect on total hours worked on impact in OECD countries. We now investigate whether this decline has changed over the last fifty years.

The shrinking contractionary effect of technology shocks on hours. To capture the gradual and continuous change in the response of hours over time, like Cantore et al. [2017], we re-estimate the effect of a permanent technology improvement on hours by running the regression eq. (5) on rolling windows of fixed length. We focus on the impact effect captured by the estimated value γ_0 and consider a window of thirty years. More specifically, we estimate γ_0, starting from 1970-1999, repeating the estimation by moving the starting date by one year until we estimate the response over the last thirty years of the sample, i.e., over 1988-2017. We have considered windows of alternative length such as $T = 20$ and $T = 25$ and find that all the conclusions hold. As shown in Fig. 4(a), the decline in hours after a 1% permanent increase in utilization-adjusted aggregate TFP shrinks over time as total hours worked fall by -0.26% on impact over 1970-1999 and by -0.11% only over the last thirty years. Online Appendix L.6 shows that the time-increasing impact response of hours to a technology shock only operates at the intensive margin.

The increasing importance of asymmetric technology shocks. As shown in Fig. 4(d), the shrinking impact labor response is concomitant to the rise in the share of technology improvements driven by asymmetric technology shocks between sectors. The forecast



(a) Time-Varying Response of L_{it} (b) Time-Varying Response of P^N_{it}/P^H_{it} (c) Time-Varying Response of L^N_{it}

(d) Variance Share of Asym. Tech. Shocks (e) Time-Varying Depreciation of P^H_{it} (f) Time-Varying Response of L^H_{it}

Figure 4: Time-Varying Effects of a Technology Shock. Notes: While the vertical axis of Fig. 4(a) shows the point estimate (i.e., γ_0) for the impact response of hours (L_{it}) to a 1% permanent increase in utilization-adjusted-aggregate-TFP obtained from estimating eq. (5) on rolling subs-samples, the horizontal axis shows the end year of the corresponding window. Light (dark) shaded areas represent 90 (68) percent confidence intervals based on Newey-West standard errors. In Fig. 4(d), we show the fraction of the (conditional) variance of utilization-adjusted-TFP growth which is attributable to the variance of asymmetric technology shocks across sectors. In column 2 we show the impact responses estimated on rolling windows (of fixed length of thirty years) of the relative price of non-tradables (P^N_{it}/P^H_{it}), see Fig. 4(b), and the terms of trade (P^H_{it}), see Fig. 4(e), respectively. In column 3, we show time-varying impact responses of non-traded (L^N_{it}) and traded (L^H_{it}) hours worked to an aggregate technology shock, both re-scaled by the labor compensation share so that the sum response of sectoral hours worked are expressed in percentage point of total hours. Sample: 17 OECD countries, 1970-2017, annual data.

error variance decomposition estimated over rolling sub-samples reveals that the contribution of asymmetric technology shocks to the variance of aggregate technology improvements has increased substantially over time from 10% the first thirty years to 40% over the recent period. Column 2 shows further evidence pointing out the increasing importance of asymmetric technology shocks across sectors. We plot impact responses of the relative price of non-tradables and the terms of trade to an aggregate technology shock over rolling windows. Because technology improvements are not uniformly distributed across sectors and instead are concentrated toward traded industries, a technology shock produces an excess demand for non-traded goods which appreciates the relative price of non-tradables as displayed by Fig. 4(b). Conversely, an excess supply on the traded goods market shows up which leads to a depreciation in the terms of trade as can be seen in Fig. 4(e). As shown in Fig. 4(b), the appreciation in the relative price of non-tradables tends to be more pronounced while Fig. 4(e) reveals that the terms of trade depreciate more over time. The greater appreciation in the relative price of non-tradables and the more pronounced depreciation in the terms of trade suggest that aggregate technology shocks are increasingly driven by asymmetric technology improvements between sectors.

The decline in both non-traded and traded hours worked shrinks. By increasing the share of expenditure spent on non-tradables, the appreciation in the relative price of non-tradables displayed by Fig. 4(b) has a strong expansionary effect on labor demand in the non-traded sector. By amplifying the appreciation in non-traded goods prices, the growing variance share of asymmetric technology shocks, as displayed by Fig. 4(d), should increase the impact response of non-traded hours worked to aggregate technology shocks. In accordance with this hypothesis, Fig. 4(c) shows that the decline in non-traded hours worked shrinks over time. However, by giving rise to greater incentives to shift labor toward the non-traded sector, the greater appreciation in the relative price of non-tradables should lead to larger negative values for the response of traded hours worked to a technology improvement. Fig. 4(f) shows that it is not the case as the decline in traded hours worked also shrinks over time. Such a finding is driven by two factors. First, as detailed later in section 4.2, the terms of trade depreciation stimulates labor demand in the traded sector which partly offsets the incentives to shift labor toward the non-traded sector. This factor is not sufficient on its own to generate the time-increasing impact response of L^H. As shown in section 4.4, it is only once we allow for technological change biased toward labor that the model can generate the response of traded hours worked displayed by Fig. 4(f).

3 Open Economy Model with Tradables and Non-Tradables

We consider an open economy with an infinite horizon which is populated by a constant number of identical households and firms, both having perfect foresight. Like Kehoe and Ruhl [2009], Bertinelli et al. [2022], Chodorow-Reich et al. [2023], the country is large enough on world good markets to influence the price of its export goods so that exports are price-elastic. We assume that the open economy takes the world interest rate, $r^\star$, and the world output as given.[4] Our setup is in line with our empirical strategy which aimed at estimating the dynamic adjustment of a representative OECD economy, the technology shocks being uncorrelated across countries. The open economy produces a traded good (denoted by the superscript H) which can be exported, consumed or invested and also imports consumption and investment goods (denoted by the superscript F). The economy produces a non-traded good, denoted by the superscript N, for domestic absorption only. The foreign good is chosen as the numeraire. Time is continuous and indexed by t. We provide more details about the model in Online Appendices N and O.

3.1 Firms

We denote value added in sector j by $Y^j(t)$. Both the traded and non-traded sectors use physical capital (inclusive of capital utilization chosen by households), denoted by $\tilde{K}^j(t) \equiv u^{K,j}(t)K^j(t)$, and labor, $L^j(t)$, according to a constant returns-to-scale technology

[4] Neither the world interest rate nor the world output are found empirically to respond significantly to a country-level technology shock. Monacelli and Perotti [2010] compare numerical results obtained in a small open economy with those obtained under a two-country structure and find that the effects are only slightly different quantitatively.

described by a CES production function:

$$Y^j(t) = \left[\gamma^j \left(A^j(t)L^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right)\left(B^j(t)\tilde{K}^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}, \tag{6}$$

where $0 < \gamma^j < 1$ is the weight of labor in the production technology and σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$. We allow for labor- and capital-augmenting efficiency denoted by $A^j(t)$ and $B^j(t)$. Factor-augmenting productivity is made up of a symmetric component (across sectors) denoted by the subscript S and an asymmetric component denoted by the subscript D:

$$A^j(t) = \left(A^j_S(t)\right)^{\eta}\left(A^j_D(t)\right)^{1-\eta}, \qquad B^j(t) = \left(B^j_S(t)\right)^{\eta}\left(B^j_D(t)\right)^{1-\eta}, \tag{7}$$

where the elasticity of factor-augmenting productivity w.r.t. its symmetric component, denoted by η, captures the share of technology improvements which are uniformly distributed between sectors. The VAR-based decomposition of technology shocks into a symmetric and an asymmetric component imposes that only the symmetric component of utilization-adjusted-TFP must improve at the same rate across sectors. By contrast, the variations in the symmetric component of factor-augmenting productivity can differ across sectors, thus explaining why we do not drop the superscript $j = H, N$ for A^j_S and B^j_S. Because capital-augmenting productivity has a symmetric and an asymmetric component, capital technology utilization rate must also have both a symmetric and asymmetric component:

$$u^{K,j}(t) = \left(u^{K,j}_S(t)\right)^{\eta}\left(u^{K,j}_D(t)\right)^{1-\eta}, \tag{8}$$

which ensures that symmetric and asymmetric components of TFP are well-defined.

Both sectors are assumed to be perfectly competitive and thus choose capital and labor services by taking prices P^j as given. The movements in capital and labor across sectors are subject to frictions which imply that the capital rental cost and the wage rate equal to $R^j(t)$ and $W^j(t)$, respectively, are sector-specific:

$$P^j(t)\gamma^j \left(A^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(L^j(t)\right)^{-\frac{1}{\sigma^j}} \left(Y^j(t)\right)^{\frac{1}{\sigma^j}} \equiv W^j(t), \tag{9a}$$

$$P^j(t)\left(1-\gamma^j\right)\left(B^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(u^{K,j}(t)K^j(t)\right)^{-\frac{1}{\sigma^j}} \left(Y^j(t)\right)^{\frac{1}{\sigma^j}} = R^j(t). \tag{9b}$$

Demand for inputs can be rewritten in terms of their respective cost in value added; for labor, we have $s^j_L(t) = \gamma^j \left(A^j(t)/y^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}}$ where $y^j(t) = Y^j(t)/L^j(t)$. Applying the same logic for capital and denoting the ratio of labor to capital income share by $S^j(t) \equiv \frac{s^j_L(t)}{1-s^j_L(t)}$, we have:

$$S^j(t) \equiv \frac{s^j_L(t)}{1-s^j_L(t)} = \frac{\gamma^j}{1-\gamma^j}\mathrm{FBTC}^j(t)\left(\frac{u^{K,j}(t)K^j(t)}{L^j(t)}\right)^{\frac{1-\sigma^j}{\sigma^j}}, \tag{10}$$

where $\mathrm{FBTC}^j(t) = \left(B^j(t)/A^j(t)\right)^{\frac{1-\sigma^j}{\sigma^j}}$ is utilization-adjusted-factor-biased-technological-change. According to our own estimates and the evidence documented in the literature, e.g., Chirinko and Mallick [2017], Oberfield and Raval [2021], capital and labor are gross complements in production, i.e., $\sigma^j < 1$. An increase in FBTC^j means that technological change is biased toward labor which has an expansionary on labor demand in sector j and thus on the labor income share $s_L^j(t)$.

3.2 Technology Frontier

Following Caselli and Coleman [2006] and Caselli [2016], firms within each sector $j = H, N$ must decide about the split of utilization-adjusted-TFP, $Z^j(t)$, between labor- and capital-augmenting efficiency (i.e., $A^j(t)$ and $B^j(t)$) along a technology frontier:

$$\left[\gamma_Z^j \left(A^j(t)\right)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}} + \left(1 - \gamma_Z^j\right) \left(B^j(t)\right)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}}\right]^{\frac{\sigma_Z^j}{\sigma_Z^j - 1}} \leq Z^j(t), \tag{11}$$

where $Z^j(t) > 0$ is the height of the technology frontier, $0 < \gamma_Z^j < 1$ is the weight of labor efficiency in utilization-adjusted-TFP and $\sigma_Z^j > 0$ corresponds to the elasticity of substitution between labor- and capital-augmenting productivity. Firms choose a mix of labor and capital efficiency so as to minimize the unit cost for producing. The unit cost minimization requires that the contribution of labor-augmenting productivity to technological change in sector j collapses to the LIS, i.e., $s_L^j = \gamma_Z^j \left(\frac{A^j(t)}{Z^j(t)}\right)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}}$ (see Online Appendix D). Inserting this equality into the log-linearized version of the technology frontier (11) shows that technological change in sector j is a factor-income-share-weighted sum of changes in factor-augmenting efficiency:

$$\hat{Z}^j(t) = s_L^j \hat{A}^j(t) + \left(1 - s_L^j\right) \hat{B}^j(t). \tag{12}$$

The structure imposed by eq. (12) on technology improvement is essential as it ensures that technology shocks identified in the empirical part by making use of the utilization-adjusted-Solow residual can potentially be factor-biased. Our approach based on the technological frontier thus gives rise to a clear mapping between factor-augmenting technology shocks (i.e., shocks to $A^j(t)$ and $B^j(t)$) we consider in the theoretical part and shocks to utilization-adjusted TFP (i.e., shocks to $Z^j(t)$) in the empirical part.

Totally differentiating (7), plugging the outcome into (12) and using the fact that aggregate technology improvement is a value-added-share-weighted-average of sectoral technology improvements (see eq. (2)), shows that utilization-adjusted-aggregate-TFP growth can be decomposed into a symmetric and an asymmetric component across sectors:

$$\hat{Z}^A(t) = \eta \hat{Z}_S^A(t) + (1 - \eta)\, \hat{Z}_D^A(t). \tag{13}$$

Note that $\hat{Z}_S^A(t) = \hat{Z}_S^H(t) = \hat{Z}_S^N(t)$ while $\hat{A}_S^H(t) \neq \hat{A}_S^N(t)$, $\hat{B}_S^H(t) \neq \hat{B}_S^N(t)$. In the quantitative analysis, we will explore the effect of an increase in the asymmetric component captured by higher values of $1 - \eta$. It is worth mentioning that $1 - \eta$ is not modelled as a shock and instead is a parameter which captures the changing nature of technological change as the economy is hit by shocks to the symmetric and asymmetric components of factor-augmenting productivity.

3.3 Households

At each instant the representative household consumes traded and non-traded goods denoted by $C^T(t)$ and $C^N(t)$, respectively, which are aggregated by means of a CES function:

$$C(t) = \left[\varphi^{\frac{1}{\phi}} \left(C^T(t)\right)^{\frac{\phi-1}{\phi}} + (1-\varphi)^{\frac{1}{\phi}} \left(C^N(t)\right)^{\frac{\phi-1}{\phi}}\right]^{\frac{\phi}{\phi-1}}, \tag{14}$$

where $0 < \varphi < 1$ is the weight of the traded good in the overall consumption bundle and ϕ corresponds to the elasticity of substitution between traded goods and non-traded goods. The traded consumption index $C^T(t)$ is defined as a CES aggregator of home-produced traded goods, $C^H(t)$, and foreign-produced traded goods, $C^F(t)$:

$$C^T(t) = \left[\left(\varphi^H\right)^{\frac{1}{\rho}} \left(C^H(t)\right)^{\frac{\rho-1}{\rho}} + \left(1-\varphi^H\right)^{\frac{1}{\rho}} \left(C^F(t)\right)^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}}, \tag{15}$$

where $0 < \varphi^H < 1$ is the weight of the home-produced traded good and ρ corresponds to the elasticity of substitution between home- and foreign-produced traded goods.

The representative household supplies labor to the traded and non-traded sectors, denoted by $L^H(t)$ and $L^N(t)$, respectively, which are assumed to be imperfect substitutes (see e.g., Horvath [2000]):

$$L(t) = \left[\vartheta_L^{-1/\epsilon_L} \left(L^H(t)\right)^{\frac{\epsilon_L+1}{\epsilon_L}} + (1-\vartheta_L)^{-1/\epsilon_L} \left(L^N(t)\right)^{\frac{\epsilon_L+1}{\epsilon_L}}\right]^{\frac{\epsilon_L}{\epsilon_L+1}}, \tag{16}$$

where $0 < \vartheta_L < 1$ parametrizes the weight attached to the supply of hours worked in the traded sector and ϵ_L is the elasticity of substitution between sectoral hours worked. Like labor, we generate imperfect capital mobility by assuming that traded $K^H(t)$ and non-traded $K^N(t)$ capital stock are imperfect substitutes:

$$K(t) = \left[\vartheta_K^{-1/\epsilon_K} \left(K^H(t)\right)^{\frac{\epsilon_K+1}{\epsilon_K}} + (1-\vartheta_K)^{-1/\epsilon_K} \left(K^N(t)\right)^{\frac{\epsilon_K+1}{\epsilon}}\right]^{\frac{\epsilon_K}{\epsilon_K+1}}, \tag{17}$$

where $0 < \vartheta_K < 1$ is the weight of capital supply to the traded sector in the aggregate capital index $K(.)$ and ϵ_K measures the ease with which sectoral capital can be substituted for each other and thereby captures the degree of capital mobility across sectors.

The representative agent is endowed with one unit of time, supplies a fraction $L(t)$ as labor, and consumes the remainder $1 - L(t)$ as leisure. Denoting the time discount rate by $\beta > 0$, at any instant of time, households derive utility from their consumption and experience disutility from working and maximize the following objective function:

$$\mathcal{U} = \int_0^{\infty} \Lambda\left(C(t), L(t)\right) e^{-\beta t} \mathrm{d}t, \tag{18}$$

where we consider the utility specification proposed by Shimer [2009]:

$$\Lambda\left(C,L\right) \equiv \frac{C^{1-\sigma}V(L)^{\sigma}-1}{1-\sigma}, \quad \text{if} \quad \sigma \neq 1, \quad V(L) \equiv \left(1+(\sigma-1)\gamma\frac{\sigma_L}{1+\sigma_L}L^{\frac{1+\sigma_L}{\sigma_L}}\right). \tag{19}$$

These preferences are characterized by two crucial parameters: σ_L is the Frisch elasticity of labor supply, and $\sigma > 0$ determines the substitutability between consumption and leisure; if $\sigma > 1$, the marginal utility of consumption is increasing in hours worked. The inverse of σ collapses to the intertemporal elasticity of substitution for consumption. When we let σ equal to one, the felicity function is additively separable in consumption and labor,

Households supply labor $L(t)$ and capital services $K(t)$ and, in exchange, receive an aggregate wage rate $W(t)$ and an aggregate capital rental rate $R^K(t)$. Households choose the level of capital utilization in sector j, which includes both a symmetric and an asymmetric component, i.e., $u_S^{K,j}(t)$ and $u_D^{K,j}(t)$ (see eq. (8)). Both components of the capital utilization rate collapse to one at the steady-state. The capital utilization adjustment costs are assumed to be an increasing and convex function of the capital utilization rate $u_c^{K,j}(t)$:

$$C_c^{K,j}(t) = \xi_{1,c}^j\left(u_c^{K,j}(t)-1\right) + \frac{\xi_{2,c}^j}{2}\left(u_c^{K,j}(t)-1\right)^2, \qquad c = S, D, \quad j = H, N, \tag{20}$$

where the subscript $c = S$ ($c = D$) refers to the symmetric (asymmetric) component and $\xi_{2,c}^j > 0$ is a free parameter; letting $\xi_{2,c}^j \to \infty$ implies that $u_c^{K,j}$ is fixed at unity.

Households can accumulate internationally traded bonds (expressed in foreign good units), $N(t)$, that yield net interest rate earnings of $r^{\star}N(t)$. The household's flow budget constraint below states that real disposable income can be saved by accumulating traded bonds, $\dot{N}(t)$, can be consumed, $P_C(t)C(t)$, invested, $P_J(t)J(t)$, or cover capital utilization adjustment costs:

$$\begin{aligned} \dot{N}(t) \quad & + P_C(t)C(t) + P_J(t)J(t) + \sum_{j=H,N} P^j(t)\left(C_S^{K,j}(t) + C_D^{K,j}(t)\right)\nu^{K,j}(t)K(t) \\ = \quad & r^{\star}N(t) + W(t)L(t) + R^K(t)K(t)\sum_{j=H,N}\alpha_K^j(t)\left(u_S^{K,j}(t)\right)^{\eta}\left(u_D^{K,j}(t)\right)^{1-\eta}, \end{aligned} \tag{21}$$

where $P_C(t)$ ($P_J(t)$) is the consumption (investment) price index; we denote the share of sectoral capital in the aggregate capital stock by $\nu^{K,j}(t) = K^j(t)/K(t)$ and the capital compensation share in sector $j = H, N$ by $\alpha_K^j(t) = \frac{R^j(t)K^j(t)}{R^K(t)K(t)}$.

Installation of new investment goods involves convex costs, assumed to be quadratic. Thus, total investment $J(t)$ differs from effectively installed new capital:

$$J(t) = I(t) + \frac{\kappa}{2}\left(\frac{I(t)}{K(t)} - \delta_K\right)^2 K(t), \tag{22}$$

where the parameter $\kappa > 0$ governs the magnitude of adjustment costs to capital accumulation. Denoting the fixed capital depreciation rate by $0 \leq \delta_K < 1$, aggregate investment, $I(t)$, gives rise to capital accumulation according to the dynamic equation:

$$\dot{K}(t) = I(t) - \delta_K K(t). \tag{23}$$

As in Fernández de Córdoba and Kehoe [2000], the investment good inclusive of installation expenditure, $J(t)$, is (costlessly) produced by using traded and non-traded inputs, i.e., $J^T(t)$ and $J^N(t)$, which are aggregated by means of a CES technology with an elasticity of substitution denoted by ϕ_J. The traded investment good (inclusive of installation) costs is a CES aggregator of home-produced traded inputs, $J^H(t)$, and foreign-produced traded inputs, $J^F(t)$, with an elasticity of substitution ρ_J.

Households choose consumption, worked hours, capital utilization rates, investment in physical capital and traded bonds by maximizing lifetime utility (18) subject to (21) and (23). Denoting by λ and Q' the co-state variables associated with the budget constraint and law of motion of physical capital, the first-order conditions characterizing the representative household's optimal plans are:

$$C(t)^{-\sigma} V(t)^{\sigma} = P_C(t)\lambda(t), \tag{24a}$$

$$C(t)^{1-\sigma} V(t)^{\sigma} \gamma L(t)^{\frac{1}{\sigma_L}} = \lambda(t) W(t), \tag{24b}$$

$$Q(t) = P_J(t)\left[1 + \kappa\left(\frac{I(t)}{K(t)} - \delta_K\right)\right], \tag{24c}$$

$$\dot{\lambda}(t) = \lambda\left(\beta - r^{\star}\right), \tag{24d}$$

$$\dot{Q}(t) = \left(r^{\star} + \delta_K\right) Q(t) - \Bigg\{ \sum_{j=H,N} \alpha_K^j(t) u^{K,j}(t) R^K(t)$$
$$- \sum_{j=H,N} P^j(t)\left(C_S^{K,j}(t) + C_D^{K,j}(t)\right)\nu^{K,j}(t) - P_J(t)\frac{\partial J(t)}{\partial K(t)}\Bigg\}, \tag{24e}$$

$$\frac{R^j(t)}{P^j(t)} \eta \frac{u^{K,j}(t)}{u_S^{K,j}(t)} = \xi_{1,S}^j + \xi_{2,S}^j\left(u_S^{K,j}(t) - 1\right), \quad j = H, N, \tag{24f}$$

$$\frac{R^j(t)}{P^j(t)}\left(1-\eta\right)\frac{u^{K,j}(t)}{u_D^{K,j}(t)} = \xi_{1,D}^j + \xi_{2,D}^j\left(u_D^{K,j}(t) - 1\right), \quad j = H, N, \tag{24g}$$

and the transversality conditions $\lim_{t\to\infty} \bar{\lambda} N(t) e^{-\beta t} = 0$ and $\lim_{t\to\infty} Q(t)K(t)e^{-\beta t} = 0$. To derive (24c) and (24e), we used the fact that $Q(t) = Q'(t)/\lambda(t)$. We impose $\beta = r^{\star}$ in order to generate an interior solution which implies that when new information about a shock arrives, λ jumps to fulfill the intertemporal solvency condition and remains constant afterwards.

Once households have chosen consumption, they allocate optimally a share $1 - \alpha_C$ of their consumption expenditure to non-traded goods:

$$1 - \alpha_C(t) = \frac{P^N(t)C^N(t)}{P_C(t)C(t)} = (1-\varphi)\left(\frac{P^N(t)}{P_C(t)}\right)^{1-\phi}. \tag{25}$$

According to eq. (25), as long as $\phi < 1$, as evidence suggests, a depreciation in non-traded goods prices $P^N(t)$ drives down the share of expenditure allocated to non-traded goods while an appreciation in $P^N(t)$ increases $1 - \alpha_C$. This assumption ensures that symmetric technology shocks have a negative impact on $L^N(t)$ while asymmetric technology improvements have a strong expansionary effect on non-traded hours worked, in accordance with our empirical findings. However, the assumption $\phi < 1$ alone without frictions into the movements of inputs leads the model to considerably overstate the shift of productive resources to the non-traded sector. To generate the reallocation of productive we estimate empirically, especially labor, we allow for capital adjustment costs which mitigate the investment boom in the non-traded sector (and thus the shift of labor toward this sector) following a technology shock. The second source of frictions originates from labor and capital mobility costs across sectors as captured by $0 < \epsilon_L < \infty$ and $0 < \epsilon_K < \infty$:

$$L^N/L = (1-\vartheta_L)\left(W^N/W\right)^{\epsilon_L} \qquad K^N/K = (1-\vartheta_K)\left(R^N/R^K\right)^{\epsilon_K}, \tag{26}$$

where mobility costs are larger when ϵ_L and ϵ_K take lower values.

The third source of frictions comes from home bias in the domestic traded good. This assumption implies that the rise in imports is mitigated following a technology improvement compared with a situation where home- and foreign-produced traded goods would be perfect substitutes. The mechanism rests on the terms of trade depreciation caused by the technology shock which leads households to substitute home- for foreign-produced traded goods. For the terms of trade to depreciate, the price-elasticity of the demand for home-produced traded goods must be larger than one. A sufficient condition for this is $\rho > \frac{1}{\alpha^H}$ where α^H is the home content of consumption expenditure in traded goods. Home bias ensures that this condition can be fulfilled for values of ρ falling in the range of empirical estimates. Because the demand for home-produced traded goods has also a foreign component (i.e., exports), the condition is less stringent, i.e., $\phi_X + \alpha^H \rho > 1$ where ϕ_X is the price-elasticity of exports.[5] This condition ensures that the terms of trade depreciate whether technology improves at the same rate across sectors, i.e., $\hat{Z}^H(t) = \hat{Z}^N(t)$, or is concentrated within traded industries, i.e., $\hat{Z}^H(t) > \hat{Z}^N(t)$. Intuitively, when (domestic and/or foreign) demand for home-produced traded goods is elastic enough w.r.t. the terms of trade, it is optimal for traded firms to lower prices to sell additional units of the home-produced traded good because the decline in P^H is covered by the fall in the marginal cost. By stimulating the demand for home-produced traded goods, the terms of trade depreciation amplifies the rise in the share of tradables (i.e., α_C takes higher values) when technology improves at the same rate in both sectors, or mitigates the decline in α_C when technology improvements are concentrated within traded industries. The terms of trade depreciation thus either amplifies the labor inflow in the traded sector or mitigates the labor outflow experienced by traded industries.

[5]This condition is derived by abstracting from physical capital otherwise the model would be analytically untractable. Since we are interested in impact effects and capital is a state variable which remains unchanged on impact, abstracting from physical capital serves our purpose. Analytical derivations are available from the authors upon request.

3.4 Model Closure and Equilibrium

Market clearing conditions and the current account. To fully describe the equilibrium, denoting exports of home-produced goods by X^H, we impose goods market clearing conditions for non-traded and home-produced traded goods:

$$Y^N(t) = C^N(t) + J^N(t) + \left(C_S^{K,N}(t) + C_D^{K,N}(t)\right) K^N(t), \tag{27a}$$

$$Y^H(t) = C^H(t) + J^H(t) + X^H(t) + \left(C_S^{K,H}(t) + C_D^{K,H}(t)\right) K^H(t), \tag{27b}$$

where investment expenditure are inclusive of installation costs (thus explaining why we use J instead of I to refer to investment) and exports are assumed to be a decreasing function of the terms of trade, P^H:

$$X^H(t) = \varphi_X \left(P^H(t)\right)^{-\phi_X}, \tag{28}$$

where $\varphi_X > 0$ is a scaling parameter and ϕ_X is the price-elasticity of exports. Using the properties of constant returns to scale in production, $P_C(t)C(t) = \sum_g P^g(t)C^g(t)$ and $P_J(t)J(t) = \sum_g P^g(t)J^g(t)$ (with $g = F, H, N$), and market clearing conditions (27), the current account equation (21) can be rewritten as a function of the trade balance:

$$\dot{N}(t) = r^\star N(t) + P^H(t)X^H(t) - M^F(t), \tag{29}$$

where $M^F(t) = C^F(t) + G^F(t) + J^F(t)$ stands for imports.

Setting the dynamics of factor-augmenting productivity. We drop the time index below to denote steady-state values. Eq. (12) shows that technology improvements are driven by the dynamics of labor- and capital-augmenting efficiency, i.e., $\hat{Z}^j(t) = s_L^j \hat{A}^j(t) + \left(1 - s_L^j\right) \hat{B}^j(t)$. In the same spirit as Galí [1999], we abstract from trend growth and consider a technology shock that increases permanently utilization-adjusted-TFP.[6] Because we want to assess the ability of the model to reproduce the response of hours we estimate empirically, we generate the same technology adjustment we get after a permanent increase in utilization-adjusted-TFP of 1% in the long-run. Since we consider symmetric and asymmetric technology shocks, we have to set the dynamics of labor- and capital-augmenting efficiency for both shocks. Denoting the factor-augmenting efficiency by $X_c^j = A_c^j, B_c^j$ for symmetric ($c = S$) and asymmetric technology shocks ($c = D$), respectively, the adjustment of $X_c^j(t)$ toward its long-run level X_c^j expressed in percentage deviation from initial steady-state is governed by the following continuous time process:

$$\hat{X}_c^j(t) = \hat{X}_c^j + e^{-\xi_{X,c}^j t} - \left(1 - x_c^j\right) e^{-\chi_{X,c}^j t}, \quad X_c^j = A_c^j, B_c^j, \quad c = S, D, \quad j = H, N, \tag{30}$$

[6] We assume that the economy starts from an initial steady-state and is hit by a permanent technology improvement like in the empirical part where we estimate the deviation of hours relative to its initial steady-state following a permanent increase in utilization-adjusted-TFP. In the same spirit as Galí [1999], the accumulation of permanent technology shocks gives rise to a unit root in the time series for utilization-adjusted-aggregate-TFP, an assumption we use implicitly to identify a permanent technology shock in the empirical part. We do not characterize the convergence of the economy toward a balanced growth path which is supposed to exist, in line with the theoretical findings by Kehoe et al. [2018] who let the labor intensity of production vary across sectors.

where $x_c^j = \hat{X}_c^j(0) - \hat{X}_c^j$, and both parameters $\xi_{X,c}^j > 0$ and $\chi_{X,c}^j > 0$ measure the speed at which productivity closes the gap with its long-run level. When $\xi_{X,c}^j \neq \chi_{X,c}^j$ (with $c = S, D$), the above law of motion allows us to generate a hump-shaped adjustment of factor-augmenting productivity in accordance with the non-monotonic adjustment found in the data. Letting time tend toward infinity into (30) leads to $\hat{X}_c^j(\infty) = \hat{X}_c^j$ where $\hat{X}_c^j$ is the steady-state (permanent) change in factor-augmenting efficiency in percentage. Inserting (30) into the log-linearized version of the technology frontier allows us to recover the dynamics of utilization-adjusted-TFP in sector j, i.e., $\hat{Z}_c^j(t) = s_L^j \hat{A}_c^j(t) + \left(1 - s_L^j\right) \hat{B}_c^j(t)$, which converges toward its new higher steady-state level.

Solving the model. The adjustment of the open economy toward the steady state is described by a dynamic system which comprises two equations that are functions of $K(t)$, $Q(t)$, and the vector of factor-augmenting productivity $V_S(t) = \left(A_S^H(t), B_S^H(t), A_S^N(t), B_S^N(t)\right)$ and $V_D(t) = \left(A_D^H(t), B_D^H(t), A_D^N(t), B_D^N(t)\right)$:

$$\dot{K}(t) = \Upsilon\left(K(t), Q(t), V_S(t), V_D(t)\right), \quad \dot{Q}(t) = \Sigma\left(K(t), Q(t), V_S(t), V_D(t)\right). \tag{31}$$

Linearizing the dynamic equations (31) in the neighborhood of the steady-state and inserting the law of motion of symmetric and asymmetric components of factor-augmenting efficiency (30) leads to a system of first-order linear differential equations which can be solved by applying standard methods. In Online Appendix P, we detail the application of the continuous time adaptation by Buiter [1984] of the solution method pioneered by Blanchard and Kahn [1980].

4 Quantitative Analysis

In this section, we take the model to the data. For this purpose we solve the model numerically.[7] Therefore, first we discuss parameter values before turning to the effects of symmetric and asymmetric technology shocks across sectors and contrasting them with responses estimated empirically after technology shocks.

4.1 Calibration

Calibration strategy. At the steady-state, capital utilization rates, $u^{K,j}$, collapse to one so that $\tilde{K}^j = K^j$. We consider an initial steady-state with Hicks-neutral technological change and normalize $A^j = B^j = Z^j$ to 1. To ensure that the initial steady-state with CES production functions is invariant when σ^j is changed, we normalize CES production functions by choosing the initial steady-state in a model with Cobb-Douglas production functions as the normalization point. Once we have calibrated the initial steady-state with Cobb-Douglas production functions, we assign values to σ^j in accordance with our

[7]Technically, the assumption $\beta = r^\star$ requires the joint determination of the transition and the steady state since the constancy of the marginal utility of wealth implies that the intertemporal solvency condition depends on eigenvalues' and eigenvectors' elements, see e.g., Turnovsky [1997].

estimates and the CES economy is endogenously calibrated to reproduce the ratios of the Cobb-Douglas economy.

To calibrate the reference model that we use to normalize the CES economy, we have estimated a set of ratios and parameters for the seventeen OECD economies in our dataset, see Table 8 relegated to Online Appendix J.1. Our reference period for the calibration is 1970-2017. Because we calibrate the reference model to a representative OECD economy, we take unweighted average values of ratios and parameters which are summarized in Table 1. Among the 25 parameters that the model contains, 13 have empirical counterparts while the remaining 12 parameters plus initial conditions must be endogenously calibrated to match ratios. For the purposes of calibration, we add government spending, $G(t)$, made up of spending on non-traded goods, G^N, and on home- and foreign-produced traded goods, G^H and G^F, i.e., $G(t) \equiv P^N(t)G^N(t)+P^H(t)G^H(t)+G^F(t) = T(t)$, where $T(t)$ is lump-sum taxes.

Twelve parameters plus initial conditions must be set to target ratios. Parameters φ and ι, are set to 0.51 and 0.32 to target a tradable content of consumption and investment expenditure of $\alpha_C = 43\%$ and $\alpha_J = 32\%$, respectively. Parameters φ^H, ι^H are set to 0.71 and 0.49 to target a home content of consumption and investment expenditure in tradables of $\alpha^H = 66\%$ and $\alpha_J^H = 42\%$, respectively. We set ϑ_L and ϑ_K to 0.38 and 0.39 to target a weight of labor supply and capital supply to the traded sector of $L^H/L = 36\%$ and $K^H/K = 39\%$, respectively. We choose a value of 0.062 for the capital depreciation rate δ_K to target an investment-to-GDP ratio of $\omega_J = 23\%$. We choose values for G, G^N and G^H to target a ratio of government spending to GDP of $\omega_G = 20\%$ $(= G/Y)$, a tradable and home-tradable share of government spending of $\omega_{G^T} = 16\%$ $(= 1-(P^NG^N/G))$, and $\omega_{G^H} = 12\%$ $(= P^HG^H/G)$; initial conditions are chosen so as trade is balanced. Because $u^{K,j} = 1$ at the steady-state, two parameters related to adjustment cost functions of capital utilization, i.e., ξ_1^H and ξ_1^N, are set to be equal to real capital rental rates in the traded and the non-traded sector, i.e., $R^H/P^H = 0.088$ and $R^N/P^N = 0.072$, respectively.

Six parameters are assigned values which are taken directly or estimated from our own data. We choose the model period to be one year. In accordance with the last column of Table 1, the world interest rate, $r^\star$, which is equal to the subjective time discount rate, β, is set to 2.7%. In line with mean values shown in columns 11 and 12 of Table 1, the shares of labor income in traded and non-traded value added, s_L^H and s_L^N, are set to 0.63 and 0.69, respectively, which leads to an aggregate labor income share of 66%.

We have estimated empirically the degree of labor mobility between sectors, ϵ_L, for one country at a time. As shown in Online Appendix J.2 where we derive a structural equation, we pin down ϵ_L by running the regression in panel format on annual data of the percentage change in the hours worked share of sector j on the percentage change in the relative share of value added paid to labor in sector j over 1970-2017. The degree of labor mobility across sectors is set to 0.8, in line with the average of our estimates (see column 17 of Table 1). This value is close to the value of 1 (estimated by Horvath [2000] on U.S. data) commonly chosen in the literature allowing for imperfect mobility of labor. We have also estimated the degree of mobility of capital across sectors by running the regression of the percentage change in K^j_{it}/K_{it} on the percentage change in the relative share of value added paid to capital in sector j over 1970-2017. We choose a degree of capital mobility across sectors of 0.15, in line with the average of our estimates (see column 18 of Table 1).

To pin down the elasticity of substitution between traded and non-traded consumption goods ϕ, we use the optimal allocation of consumption expenditure between C^T and C^N (see eq. (25)) and run the regression of the logged share of non-tradables on logged $P^N(t)/P_C(t)$. Time series for $1-\alpha_C(t)$ are constructed by using the market clearing condition for non-tradables. Building on our panel data estimates, the elasticity of substitution ϕ between traded and non-traded goods is set to 0.35 (see column 13 of Table 1), since this value corresponds to our panel data estimates, see Online Appendix J.5. This value is close to the estimated elasticity by Stockman and Tesar [1995] who report a value of 0.44 by using cross-section data for the year 1975.

Seven parameters are taken from external research works. As pointed out recently by Best et al. [2020], there exists no consensus on a reasonable value for the intertemporal elasticity of substitution for consumption as estimates in the literature range between 0 and 2. We choose a value of $\sigma = 2$ which implies that consumption and leisure are substitutes and the intertemporal elasticity of substitution for consumption is equal to 0.5. In line with the estimates recently documented by Peterman [2016], we set the Frisch elasticity of labor supply σ_L to 3. We choose the value of parameter κ which captures the magnitude of capital adjustment costs so that the elasticity of I/K with respect to Tobin's q, i.e., Q/P_J, is equal to the value implied by estimates in Eberly et al. [2008]. The resulting value of κ is equal to 17.

In line with the empirical findings documented by Bems [2008] who finds that the non-tradable content of investment expenditure is stable in OECD countries, we set the elasticity of substitution, ϕ_J, between J^T and J^N to 1. We set the elasticity of substitution in consumption (investment), ρ (ρ_J), between home- and foreign-produced traded goods (inputs) to 1.3 (see columns 14-15 of Table 1) which fits estimates by Bertinelli et al. [2022] who find a value of 1.3 for $\rho = \rho_J$ for OECD countries which is close to the value of 1.5 chosen by Backus et al. [1994]. Assuming that all countries have the same elasticities, since the price elasticity of exports is a weighted average of ρ and ρ_J, we set $\phi_X = 1.3$ (see column 16 of Table 1). A value larger than one is in line with the structural estimates of the price elasticities of aggregate exports documented by Imbs and Mejean [2015].

Table 1: Data to Calibrate the Two-Sector Open Economy Model

Tradable share						Home share				Labor Share	
GDP	Cons.	Inv.	Gov.	Labor	Capital	X^H	C^H	I^H	G^H	LIS^H	LIS^N
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
0.36	0.43	0.32	0.20	0.36	0.39	0.13	0.66	0.42	0.12	0.63	0.69
Elasticities								Aggregate ratios			
ϕ	ρ	ρ_J	ϕ_X	ϵ_L	ϵ_K	σ^H	σ^N	LIS	I/Y	G/Y	$r^\star$
(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
0.35	1.30	1.30	1.30	0.80	0.15	0.81	0.86	0.66	0.23	0.20	0.027

Notes: Columns 1-5 show the GDP share of tradables, the tradable content of consumption, investment and government expenditure, the tradable content of hours. Column 6 gives the ratio of exports of final goods and services to GDP; columns 7 and 8 show the home share of consumption and investment expenditure in tradables and column 9 shows the content of government spending in home-produced traded goods; LIS^j stands for the labor income share in sector $j = H, N$ while LIS refers to the aggregate LIS; I/Y is the investment-to-GDP ratio and G/Y is government spending as a share of GDP. The real interest rate is the real long-term interest rate calculated as the nominal interest rate on 10 years government bonds minus the rate of inflation which is the rate of change of the Consumption Price Index.

Calibrating the CES economy. To calibrate the CES economy, we proceed as follows. First, we choose the same values for the thirteen parameters which have empirical counterparts as above, except for the labor income shares which are now endogenously calibrated. Thus in addition to σ, σ_L, κ, ϕ_J, ρ, ρ_J, ϕ_X, $r^\star$, ϵ_L, ϵ_K, ϕ, we have to choose values for the elasticity of substitution between capital and labor for tradables and non-tradables, σ^H and σ^N. We estimate σ^H and σ^N over 1970-2017 on panel data so as to have consistent estimates in accordance with our classification of industries as tradables and non-tradables and sample composition. In line with our panel data estimates, we choose $\sigma^H = 0.81$ and $\sigma^N = 0.86$ (see columns 19 and 20 of Table 1).

Given the set of elasticities above, the remaining parameters are set so as to maintain the steady-state of the CES economy equal to the normalization point. Therefore, we calibrate the model with CES production functions so that sixteen parameters φ, ι, φ^H, ι^H, ϑ_L, ϑ_K, δ_K, G, G^N, G^H, N_0, K_0, Z^H, Z^N, γ^H, γ^N are endogenously set to target $1-\bar{\alpha}_C$, $1-\bar{\alpha}_J$, $\bar{\alpha}^H$, $\bar{\alpha}^H_J$, $\bar{L}^N/\bar{L}$, $\bar{K}^N/\bar{K}$, $\bar{\omega}_J$, $\bar{\omega}_G$, $\bar{\omega}_{G^N}$, $\bar{\omega}_{G^H}$, $\bar{\upsilon}_{NX}$, $\bar{K}$, $\bar{y}^H$, $\bar{y}^N$, $\bar{s}^H_L$, $\bar{s}^N_L$, respectively, where a bar indicates that the ratio is obtained from the Cobb-Douglas economy. In addition, we have to set the dynamic processes of factor-augmenting-efficiency and capital utilization rates.

Share η of symmetric technology shocks across sectors. Before setting the dynamic processes of symmetric and asymmetric technology shocks, we have to calibrate the share η of symmetric technology shocks across sectors. By using the fact that the adjustment in utilization-adjusted-aggregate-TFP, $\hat{Z}^A(t)$, following an aggregate technology shock must collapse to its adjustment driven by symmetric and asymmetric technology shocks, we choose the value of η minimizing the discrepancy between these two adjustments. We find a value of $\eta = 0.6$, see Online Appendix J.8 for more details.

Capital utilization adjustment costs. We set the magnitude of the adjustment cost in the capital utilization rate, i.e., $\xi^j_{2,c}$, in eqs. (24f)-(24g), so as to account for empirical responses of $u_S^{K,j}(t)$ and $u_D^{K,j}(t)$, conditional on symmetric and asymmetric technology shocks across sectors, respectively. We set $\xi^H_{2,S} = 0.5$ and $\xi^N_{2,S} = 0.6$ when technology shocks are symmetric and $\xi^H_{2,D} = 0.03$ and $\xi^N_{2,D} = 0.5$ when technology shocks are asymmetric between sectors.

Factor-augmenting efficiency. Since the response of hours in Fig. 2(e) we estimate empirically is conditional on the dynamic process of the technology shock shown in Fig. 2(a), we have to generate a shock which displays the same dynamic properties and is also consistent with the productivity differential shown in Fig. 2(b). Moreover, because our empirical findings show that technology shocks are factor-biased, we calibrate (the symmetric and asymmetric components of) the adjustment in factor-augmenting efficiency described by eq. (30). But we have only estimates of utilization-adjusted-TFP and thus we have to first recover the dynamics of factor-augmenting technology improvements in the data by adopting a wedge analysis, in the same spirit as Caselli and Coleman [2006]. To avoid confusion, we add below the superscript 'data' to make the distinction with numerical estimates. As detailed in Online Appendix J.10, the log-linearized versions of labor (relative to capital) demand (10) and of the technology frontier (12) can be solved for deviations of $A_c^{j,data}(t)$ and $B_c^{j,data}(t)$ relative to their initial values:

$$\hat{A}_c^{j,data}(t) = \hat{Z}_c^{j,data}(t) - \left(1 - s_L^j\right) \Gamma^{j,data}(t), \tag{32a}$$

$$\hat{B}_c^{j,data}(t) = \hat{Z}_c^{j,data}(t) + s_L^j \Gamma^{j,data}(t), \tag{32b}$$

where we have set

$$\Gamma^{j,data}(t) \equiv \left[\left(\frac{\sigma^j}{1-\sigma^j}\right) \hat{S}_c^{j,data}(t) - \hat{k}_c^{j,data}(t) - \hat{u}_c^{K,j,data}(t)\right].$$

We plug estimated values for σ^j and empirically estimated responses for $S_c^{j,data}(t) = \frac{s_{L,c}^{j,data}(t)}{1-s_{L,c}^{j,data}(t)}$, $k_c^{j,data}(t)$, $u_c^{K,j,data}(t)$ following a symmetric ($c = S$) or asymmetric ($c = D$) technology shock across sectors into above equations to infer the dynamics of $A_c^{j,data}(t)$ and $B_c^{j,data}(t)$. Then, we choose parameters x_c^j, $\xi_{X,c}^j$, $\chi_{X,c}^j$ in eq. (30) so as to reproduce the dynamics of $A_c^{j,data}(t)$ and $B_c^{j,data}(t)$. Calibrated shocks to $A_c^j(t)$ and $B_c^j(t)$ give rise to the dynamic adjustment in utilization-adjusted-TFP in sector j $\hat{Z}_c^j(t) = s_L^j \hat{A}_c^j(t) + \left(1 - s_L^j\right) \hat{B}_c^j(t)$ (see eq. (12)). While Online Appendix J.11 shows the fit of the calibrated technology shock processes to the data for $\hat{Z}_c^j(t)$ and utilization-adjusted-factor-biased productivity, Online Appendix J.10 shows the values chosen to calibrate the shocks to $\hat{A}_c^j(t)$ and $\hat{B}_c^j(t)$.

4.2 Decomposition of Model's Performance

In this subsection, we analyze the role of the model's ingredients in driving the effects of a permanent technology improvement on hours. We show that the ability of the model to generate the decline in hours (on impact) by -0.15% we estimate empirically depends on the two-sector dimension and the open economy aspect of the setup.

Our baseline model includes four sets of elements. The first set is related to the biasedness of technology improvements toward traded industries together with the gross complementarity between traded and non-traded goods (i.e., $\phi < 1$). The second set of elements is related to barriers to factors' mobility which include labor mobility costs and costs of switching capital from one sector to another (i.e., $0 < \epsilon_L < \infty$ and $0 < \epsilon_K < \infty$). The third set of factors is related to trade openness, as reflected into imperfect substitutability between home- and foreign-produced traded goods (i.e., $0 < \rho < \infty$, $0 < \rho_J < \infty$, $0 < \phi_X < \infty$) which influences the extent of foreign borrowing. The fourth set of elements is related to an endogenous intensity in the use of physical capital (i.e., $0 < \xi^j_{2,c} < \infty$), and technology improvements which are factor-biased at a sector level (i.e., $\hat{A}^j_c(t) \neq \hat{B}^j_c(t)$).

To understand (and quantify) the role of each element, we first consider the simplest version of our model and add one ingredient at a time. This restricted version shown in column 7 of Table 2 collapses to the international RBC model by Fernández de Córdoba and Kehoe [2000] (FK henceforth) who consider a small open economy setup with tradables and non-tradables together with capital adjustment costs. In column 6, we allow for both labor and capital mobility costs across sectors. In column 5, we assume that home- and foreign-produced traded goods are imperfect substitutes. In column 2, we allow for CES production functions, FBTC and endogenous capital utilization. This model collapses to our baseline setup. We will discuss later the effects of symmetric and asymmetric technology shocks which are displayed by columns 3 and 4.

Table 2 reports the impact effect of selected variables, including total hours worked, $L(t)$, traded and non-traded hours worked, $L^H(t)$ and $L^N(t)$, the hours worked share of tradables, $\nu^{L,H}(t)$, the relative price of non-tradables and the terms of trade, $P(t)$ and $P^H(t)$. To further illustrate the transmission mechanism, we also show the adjustment in the real value added share of tradables, $d\nu^{Y,H}(t)$, the value added share of non-tradables at current prices, $d\omega^{Y,N}(t)$, and the current account, $CA(t)$. For comparison purposes, the first column displays the impact response of the corresponding variable which is estimated empirically by means of local projections which should be contrasted with the responses computed numerically shown in columns 2,5,6,7.

While we normalize the technology improvement to 1% in the long-run, panel A of Table 2 shows the adjustment of aggregate, traded and non-traded utilization-adjusted-TFP on impact. As shown in columns 2, 5, 6, 7, all model variants generate an increase in utilization-adjusted-aggregate-TFP by 0.94% on impact in line with the evidence and give rise to a technology improvement in tradables and non-tradables of 1.66% and 0.56% close to our estimates.

First ingredient: Barriers to factors' mobility. In column 7 of Table 2, we report results from a restricted version of the baseline model where we consider a two-sector small open economy model with capital adjustment costs which collapses to the FK model. In this model's version, home- and foreign-produced traded goods are perfect substitutes so that terms of trade are exogenous (and constant over time). Labor and capital can move freely across sectors. Production functions are Cobb-Douglas so that technological change is Hicks-neutral. We also abstract from endogenous capital utilization rates.

Contrasting the model's predictions shown in column 7 with empirically estimated values reported in column 1, the restricted version of the model substantially overstates the decline in total hours worked. Intuitively, as long as home- and foreign-produced goods are perfect substitutes, it is optimal to import traded goods and reallocate labor (and capital) toward the non-traded sector. Because labor and capital are not subject to mobility costs, the hours worked share of tradables falls dramatically by -0.33 percentage point of total hours worked, thus leading the restricted model to generate a decline in traded hours worked by -0.57 ppt of total hours worked while we empirically find a fall by -0.04 ppt only. The corollary of the shift of resources toward the non-traded sector and the surge of imports is that the open economy runs a large current account deficit, see panel E. Under these assumptions, households find it optimal to lower hours worked (see the first line of panel B) by -0.7%, a magnitude which is more than four time larger than the decline we estimate empirically (i.e., -0.15%) because the model considerably overstates the current account deficit (-0.38 ppt of GDP instead of -0.03 ppt of GDP).

In column 6, we consider the same model as in column 7 except that we allow for both labor and capital mobility costs. The frictions into the movements of factors substantially mitigate the shift of productive resources toward the non-traded sector. In particular, as shown in the last line of panel B, the decline in the hours worked share of tradables shrinks from -0.33 ppt of total hours worked (column 7) to -0.14 ppt (column 6). Because less productive resources move toward the non-traded sector, households must give up a significant share of the rise in leisure, thus resulting in a shrinking decline in total hours worked to meet the demand for non-traded goods. The fall in hours by -0.42% is still too large compared with what we estimate empirically (i.e., -0.15%).

Second ingredient: Imperfect substitutability between home- and foreign-produced traded goods. As shown in column 5, the ability of the model to account for the evidence improves once we allow for imperfect substitutability between home- and foreign-produced traded goods. More specifically, as households are getting more reluctant to substitute imported goods for domestic goods, there is a shift of demand toward home-produced traded goods. The reallocation of labor toward non-traded industries further shrinks from -0.14 ppt to -0.06 ppt of total hours worked (see the fourth row of panel B). Therefore the fall in traded hours worked is significantly mitigated because as shown in the second row of panel C, the terms of trade depreciate by -1.15% (close to what

Table 2: Impact Effects of a Technology Improvement on Hours

	Data	CES: FBTC and uK			CD: IM & TOT	CD: IML & IMK	CD: PM
	LP	AGG	SYM	ASYM	AGG	AGG	AGG
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A.Technology							
Aggregate technology, $dZ^A(t)$	0.93	0.94	1.19	0.58	0.95	0.95	0.95
T technology, $dZ^H(t)$	1.53	1.66	1.06	2.57	1.66	1.66	1.66
N technology, $dZ^N(t)$	0.55	0.56	1.26	-0.50	0.56	0.56	0.56
T capital utilization, $du^{K,H}(t)$	-0.24	-0.11	0.09	-1.81	0.00	0.00	0.00
N capital utilization, $du^{K,N}(t)$	0.12	0.03	0.11	0.00	0.00	0.00	0.00
B.Hours							
Hours, $dL(t)$	-0.15	-0.07	-0.40	0.28	-0.26	-0.42	-0.70
Traded Hours, $dL^H(t)$	-0.04	-0.03	-0.11	-0.02	-0.15	-0.28	-0.57
Non-Traded Hours, $dL^N(t)$	-0.11	-0.05	-0.30	0.29	-0.12	-0.14	-0.13
Hours Share of Tradables, $d\nu^{L,H}(t)$	0.01	-0.00	0.03	-0.11	-0.06	-0.14	-0.33
C.Relative Prices							
Relative price of N, $d(P^N/P^H)(t)$	1.05	1.63	-0.43	4.69	1.56	2.11	1.15
Terms of trade, $dP^H(t)$	-1.15	-1.09	-0.44	-1.99	-0.93	0.00	0.00
D.VA Shares							
VA share of T (constant prices) $d\nu^{Y,H}(t)$	0.18	0.23	-0.02	0.47	0.22	0.14	-0.08
VA share of N (current prices) $d\omega^{Y,N}(t)$	0.05	0.13	-0.07	0.57	0.13	0.34	0.34
E.Current Account							
Current Account, $dCA(t)$	-0.03	-0.02	-0.06	0.04	-0.02	-0.18	-0.38

Notes: This table shows impact effects of a 1% permanent increase in utilization-adjusted-aggregate-TFP in the baseline model (columns 2-4) and in restricted versions of the model (columns 5-7). 'T' refers to traded industries while 'N' refers to non-tradables. 'VA' refers to value added. In column 1, we show impact responses of corresponding variables that we estimate empirically by means of local projections. Columns 2, 5, 6, 7 show impact effects we estimate numerically. Column 3 (4) shows numerical results following a (an) symmetric (asymmetric) technology shock across sectors which increases utilization-adjusted-aggregate-TFP by 1% in the long-run.

we estimate empirically) which stimulates the demand for home-produced traded goods. Imports increase less which results in a smaller current account deficit (i.e., -0.02 ppt of GDP) close to the evidence (see panel E). Because the economy must meet the demand for home-produced traded goods, the fall in labor supply further shrinks from -0.42% to -0.26%.

Third ingredient: Factor-biased technological change. The model's predictions square well with our evidence once we let technological change be factor-biased. As shown in panel B, labor no longer shifts toward the non-traded sector (see the fourth row) while the decline in total hours worked is much less pronounced than in restricted versions of the model. Intuitively, once we let sectoral goods to be produced by means of CES production functions and because technological change is biased toward labor in the traded sector, traded production becomes more labor intensive which prevents labor from shifting toward non-traded industries and thus mitigates the decline in traded hours worked. The baseline model generates a fall in $L^H(t)$ by -0.03 ppt of total hours worked close to what we estimate empirically (i.e., -0.04 ppt). Although our model slightly understates the fall in total hours (-0.07% vs. -0.15% in the data) because it understates the decline in non-traded hours on impact, the model reproduces well the dynamics of hours worked as shown later.

Fourth ingredient: mix of symmetric and asymmetric technology shocks. So far, we have seen that the model must include frictions into the movement of inputs across sectors to account for the labor effects of a permanent technology improvement. We now highlight the necessity to consider a mix of symmetric and asymmetric technology shocks. To stress this aspect, columns 3 and 4 of Table 2 show the impact effects of symmetric and asymmetric technology shocks separately.[8]

We first focus on the effects of a symmetric technology shock displayed by column 3. As shown in panel A, technology improvements are uniformly distributed between the traded and the non-traded sector. As can be seen in the first row of panel B, a symmetric technology shock generates a decline in hours worked by -0.40% close to what we estimate empirically (-0.47% in the data). Intuitively, a symmetric technology shock across sectors lowers the marginal cost in both sectors which leads both traded and non-traded firms to cut prices. Lower prices put downward pressure on wages which generates a dramatic fall in labor supply. A symmetric technology shock also gives rise to a current account deficit which amplifies the decline in total hours worked.

In line with the evidence, the fall in total hours worked mostly originates from the non-traded sector. Because the elasticity of substitution between traded and non-traded goods is smaller than one (i.e., $\phi < 1$), the depreciation in non-traded goods prices lowers the share of expenditure allocated to non-traded goods (see the second row of panel D) and depresses labor demand in the non-traded sector. The terms of trade depreciation further tilts the demand toward traded goods which leads to a shift of labor toward the traded sector, as captured by $d\nu^{L,H}(0) = 0.03$ ppt.

Asymmetric technology shocks generate opposite effects. As shown in the first line of panel B in column 4, an asymmetric shock produces an increase in hours by 0.28% close to what we estimate empirically (i.e., 0.31% in the data). In contrast to a symmetric technology shock, panel A shows that technology improvements are concentrated in the traded sector. To compensate for the rise in the marginal cost, non-traded firms set higher prices (see the first row of panel C). The share of non-tradables increases (see the second row of panel D) which has an expansionary effect on labor demand in the non-traded sector and leads to a shift of labor away from traded industries (see the last row of panel B). This results in a decline in traded hours worked which is mitigated by technological change biased toward labor in the traded sector. In line with empirical findings, the rise in total hours worked mostly originates from the non-traded sector.

Because technology shocks uniformly distributed across sectors produce a dramatic decline in $L(0)$ and technology shocks concentrated toward the traded sector have an expansionary effect on hours worked, they cannot account separately for the moderate decline in hours (by -0.15%) we estimate after a permanent technology improvement. Therefore, it is

[8] Relegated to Online Appendix K for reasons of space, we show impact responses computed numerically for symmetric and asymmetric technology shocks across restricted versions of the baseline model.

only once we consider a mix of symmetric and asymmetric technology shocks that we can account for the effects of an aggregate technology shock on hours worked.

4.3 Dynamic Effects of a Permanent Technology Improvement

While in Table 2, we restrict our attention to impact effects, in Fig. 5, we contrast theoretical (displayed by solid black lines with squares) with empirical (displayed by solid blue lines) dynamic responses with the shaded area indicating the 90% confidence bounds.[9] We also contrast theoretical responses from the baseline model with the predictions of a restricted model which imposes Hicks-neutral technological change (HNTC henceforth) shown in dashed red lines. As shown in Fig. 5(a), both the baseline model and its restricted version experience the same technology improvement.

Dynamics. As displayed by Fig. 5(c), both models generate a decline in hours worked. While the technology shock produces a current account deficit in the short-run of the same magnitude, see Fig. 5(j), only the baseline model with technological change biased toward labor can account for the dynamics of total hours worked. The reason for this is that as shown in Fig. 5(e), the model imposing HNTC overstates the decline in L^H by generating a strong reallocation of labor away from traded industries as displayed by Fig. 5(f). This shift is caused by the concentration of technology improvements within traded industries, see Fig. 5(b), which in turn leads non-traded industries to set higher prices. As the appreciation in the relative price of non-tradables builds up over time, as displayed by Fig. 5(k), more labor shifts toward non-traded industries as households allocate a greater share of their expenditure to non-traded goods.

However, the so-called deindustrialization movement reflected into the decline in the hours worked share of tradables is gradual and shows up only in the long-run in the data. The reason is that the reallocation of productive resources across sectors is subject to frictions. First, the terms of trade depreciation displayed by Fig. 5(l) caused by the rise in the value added share of tradables, mitigates the rise in the share of non-tradables. Second, as shown in Fig. 5(g), the technology improvement produces a differential between the non-traded and the aggregate wage rate as a result of labor mobility costs which further hamper the reallocation of labor. Third, as shown in Fig. 5(h) and Fig. 5(i), traded output becomes more labor intensive than non-traded output, especially in the short-run, which hampers the shift of labor away from traded industries. It is only once we allow for these three elements that the model can account for the dynamics of total hours worked, see Fig. 5(c).

[9]For reasons of space, we relegate to Online Appendix J.11 the dynamics of utilization-adjusted-TFP, capital utilization rates and FBTC for tradables and non-tradables following a symmetric and an asymmetric technology shock together with an aggregate technology shock.

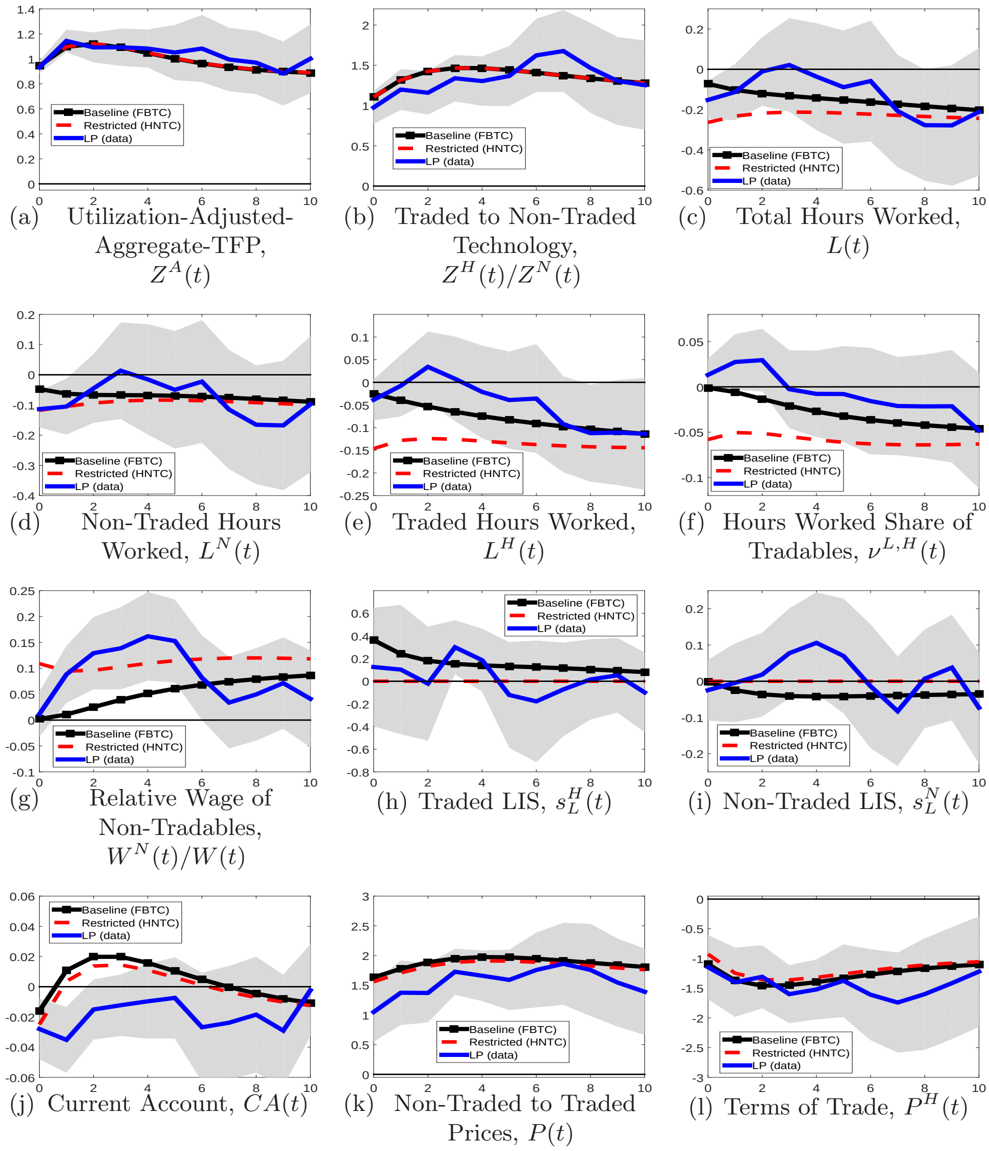
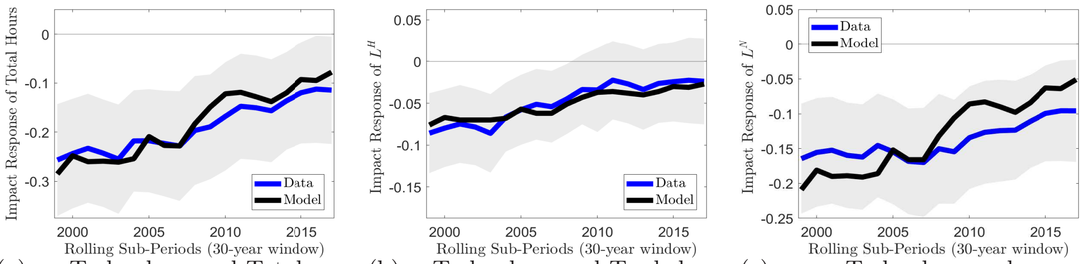


Figure 5: Theoretical vs. Empirical Responses Following a Technology Shock. Notes: $Z^H(t)/Z^N(t)$ is utilization-adjusted-TFP of tradables relative to non-tradables. 'LP (data)' refers to the solid blue line which displays point estimate from local projections with shaded areas indicating 90% confidence bounds; 'Baseline (FBTC)' refers to the thick solid black line with squares which displays model predictions in the baseline scenario with capital utilization rates together with factor-biased technological change (FBTC), while 'Restricted (HNTC)' refers to the dashed red line which shows predictions of a model with Cobb-Douglas production functions which amount to imposing Hicks-neutral technological change (HNTC) and abstracting from endogenous capital utilization.

4.4 Time-Varying Impact Effects of a Permanent Technology Shock

The vanishing decline in hours after a permanent technology shock. The main objective of our paper is to rationalize the time-increasing impact response of hours worked to a 1% permanent technology improvement we document empirically as shown in the blue line in Fig. 6(a). To assess the ability of our open economy model with tradables and non-tradables to account for the reduction in the decline in hours we estimate empirically, we keep the same calibration and estimate the impact response of hours worked to a 1% permanent technology improvement by letting the share of asymmetric technology shocks $1-\eta$ increase over time in line with our empirical estimates over rolling windows (see Fig. 4(d)). Online Appendix J.12 details our calibration strategy and displays calibrated values.



(a) Technology and Total Hours Worked (b) Technology and Traded Hours Worked (c) Technology and Non-Traded Hours Worked

Figure 6: Time-Varying Impact Effects of a Technology Shock. Notes: The figure shows impact responses of total, traded and non-traded hours worked to a 1% permanent increase in utilization-adjusted aggregate TFP. The solid blue line shows the impact response we estimate empirically on rolling sub-periods by using Jordà's [2005] single-equation method. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. The solid black line shows the impact response we compute numerically by letting the share of technology improvements driven by asymmetric technology shocks increase in accordance with the values taken from the FEVD we estimate on rolling windows and shown in Fig. 4(d). The horizontal axis shows the end year of the corresponding window and the vertical line displays the point estimate of the impact effect of technology on hours worked.

As shown in the black line in Fig. 6(a), as we lower the share of technology shocks uniformly distributed across sectors from 90% to 60%, the baseline model can generate the shrinking contractionary effect of technology improvements on hours we estimate empirically (see the blue line). Intuitively, because asymmetric technology shocks increase labor supply, their increasing importance (partly) offsets the negative effect of symmetric technology shocks on hours.

Sectoral decomposition of the time-varying response of hours worked. In Fig. 6(b) and Fig. 6(c), we investigate the ability of the baseline model's predictions shown in the black line to account for the shrinking contractionary effect (on impact) of a 1% permanent technology improvement on both traded and non-traded hours worked. As it stands out, the model reproduces well the time-increasing impact response of $L^H(t)$ as it generates a shrinking decline from -0.076 ppt (-0.086 ppt in the data) the first thirty years to -0.027 ppt (-0.024 ppt in the data) the last thirty years. The performance of the model relies upon one key ingredient which is FBTC.

Relegated to Online Appendix K.2 for reasons of space, a model imposing HNTC would produce a time-decreasing impact response of L^H, traded hours worked declining on impact by -0.11 ppt over 70-99 and by -0.15 ppt over 88-17, because asymmetric technology shocks reallocate labor toward non-traded industries and exert a strong negative impact on L^H. By allowing for technological change strongly biased toward labor in the traded sector which neutralizes the incentives to shift labor away from traded industries in the short-run, the baseline model can account for the shrinking contractionary effect of a technology improvement on L^H. We may notice that the baseline model can also generate the time-increasing impact response of L^N in line with the data as the black line lies within the confidence bounds of the empirical point estimate.

5 Conclusion

In this paper, we investigate the effects of technology improvements on hours across time. We find empirically that a 1% permanent increase in utilization-adjusted-aggregate-TFP produces a decline in hours which gradually vanishes over time. To rationalize the decline in hours and its disappearance, we decompose technology shocks into symmetric and asymmetric technology improvements. Because symmetric technology shocks have a strong negative impact on hours and drive the lion's share of the variations in technology improvements, hours worked fall in OECD countries when technology improves. Conversely asymmetric technology shocks are found empirically to significantly increase hours. Therefore, their growing contribution to the variations in utilization-adjusted-aggregate-TFP we document empirically can potentially rationalize the reduction in the decline in hours after a permanent technology improvement.

To test our assumptions, we simulate an open economy model with tradables and non-tradables and investigate the overall effect on hours of symmetric and asymmetric technology shocks. The model can generate the magnitude of the decline in hours worked we estimate empirically once we include barriers to factors' mobility, home bias, and factor-biased technological change. When we increase the contribution of asymmetric shocks to technology improvements from 10% to 40%, the model can generate the shrinking contractionary effect of a permanent technology improvement on both total and sectoral hours, in line with our estimates. This performance crucially relies upon the assumption of technological change biased toward labor in the traded sector.

Our findings raise an important question: What is the main driver behind the rising importance of asymmetric technology shocks? In a longer version of the paper, we extend our two-sector open economy setup to endogenous technology decisions. Our results show that more than 70% of the progression of asymmetric technology shocks is driven by the greater exposition of traded industries to the international stock of knowledge. Because the stock of knowledge is found empirically to have a significant effect on technology in traded industries only, the combined effect of the increase in the world stock of ideas and the growing intensity of traded technology in the international stock of knowledge has amplified the dispersion of technology improvements between the traded and the non-traded sector and has further increased the variance share driven by asymmetric technology improvements.

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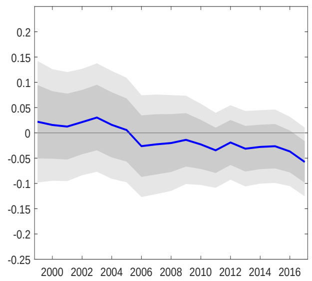
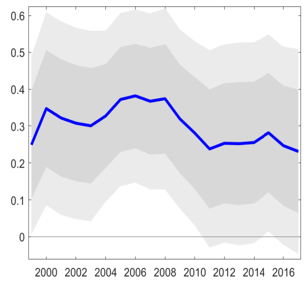
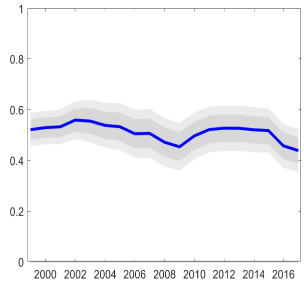


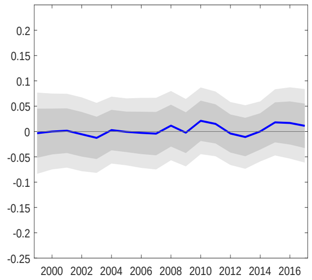
(a) Impact Response (rolling windows) of Short-Term Interest Rate



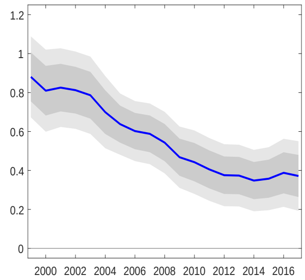
(b) Impact Response (rolling windows) of utilization-adjusted-FBTC



(c) Elasticity of Substitution between Capital and Labor (estimated on rolling windows)



(d) Impact Response (rolling windows) of Employment



(e) Impact Response (rolling windows) of the Real Wage

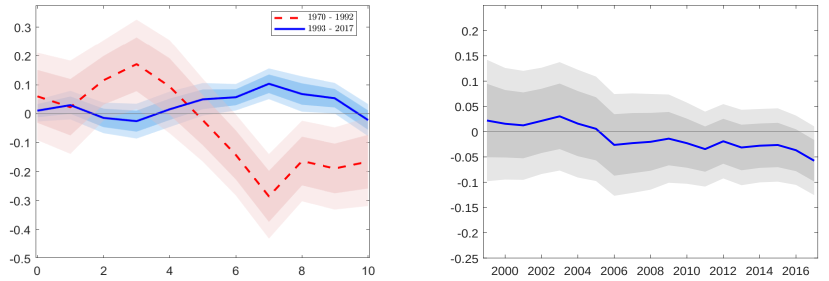
Figure 7: Testing Competing Theories Notes: In all panels, we plot the impact response of the corresponding variable to a 1% permanent increase in utilization-adjusted-TFP which has been estimated on rolling windows of fixed length of $T = 30$ years. Figures 8(a), 7(e), 7(d), 7(b) show the response of the short-term interest rate, the real wage, employment, and utilization-adjusted-factor-biased-technological-change to a 1% permanent increase in utilization-adjusted-TFP on rolling windows. We first identify the permanent technology shock by estimating a VAR model which includes utilization-adjusted-aggregate-TFP together with a set of variables and impose long-run restrictions. In a second step, we estimate the impact response of the short-term interest rate by means of local projections over the sub-period of interest. Fig. 7(c) plots values of the elasticity of substitution between capital and labor for production. The values are estimated on rolling windows of fixed length of 30 years. Solid lines represent point estimates and light (dark) shaded areas represent 90 (68) percent confidence intervals. Vertical axis measures deviation from the pre-shock trend/level in percent. Sample: 17 OECD countries, 1970-2017.

A Competing Interpretations of the Shrinking Decline in Hours after Technology Shocks

In this section, we test the four competing interpretations which have been put forward by the literature to rationalize the vanishing decline in hours after technology shocks in the United States. None of these competing interpretations find some support in the data for our panel of seventeen OECD countries over 1970-2017. We first summarize our empirical findings and next we detail our empirical strategy and results.

A.1 Can Existing Theories Rationalize the Vanishing Decline in Hours after a Technology Shock in OECD Countries? Summary of the Evidence

First, as shown in Fig. 7(a), we do not find that monetary policies are significantly more accommodating with technology shocks in industrialized countries. Second, our evidence displayed by Fig. 7(b) reveals that technology shocks are not biased toward capital as our measure of FBTC does not decline and instead is essentially flat in OECD countries; moreover, the elasticity of substitution between capital and labor has not increased but has remained stable over time, see Fig. 7(c). Third, our estimates shown in Fig. 7(d) reveal that the response of employment to a technology shock remains muted on impact. In addition, as documented in Online Appendix A.5, on average, in OECD countries, the relative volatility of employment has remained fairly stable which is not surprising since the evidence gathered by Gali and Van Rens in their online appendix of indicates that most of the OECD countries did not experience the decline in labor market frictions observed in the United States. Fourth, as shown in Fig. 7(e), we find a significant time-declining response of the real wage to technology shocks which is hard to reconcile with the assumption of a rising performance pay.



(a) Response of Short-Term Interest Rate: 70-92 vs. 93-17

(b) Response of Short-Term Interest Rate: Rolling Windows

Figure 8: Testing the Assumption of More Pro-Cyclical Monetary Policies in OECD countries Notes: Fig. 8(a) shows that response of the short-term interest rate to a 1% permanent increase in utilization-adjusted-TFP before (dashed red line) and after (blue line) 1992. Solid and dashed lines represent point estimates and light (dark) shaded areas represent 90 (68) percent confidence intervals. Vertical axis measures deviation from the pre-shock trend/level in percent. We first identify the permanent technology shock by estimating a VAR model which includes utilization-adjusted-aggregate-TFP together with a set of variables and impose long-run restrictions. In a second step, we estimate the impact response of the short-term interest rate by means of local projections over the sub-period of interest. In Fig. 8(b), we estimate the impact response of the short-term interest rate to a technology shock on rolling windows of fixed time length of 30 years. Sample for both panels: 17 OECD countries, 1970-2017.

A.2 Has Monetary Policy been More Pro-Cyclical?

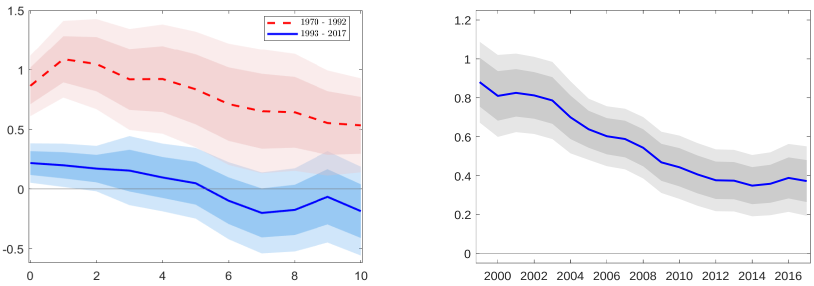
By using U.S. data, Gali and Gambetti [2009] document evidence which reveals that hours decline less on impact after a permanent increase in labor productivity in the post-1984 period than in the pre-1984 period. To rationalize the shrinking contractionary effect of technology shocks on hours worked, the authors put forward the change in the monetary policy rule reflected by more accommodating US monetary policy. Intuitively, in a pioneer article, Gali [1999] investigates the effect of productivity shock by assuming that money supply is fixed. Because a technology shock generates an excess supply on the goods market and prices are sticky, hours must decline to bring the goods market back to equilibrium. Dotsey [1999] points out that once we calibrate the model with sticky prices by considering the Taylor rule estimated by Clarida, Gali and Gertler [1999], then a productivity shock produces an increase in hours instead of a decline. Broadly speaking, as the monetary policy is getting more accommodating after a technology shock, the decline in hours will vanish over time.

Gali and Gambetti [2009] hypothesize that a more pro-cyclical monetary policy could potentially account for the vanishing decline in hours after a technology shock: "as discussed in Galí, López-Salido, and Vallés (2003), the Fed's greater focus on inflation stabilization should automatically lead to a greater accommodation of changes in potential output resulting from technology shocks". To test this hypothesis for our panel of OECD countries, we have estimated the response of the short-term nominal interest rate (deflated by the foreign prices as foreign goods are the numeraire in our open economy setup) to a 1% permanent increase in utilization-adjusted-TFP, as displayed in Fig 8 for our panel of seventeen OECD countries. In the left panel, we estimate the responses over two sub-periods, say over 70-92 and 93-17. We choose 1992 as the cutoff year for the whole sample because the Great Moderation occurs in the post-1992 period for European countries which account for three-fourth of our sample, see e.g., Benati [2008] for the U.K. and González Cabanillas and Ruscher [2008] for the euro area.

Inspection of Fig. 8(a) reveals that the interest rate is unresponsive on impact and peaks at 0.2 ppt after 4 years following a technology shock of 1% over the period 70-92 as shown in the dashed red line. As displayed by the blue line, the interest rate is unresponsive at all horizons to a 1% permanent increase in utilization-adjusted-TFP in the post-1992 period. Since we are interested in the impact effect of a technology shock on hours, we have assessed the effect of a permanent technology improvement on the short-term interest rate on impact on rolling windows of 30 years. Inspection of Fig. 8(b) reveals that the interest rate is unresponsive on impact to a permanent technology improvement. Although the point estimate for the impact response of the interest rate displays a slight downward trend, it remains insignificant whatever the period which is considered. To conclude, overall, the evidence does not show that monetary policy is significantly more accommodating with permanent technology shocks over time.

A.3 Is the Real Wage More Elastic to Productivity?

Nucci and Riggi [2013] put forward the development of performance-related pay schemes in the United States from the mid-80s to rationalize the shrinking contractionary effect of technology shocks on hours worked. The authors assume that workers can choose hours and labor efforts. The labor compensation is made up of two components, i.e., the standard wage rate per hour and the wage rate per unit of effort. The latter wage component captures the performance-related pay



(a) Response of the Real Wage: 70-92 vs. 93-17

(b) Response of the Real Wage: Rolling Windows

Figure 9: Testing the Assumption of Increasing Elasticity of Real Wages to Productivity Notes: Fig. 9(a) shows that response of the real wage rate to a 1% permanent increase in utilization-adjusted-TFP before (dashed red line) and after (blue line) 1992. Solid and dashed lines represent point estimates and light (dark) shaded areas represent 90 (68) percent confidence intervals. Vertical axis measures deviation from the pre-shock trend/level in percent. We first identify the permanent technology shock by estimating a VAR model which includes utilization-adjusted-aggregate-TFP together with a set of variables and impose long-run restrictions. In a second step, we estimate the impact response of the real wage by means of local projections over the sub-period of interest. In Fig. 9(b), we estimate the impact response of the real wage to a technology shock on rolling windows of fixed time length of 30 years. Sample for both panels: 17 OECD countries, 1970-2017.

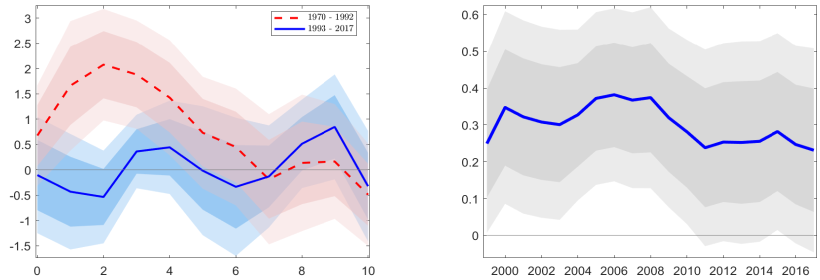
scheme. The development of performance-related pay schemes is modelled by assuming a higher elasticity of the flexible component of labor compensation w.r.t. the business cycle (say economic conditions which include a technology improvement).

The implication of assuming a larger fraction of the labor compensation being driven by a shift towards the performance pay is that a 1% permanent technology improvement leads to a reduction in the decline in hours. More specifically, an increase in performance pay will lead firms to adjust the worker's performance instead of hours. Thus a higher wage flexibility will result in a smaller decline in hours after a positive technology shock because firms find it profitable to reduce worker efforts (because efforts are observable). An another implication is that a technology shock increases the wage rate and this increase is larger when the performance pay tends to rise as the wage rate is more elastic to productivity. Nucci and Riggi [2013] document some evidence for the U.S. showing that there has been a change in the pay structure in the last 1970s. The incidence of performance-pay jobs has risen from 30% in the pre-1984 period to 60% for the post-1984 period. This large increase in performance pay stands in sharp contrast with the evolution in Europe. As stressed by Lucifora and Origo [2022], in Europe, data from the European Working Conditions Survey show that the share of employees whose earnings partly depend on some form of performance-related pay slightly increased between 2005 and 2015 (from 19% to 23%). Because three-fourths of our sample is made up of European countries, we might expect a small impact of the development of performance pay schemes.

By increasing the elasticity of the flexible component of the wage rate to the business cycle, including technology shocks, the development of the performance pay scheme should result in a larger increase in the wage rate following a technology shock. To test this prediction, we have estimated the response of the wage rate over two sub-periods, i.e., before and after 1992. Fig. 9(a) reveals that the wage rate increases by 0.9% on impact following a technology shock of 1% in the pre-1992 period while the wage rate increases by only 0.2% on impact in the post-1992 period. Inspection of Fig. 9(b) which plots the impact response of the wage rate on rolling sub-samples, reveals that the elasticity of the wage rate to technology declines over time while the development of performance pay schemes should produce the opposite. While Nucci and Riggi [2013] convincingly demonstrate that the rise in the flexible component of labor compensation should have contributed to reduce the decline in hours after a technology shock in the U.S., this explanation cannot rationalize the vanishing decline in hours after a technology shock we document for OECD countries. One reason to this is that the development of performance-pay related schemes has been much less pronounced in European countries.

A.4 Does FBTC Vary across Time?

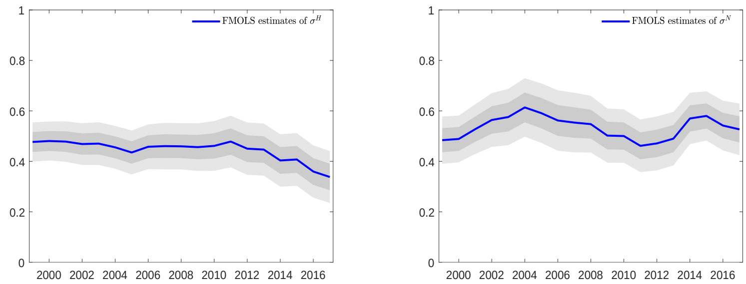
In this subsection, we test the assumption for our panel of seventeen OECD countries put forward by Cantore et al. [2017] related to the greater substitutability between capital and labor in production over time to explain the gradual vanishing decline in hours after technology shocks in the United States. Intuitively, the authors put forward technological biased toward capital to rationalize the decline in hours after a technology shocks and assume that the elasticity of substitution between capital and labor in production (which is smaller than one) increases over time thus reducing the extent of technological change biased toward capital. The starting point is that labor-augmenting productivity growth generates technological change biased toward capital as long as the elasticity of substitution between capital and labor in production is smaller than one, as evidence suggests. By



(a) Response of utilization-adjusted-FBTC: 70-92 vs. 93-17

(b) Response of utilization-adjusted-FBTC: Rolling Windows

Figure 10: Are Technology Shocks Factor-Biased and if Yes, Does FBTC Vary across Time? Notes: Fig. 10(a) shows that response of utilization-adjusted-factor-biased technological change (FBTC) to a 1% permanent increase in utilization-adjusted-TFP before (dashed red line) and after (blue line) 1992. Solid and dashed lines represent point estimates and light (dark) shaded areas represent 90 (68) percent confidence intervals. Vertical axis measures deviation from the pre-shock trend/level in percent. We first identify the permanent technology shock by estimating a VAR model which includes utilization-adjusted-aggregate-TFP together with a set of variables and impose long-run restrictions. In a second step, we estimate the impact response of utilization-adjusted-FBTC by means of local projections over the sub-period of interest. In Fig. 10(b), we estimate the impact response of utilization-adjusted-FBTC to a technology shock on rolling windows of fixed time length of 30 years. Sample for both panels: 17 OECD countries, 1970-2017.



(a) Elasticity of Substitution between Capital and Labor for Tradables: Rolling Windows

(b) Elasticity of Substitution between Capital and Labor for Non-Tradables: Rolling Windows

Figure 11: Did the Elasticity of Substitution between Capital and Labor Increase over Time in OECD countries? Notes: In Fig. 11, we estimate the elasticity of substitution between capital and labor in production for the traded (see Fig. 11(a)) and the non-traded sector on rolling windows of fixed time length of 30 years. The empirical strategy to estimate the elasticity of substitution between capital and labor is detailed in section J.6. Sample for both panels: 17 OECD countries, 1970-2017.

producing a negative impact on labor demand, technological change biased toward capital lowers hours worked after a technology shock. As the elasticity of substitution between capital and labor converges toward a value of one, technological change turns out to be less biased toward capital which mitigates the decline in hours worked.

The objective is to test this assumption for our panel of seventeen OECD countries. First, in Fig. 10, we investigate whether technological change is biased toward capital. We construct time series for utilization-adjusted-FBTC by using the ratio of the demand for labor to the demand for capital (expressed in elasticity terms) as detailed in section F.1. An increase (a decline) in our measure of utilization-adjusted-FBTC implies that technological change is biased toward labor (capital). As displayed by Fig. 10(a), technological change is biased toward labor in the short-run before 1992 (see the dashed red line) while the response of FBTC is muted at all horizons after 1992. When we estimate the impact response of utilization-adjusted-FBTC on rolling windows, we find that the response slightly declines over time. To conclude, in contrast to the hypothesis by Cantore et al. [2017] for the US that technological change is biased toward capital, we find that technological change is biased toward labor for our panel of OECD countries and thus cannot lower hours. Besides the fact that technological change biased toward labor has a positive impact on hours, the fact that technological change tends to be less biased toward labor over time will tend to put downward pressure on the hours and thus cannot explain the gradual disappearance of the decline in hours.

To test the assumption that the elasticity of substitution between capital and labor increases over time, we have estimated the elasticities for the traded and the non-traded sector, i.e., σ^H and σ^N, by using cointegration methods, see section J.6 which details the empirical strategy, and we have estimated the elasticity σ^j over rolling windows of fixed time length. Inspection of Fig. 11(a) and Fig. 11(b) reveals that σ^H and σ^N are constant over time for our panel of seventeen OECD

Table 3: Standard Errors: Raw Series

	Volatility of Employment	
	1970-1992	1993-2017
AUS	0.031	0.041
AUT	0.047	0.031
BEL	0.039	0.032
CAN	0.041	0.035
DEU	0.029	0.065
DNK	0.016	0.026
ESP	0.077	0.088
FIN	0.032	0.066
FRA	0.038	0.026
GBR	0.037	0.032
IRL	0.052	0.079
ITA	0.012	0.045
JPN	0.011	0.029
NLD	0.043	0.056
NOR	0.050	0.042
SWE	0.034	0.028
USA	0.023	0.033
Mean	0.037	0.045

Notes: Sample: 17 OECD countries, 1970-2017, annual data. The figures show the standard deviation of employment for the seventeen OECD countries of our sample over two sub-periods. To stick to the standard cut-off considered by the literature for the U.S., we show the figures for 1970-84 and 1985-2017, respectively

countries.

To conclude, our evidence for our panel of 17 OECD countries reveals that technology improvements tend to be biased toward labor and the biasedness toward labor slightly declines over time. In addition, the elasticity of substitution between capital and labor is constant over time. Therefore, technological change biased toward capital and a time increasing σ does not square with the data for OECD countries and cannot rationalize the reduction in the decline of hours.

A.5 Did Labor Market Frictions Decline over Time in OECD Countries?

To rationalize the vanishing decline in hours after technology shocks in the U.S., Galí and Van Rens [2021] put forward the reduction of labor market frictions which have led firms to adjust increasingly employment to the expense of hours. The reduction of labor market frictions should be reflected in smaller values in the job separation rate. The online appendix B.2 of Galí and Van Rens [2021] provides international evidence to check whether labor market frictions have declined over time in OECD countries by comparing the 1985-90 period with the 2002-2007 period. Only the U.S. and Ireland have experienced a decline in the labor turnover as captured by a decline in the separation rate. The remaining OECD countries experience no change or an increase. Therefore, the assumption of a reduction in labor market frictions cannot rationalize the vanishing decline in hours in OECD countries.

While the decline in the job turnover may have been the main driver of the reduction in labor market frictions in the U.S., the liberalization of the labor market could reduce frictions. However, only a few countries such as Italy and Spain have significantly reduced the level of employment protection legislation. In this regard, we have computed the volatility of employment (relative to the volatility of output) and compared the values between 70-92 and 93-17, see Table 3. In line with the evidence documented by Galí and Van Rens [2021], the volatility of employment has increased over time in the United States. It has also increased in nine additional countries of our sample but the relative volatility of employment has declined in seven remaining OECD countries. If we consider the country mean, the relative volatility of employment has remained relatively stable on average.

Finally, following a positive technology shock, firms meet their demand by decreasing hours since employment takes time to adjust. Because a decline in hiring costs affects employment (which adjusts gradually because it is a state variable), the line of explanation based on the reduction of hiring frictions cannot account for the time-increasing impact response of hours to a technology shock we document as it only operates at the intensive margin.

B Response of Total Hours Worked to a Technology Shock across Variants of the RBC Model

To discipline and guide our empirical investigation, we derive below a formal expression for the equilibrium level of total hours worked which enables us to discuss the link between technology and labor.

B.1 The Framework

Households. We assume non-separable preferences between consumption and leisure in the lines of Shimer [2009]:

$$\Lambda \equiv \frac{C^{1-\sigma}V(L)^{\sigma}-1}{1-\sigma}, \quad \text{if} \quad \sigma \neq 1, \quad V(L) \equiv \left(1+(\sigma-1)\gamma\frac{\sigma_L}{1+\sigma_L}L^{\frac{1+\sigma_L}{\sigma_L}}\right) \tag{33}$$

and

$$\Lambda \equiv \log C - \gamma\frac{\sigma_L}{1+\sigma_L}L^{\frac{1+\sigma_L}{\sigma_L}}, \quad \text{if} \quad \sigma = 1. \tag{34}$$

These preferences are characterized by two crucial parameters: σ_L is the Frisch elasticity of labor supply, and $\sigma > 0$ determines the substitutability between consumption and leisure; it is worthwhile noticing that if $\sigma > 1$, the marginal utility of consumption is increasing in hours worked. Such preferences imply that the Frisch elasticity of labor supply is constant.

Households can accumulate internationally traded bonds (expressed in foreign good units), N_t, that yield net interest rate earnings of $r^{\star}N_t$. Denoting lump-sum taxes by T_t, household's flow budget constraint states that real disposable income (on the RHS of the equation below) can be saved by accumulating traded bonds, consumed, $P_{C,t}C_t$, invested, $P_{J,t}J_t$ or is used to cover adjustment costs of capital utilization:

$$\begin{aligned} \dot{N}_t \quad & + P_{C,t}C_t + P_{J,t}J_t + \sum_{j=H,N} P_t^j C_t^{K,j}\nu_t^{K,j}K_t \\ = \quad & r^{\star}N_t + W_tL_t - T_t + R_t^K K_t \sum_{j=H,N}\alpha_{K,t}^j u_t^{K,j}, \end{aligned} \tag{35}$$

where we denote the share of sectoral capital in the aggregate capital stock by $\nu_t^{K,j} = K_t^j/K_t$ and the capital compensation share in sector $j = H, N$ by $\alpha_{K,t}^j = \frac{R_t^j K_t^j}{R_t^K K_t}$.

Partial derivatives of (33) w.r.t. C and L read:

$$\Lambda_C = C^{-\sigma}V(L)^{\sigma}, \tag{36a}$$

$$\Lambda_L = -C^{1-\sigma}\sigma V(L)^{\sigma-1}\gamma L^{\frac{1}{\sigma_L}}, \tag{36b}$$

$$\Lambda_{CL} = -\frac{\Lambda_L(\sigma-1)}{C}, \tag{36c}$$

where $\Lambda_C = \frac{\partial \Lambda}{\partial C}$ and $\Lambda_L = \frac{\partial \Lambda}{\partial L}$. According to eq. (36c), the marginal utility of consumption is increasing in labor supply as long as $\sigma > 1$, i.e., if consumption and leisure are gross substitutes.

The representative household chooses C_t and L_t so as to maximize his/her lifetime utility with an instantaneous utility given by (33) subject to (35) and $\dot{K}_t = I_t - \delta_K K_t$. Because we are only interested in investigating the role of each ingredient in influencing the impact response of total hours worked, we will restrict ourselves to optimal decisions about consumption and labor supply:

$$\Lambda_C(C_t, L_t) = P_{C,t}\lambda_t, \tag{37a}$$

$$-\Lambda_L(C_t, L_t) = W\lambda_t, \tag{37b}$$

where $\Lambda_C = C^{-\sigma} V(L)^{\sigma}$ and $-\Lambda_L = C^{1-\sigma} \sigma \gamma L^{1/\sigma_L} V(L)^{\sigma-1}$.

First, eliminating the marginal utility of wealth λ from (37b) by using (37a), i.e., $\lambda = \frac{\Lambda_C}{P_C}$, leads to

$$-\frac{\Lambda_L}{\Lambda_C} = \frac{\sigma}{\sigma-1} \frac{CV_L}{V} = \frac{W}{P_C},$$

where $V_L = \frac{\partial V(L)}{\partial L} = (\sigma - 1) \gamma L^{\frac{1}{\sigma_L}}$. Rearranging the FOC for consumption (37a), i.e., $C_t = \left(\frac{\Lambda_C}{V^{\sigma}}\right)^{-\frac{1}{\sigma}}$, and plugging the latter equation into the above equation leads allows us to rearrange the optimal decision on total hours worked (37b) as follows:

$$\gamma L_t^{\frac{1}{\sigma_L}} = \frac{W_t}{P_{C,t}} \frac{(\Lambda_{C,t})^{\frac{1}{\sigma}}}{\sigma}. \tag{38}$$

Firms. Both the traded and non-traded sectors use physical capital (inclusive of capital utilization), denoted by $\tilde{K}_t^j = u_t^{K,j} K_t^j$, and labor, L^j, according to a constant returns-to-scale technology described by a CES production function:

$$Y_t^j = \left[\gamma^j \left(A_t^j L_t^j\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right) \left(B_t^j \tilde{K}_t^j\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}, \tag{39}$$

where $0 < \gamma^j < 1$ is the weight of labor in the production technology, respectively, σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$, and A_t^j and B_t^j are labor- and capital-augmenting efficiency.

We denote the wage rate and capital rental rate by W^j and R^j which are sector-specific as we allow for labor and capital mobility costs. Because goods and factor markets are perfect competitive and the production function displays constant returns to scale, these assumptions imply that the elasticity of value added w.r.t. labor and capital is equal to the cost of these factors in value added:

$$\frac{\partial Y^j}{\partial L^j} \frac{L^j}{Y^j} = s_L^j, \qquad \frac{\partial Y^j}{\partial K^j} \frac{K^j}{Y^j} = 1 - s_L^j, \tag{40}$$

where $s_L^j = \frac{W^j L^j}{P^j Y^j}$ is the labor income share. Dividing the demand for labor by the demand for capital leads to a relationship between the labor income share in sector j and technological change biased toward labor (last term on the RHS):

$$\frac{s_{L,t}^j}{1 - s_{L,t}^j} = \frac{\gamma^j}{1-\gamma^j} \left(u_t^{K,j} k_t^j\right)^{\frac{1-\sigma^j}{\sigma^j}} \left(\frac{B_t^j}{A_t^j}\right)^{\frac{1-\sigma^j}{\sigma^j}}. \tag{41}$$

When the term $\left(\frac{B_t^j}{A_t^j}\right)^{\frac{1-\sigma^j}{\sigma^j}}$ increases, firms tilt their demand toward labor, thus leading to a rise in the labor income share.

Equilibrium level of total hours worked. Using the fact $W^j L^j = s_L^j P^j Y^j$ and summing across sectors leads to $\sum_j W^j L^j = \sum_j s_L^j P^j Y^j = WL$. Denoting the aggregate labor income share by s_L, by definition, we have $WL = s_L Y$ where Y is nominal GDP. Making use of this expression to eliminate the wage rate from the labor supply decision and solving leads to the equilibrium level for total hours worked:

$$\gamma L_t^{\frac{1+\sigma_L}{\sigma_L}} = s_{L,t} \frac{Y_t}{P_{C,t}} \frac{(\Lambda_{C,t})^{\frac{1}{\sigma}}}{\sigma}. \tag{42}$$

Column 4 of Table 4 shows the impact response of total hours worked for the baseline model (11th row) which is contrasted with the responses from ten restricted versions of the baseline model. Across all variants, we consider a permanent increase in utilization-adjusted-aggregate-TFP by 1% and we assume that technology adjusts instantaneously to its new long-run level.

B.2 Quantifying the role of each ingredient across baseline model's variants

In Table 4, we consider eleven variants of a RBC model to investigate the role of each element for the link between hours and technology. In each variant, we assume that aggregate utilization-adjusted aggregate TFP increases by 1% initially and remains permanently to this level. When we consider a two-sector economy, we assume that traded and non-traded technology improves by 1.7% and 0.6% respectively, in line with our evidence. When we relax the assumption of Hicks-neutral technological change (HNTC henceforth), we let technological change to be biased toward labor in the traded sector (by 1.60%) and the non-traded sector (by 0.29%), in line with our estimates.

Response of hours to technology improvements in a closed economy setup. In order to understand the role played by each element we first assume that the production function is Cobb-Douglas and technological change is Hicks-neutral (i.e., $A^j(t) = B^j(t) = Z^j(t)$). We assume that capital utilization rate is fixed. In a closed economy model where households consume one unique final good, the consumption price index P_C collapses to 1. Assuming that the parameter σ is equal to one, the equilibrium level for hours worked (42) collapses to: $\gamma L(t)^{\frac{1}{\sigma_L}} = W(t)C(t)^{-1}$. By increasing the wage rate, a technology shock encourages agents to supply more labor through the substitution channel. A technology shock also produces a positive wealth effect which encourages households to consume more goods and more leisure and to lower their labor supply.

As is well-known, in a closed economy, a technology shock leads to an increase in hours worked on impact which is necessary to meet higher demand for consumption and investment goods. As shown in the first row of Table 4, total hours worked increase by 0.075%. When we consider a two-sector closed economy model which produces goods and services, the relative price of leisure collapses to the real consumption wage denoted $W_C(t)$. As shown in the second row of Table 4, a technology improvement further increases total hours worked by 0.11%. Intuitively, in line with the evidence, technology improvements are more pronounced in Manufacturing than in Services which leads the latter sector to charge higher prices to compensate for its higher marginal cost. Because goods and services are complements, the appreciation in the relative price of services disproportionately increases the share of services in total expenditure which leads labor to shift toward the service sector. Since worker experience mobility costs, firms in the service sector must pay higher wages which amplifies the substitution effect and further increases labor supply.

Moving from a closed to a small open economy. We now assume that the economy has perfect access to world capital markets. For pedagogical purposes, we consider first a one-sector economy with no capital adjustment costs. As shown in the third row of Table 4, total hours worked decline dramatically in a small open economy by -0.492%. Intuitively, because domestic goods and foreign goods are perfect substitutes, the open economy finds it optimal to work less and import goods and services from abroad by running a current account deficit. As shown in the last column Table 4, consumption increases less once we allow for capital adjustment costs (see the fourth row), leading labor supply to fall less (i.e., by -0.418%) because domestic capital and foreign bonds are no longer perfect substitutes in the short-run which mitigates the current account deficit.

Moving from a one-sector to a two sector open economy. We now consider an economy which produces traded goods that can be exported and non-traded goods for domestic absorption only. The decline in labor supply by -0.348% is less pronounced than in a one-sector small open economy because the economy must produce non-traded goods which cannot be imported from abroad. While traded hours worked decline by almost the same amount as in one-sector economy, labor now shifts toward non-traded industries. Note that by raising the marginal revenue product of labor, the appreciation in the relative price of non-tradables increases the wage rate which leads agents to supply more labor.

As shown in the sixth row, when we allow for labor mobility costs. hours worked fall by a smaller magnitude, i.e., by -0.219%. Intuitively, in a model where workers experience switching costs, less labor can move toward the non-traded sector. Therefore workers must reduce their labor supply by a smaller magnitude so that the production of non-traded goods meets additional demand.

Table 4: Impact Response of Total Hours Worked to A Permanent Technology Improvement across Variants of the RBC Model

Model Variants		Tech. Change	Relative Risk	Impact effects			
	Variant	HNTC	Aversion	Hours	Wage	Real Wage	Cons.
		vs. FBTC	σ	$\hat{L}(0)$	$\hat{W}(0)$	$\hat{W}_C(0)$	$dC(0)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Closed Economy without CAC	1	HNTC	$\sigma = 1$	0.075	0.96	0.96	0.50
Two-Sector Closed Economy without CAC	2	HNTC	$\sigma = 1$	0.110	1.99	1.05	0.53
Small Open Economy (SOE) without CAC	3	HNTC	$\sigma = 1$	-0.492	1.17	1.18	0.92
Small Open Economy (SOE) with CAC	4	HNTC	$\sigma = 1$	-0.418	1.14	1.15	0.87
Two-Sector SOE with PML	5	HNTC	$\sigma = 1$	-0.348	1.83	1.18	0.86
Two-Sector SOE with IML	6	HNTC	$\sigma = 1$	-0.219	2.03	1.17	0.79
Two-Sector SSOE with IML	7	HNTC	$\sigma = 1$	-0.111	0.75	0.94	0.60
Two-Sector SSOE with IML & IMK	8	HNTC	$\sigma = 1$	-0.093	0.83	0.98	0.61
Two-Sector SSOE with IML & IMK	9	FBTC	$\sigma = 1$	-0.074	1.05	1.19	0.72
Two-Sector SSOE with IML & IMK	10	FBTC	$\sigma = 2$	-0.105	1.10	1.20	0.71
Two-Sector SSOE with IML & IMK & Cap Ut	11	FBTC	$\sigma = 2$	-0.106	1.09	1.18	0.70

Notes: Column 1 indicates the variant of the model which is considered. In column 2, we specify whether technological change is Hicks-Neutral (HNTC) or factor-biased (FBTC). Column 3 gives the value of the coefficient of relative risk aversion which collapses to the degree of substitutability between consumption and leisure. Column 4 reports the numerically estimated impact response of total hours worked following a permanent increase in total factor productivity. Columns 5-7 show the responses of the aggregate wage rate, W, of the real consumption wage, W/P_C, and consumption. An increase in the aggregate wage rate or in the real consumption wage has a positive impact on total hours worked by encouraging households to supply more labor through the substitution effect. Because a technology shock produces a positive wealth effect which encourages households to increase both consumption and leisure and thus to reduce labor supply. Note that the impact response of consumption shown in column 7 is measured in percentage point of GDP.

Moving from a small to a semi-small open economy. We now assume that home- and foreign-produced traded goods are imperfect substitutes. As shown in the seventh row of Table 4, total hours worked decline less following a technology improvement, i.e., $\hat{L}(0) = -0.111$. Intuitively, households are now reluctant to substitute foreign- for home-produced traded which in turn leads the traded sector to produce more to meet higher demand. Because the open economy reduces its imports, the decline in hours worked must be less pronounced. As displayed by the eight row of Table 4, capital mobility costs further mitigate the magnitude of the decline in total hours worked.

Factor-biased technological change and preferences. We now add a new element by allowing production to be more intensive in one specific input. Under the assumptions of perfectly competitive markets and constant returns to scale in production, labor is paid its marginal product. Denoting the labor income share by s_L^j, the marginal revenue product of labor, $s_L^j \frac{P^j Y^j}{L^j}$, must equate the wage rate W^j. The same logic applies at an aggregate level, i.e., $s_L \frac{Y}{L} = W$ where s_L is the aggregate labor income share (LIS henceforth) and Y is GDP at current prices. Plugging labor demand $s_L \frac{Y}{L} = W$ into labor supply (38) to eliminate W and solving leads to the equilibrium level of total hours worked:

$$\gamma L(t)^{\frac{1+\sigma_L}{\sigma_L}} = s_L(t) \frac{Y(t)}{P_C(t)} \frac{(\Lambda_C(t))^{\frac{1}{\sigma}}}{\sigma}. \tag{43}$$

If we assume that production functions are of the CES type and technological change is factor-biased, the aggregate LIS varies following a permanent technology improvement which in turn influences the equilibrium level of total hours worked. Column 4 in the ninth row indicates that technological change biased toward labor mitigates the magnitude of the decline in hours worked from -0.093% to -0.074%. Formally, technological change biased toward labor is reflected into an increase in s_L , as captured by term on the RHS of eq. (43) which raises the marginal revenue product of labor, pushes up labor demand and increases wages.

More specifically, technological change biased toward labor implies that production in both sectors turns out to be more intensive in labor which has an expansionary effect on hours worked.[10] In the tenth row, we assume that consumption and leisure are substitutes so that the coefficient of relative risk aversion σ collapses to two. The decline in total hours worked is more pronounced, passing from -0.074% to -0.105%. Because the marginal utility of consumption declines more rapidly as consumption increases, households allocate a greater share of their additional wealth to leisure time which amplifies the decline in total hours worked. In the last row, we allow for an endogenous capital utilization at a sectoral level. The decline in L slightly shrinks at -0.106%. On one hand, capital utilization falls substantially in the traded sector because technological change is strongly biased toward labor which has a negative impact on traded hours worked. On the other hand, capital utilization increases in the non-traded sector because non-traded prices appreciate which has a positive effect on non-traded hours worked. The latter effect more than offsets the former.

C Unit Cost for Producing

In this section, we derive the expression for the unit cost for producing.

Both sectors are assumed to be perfectly competitive and thus choose capital and labor by taking prices as given:

$$\max_{\tilde{K}_t^j, L_t^j} \Pi_t^j = \max_{K_t^j, L_t^j} \left\{ P_t^j Y_t^j - W_t^j L_t^j - R_t^j \tilde{K}_t^j \right\}. \tag{44}$$

Because we assume labor and capital mobility costs, the value of marginal products in the traded and non-traded sectors equalizes while costly labor mobility implies a differential in

[10]The effect looks small because an aggregate technology shock is a mix of symmetric and asymmetric technology shocks. Although asymmetric technology improvements are strongly biased toward labor, symmetric technology shocks which are predominant and biased toward capital.

wage rates and capital rental rates across sectors:

$$P_t^j \gamma^j \left(A_t^j\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(L_t^j\right)^{-\frac{1}{\sigma^j}} \left(Y_t^j\right)^{\frac{1}{\sigma^j}} \equiv W_t^j, \tag{45a}$$

$$P_t^j \left(1-\gamma^j\right) \left(B_t^j\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(\tilde{k}_t^j\right)^{-\frac{1}{\sigma^j}} \left(y_t^j\right)^{\frac{1}{\sigma^j}} \equiv R_t^j, \tag{45b}$$

where we denote by $\tilde{k}_t^j \equiv \tilde{K}_t^j / L_t^j$ the capital-labor ratio for sector $j = H, N$, and $y_t^j \equiv Y_t^j / L_t^j$ value added per hours worked described by

$$y_t^j = \left[\gamma^j \left(A_t^j\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right) \left(B_t^j \tilde{k}_t^j\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}. \tag{46}$$

Dividing (45a) by (45b) leads to a positive relationship between the relative cost of labor and the capital-labor ratio in sector j:

$$\frac{W^j}{R} = \frac{\gamma^j}{1-\gamma^j} \left(\frac{B^j}{A^j}\right)^{\frac{1-\sigma^j}{\sigma^j}} \left(\frac{\tilde{K}^j}{L^j}\right)^{\frac{1}{\sigma^j}}, \tag{47}$$

where $\tilde{K}^j = u^{K,j} K^j$. We manipulate (47) To to determine the conditional demands for both inputs:

$$L^j = \tilde{K}^j \left(\frac{\gamma^j}{1-\gamma^j}\right)^{\sigma^j} \left(\frac{B^j}{A^j}\right)^{1-\sigma^j} \left(\frac{W^j}{R}\right)^{-\sigma^j}, \tag{48a}$$

$$\tilde{K}^j = L^j \left(\frac{1-\gamma^j}{\gamma^j}\right)^{\sigma^j} \left(\frac{B^j}{A^j}\right)^{\sigma^j-1} \left(\frac{W^j}{R}\right)^{\sigma^j}. \tag{48b}$$

Inserting eq. (48a) (eq. (48b) resp.) in the CES production function (39) and solving for L^j ($\tilde{K}^j$ resp.) leads to the conditional demand for labor (capital resp.):

$$\gamma^j \left(A^j L^j\right)^{\frac{\sigma^j-1}{\sigma^j}} = \left(Y^j\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(\gamma^j\right)^{\sigma^j} \left(\frac{W^j}{A^j}\right)^{1-\sigma^j} \left(X^j\right)^{-1}, \tag{49a}$$

$$\left(1-\gamma^j\right) \left(B^j \tilde{K}^j\right)^{\frac{\sigma^j-1}{\sigma^j}} = \left(Y^j\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(\frac{R}{B^j}\right)^{\sigma^j} \left(X^j\right)^{\frac{\sigma^j}{1-\sigma^j}}, \tag{49b}$$

where X^j is given by:

$$X^j = \left(\gamma^j\right)^{\sigma^j} \left(A^j\right)^{\sigma^j-1} \left(W^j\right)^{1-\sigma^j} + \left(1-\gamma^j\right)^{\sigma^j} \left(B^j\right)^{\sigma^j-1} R^{1-\sigma^j}. \tag{50}$$

Total cost is equal to the sum of the labor and capital cost:

$$C^j = W^j L^j + R\tilde{K}^j. \tag{51}$$

Inserting conditional demand for inputs (49) into total cost (51), we find that C^j is homogenous of degree one with respect to value added:

$$C^j = c^j Y^j, \quad \text{with} \quad c^j = \left(X^j\right)^{\frac{1}{1-\sigma^j}}, \tag{52}$$

where the unit cost for producing is:

$$c^j = \left[\left(\gamma^j\right)^{\sigma^j} \left(\frac{W^j}{A^j}\right)^{1-\sigma^j} + \left(1-\gamma^j\right)^{\sigma^j} \left(\frac{R}{B^j}\right)^{1-\sigma^j}\right]^{\frac{1}{1-\sigma^j}}. \tag{53}$$

D Technology Frontier and FBTC

Following Caselli and Coleman [2006] and Caselli [2016], the menu of possible choices of production functions is represented by a set of possible (A^j, B^j) pairs. These pairs are chosen along the technology frontier which is assumed to take a CES form:

$$\left[\gamma_Z^j \left(A^j(t)\right)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}} + \left(1 - \gamma_Z^j\right) \left(B^j(t)\right)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}}\right]^{\frac{\sigma_Z^j}{\sigma_Z^j - 1}} \leq Z^j(t), \tag{54}$$

where $Z^j > 0$ is the height of the technology frontier, $0 < \gamma_Z^j < 1$ is the weight of labor efficiency along the technology frontier and $\sigma_Z^j > 0$ corresponds to the elasticity of substitution between labor and capital efficiency. Log-linearizing (54) leads to

$$\begin{aligned} 0 &= \gamma_Z^j \left(A^j(t)\right)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}} \hat{A}^j(t) + \left(1 - \gamma_Z^j\right) \left(B^j(t)\right)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}} \hat{B}^j(t), \\ \frac{\hat{B}^j(t)}{\hat{A}^j(t)} &= -\frac{\gamma_Z^j}{1 - \gamma_Z^j} \left(\frac{B^j(t)}{A^j(t)}\right)^{\frac{1 - \sigma_Z^j}{\sigma_Z^j}}. \end{aligned} \tag{55}$$

Firms choose A^j and B^j along the technology frontier so as to minimize the unit cost function described by (53) subject to (54) which holds as an equality. Differentiating (53) w.r.t. A^j and B^j (while keeping W^j and R^j fixed) leads to:

$$\hat{c}^j(t) = -\left(\gamma^j\right)^{\sigma^j} \left(\frac{W^j(t)}{A^j(t)}\right)^{1-\sigma^j} \left(c^j(t)\right)^{\sigma^j - 1} \hat{A}^j(t) - \left(1 - \gamma^j\right)^{\sigma^j} \left(\frac{R^j(t)}{B^j(t)}\right)^{1-\sigma^j} \left(c^j(t)\right)^{\sigma^j - 1} \hat{B}^j(t). \tag{56}$$

Using the fact that $\left(\gamma^j\right)^{\sigma^j} \left(\frac{W^j(t)}{A^j(t)}\right)^{1-\sigma^j} \left(c^j(t)\right)^{\sigma^j - 1} = s_L^j(t)$, eq. (56) can be rewritten as $-s_L^j \hat{A}^j(t) - \left(1 - s_L^j\right) \hat{B}^j(t) = \hat{c}^j(t)$. Setting this equality to zero and inserting (55) leads to:

$$\frac{\gamma_Z^j}{1 - \gamma_Z^j} \left(\frac{B^j(t)}{A^j(t)}\right)^{\frac{1 - \sigma_Z^j}{\sigma_Z^j}} = \frac{s_L^j(t)}{1 - s_L^j(t)} \equiv S^j(t). \tag{57}$$

Solving (57) for s_L^j leads to:

$$s_L^j = \gamma_Z^j \left(\frac{A^j}{Z^j}\right)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}}. \tag{58}$$

Inserting (58) into (55) allows us to rewrite the log-linearized version of the technology frontier as follows:

$$\hat{Z}_t^j = s_L \hat{A}_t^j + \left(1 - s_L^j\right) \hat{B}_t^j. \tag{59}$$

E Sectoral Decomposition of Aggregate TFP

We consider an open economy which produces domestic traded goods, denoted by a superscript H, and non-traded goods, denoted by a superscript N. The foreign-produced traded good is the numeraire and its price is normalized to 1. We consider an initial steady-state where prices are those at the base year so that initially real GDP, denoted by Y_R, and the value added share at constant prices, denoted by $\nu^{Y,j}$, collapse to nominal GDP (i.e., Y) and the value added share at current prices, respectively.

Summing value added at constant prices across sectors gives real GDP:

$$Y_{R,t} = P^H Y_t^H + P^N Y_t^N, \tag{60}$$

where P^H and P^N stand for the price of home-produced traded goods and non-traded goods, respectively, which are kept fixed since we consider value added at constant prices.

Log-linearizing (60), and denoting the percentage deviation from initial steady-state by a hat leads to:

$$\hat{Y}_{R,t} = \nu^{Y,H}\hat{Y}^H_t + \left(1-\nu^{Y,H}\right)\hat{Y}^N_t, \tag{61}$$

where $\nu^{Y,H} = \frac{P^H Y^H}{Y}$ is the value added share of home-produced traded goods evaluated at the initial steady-state. We drop the time index below as long as it does not cause confusion.

Sectoral goods are produced from CES production functions (39). Log-linearizing (39) and invoking the property of constant returns to scale together with the assumptions of perfect competition in goods and factor market are perfectly competitive, i.e., inserting eq. (40), leads to:

$$\hat{Y}^j_t = s_L\left(\hat{A}^j_t + \hat{L}^j_t\right) + \left(1-s^j_L\right)\left(\hat{B}^j_t + \hat{u}^{K,j}_t + \hat{K}^j_t\right). \tag{62}$$

We assume that firms choose a mix of labor- and capital-augmenting efficiency, A^j and B^j, along a technology frontier whose height is measured by capital-utilization-TFP. The technology frontier is described by eq. (54). Inserting the log-linearized version of the technology frontier (59) implies that the log-linearized version of the CES production function (62) now reads:

$$\hat{Y}^j_t = \hat{Z}^j_t + s_L\hat{L}^j_t + \left(1-s^j_L\right)\left(\hat{u}^{K,j}_t + \hat{K}^j_t\right). \tag{63}$$

Since TFP growth, $\hat{\text{TFP}}^j_t$, includes both technology improvement $\hat{Z}^j_t$ and the adjustment in capital utilization $\left(1-s^j_L\right)\hat{u}^{K,j}_t$, the change in value added can be rewritten as follows:

$$\hat{Y}^j_t = \hat{\text{TFP}}^j_t + s^j_L\hat{L}^j_t + \left(1-s^j_L\right)\hat{K}^j_t. \tag{64}$$

Summing capital income and labor income across sectors and denoting the aggregate capital rental rate by R and the aggregate wage rate by W implies:

$$\sum_j W^j_t L^j_t = W_t L_t, \tag{65a}$$

$$\sum_j R^j_t K^j_t = R_t K_t, \quad \sum_j R^j_t \tilde{K}^j_t = R_t\tilde{K}_t, \tag{65b}$$

where $\tilde{K}^j = u^{K,j}K^j$ and $\tilde{K} = u^K K$. Log-linearizing (65a)-(65b) while keeping factor prices constant and dividing by nominal GDP leads to:

$$s_L\hat{L}_t = \sum_j \nu^{Y,j} s^j_L \hat{L}^j_t, \tag{66a}$$

$$\left(1-s_L\right)\hat{K}_t = \sum_j \nu^{Y,j}\left(1-s^j_L\right)\hat{K}^j_t. \tag{66b}$$

Inserting (64) into (61) allows us to rewrite the percentage deviation of real GDP as follows:

$$\hat{Y}_{R,t} = \sum_j \nu^{Y,j}\left[\hat{\text{TFP}}^j_t + s^j_L\hat{L}^j_t + \left(1-s^j_L\right)\hat{K}^j_t\right]. \tag{67}$$

Making use of (66a) and (66b), eq. (67) can be rewritten in the following form:

$$\hat{Y}_{R,t} = T\hat{F}P^A_t + s_L\hat{L}_t + \left(1-s^j_L\right)\hat{K}^j_t, \tag{68}$$

where

$$T\hat{F}P^A_t = \nu^{Y,H}T\hat{F}P^H + \left(1-\nu^{Y,H}\right)T\hat{F}P^N. \tag{69}$$

Log-linearizing $\sum_j R^j_t\tilde{K}^j_t = R_t\tilde{K}_t$ w.r.t. $u^{K,j}$ and divided by nominal GDP leads to:

$$\left(1-s_L\right)\hat{u}^K_t = \sum_j\left(1-s^j_L\right)\nu^{Y,j}\hat{u}^{K,j}_t. \tag{70}$$

Inserting the definition of TFP growth

$$T\hat{F}P_t^j = \hat{Z}^j + \left(1 - s_L^j\right)\hat{u}_t^{K,j}, \tag{71}$$

and using (70) allows us to rewrite (69) as follows:

$$\hat{Z}^A = \nu^{Y,H}\hat{Z}^H + \left(1 - \nu^{Y,H}\right)\hat{Z}^N. \tag{72}$$

F Recovering and Calibrating the Dynamics of FBTC at a Sectoral Level

In this section, we detail the methodology to construct time series for capital-utilization-adjusted-FBTC in sector $j = H, N$ and we detail how we choose parameters to account for the dynamics of both symmetric and asymmetric components of factor-augmenting efficiency $A_c^j(t)$ and $B_c^j(t)$ (with $c = S, D$, $j = H, N$) we estimate empirically.

F.1 Construction of Time Series for FBTC at a Sectoral Level

The starting point is the ratio of the labor to the capital income share in sector j given by eq. (10) which can be solved for capital-utilization-adjusted-FBTC in sector j:

$$\text{FBTC}_t^j \equiv \left(\frac{B_t^j}{A_t^j}\right)^{\frac{1-\sigma^j}{\sigma^j}} = S_t^j \frac{1-\gamma^j}{\gamma^j}\left(k_t^j\right)^{-\frac{1-\sigma^j}{\sigma^j}}\left(u_t^{K,j}\right)^{-\frac{1-\sigma^j}{\sigma^j}}, \tag{73}$$

where $u_t^{K,j}$ is constructed by using the formula (91).

Since we normalize CES production functions so that the relative weight of labor and capital is consistent with the labor and capital income share in the data, solving for γ^j leads to:

$$\gamma^j = \left(\frac{\bar{A}^j}{\bar{y}^j}\right)^{\frac{1-\sigma^j}{\sigma^j}} \bar{s}_L^j, \tag{74a}$$

$$1 - \gamma^j = \left(\frac{\bar{B}^j \bar{u}^{K,j}\bar{k}^j}{\bar{y}^j}\right)^{\frac{1-\sigma^j}{\sigma^j}}\left(1 - \bar{s}_L^j\right). \tag{74b}$$

Dividing (74a) by (74b) leads to:

$$\bar{S}^j = \frac{\gamma^j}{1-\gamma^j}\left(\frac{\bar{B}^j \bar{u}^{K,j}\bar{k}^j}{\bar{A}^j}\right)^{\frac{1-\sigma^j}{\sigma^j}}, \tag{75}$$

where variables with a bar are averaged values of the corresponding variables over 1970-2017.

The methodology adopted to calculate γ^j amounts to using averaged values as the normalization point to compute time series for FBTC:

$$\left(\frac{B_t^j/\bar{B}^j}{A_t^j/\bar{A}^j}\right)^{\frac{1-\sigma^j}{\sigma^j}} = \frac{S_t^j}{\bar{S}^j}\left(\frac{k_t^j}{\bar{k}^j}\right)^{-\frac{1-\sigma^j}{\sigma^j}}\left(\frac{u_t^{K,j}}{\bar{u}^{K,j}}\right)^{-\frac{1-\sigma^j}{\sigma^j}}. \tag{76}$$

Factor-Biased Technological Change (FBTC). Within each sector, we allow for labor- and capital-augmenting efficiency to increase at different rates so that technological change can potentially be factor-biased. To investigate empirically whether technological change is biased toward capital or labor, we have to constuct time series for FBTC within sector $j = H, N$. We draw on Caselli and Coleman [2006] and Caselli [2016] to construct time series for FBTC which must be adjusted with the capital utilization rate. Using (76), our measure of capital-utilization-adjusted-FBTC, denoted by FTBC_{it}^j, reads

$$\text{FBTC}_{it}^j = \left(\frac{B_{it}^j/\bar{B}_i^j}{A_{it}^j/\bar{A}_i^j}\right)^{\frac{1-\sigma_i^j}{\sigma_i^j}} = \frac{S_{it}^j}{\bar{S}_i^j}\left(\frac{k_{it}^j}{\bar{k}_i^j}\right)^{-\frac{1-\sigma_i^j}{\sigma_i^j}}\left(\frac{u_{it}^{K,j}}{\bar{u}_i^{K,j}}\right)^{-\frac{1-\sigma_i^j}{\sigma_i^j}}, \tag{77}$$

where a bar refers to averaged values of the corresponding variable over 1970-2017. To construct time series for FBTC_{it}^{j}, we plug time series for the ratio of the labor to the capital income share, $S_t^j = s_{L,it}^j / \left(1 - s_{L,it}^j\right)$, the capital-labor ratio, k_{it}^j, the capital utilization rate defined later, $u_{it}^{K,j}$. We also plug values for σ_i^j we have estimated for each country of our sample, see sectionJ.6 for a detailed exposition of our empirical strategy. As shown in Table 1, we find values for σ_i^j smaller than one for the whole sample (and most of countries/sectors), thus corroborating the gross complementarity between capital and labor documented by Oberfield and Raval [2021], Chirinko and Mallick [2017]. When FBTC_{it}^{j} increases, technological change is biased toward labor while a fall indicates that technological change is biased toward capital. To compute aggregate FBTC, we calculate the labor compensation share weighted sum of sectoral FBTC adjusted with the capital income share, i.e., $\hat{\text{FBTC}}_{it}^{A} = \sum_{j=H,N} \alpha_{L,i}^j \left(1 - s_{L,i}^j\right) \hat{\text{FBTC}}_{it}^{j}$.

To get estimates of σ^j at a sectoral level, following Antràs [2004], we run the regression of logged real value added per hours worked on the logged real wage in this sector with country-specific linear trends over 1970-2017. Since all variables display unit root process, we use the fully modified OLS (FMOLS) procedure for cointegrated panel proposed by Pedroni [2000] to estimate the cointegrating relationship. Columns 17 and 18 of Table 8 report estimates for σ^H and σ^N we use to recover FBTC from (76). FMOLS estimated values for the whole sample, i.e., $\sigma^H = 0.81$ and $\sigma^N = 0.86$, reveal that capital and labor are gross complements in both sectors.[11]

G Identification of Technology Shocks

In this section we detail the identification strategy of technology shocks.

Empirical identification of technology shocks. To identify a permanent technology improvement, we consider a vector of n observables $\hat{X}_{it} = [\hat{Z}_{it}, \hat{V}_{it}]$ where $\hat{Z}_{it}$ consists of the first difference of the (logarithm of the) utilization-adjusted TFP (as defined in eq. (1)) and $\hat{V}_{it}$ denotes the $n-1$ variables of interest (in growth rate) detailed later. Let us consider the following reduced form of the VAR(p) model:

$$C(L)\hat{X}_{it} = \eta_{it}, \tag{78}$$

where $C(L) = I_n - \sum_{k=1}^{p} C_k L^k$ is a p-order lag polynomial and η_{it} is a vector of reduced-form innovations with a variance-covariance matrix given by Σ. We estimate the reduced form of the VAR model by panel OLS regression with country and time fixed effects which are omitted in (83) for expositional convenience. The matrices C_k and Σ are assumed to be invariant across time and countries and all VARs have two lags. The vector of orthogonal structural shocks $\varepsilon_{it} = [\varepsilon_{it}^Z, \varepsilon_{it}^V]$ is related to the vector of reduced form residuals η_{it} through:

$$\eta_{it} = A_0 \varepsilon_{it}, \tag{79}$$

which implies $\Sigma = A_0 A_0'$ with A_0 the matrix that describes the instantaneous effects of structural shocks on observables. The linear mapping between the reduced-form innovations and structural shocks leads to the structural moving average representation of the VAR model:

$$\hat{X}_{it} = B(L) A_0 \varepsilon_{it}, \tag{80}$$

where $B(L) = C(L)^{-1}$. Let us denote $A(L) = B(L)A_0$ with $A(L) = \sum_{k=0}^{\infty} A_k L^k$. To identify a permanent technology improvement, ε_{it}^Z, we use the restriction that the unit root in utilization-adjusted TFP originates exclusively from technology shocks which implies that the upper triangular elements of the long-run cumulative matrix $A(1) = B(1)A_0$ must be zero. Once the reduced form has been estimated using OLS, structural shocks can then be recovered from $\varepsilon_{it} = A(1)^{-1} B(1) \eta_{it}$ where the matrix $A(1)$ is computed as the Cholesky decomposition of $B(1)\Sigma B(1)'$.

[11] Online Appendix J.6 provides more details about our empirical strategy to estimate σ^j. All FMOLS estimated coefficients are positive and statistically significant except the estimated value for σ^H for Ireland which is negative. As in Antràs [2004], we alternatively run the regression of the ratio of value added to capital stock at constant prices on the real capital cost R/P^j in sector j and replace the inconsistent estimate for σ^H obtained from labor demand with that obtained from the demand of capital.

Table 5: Sample Range for Empirical and Numerical Analysis

Country	Code	Period	Obs.
Australia	(AUS)	1970 - 2017	48
Austria	(AUT)	1970 - 2017	48
Belgium	(BEL)	1970 - 2017	48
Canada	(CAN)	1970 - 2017	48
Germany	(DEU)	1970 - 2017	48
Denmark	(DNK)	1970 - 2017	48
Spain	(ESP)	1970 - 2017	48
Finland	(FIN)	1970 - 2017	48
France	(FRA)	1970 - 2017	48
Great Britain	(GBR)	1970 - 2016	47
Ireland	(IRL)	1970 - 2017	48
Italy	(ITA)	1970 - 2017	48
Japan	(JPN)	1973 - 2015	43
Netherlands	(NLD)	1970 - 2017	48
Norway	(NOR)	1970 - 2017	48
Sweden	(SWE)	1970 - 2017	48
United States	(USA)	1970 - 2017	48
Total number of obs.			810
Main data sources		EU KLEMS & OECD STAN	

Notes: Column 'period' gives the first and last observation available. Obs. refers to the number of observations available for each country.

H Data Description for Empirical Analysis

Sources: Our primary sources for sectoral data are the OECD and EU KLEMS databases. We use data from EU KLEMS ([2011], [2017]) March 2011 and July 2017 releases. The EU KLEMS dataset covers all countries of our sample, with the exceptions of Canada and Norway. For these two countries, sectoral data are taken from the Structural Analysis (STAN) database provided by the OECD ([2011], [2017]). For both EU KLEMS and STAN databases, the March 2011 release provides data for eleven 1-digit ISIC-rev.3 industries over the period 1970-2007 while the July 2017 release provides data for thirteen 1-digit-rev.4 industries over the period 1995-2017.

The construction of time series for sectoral variables over the period 1970-2017 involves two steps. First, we identify tradable and non-tradable sectors. The methodology adopted to classify industries as tradables or non-tradables is described in section L.2. We map the ISIC-rev.4 classification into the ISIC-rev.3 classification in accordance with the concordance Table 6. Once industries have been classified as traded or non-traded, for any macroeconomic variable X, its sectoral counterpart X^j for $j = H, N$ is constructed by adding the X_k of all sub-industries k classified in sector $j = H, N$ as follows $X^j = \sum_{k \in j} X_k$. Second, series for tradables and non-tradables variables from EU KLEMS [2011] and OECD [2011] databases (available over the period 1970-2007) are extended forward up to 2017 using annual growth rate estimated from EU KLEMS [2017] and OECD [2017] series (available over the period 1995-2017).

Construction of sectoral variables. Once industries have been classified as traded or non-traded, we construct sectoral variables by taking time series from EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. These two databases provide data, for each industry and year, on value added at current and constant prices, permitting the construction of sectoral deflators of value added, as well as details on labor compensation and hours worked data, allowing the construction of sectoral wage rates. Time and countries are indexed by subscripts i and t below while the sector is indexed by the superscript $j = H, N$.

All quantity variables are scaled by the working age population (15-64 years old). Source: OECD ALFS Database for the working age population (data coverage: 1970-2017). We describe below the construction for the sectoral data employed in the main text (mnemonics are given in parentheses):

- **Sectoral value added**, Y_{it}^j: sectoral value added at constant prices in sector $j = H, N$ (VA_QI). Series for sectoral value added in current (constant) prices are con-

Table 6: Summary of Sectoral Classifications

Sector	ISIC-rev.4 Classification (sources: EU KLEMS [2017] and OECD ([2017]))		ISIC-rev.3 Classification (sources: EU KLEMS [2011] and OECD ([2011]))	
	Industry	Code	Industry	Code
Tradables (H)	Agriculture, Forestry and Fishing	A	Agriculture, Hunting, Forestry and Fishing	AtB
	Mining and Quarrying	B	Mining and Quarrying	C
	Total Manufacturing	C	Total Manufacturing	D
	Transport and Storage	H	Transport, Storage and Communication	I
	Information and Communication	J		
	Financial and Insurance Activities	K	Financial Intermediation	J
Non Tradables (N)	Electricity, Gas and Water Supply	D-E	Electricity, Gas and Water Supply	E
	Construction	F	Construction	F
	Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles	G	Wholesale and Retail Trade	G
	Accommodation and Food Service Activities	I	Hotels and Restaurants	H
	Real Estate Activities	L	Real Estate, Renting and Business Services	K
	Professional, Scientific, Technical, Administrative and Support Service Activities	M-N		
	Community Social and Personal Services	O-U	Community Social and Personal Services	LtQ

structed by adding value added in current (constant) prices for all sub-industries k in sector $j = H, N$, i.e., $P^j_{it} Y^j_{it} = \sum_k P^j_{k,it} Y^j_{k,it}$ ($\bar{P}^j_{it} Y^j_{it} = \sum_k \bar{P}^j_{k,it} Y^j_{k,it}$ where the bar indicates that prices P^j are those of the base year), from which we construct price indices (or sectoral value added deflators), P^j_{it}. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

- **Sectoral value added share**, $\nu^{Y,j}_{it}$, is constructed as the ratio of value added at constant prices in sector j to GDP at constant prices, i.e., $Y^j_{it}/(Y^H_{it}+Y^N_{it})$ for $j = H, N$.

- **Relative price of non-tradables**, P_{it}. Normalizing base year price indices $\bar{P}^j$ to 1, the relative price of non-tradables, P_{it}, is constructed as the ratio of the non-traded value added deflator to the traded value added deflator (i.e., $P_{it} = P^N_{it}/\mathsf{P}^H_{it}$). The sectoral value added deflator P^j_{it} for sector $j = H, N$ is calculated by dividing value added at current prices (VA) by value added at constant prices (VA_QI) in sector j. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

- **Terms of trade**, $\text{TOT}_{it} = P^H_{it}/P^{H,\star}_{it}$, is computed as the ratio of the traded value added deflator of the home country i, P^H_{it}, to the geometric average of the traded value added deflator of the seventeen trade partners of the corresponding country i, $P^{H,\star}_{it}$, the weight being equal to the share $\alpha^{M,k}_i$ of imports from the trade partner k. We use the traded value added deflator to approximate foreign prices as it corresponds to a value-added concept. The Direction of Trade Statistics (DOTS, IMF) gives the share of imports $\alpha^{M,k}_i$ of country i by trade partner k for all countries of our sample over 1970-2017. The traded value added deflator P^H_{it} is calculated by dividing value added at current prices (VA) by value added at constant prices (VA_QI) in sector H. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) for P^H. Prices of foreign goods and services are calculated as follows: $P^{H,\star}_{it} = \Pi_{k\neq i}\left(P^{H,k}_t\right)^{\alpha^{M,k}_i}$. While the seventeen trade partners of a representative home country do not fully account for the totality of trade between country i and its trade partners $k \neq i$, it covers 58% of total trade on average for a representative OECD country of our sample. Source: Direction of Trade Statistics [2017]. Period: 1970-2017 for all countries except for Belgium (1997-2017).

- **Sectoral hours worked**, L^j_{it}, correspond to hours worked by persons engaged in sector j (H_EMP). Likewise sectoral value added, sectoral hours worked are constructed by adding hours worked for all sub-industries k in sector $j = H, N$, i.e., $L^j_{it} = \sum_k L^j_{k,it}$. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

- **Sectoral labor share**, $\nu^{L,j}_{it}$, is constructed as the ratio of hours worked in sector j

to total hours worked, i.e., $L^j_{it}/(L^H_{it} + L^N_{it})$ for $j = H, N$.

- **Sectoral nominal wage**, W^j_{it} is calculated as the ratio of the labor compensation (compensation of employees plus compensation of self-employed) in sector $j = H, N$ (LAB) to total hours worked by persons engaged (H_EMP) in that sector. ources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

- **Relative wage**, W^j_{it}/W_{it}, is constructed as the ratio of the nominal wage in the sector j to the aggregate nominal wage W.

- **Labor income share (LIS)**, $s^j_{L,it}$, is constructed as the ratio of labor compensation (compensation of employees plus compensation of self-employed) in sector $j = H, N$ (LAB) to value added at current prices (VA) of that sector. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

We detail below the data construction for aggregate variables (mnemonics are in parentheses). For all variables, the reference period is running from 1970 to 2017:

- **Real gross domestic product**, $Y_{R,it}$, is the sum of traded and non-traded value added at constant prices. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

- **Total hours worked**, L_{it}, are total hours worked by persons engaged (H_EMP). By construction, total hours worked is the sum of traded and non-traded hours worked. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

- **Real consumption wage**, $W_{C,it} = W_{it}/P_{C,it}$, is constructed as the nominal aggregate wage divided by the consumer price index (CPI). Source: OECD Prices and Purchasing Power Parities Database [2017] for the consumer price index. The nominal aggregate wage is calculated by dividing labor compensation (LAB) by total hours worked by persons engaged (H_EMP). Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

- **Aggregate total factor productivity**, TFP$_{it}$, is constructed as the Solow residual from constant-price domestic currency series of GDP, capital, LIS $s_{L,i}$, and total hours worked. We compute the overall capital stock by adopting the perpetual inventory approach, using constant-price investment series taken from the OECD's Annual National Accounts, see the next section I. The aggregate LIS, s_L, i, is the ratio of labor compensation (compensation of employees plus compensation of self-employed) (LAB) to GDP at current prices (VA) in sector averaged over the period 1970-2017 (except Japan: 1973-2015). Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

I Construction of Utilization-Adjusted-TFP Time Series at a Sectoral Level

We construct time-varying capital utilization time series using the procedure discussed in Imbs [1999] to construct our own series of utilization-adjusted-TFP. We assume perfectly competitive factor and product markets. We abstract from capital adjustment costs and capital mobility costs across sectors. Both the traded and non-traded sectors use physical capital, K^j, and labor, L^j, according to constant returns to scale production functions which are assumed to take a CES form:

$$Y^j_t = \left[\gamma^j \left(A^j_t L^j_t\right)^{\frac{\sigma^j - 1}{\sigma^j}} + \left(1 - \gamma^j\right) \left(B^j_t u^{K,j}_t K^j_t\right)^{\frac{\sigma^j - 1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j - 1}}. \tag{81}$$

We denote the capital utilization rate by $u^{K,j}_t$. Because more intensive capital use depreciates the capital more rapidly, we assume the following relationship between capital use and depreciation:

$$\delta^j_{K,t} = \delta_K \left(u^{K,j}_t\right)^{\phi_K}, \tag{82}$$

where δ_K is the capital depreciation rate and ϕ_K is the parameter which must be determined. At the steady-state, we have $u^{K,j} = 1$ and thus capital depreciation collapses to δ_K which is assumed to be symmetric across sectors. Firms also choose A^j and B^j along the technology frontier that we assume to be Cobb-Douglas without loss of generality:

$$Z^j_t = \left(A^j_t\right)^{s^j_{L,t}} \left(B^j_t\right)^{1-s^j_{L,t}}. \tag{83}$$

While in the main text, we assume that the technology frontier is CES and above we assume it is Cobb-Doublas, it leads to the same outcome, i.e., $\hat{Z}^j_t = s^j_L \hat{A}^j_t + \left(1 - s^j_L\right) \hat{B}^j_t$.

Denoting the capital rental cost by $R_t = P_{J,t}\left(\delta_{K,t} + r^\star\right)$, and the labor cost by W^j_t, firms choose the capital stock, capital utilization and labor so as the maximize profit:

$$\Pi^j_t = P^j_t Y^j_t - W^j_t L^j_t - R_t K^j_t. \tag{84}$$

Profit maximization leads to first order conditions on K^j, $u^{K,j}$, L^j:

$$P^j_t\left(1-\gamma^j\right)\left(B^j_t u^{K,j}_t\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(K^j_t\right)^{-\frac{1}{\sigma^j}} \left(Y^j_t\right)^{\frac{1}{\sigma^j}} = R_t, \tag{85a}$$

$$P^j_t\left(1-\gamma^j\right)\left(B^j_t K^j_t\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(u^{K,j}_t\right)^{-\frac{1}{\sigma^j}} \left(Y^j_t\right)^{\frac{1}{\sigma^j}} = P_{J,t}\delta_K\phi_K\left(u^{K,j}_t\right)^{\phi_K-1} K^j, \tag{85b}$$

$$P^j_t\gamma^j\left(A^j_t\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(L^j_t\right)^{-\frac{1}{\sigma^j}} \left(Y^j_t\right)^{\frac{1}{\sigma^j}} = W^j_t. \tag{85c}$$

Multiplying both sides of the first equality by K^j and dividing by sectoral value added leads to the capital income share:

$$1 - s^j_{L,t} = \left(1-\gamma^j\right)\left(\frac{B^j_t u^{K,j}_t K^j_t}{Y^j_t}\right)^{\frac{\sigma^j-1}{\sigma^j}}. \tag{86}$$

By using the definition of the capital income share above and inserting the expression for the capital rental cost, first-order conditions can be rewritten as follows:

$$\left(1 - s^j_L\right)\frac{P^j_t Y^j_t}{P_{J,t}K^j_t} = \left(\delta_{K,t} + r^\star\right), \tag{87a}$$

$$\left(1 - s^j_L\right)\frac{P^j_t Y^j_t}{P_{J,t}K^j_t} = \delta_{K,t}\phi_K, \tag{87b}$$

$$s^j_{L,t}\frac{P^j_t Y^j_t}{L^j_t} = W^j_t. \tag{87c}$$

Evaluating (87a) and (87b) at the steady-state and rearranging terms leads to:

$$\left(r^\star + \delta_K\right) = \delta_K\phi_K, \tag{88}$$

which allows us to pin down ϕ_K. We let the capital depreciation rate δ_K and the real interest rate $r^\star$ (long-run interest rate minus CPI inflation rate) vary across countries to compute ϕ_K.

In the line of Garofalo and Yamarik [2002], we use the value added share at current prices to allocate the aggregate capital stock to sector j:

$$K^j_t = \omega^{Y,j}_t K_t, \tag{89}$$

where K_t is the aggregate capital stock at constant prices and $\omega^{Y,j}_t = \frac{P^j_t Y^j_t}{P_t Y_{R,t}}$ is the value added share of sector $j = H, N$ at current prices. The methodology by Garofalo and

Yamarik [2002] is based on the assumption of perfect mobility of capital across sectors and a small discrepancy in the LIS across sectors, i.e., $s_L^H \simeq s_L^N$. Inserting (89) into (87a)-(87b), first order conditions on K^j and $u^{K,j}$ now read as follows:

$$\left(1 - s_{L,t}^j\right) \frac{P_t Y_{R,t}}{P_{J,t} K_t} = \left(\delta_{K,t} + r^\star\right), \tag{90a}$$

$$\left(1 - s_{L,t}^j\right) \frac{P_t Y_{R,t}}{P_{J,t} K_t} = \delta_{K,t} \phi_K. \tag{90b}$$

Solving (90b) for $u_t^{K,j}$ leads to:

$$u_t^{K,j} = \left[\frac{\left(1 - s_{L,t}^j\right)}{\delta_K \phi_K} \frac{P_t Y_{R,t}}{P_{J,t} K_t}\right]^{\frac{1}{\phi_K}}, \tag{91}$$

where $\phi_K = \frac{r^\star + \delta_K}{\delta_K}$ (see eq. (88)). Dropping the time index to denote the steady-state value, the capital utilization rate is:

$$u^{K,j} = \left[\frac{\left(1 - s_L^j\right)}{\delta_K \phi_K} \frac{P Y_R}{P_J K}\right]^{\frac{1}{\phi_K}}. \tag{92}$$

Dividing (91) by (92) leads to the capital utilization rate relative to its steady-state:

$$\frac{u_t^{K,j}}{u^{K,j}} = \left[\left(\frac{1 - s_{L,t}^j}{1 - s_L^j}\right) \frac{P_t Y_{R,t}}{P Y_R} \frac{P_J K}{P_{J,t} K_t}\right]^{\frac{1}{\phi_K}}, \tag{93}$$

We denote total factor productivity in sector $j = H, N$ by TFP^j which is defined as follows:

$$\text{TFP}_t^j = \frac{Y_t^j}{\left[\gamma^j \left(L_t^j\right)^{\frac{\sigma^j - 1}{\sigma^j}} + \left(1 - \gamma^j\right) \left(K_t^j\right)^{\frac{\sigma^j - 1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j - 1}}}. \tag{94}$$

Log-linearizing (94), the Solow residual is:

$$T\hat{F}P_t^j = \hat{Y}_t^j - s_L^j \hat{L}_t^j - \left(1 - s_L^j\right) \hat{K}_t^j. \tag{95}$$

Log-linearizing the production function (81) shows that the Solow residual can alternatively be decomposed into utilization-adjusted TFP and capital utilization correction:

$$\text{T}\hat{\text{F}}\text{P}_t^j = \hat{Z}_t^j + \left(1 - s_L^j\right) \hat{u}_t^{K,j}, \tag{96}$$

where utilization-adjusted TFP denoted by Z^j is equal to:

$$\hat{Z}_t^j = s_L^j \hat{A}_t^j + \left(1 - s_L^j\right) \hat{B}_t^j. \tag{97}$$

Construction of time series for sectoral capital stock, K_t^j. To construct the series for the sectoral capital stock, we proceed as follows. We first construct time series for the aggregate capital stock for each country in our sample. To construct K_t, we adopt the perpetual inventory approach. The inputs necessary to construct the capital stock series are a i) capital stock at the beginning of the investment series, K_{1970}, ii) a value for the constant depreciation rate, δ_K, iii) real gross capital formation series, I_t. Real gross capital formation is obtained from OECD National Accounts Database [2017] (data in millions of national currency, constant prices). We construct the series for the capital stock using the law of motion for capital in the model:

$$K_{t+1} = I_t + \left(1 - \delta_K\right) K_t. \tag{98}$$

for $t = 1971, ..., 2017$. The value of δ_K is chosen to be consistent with the ratio of capital depreciation to GDP observed in the data and averaged over 1970-2017:

$$\frac{1}{48}\sum_{t=1970}^{2017}\frac{\delta_K P_{J,t} K_t}{Y_t} = \frac{CFC}{Y}, \tag{99}$$

where $P_{J,t}$ is the deflator of gross capital formation series, Y_t is GDP at current prices, and CFC/Y is the ratio of consumption of fixed capital at current prices to nominal GDP averaged over 1970-2017. Deflator of gross capital formation, GDP at current prices and consumption of fixed capital are taken from the OECD National Account Database [2017]. The second column of Table 7 shows the value of the capital depreciation rate obtained by using the formula (99). The capital depreciation rate averages to 5%.

To have data on the capital stock at the beginning of the investment series, we use the following formula:

$$K_{1970} = \frac{I_{1970}}{g_I + \delta_K}, \tag{100}$$

where I_{1970} corresponds to the real gross capital formation in the base year 1970, g_I is the average growth rate from 1970 to 2017 of the real gross capital formation series. The system of equations (98), (99) and (100) allows us to use data on investment to solve for the sequence of capital stocks and for the depreciation rate, δ_K. There are 49 unknowns: K_{1970}, δ_K, K_{1971}, ..., and K_{2017}, in 49 equations: 47 equations (98), where $t = 1971, ..., 2017$, (99), and (100). Solving this system of equations, we obtain the sequence of capital stocks and a calibrated value for depreciation, δ_K. Following Garofalo and Yamarik [2002], the gross capital stock is then allocated to traded and non-traded industries by using the sectoral value added share, see eq. (89).

Construction of time series for sectoral TFPs. Sectoral TFPs, TFP^j_t, at time t are constructed as Solow residuals from constant-price (domestic currency) series of value added, Y^j_t, capital stock, K^j_t, and hours worked, L^j_t, by using eq. (95). The LIS in sector j, s^j_L, is the ratio of labor compensation (compensation of employees plus compensation of self-employed) to nominal value added in sector $j = H, N$, averaged over the period 1970-2017 (except Japan: 1973-2015). Data for the series of constant price value added (VA_QI), current price value added (VA), hours worked (H_EMP) and labor compensation (LAB) are taken from the EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases.

Construction of time series for real interest rate, $r^\star$. The real interest rate is computed as the real long-term interest rate which is the nominal interest rate on 10 years government bonds minus the rate of inflation which is the rate of change of the Consumption Price Index (CPI). Sources: OECD Economic Outlook Database [2017] for the long-term interest rate on government bonds and OECD Prices and Purchasing Power Parities Database [2017] for the CPI. Data coverage: 1970-2017 except for IRL (1990-2017) and KOR (1983-2017). The first column of Table 7 shows the value of the real interest rate which averages 2.7% over the period 1970-2017.

Construction of time series for capital utilization, $u^{K,j}_t$. To construct time series for the capital utilization rate, $u^{K,j}_t$, we proceed as follows. We use time series for the real interest rate, $r^\star$ and for the capital depreciation rate, δ_K to compute $\phi = \frac{r^\star+\delta_K}{\delta_K}$ (see eq. (88)). Once we have calculated ϕ for each country, we use time series for the LIS in sector j, $s^j_{L,t}$, GDP at current prices, $P_t Y_{R,t} = Y_t$, the deflator for investment, $P_{J,t}$, and times series for the aggregate capital stock, K_t to compute time series for $u^{K,j}_t$ by using the formula (91).

Construction of time series for utilization-adjusted TFP, Z^j_t. According to (96), capital utilization-adjusted sectoral TFP expressed in percentage deviation relative to the steady-state reads:

$$\begin{aligned} \hat{Z}^j_t &= \hat{\text{TFP}}^j_t - \left(1 - s^j_L\right)\hat{u}^{K,j}_t, \\ \ln Z^j_t - \ln \bar{Z}^j_t &= \left(\ln \text{TFP}^j_t - \ln \bar{\text{TFP}}^j_t\right) - \left(1 - s^j_L\right)\left(\ln u^{K,j}_t - \ln \bar{u}^{K,j}_t\right). \end{aligned} \tag{101}$$

Table 7: Data on Real Interest Rate ($r^\star$) and Fixed Capital Depreciation Rate (δ_K)

Country	$r^\star$	δ_K
AUS	0.028	0.058
AUT	0.029	0.040
BEL	0.031	0.041
CAN	0.031	0.100
DEU	0.022	0.062
DNK	0.044	0.036
ESP	0.020	0.048
FIN	0.024	0.043
FRA	0.031	0.031
GBR	0.023	0.042
IRL	0.033	0.029
ITA	0.025	0.050
JPN	0.017	0.061
NLD	0.028	0.035
NOR	0.025	0.102
SWE	0.029	0.038
USA	0.025	0.026
OECD	0.027	0.050

The percentage deviation of variable X_t from initial steady-state is denoted by $\hat{X}_t = \ln X_t - \ln \bar{X}_t$ where we let the steady-state vary over time; the time-varying trend $\ln \bar{X}_t$ is obtained by applying a HP filter with a smoothing parameter of 100 to logged time series. To compute $T\hat{F}P^j_t$, we take the log of TFP^j_t and subtract the trend component extracted from a HP filter applied to logged TFP^j_t, i.e., $\ln \text{TFP}^j_t - \ln \bar{\text{TFP}}^j_t$. The same logic applies to $u^{K,j}_t$. Once we have computed the percentage deviation $\ln Z^j_t - \ln \bar{Z}^j_t$, we reconstruct time series for $\ln Z^j_t$:

$$\ln Z^j_t = \left(\ln Z^j_t - \ln \bar{Z}^j_t\right) + \ln \bar{Z}^j_t. \tag{102}$$

The construction of time series of logged sectoral TFP, $\ln \text{TFP}^j_t$, capital utilization-adjusted sectoral TFP, $\ln Z^j_t$, is consistent with the movement of capital utilization along the business cycle.

J Data for Calibration

J.1 Non-Tradable Content of GDP and its Demand Components

Table 8 shows the non-tradable content of GDP, consumption, investment, government spending, labor and labor compensation (columns 1 to 6). The home content of consumption and investment expenditure in tradables and the home content of government spending are reported in columns 8 to 10. Column 7 shows the ratio of exports to GDP. Columns 11 and 12 shows the labor income share in the traded and non-traded sector. Columns 13-14 display the investment-to-GDP ratio and government spending in % of GDP, respectively. Our sample covers the 17 OECD countries displayed by Table 5. The reference period for the calibration of labor variables is 1970-2017 while the reference period for demand components is 1995-2014 due to data availability, as detailed below. When we calibrate the model to a representative economy, we use the last line which shows the (unweighted) average of the corresponding variable.

Aggregate ratios. Columns 13-14 show the investment-to-GDP ratio, ω_J and government spending as a share of GDP, ω_G. To calculate ω_J, we use time series for gross capital formation at current prices and GDP at current prices, both obtained from the OECD National Accounts Database [2017]. Data coverage: 1970-2017 for all countries. To calculate ω_G, we use time series for final consumption expenditure of general government (at current prices) and GDP (at current prices). Source: OECD National Accounts Database [2017]. Data coverage: 1970-2017 for all countries. We consider a steady-state where trade is initially balanced and we calculate the consumption-to-GDP ratio, ω_C by using the accounting identity between GDP and final expenditure:

$$\omega_C = 1 - \omega_J - \omega_G. \tag{103}$$

As displayed by the last line of Table 8, investment expenditure (see column 13) and government spending (see column 14) as a share of GDP average to 23% and 20%.

Non-traded demand components. Online Appendix of Cardi and Restout [2023] details the construction of time series for non-traded government consumption, G_t^N, non-traded consumption, C_t^N, and non-traded investment, J_t^N by using the World Input-Output Databases ([2013], [2016]). Columns 2 to 4 show non-tradable content of consumption (i.e., $1-\alpha_C$), investment (i.e., $1-\alpha_J$), and government spending (i.e., ω_{G^N}), respectively. These demand components have been calculated by adopting the methodology described in Online Appendix F of Cardi and Restout [2023]. Sources: World Input-Output Databases ([2013], [2016]). Data coverage: 1995-2014 except for NOR (2000-2014). The non-tradable content of consumption, investment and government spending shown in column 2 to 4 of Table 8 averages to 57%, 69% and 84%, respectively.

In the empirical analysis, we use data from EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases for constructing sectoral value added over the period running from 1970 to 2017. Since the demand components for non-tradables are computed over 1995-2014 by using the WIOD dataset, to ensure that the value added is equal to the sum of its demand components, we have calculated the non-tradable content of value added shown in column 1 of Table 8 as follows:

$$\begin{aligned} \omega^{Y,N} &= = \frac{P^N Y^N}{Y}, \\ &= \omega_C (1-\alpha_C) + \omega_J (1-\alpha_J) + \omega_{G^N}\omega_G, \end{aligned} \tag{104}$$

where $1-\alpha_C$ and $1-\alpha_J$ are the non-tradable content of consumption and investment expenditure shown in columns 2 and 3, ω_{G^N} is the non-tradable content of government spending shown in column 4, ω_C and ω_J are consumption- and investment-to-GDP ratios, and ω_G is government spending as a share of GDP.

Non-tradable content of hours worked and labor compensation. To calculate the non-tradable share of labor shown in column 5 and labor compensation shown in column 6, we split the eleven industries into traded and non-traded sectors by adopting the classification detailed in section L.2. Details about data construction for sectoral output and sectoral labor are provided above. We calculate the non-tradable share of labor compensation as the ratio of labor compensation in the non-traded sector (i.e., $W^N L^N$) to overall labor compensation (i.e., WL). Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. Data coverage: 1970-2017 for all countries (except Japan: 1973-2015). The non-tradable content of labor and labor compensation, shown in columns 5 and 6 of Table 8, average to 64% and 63% respectively.

Home content of consumption and investment expenditure in tradables. Online Appendix of Cardi and Restout [2023] details the construction of time series for the home content of consumption and investment in traded goods by using data taken from WIOD which allows to differentiate between domestic demand for home- and foreign-produced goods. Columns 8 to 9 of Table 8 show the home content of consumption and investment in tradables, denoted by α^H and α_J^H in the model. These shares are obtained from time series calculated by using the formulas derived in Online Appendix F of Cardi and Restout [2023]. Sources: World Input-Output Databases [2013], [2016]. Data coverage: 1995-2014 except for NOR (2000-2014). Column 10 shows the content of government spending in home-produced traded goods. Taking data from the WIOD dataset, time series for ω_{G^H} are constructed by using the formula in Online Appendix F of Cardi and Restout [2023]. Data coverage: 1995-2014 except for NOR (2000-2014). As shown in the last line of columns 8 and 9, the home content of consumption and investment expenditure in traded goods averages to 66% and 42%, respectively, while the share of home-produced traded goods in government spending averages 12%. Since the non-tradable content of government spending averages 84% (see column 4), the import content of government spending is 4% only.

Table 8: Data to Calibrate the Two-Sector Model

Countries	Non-tradable share						Home share				LIS		Aggregate ratios		Elasticities				Interest
	GDP	Cons.	Inv.	Gov.	Labor	Lab. comp.	X^H	C^H	I^H	G^H	LIS^H	LIS^N	I/Y	G/Y	ϵ_L	ϵ_K	σ^H	σ^N	r
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
AUS	0.62	0.58	0.76	0.54	0.65	0.64	0.09	0.76	0.49	0.17	0.58	0.67	0.27	0.18	0.48	0.06	0.52	0.83	0.028
AUT	0.64	0.56	0.60	0.91	0.61	0.62	0.17	0.56	0.42	0.11	0.68	0.68	0.25	0.18	1.10	0.18	0.95	1.21	0.029
BEL	0.65	0.53	0.63	0.97	0.65	0.64	0.22	0.44	0.20	0.00	0.66	0.68	0.23	0.22	0.60	0.23	0.75	1.15	0.031
CAN	0.62	0.49	0.66	0.95	0.67	0.66	0.14	0.68	0.31	0.20	0.54	0.63	0.22	0.21	0.36	0.11	0.89	0.95	0.031
DEU	0.63	0.53	0.61	0.94	0.61	0.58	0.14	0.69	0.43	0.09	0.75	0.64	0.23	0.20	1.00	0.04	0.72	1.09	0.022
DNK	0.68	0.60	0.73	0.83	0.67	0.68	0.16	0.49	0.22	0.22	0.64	0.70	0.21	0.25	0.27	n.a.	0.56	0.94	0.044
ESP	0.64	0.59	0.77	0.65	0.61	0.63	0.11	0.73	0.38	0.15	0.59	0.65	0.24	0.16	0.95	0.00	0.98	0.54	0.020
FIN	0.66	0.57	0.73	0.81	0.59	0.61	0.12	0.67	0.41	0.17	0.64	0.74	0.25	0.20	0.42	0.10	0.73	0.84	0.024
FRA	0.71	0.57	0.76	0.98	0.65	0.66	0.10	0.71	0.46	0.00	0.72	0.69	0.23	0.22	1.31	0.09	0.87	1.33	0.031
GBR	0.65	0.58	0.70	0.81	0.66	0.61	0.12	0.66	0.42	0.19	0.69	0.74	0.20	0.20	0.62	0.09	0.61	0.58	0.023
IRL	0.62	0.50	0.74	0.87	0.59	0.61	0.21	0.48	0.19	0.15	0.49	0.68	0.23	0.18	0.10	n.a.	0.65	0.82	0.033
ITA	0.64	0.55	0.64	0.98	0.59	0.59	0.09	0.79	0.60	0.08	0.73	0.67	0.22	0.18	1.63	0.00	0.93	0.71	0.025
JPN	0.67	0.66	0.71	0.61	0.62	0.64	0.04	0.85	0.82	0.16	0.59	0.66	0.30	0.16	0.96	0.60	0.95	0.40	0.017
NLD	0.66	0.52	0.69	0.97	0.68	0.68	0.18	0.55	0.25	0.00	0.61	0.74	0.22	0.23	0.22	0.03	1.14	0.83	0.028
NOR	0.62	0.53	0.63	0.86	0.63	0.63	0.14	0.66	0.49	0.16	0.50	0.68	0.25	0.20	0.17	0.00	0.94	0.72	0.025
SWE	0.67	0.56	0.60	0.97	0.66	0.65	0.15	0.63	0.38	0.06	0.67	0.74	0.24	0.25	0.55	0.00	0.64	0.80	0.029
USA	0.67	0.69	0.61	0.63	0.71	0.67	0.06	0.83	0.68	0.16	0.61	0.62	0.22	0.16	2.89	0.13	0.92	0.97	0.025
OECD	0.65	0.57	0.68	0.84	0.64	0.63	0.13	0.66	0.42	0.12	0.63	0.68	0.23	0.20	0.80	0.15	0.81	0.86	0.027

Notes: Columns 1-6 show the GDP share of non-tradables, the non-tradable content of consumption, investment and government expenditure, the share of non-tradables in labor, and the non-tradable content of labor compensation. Column 7 gives the ratio of exports of final goods and services to GDP; columns 8 and 9 show the home share of consumption and investment expenditure in tradables and column 10 shows the content of government spending in home-produced traded goods; LIS^j stands for the labor income share in sector $j = H, N$; I/Y is the investment-to-GDP ratio and G/Y is government spending as a share of GDP; ϕ is the elasticity of substitution between traded and non-traded goods in consumption; estimates of the elasticity of substitution between home- and foreign-produced traded goods ρ (with $\rho = \rho_J = \phi_X$) is taken from Bertinelli et al. [2022]; ϵ_L is the elasticity of labor supply across sectors; ϵ_K is the elasticity of capital supply across sectors; σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$. The real interest rate is the real long-term interest rate calculated as the nominal interest rate on 10 years government bonds minus the rate of inflation which is the rate of change of the Consumption Price Index.

Table 9: Baseline Parameters (Representative OECD Economy)

Definition	Value		Reference
	CD	CES/Restricted	
Period of time	year	year	data frequency
A.Preferences			
Subjective time discount rate, β	2.7%	2.7%	equal to the world interest rate
Intertemporal elasticity of substitution for consumption, σ	2	2	Shimer [2009]
Intertemporal elasticity of substitution for labor, σ_L	3	3	Peterman [2016]
Elasticity of substitution between C^T and C^N, ϕ	0.35	0.35	our estimates (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
Elasticity of substitution between J^T and J^N, ϕ_J	1	1	Bems [2008]
Elasticity of substitution between C^H and C^F, ρ	1.3	1.3	Bertinelli, Cardi, and Restout [2022]
Elasticity of substitution between J^H and J^F, ρ_J	1.3	1.3	Bertinelli, Cardi, and Restout [2022]
Elasticity of labor supply across sectors, ϵ_L	0.80	0.80	our estimates (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
Elasticity of capital supply across sectors, ϵ_K	0.15	0.15	our estimates (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
B.Non-tradable share			
Weight of consumption in non-traded goods, $1-\varphi$	0.49	0.49	set to target $1-\alpha_C = 57\%$ (United Nations, COICOP [2017])
Weight of labor supply to the non-traded sector, $1-\vartheta_L$	0.62	0.62	set to target $L^N/L = 64\%$ (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
Weight of capital supply to the non-traded sector, $1-\vartheta_K$	0.61	0.61	set to target $K^N/K = 61\%$ (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
Weight of non-traded investment, $1-\iota$	0.68	0.68	set to target $1-\alpha_J = 69\%$ (OECD Input-Output database [2017])
Non-tradable content of government expenditure, ω_{G^N}	0.84	0.84	our estimates (Input-Output dataset, WIOD [2013])
C.Home share			
Weight of consumption in home traded goods, φ^H	0.71	0.71	set to target $\alpha^H = 66\%$ (Input-Output dataset, WIOD [2013])
Weight of home traded investment, ι^H	0.49	0.49	set to target $\alpha_J^H = 42\%$ (Input-Output dataset, WIOD [2013])
Home traded content of government expenditure, ω_{G^H}	0.12	0.12	our estimates (Input-Output dataset, WIOD [2013])
Export price elasticity, ϕ_X	1.3	1.3	Bertinelli, Cardi, and Restout [2022]
C.Production			
Labor income share in the non-traded sector, θ^N	0.68	0.68	our estimates (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
Labor income share in the traded sector, θ^H	0.63	0.63	our estimates (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
Elasticity of of substitution between K^H and L^H, σ^H	1	0.81	our estimates (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
Elasticity of of substitution between K^N and L^N, σ^N	1	0.86	our estimates (EU KLEMS [2011], [2017] and OECD STAN [2011], [2017] databases)
D.GDP demand components			
Physical capital depreciation rate, δ_K	6.2%	6.2%	set to target $\omega_J = 23\%$ (Source: OECD Economic Outlook Database)
Parameter governing capital adjustment cost, κ	17	17	set to match the elasticity I/K to Tobin's q (Eberly et al. [2008])
Government spending as a ratio of GDP, ω_G	20%	20%	our estimates (Source: OECD Economic Outlook Database)
E.Capital utilization adjustment costs			
Parameter governing capital utilization cost, $\xi^H_{2,S}$	0.50	∞	set to reproduce IRF for $u^{K,H}_S(t)$
Parameter governing capital utilization cost, $\xi^N_{2,S}$	0.60	∞	set to reproduce IRF for $u^{K,N}_S(t)$
Parameter governing capital utilization cost, $\xi^H_{2,D}$	0.03	∞	set to reproduce IRF for $u^{K,H}_D(t)$
Parameter governing capital utilization cost, $\xi^N_{2,D}$	0.50	∞	set to reproduce IRF for $u^{k,N}_D(t)$

Notes: 'CD' refers to the Cobb-Douglas model which is taken as the reference point; 'CES' refers to the baseline model where production functions are of the CES type with $\sigma^j < 1$.

Since we set initial conditions so that the economy starts with balanced trade, export as a share of GDP, ω_X, shown in column 7 of Table 8 is endogenously determined by the import content of consumption, $1-\alpha^H$, investment expenditure, $1-\alpha_J^H$, and government spending, ω_{G^F}, along with the consumption-to-GDP ratio, ω_C, the investment-to-GDP ratio, ω_J, and government spending as a share of GDP, ω_G. More precisely, dividing the current account equation at the steady-state by GDP, Y, leads to an expression that allows us to calculate the GDP share of exports of final goods and services produced by the home country:

$$\omega_X = \frac{P^H X^H}{Y} = \omega_C \alpha_C \left(1-\alpha^H\right) + \omega_J \alpha_J \left(1-\alpha_J^H\right) + \omega_G \omega_{G^F}, \tag{105}$$

$\omega_{G^F} = 1 - \omega_{G^{N,D}} - \omega_{G^{H,D}}$. The last line of column 7 of Table 8 shows that the export to GDP ratio averages 13%.

Sectoral labor income shares. The labor income share for the traded and non-traded sector, denoted by s_L^H and s_L^N, respectively, are calculated as the ratio of labor compensation of sector j to value added of sector j at current prices. Sources: EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. Data coverage: 1970-2017 for all countries (except Japan: 1973-2015). As shown in columns 11 and 12 of Table 8, s_L^H and s_L^N averages 0.63 and 0.68, respectively.

Estimated elasticities. Columns from 15 to 18 of Table 8 display estimates of the elasticity of substitution between tradables and non-tradables in consumption, ϕ, the elasticity of labor supply across sectors, ϵ_L, the elasticity of capital supply across sectors, ϵ_K, the elasticity of substitution between capital and labor in the traded and the non-traded sector, i.e., σ^H and σ^N.

J.2 Estimates of ϵ_L: Empirical Strategy and Estimates

Framework. The economy consists of M distinct sectors, indexed by $j = 0, 1, ..., M$ each producing a different good. Along the lines of Horvath [2000], the aggregate labor index is assumed to take the form:

$$L = \left[\int_0^M \left(\vartheta^j\right)^{-\frac{1}{\epsilon^L}} \left(L^j\right)^{\frac{\epsilon^L+1}{\epsilon^L}} dj\right]^{\frac{\epsilon^L}{\epsilon^L+1}}, \tag{106}$$

The agent seeks to maximize her labor income

$$\int_0^M W^j L^j dj = X^L, \tag{107}$$

for given utility loss; L^j is labor supply to sector j, W^j the wage rate in sector j and X^L total labor income. The form of the aggregate labor index (106) implies that there exists an aggregate wage index $W(.)$, whose expression will be determined later. Thus equation (107) can be rewritten as follows:

$$\int_0^M W^j L^j dj = WL. \tag{108}$$

Writing down the Lagrangian and denoting by μ the Lagrangian multiplier to the constraint, the first-order reads as:

$$\left(\vartheta^j\right)^{-\frac{1}{\epsilon^L}} \left(L^j\right)^{\frac{1}{\epsilon^L}} L^{-\frac{1}{\epsilon^L}} = \mu W^j. \tag{109}$$

Left-multiplying both sides of eq. (109) by L^j, summing over the M sectors and using eqs. (106) and (108) implies that $\mu = \frac{1}{W}$. Plugging the expression for the Lagrangian multiplier into (109) and rearranging terms leads to optimal labor supply L^j to sector j:

$$L^j = \vartheta^j \left(\frac{W^j}{W}\right)^{\epsilon^L} L. \tag{110}$$

Each sector consists of a large number of identical firms which use labor, L^j, and physical capital, K^j, according to a constant returns to scale technology described by a

CES production function. The representative firm faces two cost components: a capital rental cost equal to R^j, and a wage rate equal to W^j, respectively. Since each sector is assumed to be perfectly competitive, the representative firm chooses capital and labor by taking prices as given:

$$\max_{K^j,L^j} \Pi^j = \max_{K^j,L^j} \left\{P^j Y^j - W^j L^j - R^j K^j\right\}. \tag{111}$$

First-order conditions lead to the demand for labor and capital which read as follows:

$$s^j_L \frac{P^j Y^j}{L^j} = W^j, \tag{112a}$$

$$\left(1 - s^j_L\right) \frac{P^j Y^j}{K^j} = R^j. \tag{112b}$$

Inserting labor demand (112a) into labor supply to sector j (110) and solving leads the share of sector j in aggregate labor:

$$\frac{L^j}{L} = \left(\vartheta^j\right)^{\frac{1}{\epsilon^L+1}} \left(\frac{s^j_L P^j Y^j}{\int_0^M s^j_L P^j Y^j dj}\right)^{\frac{\epsilon^L}{\epsilon^L+1}}, \tag{113}$$

where we combined (108) and (112a) to rewrite the aggregate wage as follows:

$$W = \frac{\int_0^M s^j_L P^j Y^j dj}{L}. \tag{114}$$

We denote by β^j the fraction of labor's share of value added accumulating to labor in sector j:

$$\beta^j = \frac{s^j_L P^j Y^j}{\sum_{j=1}^M s^j_L P^j Y^j}. \tag{115}$$

Using (115), the labor share in sector j (113) can be rewritten as follows:

$$\frac{L^j}{L} = \left(\vartheta^j\right)^{\frac{1}{\epsilon^L+1}} \left(\beta^j\right)^{\frac{\epsilon^L}{\epsilon^L+1}}. \tag{116}$$

Introducing a time subscript and taking logarithm, eq. (116) reads as:

$$\ln\left(\frac{L^j}{L}\right)_t = \frac{1}{\epsilon^L+1} \ln \vartheta^j + \frac{\epsilon^L}{\epsilon^L+1} \ln \beta^j_t. \tag{117}$$

Totally differentiating (117), denoting the rate of growth of the variable with a hat, including country fixed effects captured by country dummies, f_i, sector dummies, f_j, and common macroeconomic shocks by year dummies, f_t, leads to:

$$\hat{L}^j_{it} - \hat{L}_{it} = f_i + f_t + \gamma_i \hat{\beta}^j_{it} + \nu^j_{it}, \tag{118}$$

where

$$\hat{L}_{it} = \sum_{j=1}^M \beta^j_{i,t-1} \hat{L}^j_{i,t}. \tag{119}$$

and

$$\beta^j_{it} = \frac{s^j_{L,i} P^j Y^j_{it}}{\sum_{j=1}^M s^j_{L,i} P^j_{it} Y^j_{it}}, \tag{120}$$

where $s^j_{L,i}$ is the labor income share in sector j in country i which is averaged over 1970-2017. Y^j is value added.

Elasticity of labor supply across sectors. We use panel data to estimate (118) where $\gamma_i = \frac{\epsilon^L_i}{\epsilon^L_i+1}$ and β^j_{it} is given by (115). The LHS term of (118) is calculated as the difference between changes (in percentage) in hours worked in sector j, $\hat{L}^j_{i,t}$, and in total

Table 10: Estimates of Elasticity of Labor Supply across Sectors (ϵ)

Country	Elasticity of labor supply across Sectors (ϵ_L)
AUS	0.480^a (3.84)
AUT	1.096^a (3.08)
BEL	0.599^a (3.66)
CAN	0.362^a (4.24)
DEU	0.998^a (3.62)
DNK	0.273^b (2.55)
ESP	0.950^a (3.84)
FIN	0.417^a (4.52)
FRA	1.309^a (3.03)
GBR	0.616^a (4.14)
IRL	0.105^a (3.17)
ITA	1.628^a (3.14)
JPN	0.961^a (3.67)
NLD	0.221^b (2.25)
NOR	0.166^a (2.77)
SWE	0.547^a (4.57)
USA	2.889^b (2.03)
Countries	17
Observations	794
Data coverage	1971-2017
Country fixed effects	yes
Time dummies	yes
Time trend	no

Notes: ^{a}, ^{b} and ^{c} denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses.

hours worked, $\hat{L}_{i,t}$. The RHS term β^j corresponds to the fraction of labor's share of value added accumulating to labor in sector j. Denoting by $P_t^j Y_t^j$ value added at current prices in sector $j = H, N$ at time t, β_t^j is computed as $\frac{s_L^j P_t^j Y_t^j}{\sum_{j=H}^N s_L^j P_t^j Y_t^j}$ where s_L^j is the LIS in sector $j = H, N$ defined as the ratio of the compensation of employees to value added in the jth sector, averaged over the period 1970-2017. Because hours worked are aggregated by means of a CES function, percentage change in total hours worked, $\hat{L}_{i,t}$, is calculated as a weighted average of sectoral hours worked percentage changes, i.e., $\hat{L}_t = \sum_{j=H}^N \beta_{t-1}^j \hat{L}_t^j$. The parameter we are interested in, say the degree of substitutability of hours worked across sectors, is given by $\epsilon_i^L = \gamma_i/(1-\gamma_i)$. In the regressions that follow, the parameter γ_i is assumed to be different across countries when estimating ϵ_i^L for each economy ($\gamma_i \neq \gamma_{i'}$ for $i \neq i'$).

To construct $\hat{L}^j$ and $\hat{\beta}^j$ we combine raw data on hours worked L^j, nominal value added $P^j Y^j$ and labor compensation $W^j L^j$. All required data are taken from the EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. The sample includes the 17 OECD countries mentioned above over the period 1971-2017 (except for Japan: 1974-2015).

Table 10 reports empirical estimates that are consistent with $\epsilon_L > 0$. All values are statistically significant at 10%. Since the estimated value for ϵ is not statistically significant for Norway, we run the same regression as in eq. (118) but use output instead of value added to construct $\hat{\beta}^j$. We find a value of 0.17, as reported in column 17 of Table 10, and this estimated value is statistically significant. Overall, we find that ϵ_L ranges from a low of 0.1 of Ireland and 0.2 for Norway to a high of 2.89 for the United States.

J.3 Estimates of ϵ_K: Empirical Strategy and Estimates

Framework. The economy consists of M distinct sectors, indexed by $j = 0, 1, ..., M$ each producing a different good. Along the lines of Horvath [2000], the aggregate capital index is assumed to take the form:

$$K = \left[\int_0^M \left(\vartheta_K^j \right)^{-\frac{1}{\epsilon^K}} \left(K^j \right)^{\frac{\epsilon^K + 1}{\epsilon^K}} dj \right]^{\frac{\epsilon^K}{\epsilon^K + 1}}, \tag{121}$$

The agent seeks to maximize capital income

$$\int_0^M R^j K^j dj = X^K, \tag{122}$$

for given utility level $K(.)$; K^j is capital supply to sector j, R^j the capital rental rate in sector j and X^K total capital income. The form of the aggregate capital index (121) implies that there exists an aggregate capital rental rate index $R^K(.)$, whose expression will be determined later. Thus equation (122) can be rewritten as follows:

$$\int_0^M R^j K^j dj = R^K K. \tag{123}$$

Writing down the Lagrangian and denoting by μ^K the Lagrangian multiplier to the constraint, the optimal decision for capital supply to sector j reads as follows:

$$\left(\vartheta_K^j \right)^{-\frac{1}{\epsilon^K}} \left(K^j \right)^{\frac{1}{\epsilon^K}} K^{-\frac{1}{\epsilon^K}} = \mu^K R^j. \tag{124}$$

Left-multiplying both sides of eq. (124) by K^j, summing over the M sectors and using eqs. (121) and (123) implies that $\mu^K = \frac{1}{R^K}$. Plugging the expression for the Lagrangian multiplier into (124) and rearranging terms leads to optimal capital supply K^j to sector j:

$$K^j = \vartheta_K^j \left(\frac{R^j}{R^K} \right)^{\epsilon^K} K. \tag{125}$$

Each sector consists of a large number of identical firms which use labor, L^j, and physical capital, K^j, according to a constant returns to scale technology described by a CES production function. The representative firm faces two cost components: a capital rental cost equal to R^j, and a wage rate equal to W^j, respectively. Since each sector is assumed to be perfectly competitive, the representative firm chooses capital and labor by taking prices as given:

$$\max_{L^j, K^j} \Pi^j = \max_{L^j, K^j} \left\{ P^j Y^j - W^j L^j - R^j K^j \right\}. \tag{126}$$

First-order conditions lead to the demand for labor and capital which can be rewritten as follows:

$$s_L^j \frac{P^j Y^j}{L^j} = W^j, \tag{127a}$$

$$\left(1 - s_L^j \right) \frac{P^j Y^j}{K^j} = R^j. \tag{127b}$$

Inserting labor demand (127a) into capital supply to sector j (125) and solving leads the share of sector j in aggregate labor:

$$\frac{K^j}{K} = \left(\vartheta_K^j \right)^{\frac{1}{\epsilon^K + 1}} \left(\frac{\left(1 - s_L^j \right) P^j Y^j}{\int_0^M \left(1 - s_L^j \right) P^j Y^j dj} \right)^{\frac{\epsilon^K}{\epsilon^K + 1}}, \tag{128}$$

where we combined (123) and (127a) to rewrite the aggregate capital rental rate as follows:

$$R^K = \frac{\int_0^M \left(1 - s_L^j \right) P^j Y^j dj}{K}. \tag{129}$$

We denote by $\beta^{K,j}$ the ratio of capital income in sector j to overall capital income:

$$\beta^{K,j} = \frac{\left(1 - s_L^j\right) P^j Y^j}{\sum_{j=1}^M \left(1 - s_L^j\right) P^j Y^j}. \tag{130}$$

Using (130), the share of capital in sector j (128) can be rewritten as follows:

$$\frac{K^j}{K} = \left(\vartheta_K^j\right)^{\frac{1}{1+\epsilon^K}} \left(\beta^{K,j}\right)^{\frac{\epsilon^K}{\epsilon^K+1}}. \tag{131}$$

Introducing a time subscript and taking logarithm, eq. (131) reads as:

$$\ln\left(\frac{K^j}{K}\right)_t = \frac{1}{\epsilon^K + 1} \ln \vartheta_K^j + \frac{\epsilon^K}{\epsilon^K + 1} \ln \beta_t^{K,j}. \tag{132}$$

We denote the rate of growth of the variable with a hat. We totally differentiate (132) and include country fixed effects captured by country dummies, g_i, sector dummies, g_j, and common macroeconomic shocks captured by year dummies, g_t:

$$\hat{K}_{it}^j - \hat{K}_{it} = g_i + g_t + g_j + \gamma_i^K \hat{\beta}_{it}^{K,j} + \nu_{it}^{K,j}, \tag{133}$$

We use panel data to estimate (133). We run the regression of the percentage change in the share of capital in sector j on the percentage change in the capital income share of sector j relative to the aggregate economy. Intuitively, when the demand for capital rises in sector j, $\beta^{K,j}$ increases which provides incentives for households to shift capital toward this sector. To calculate $\beta_{it}^{K,j}$ for sector j, in country i at time t, we proceed as follows:

$$\hat{K}_{it} = \sum_{j=1}^{M} \beta_{i,t-1}^{K,j} \hat{K}_{i,t}^j. \tag{134}$$

and

$$\beta_{it}^{K,j} = \frac{\left(1 - s_{L,i}^j\right) P_{it}^j Y_{it}^j}{\sum_{j=1}^M \left(1 - s_{L,i}^j\right) P_{it}^j Y_{it}^j}, \tag{135}$$

where $\left(1 - s_{L,i}^j\right)$ is the capital income share in sector j in country i which is averaged over 1970-2017. Y^j is value added and P^j is the value added deflator.

Data: Source and Construction. We take capital stock series from the EU KLEMS [2011] and [2017] databases which provide disaggregated capital stock data (at constant prices) at the 1-digit ISIC-rev.3 level for up to 11 industries, but only for thirteen countries of our sample which include Australia, Canada, Denmark, Finland, Great-Britain, Italy, the Netherlands, Spain, the United States, over the entire period 1970-2017, plus Austria (1976-2017), France (1978-2017), Japan (1973-2006), Korea (1970-2014). In efforts to have time series of a reasonable length, we exclude Belgium (1995-2017) and Sweden (1993-2017) because the period is too short while Ireland, and Norway do not provide disaggregated capital stock series. To construct $\hat{K}_{it}^j$ and $\hat{\beta}_{it}^{K,j}$ we combine raw data on capital stock K^j, nominal value added $P^j Y^j$ and labor compensation $W^j L^j$ to calculate $1 - s_L^j$.

Degree of capital mobility across sectors. We use panel data to estimate (133) where $\gamma_i^K = \frac{\epsilon_{K,i}}{\epsilon_{K,i}+1}$ and $\beta_{it}^{K,j}$ is given by (135). Table 11 reports empirical estimates that are consistent with $\epsilon_K > 0$. We average positive values for ϵ_K and exclude negative values as they are inconsistent. We find an average value for ϵ_K of 0.15 which suggests high capital mobility costs across sectors in OECD countries.

J.4 Estimates of ϵ_S and ϵ_U: Empirical Strategy and Estimates

Framework. The economy consists of M distinct sectors, indexed by $j = 0, 1, ..., M$ each producing a different good. Along the lines of Horvath [2000], the aggregate skilled labor index is assumed to take the form:

$$S = \left[\int_0^M \left(\vartheta_S^j\right)^{-\frac{1}{\epsilon^S}} \left(L^j\right)^{\frac{\epsilon^S+1}{\epsilon^S}} dj\right]^{\frac{\epsilon^S}{\epsilon^S+1}}, \tag{136}$$

Table 11: Elasticity of Capital Supply across Sectors (ϵ_K)

Country	Elasticity of capital supply across Sectors (ϵ_K)
AUS	0.065 (1.10)
AUT	0.178^c (1.71)
BEL	0.229^c (1.69)
CAN	0.107^b (2.50)
DEU	0.041 (0.62)
DNK	-0.145^a (−3.88)
ESP	−0.045 (−1.01)
FIN	0.101^b (2.38)
FRA	0.090 (1.07)
GBR	0.087^c (1.72)
IRL	-0.156^a (−9.54)
ITA	−0.028 (−0.54)
JPN	0.597^a (4.59)
NLD	0.034 (0.62)
NOR	−0.007 (−0.32)
SWE	−0.038 (−0.59)
USA	0.128 (1.43)
Countries	17
Observations	699
Data coverage	1970-2017
Country fixed effects	yes
Time dummies	yes
Time trend	no

Notes: ^{a}, ^{b} and ^{c} denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses.

The agent seeks to maximize her labor income

$$\int_0^M W^{S,j} S^j dj = X^S, \tag{137}$$

for given utility loss; S^j is the supply of skilled labor to sector j, $W^{S,j}$ the wage rate paid in exchange for each hour of skilled labor services in sector j and X^S stands for total skilled labor income. The form of the aggregate skilled labor index (136) implies that there exists an aggregate wage index $W^S(.)$, whose expression will be determined later. Thus equation (137) can be rewritten as follows:

$$\int_0^M W^{S,j} S^j dj = W^S S. \tag{138}$$

Writing down the Lagrangian and denoting by μ^S the Lagrangian multiplier to the constraint, the first-order reads as:

$$\left(\vartheta_S^j\right)^{-\frac{1}{\epsilon^S}} \left(S^j\right)^{\frac{1}{\epsilon^S}} S^{-\frac{1}{\epsilon^S}} = \mu^S W^{S,j}. \tag{139}$$

Left-multiplying both sides of eq. (139) by S^j, summing over the M sectors and using eqs. (136) and (138) implies that $\mu^S = \frac{1}{W^S}$. Plugging the expression for the Lagrangian multiplier into (139) and rearranging terms leads to optimal labor supply S^j to sector j:

$$S^j = \vartheta_S^j \left(\frac{W^{S,j}}{W^S}\right)^{\epsilon^S} S. \tag{140}$$

We assume that within each sector, there is a large number of identical firms which produces Y^j by using labor L^j and capital K^j according to constant returns to scale in production. Labor is made up of skilled S^j and unskilled U^j workers. The representative firm faces two cost components: a capital rental cost equal to R^j, a skilled labor wage rate $W^{S,j}$, and an unskilled labor wage rate $W^{U,j}$. Since each sector is assumed to be perfectly competitive, the representative firm chooses capital and labor by taking prices as given:

$$\max_{K^j,S^j,U^j} \Pi^j = \max_{K^j,S^j,U^j} \left\{P^j Y^j - W^{S,j} S^j - W^{U,j} U^j - R^j K^j\right\}. \tag{141}$$

Since the production function displays constant returns to scale and using the fact that factors are paid their marginal product, the demand for labor and capital are: $\partial Y^j/\partial L^j = W^j/P^j$ and $\partial Y^j/\partial K^j = R/P^j$, respectively; denoting the LIS in sector j by s_L^j, the demand for capital and labor can be rewritten as follows:

$$s_L^j P^j \frac{\partial Y^j}{\partial L^j} \frac{\partial L^j}{\partial S^j} = W^{S,j}, \tag{142a}$$

$$s_L^j P^j \frac{\partial Y^j}{\partial L^j} \frac{\partial L^j}{\partial U^j} = W^{U,j}, \tag{142b}$$

$$\left(1 - s_L^j\right) \frac{P^j Y^j}{K^j} = R^j, \tag{142c}$$

where $s_L^j P^j \frac{\partial Y^j}{\partial L^j} = W^j$. By inserting the latter equation into eqs. (142a)-(142b), multiplying both sides of eq. (142a) by S^j/L^j and both sides of eq. (142b) by U^j/L^j leads to:

$$\frac{\partial L^j}{\partial S^j} \frac{S^j}{L^j} = s_S^j = \frac{W^{S,j} S^j}{W^j S^j}, \tag{143a}$$

$$\frac{\partial L^j}{\partial U^j} \frac{U^j}{L^j} = 1 - s_S^j = \frac{W^{U,j} U^j}{W^j L^j}. \tag{143b}$$

Inserting labor demand for skilled labor, i.e., using (143a) to replace $W^{S,j}$ with $s_S^j \frac{W^j L^j}{S^j}$, into skilled labor supply to sector j (140) and solving leads to the share of sector j in aggregate skilled labor:

$$
\begin{aligned}
\frac{S^j}{S} &= \vartheta_S^j \left(\frac{S}{S^j} \frac{s_S^j s_L^j P^j Y^j}{\int_0^M s_S^j s_L^j P^j Y^j dj} \right)^{\epsilon^S}, \\
\frac{S^j}{S} &= \left(\vartheta_S^j \right)^{\frac{1}{\epsilon^S+1}} \left(\frac{s_S^j s_L^j P^j Y^j}{\int_0^M s_S^j s_L^j P^j Y^j dj} \right)^{\frac{\epsilon^S}{\epsilon^S+1}}, \qquad (144)
\end{aligned}
$$

where we combined (138) and used the fact that $W^S S = \int_0^M W^{S,j} S^j dj = \int_0^M s_S^j s_L^j P^j Y^j dj$ to rewrite the aggregate skilled labor wage rate as follows:

$$
W^S = \frac{\int_0^M s_S^j s_L^j P^j Y^j dj}{S}. \qquad (145)
$$

We denote by $\beta^{S,j}$ the fraction of skilled labor income in sector j relative to aggregate skilled labor income:

$$
\beta^{S,j} = \frac{s_S^j s_L^j P^j Y^j}{\sum_{j=1}^M s_S^j s_L^j P^j Y^j}. \qquad (146)
$$

Using (146), the skilled hours worked share in sector j (144) can be rewritten as follows:

$$
\frac{S^j}{S} = \left(\vartheta_S^j \right)^{\frac{1}{\epsilon^S+1}} \left(\beta^{S,j} \right)^{\frac{\epsilon^S}{\epsilon^S+1}}. \qquad (147)
$$

Introducing a time subscript and taking logarithm, eq. (147) reads as:

$$
\ln \left(\frac{S^j}{S} \right)_t = \frac{1}{\epsilon^S+1} \ln \vartheta_S^j + \frac{\epsilon^S}{\epsilon^S+1} \ln \beta_t^{S,j}. \qquad (148)
$$

Totally differentiating (148) and denoting the rate of change of the variable with a hat, we find that the change in skilled hours worked in sector j caused by labor reallocation across sectors is driven by the change in the skilled labor income share in sector j:

$$
\hat{S}_t^j - \hat{S}_t = \gamma^S \hat{\beta}_t^{S,j}, \qquad (149)
$$

where $\gamma^S = \frac{\epsilon^S}{\epsilon^S+1}$.

We use panel data to estimate (149). Including country fixed effects captured by country dummies, h_i, common macroeconomic shocks by year dummies, h_t, sector dummies, h_j, (149) can be rewritten as follows:

$$
\hat{S}_{it}^j - \hat{S}_{it} = h_i + h_j + h_t + \gamma_i^S \hat{\beta}_{it}^{S,j} + \nu_{it}^{S,j}, \qquad (150)
$$

where $\gamma_i^S = \frac{\epsilon_i^S}{\epsilon_i^S+1}$ and $\beta_{it}^{S,j}$ is given by (146); j indexes the sector, i the country, and t indexes time (i.e., years). The LHS and RHS variables are defined as follows:

$$
\hat{S}_{it} = \sum_{j=1}^M \beta_{i,t-1}^{S,j} \hat{S}_{i,t}^j. \qquad (151)
$$

and

$$
\beta_{it}^{S,j} = \frac{s_{S,i}^j s_{L,i}^j P_{it}^j Y_{it}^j}{\sum_{j=1}^M s_{S,i}^j s_{L,i}^j P_{it}^j Y_{it}^j}, \qquad (152)
$$

where $s_{S,i}^j$ is the share of skilled labor compensation in labor compensation in sector j, in country i averaged over 1970-2017, $s_{L,i}^j$ is the labor income share in sector j in country i which is averaged over 1970-2017. When exploring empirically (150), the coefficient γ^S is alternatively assumed to be identical, i.e., $\gamma_i^S = \gamma^S$, or to vary across countries. The LHS term of (150), i.e., $\hat{S}_{it}^j - \hat{S}_{it}$, gives the percentage change in skilled hours worked in sector j driven by the pure reallocation of skilled labor across sectors.

The same logic applies to derive the empirical strategy for estimating the degree of labor mobility of unskilled labor. Including country fixed effects and year dummies:

$$\hat{U}^j_{it} - \hat{U}_{it} = n_i + n_j + n_t + \gamma^U_i \hat{\beta}^{U,j}_{it} + \nu^{U,j}_{it}, \tag{153}$$

where $\gamma^U_i = \frac{\epsilon^U_i}{\epsilon^U_i + 1}$ and $\beta^{U,j}_{it}$ is given by (155); j indexes the sector, i the country, and t indexes time (i.e., years). The LHS and RHS variables are defined as follows:

$$\hat{U}_{it} = \sum_{j=1}^{M} \beta^{U,j}_{i,t-1} \hat{U}^j_{i,t}. \tag{154}$$

and

$$\beta^{U,j}_{it} = \frac{s^j_{U,i} s^j_{L,i} P^j_{it} Y^j_{it}}{\sum_{j=1}^{M} s^j_{U,i} s^j_{L,i} P^j_{it} Y^j_{it}}, \tag{155}$$

where $s^j_{U,i}$ is the share of unskilled labor compensation in labor compensation in sector j, in country i averaged over 1970-2017. When exploring empirically (153), the coefficient γ^U is alternatively assumed to be identical, i.e., $\gamma^U_i = \gamma^U$, or to vary across countries. The LHS term of (153), i.e., $\hat{U}^j_{it} - \hat{U}_{it}$, gives the percentage change in unskilled hours worked in sector j driven by the pure reallocation of unskilled labor across sectors.

Source and Coverage. Time series about high- (denoted by the superscript S), medium- (denoted by the superscript M), and low-skilled labor (denoted by the superscript U) are taken from EU KLEMS Database, Timmer et al. [2008]. Data are available for all countries except Norway. The baseline period is running from 1970 to 2017 but is different and shorter for several countries as indicated in braces for the corresponding countries: Austria (1980-2017), Belgium (1980-2017), Canada (1970-2005), Denmark (1980-2017), Finland (1970-2017), Ireland (2008-2017), Italy (1970-2017), Japan (1973-2017), the Netherlands (1979-2017), Spain (1980-2017), the United Kingdom (1970-2017), and the United States (1970-2005). We calculate the share of labor compensation in industry j for skilled labor as the ratio of the sum of labor compensation of high- and medium-skilled labor to total labor compensation in sector j, i.e., $s^j_S = \frac{W^{S,j} S^j + W^{M,j} M^j}{W^j L^j}$.

Estimates. We average consistent positive values which are statistically significant. We find $\epsilon_S = 0.63$ and $\epsilon_U = 1.13$. In accordance with the evidence documented by Kambourov and Manovskii [2009] which reveals that industry (and occupational) mobility declines with education, our empirical findings reveal that the elasticity of labor supply across sectors is twice larger for unskilled than skilled workers.

J.5 Elasticity of Substitution in Consumption between Traded and Non-Traded goods, ϕ: Empirical Strategy and Estimates

Derivation of the testable equation. To estimate the elasticity of substitution in consumption, ϕ, between traded and non-traded goods, we derive a testable equation by rearranging the demand for non-traded goods, i.e., $C^N_t = (1-\varphi) \left(\frac{P^N_t}{P_{C,t}}\right)^{-\phi} C_t$, since time series for consumption in non-traded goods are too short. More specifically, we derive an expression for the non-tradable content of consumption expenditure by using the market clearing condition for non-tradables and construct time series for $1 - \alpha_{C,t}$ by using time series for non-traded value added and demand components of GDP while keeping the non-tradable content of investment and government expenditure fixed, in line with the evidence documented by Bems [2008] for the share of non-traded goods in investment and building on our own evidence for the non-tradable content of government spending. After verifying that the (logged) share of non-tradables and the (logged) ratio of non-traded prices to the consumption price index are both integrated of order one and cointegrated, we run the regression by adding country and time fixed effects together and including a country-specific time trend and estimate the coefficient by using a Fully Modified OLS estimator.

Table 12: Elasticity of Labor Supply across Sectors for Skilled Workers (ϵ_S) and for Unskilled Workers (ϵ_U)

Country	Skilled Workers (ϵ_S)	Unskilled Workers (ϵ_U)
AUT	0.975^b (2.55)	1.783 (1.52)
BEL	0.202^c (1.82)	0.551^c (1.86)
CAN	0.386^a (3.65)	0.249^c (1.83)
DNK	0.122 (1.47)	0.250 (1.57)
ESP	0.344^a (2.98)	0.928^b (2.52)
FIN	0.337^a (4.39)	0.506^a (3.38)
GBR	0.553^a (4.33)	0.655^a (2.95)
ITA	0.821^a (3.59)	1.440^b (2.28)
JPN	0.627^a (3.82)	0.892^a (2.57)
NLD	0.065 (0.89)	0.302^c (1.73)
USA	2.546^b (2.11)	4.825 (0.95)
Countries	11	11
Observations	438	438
Data coverage	1970-2017	1970-2017
Country fixed effects	yes	yes
Time dummies	yes	yes
Time trend	no	no

Notes: ^{a}, ^{b} and ^{c} denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses.

Multiplying both sides of $C_t^N = (1-\varphi)\left(\frac{P_t^N}{P_{C,t}}\right)^{-\phi} C_t$ by P^N/P_C leads to the non-tradable content of consumption expenditure:

$$1-\alpha_{C,t} = \frac{P_t^N C_t^N}{P_{C,t}C_t} = (1-\varphi)\left(\frac{P_t^N}{P_{C,t}}\right)^{1-\phi}. \tag{156}$$

Because time series for non-traded consumption display a short time horizon for most of the countries of our sample while data for sectoral value added and GDP demand components are available for all of the countries of our sample over the period running from 1970 to 2017, we construct time series for the share of non-tradables by using the market clearing condition for non-tradables:

$$\frac{P_t^N C_t^N}{P_{C,t}C_t} = \frac{1}{\omega_{C,t}}\left[\frac{P_t^N Y_t^N}{Y_t} - (1-\alpha_J)\,\omega_{J,t} - \omega_{G^N}\omega_{G,t}\right]. \tag{157}$$

Since the time horizon is too short at a disaggregated level (for I^j and G^j) for most of the countries, we draw on the evidence documented by Bems [2008] which reveals that $1-\alpha^J = \frac{P^N J^N}{P^J J}$ is constant over time; we further assume that $\frac{P^N G^N}{G} = \omega_{G^N}$ is constant as well in line with our evidence. We thus recover time series for the share of non-tradables by using time series for the non-traded value added at current prices, $P_t^N Y_t^N$, GDP at current prices, Y_t, consumption expenditure, gross fixed capital formation, I_t, government spending, G_t while keeping the non-tradable content of investment and government expenditure, $1-\alpha_J$, and ω_{G^N}, fixed.

Empirical strategy. Once we have constructed time series for $1-\alpha_{C,t} = \frac{P_t^N C_t^N}{P_{C,t}C_t}$ by using (156), we take the logarithm of both sides of (156) and run the regression of the logged share of non-tradables on the logged ratio of non-traded prices to the consumption price index:

$$\ln(1-\alpha_{C,it}) = f_i + f_t + \alpha_i\,.t + (1-\phi)\ln\left(P^N/P_C\right)_{it} + \mu_{it}, \tag{158}$$

Table 13: Elasticity of Substitution between Tradables and Non-Tradables (ϕ)

	eq. (158)
Whole Sample	0.347^{a} (6.03)
Countries	17
Observations	810
Data coverage	1970-2017
Country fixed effects	yes
Time dummies	yes
Time trend	no

Notes: ^{a}, ^{b} and ^{c} denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses.

where f_i captures the country fixed effects, f_t are time dummies, and μ_{it} are the i.i.d. error terms. Because parameter φ in (156) may display a trend over time, we add country-specific trends, as captured by $\alpha_i t$. It is worth mentioning that P^N is the value added deflator of non-tradables.

Data source and construction. Data for non-traded value added at current prices, $P_t^N Y_t^N$ and GDP at current prices, Y_t, are taken from EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases (data coverage: 1970-2017 for all countries, except Japan: 1973-2015). To construct time series for consumption, investment and government expenditure as a percentage of nominal GDP, i.e., $\omega_{C,t}$, $\omega_{J,t}$ and $\omega_{G,t}$, respectively, we use data at current prices obtained from the OECD Economic Outlook [2017] Database (data coverage: 1970-2017). Sources, construction and data coverage of time series for the share of non-tradables in investment $(1-\alpha_J)$ and in government spending (ω_{G^N}) are described in depth above; P^N is the value added deflator of non-tradables. Data are taken from EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases (data coverage: 1970-2017 for all countries, except for Japan: 1973-2015). Finally, data for the consumer price index $P_{C,t}$ are obtained from the OECD Prices and Purchasing Power Parities [2017] database (data coverage: 1970-2017).

Results. Since both sides of (158) display trends, we ran unit root and then cointegration tests. Having verified that these two assumptions are empirically supported, we estimate the cointegrating relationships by using the fully modified OLS (FMOLS) procedure for cointegrated panel proposed by Pedroni [2000], [2001]. FMOLS estimate of (158) is reported in Table 13. We find a value for the elasticity of substitution between traded and non-traded goods in consumption of 0.35 which is close to the estimated value documented by Stockman and Tesar [1995].

J.6 Estimates of Elasticity of Substitution between Capital and Labor in Production, σ^j: Empirical strategy

To estimate the elasticity of substitution between capital and labor, σ^j, we draw on Antràs [2004]. We let labor- and capital-augmenting technological change grow at a constant rate:

$$A_t^j = A_0^j e^{a^j t}, \tag{159a}$$

$$B_t^j = B_0^j e^{b^j t}, \tag{159b}$$

where a^j and b^j denote the constant growth rate of labor- and capital-augmenting technical progress and A_0^j and B_0^j are initial levels of technology. Inserting first (159a) and (159b) into the demand for labor and capital, taking logarithm and rearranging gives:

$$\ln(Y_t^j/L_t^j) = \alpha_1 + \left(1-\sigma^j\right) a^j t + \sigma_j \ln(W_t^j/P_t^j), \tag{160a}$$

$$\ln(Y_t^j/K_t^j) = \alpha_2 + \left(1-\sigma^j\right) b^j t + \sigma_j \ln(R_t/P_t^j), \tag{160b}$$

Table 14: FMOLS Estimates of the Sectoral Elasticity of Substitution between Capital and Labor (σ^j)

	Tradables (σ^H)		Non-Tradables (σ^N)	
Dependent var.	$\ln(Y^H/K^H)$	$\ln(Y^H/L^H)$	$\ln(Y^N/K^N)$	$\ln(Y^N/L^N)$
Explanatory var.	$\ln(R/P^H)$	$\ln(W^H/P^H)$	$\ln(R/P^N)$	$\ln(W^N/P^N)$
AUS	0.214^c (1.89)	0.516^a (7.29)	0.499^a (3.78)	0.825^a (12.30)
AUT	0.526^b (2.25)	0.954^a (10.70)	0.206 (1.39)	1.213^a (15.03)
BEL	−0.078 (−0.52)	0.748^a (11.77)	0.039 (0.49)	1.145^a (11.87)
CAN	0.159 (1.11)	0.888^a (4.83)	0.691^a (6.28)	0.950^a (14.10)
DEU	0.175^c (1.79)	0.720^a (8.64)	0.549^a (9.18)	1.088^a (17.95)
DNK	−0.005 (−0.04)	0.555^a (5.82)	0.457^a (6.41)	0.938^a (9.30)
ESP	0.342^b (2.49)	0.979^a (10.59)	0.179^c (1.70)	0.535^a (3.11)
FIN	0.222 (1.26)	0.730^a (3.29)	0.374^a (4.98)	0.837^a (12.21)
FRA	0.215 (1.26)	0.867^a (8.54)	0.119^a (3.21)	1.329^a (6.96)
GBR	0.055 (0.28)	0.611^a (6.96)	0.097 (0.95)	0.580^a (4.77)
IRL	0.652 (13.40)	−0.154 (−0.91)	0.557^a (4.27)	0.819^a (3.94)
ITA	0.440^b (2.30)	0.934^a (13.38)	0.321 (1.50)	0.714^a (6.37)
JPN	0.765^a (10.17)	0.948^a (5.92)	0.553^a (8.61)	0.400^b (2.23)
NLD	0.498^a (4.26)	1.136^a (9.86)	0.230^a (8.29)	0.831^a (7.08)
NOR	0.399^a (3.15)	0.938^a (4.92)	0.547^a (8.87)	0.723^a (7.80)
SWE	0.260 (0.92)	0.643^a (12.91)	0.033 (0.34)	0.801^a (5.89)
USA	0.166 (1.32)	0.923^a (5.61)	0.324^a (5.72)	0.970^a (5.91)
Whole sample	0.294^a (11.47)	0.761^a (31.56)	0.340^a (18.42)	0.865^a (35.61)
Countries	17	17	17	17
Observations	810	810	810	810
Data coverage	1970-2017	1970-2017	1970-2017	1970-2017
Fixed effects	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes
Time trend	yes	yes	yes	yes

Notes: ^{a}, ^{b} and ^{c} denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses.

where $\alpha_1 = \left[(1-\sigma^j)\ln A_0^j - \sigma^j \ln \gamma^j\right]$ and $\alpha_2 = \left[(1-\sigma^j)\ln B_0^j - \sigma^j \ln(1-\gamma^j)\right]$ are constants. Above equations describe firms' demand for labor and capital respectively.

We estimate the elasticity of substitution between capital and labor in sector $j = H, N$ from first-order conditions (160a)-(160b) in panel format on annual data. Adding an error term and controlling for country fixed effects, we explore empirically the following equations:

$$\ln(Y_{it}^j/L_{it}^j) = \alpha_{1i} + \lambda_{1i}t + \sigma_i^j \ln(W_{it}^j/P_{it}^j) + u_{it}, \tag{161a}$$

$$\ln(Y_{it}^j/K_{it}^j) = \alpha_{2i} + \lambda_{2i}t + \sigma_i^j \ln(R_{it}/P_{it}^j) + v_{it}, \tag{161b}$$

where i and t index country and time and u_{it} and v_{it} are i.i.d. error terms. Country fixed effects are represented by dummies α_{1i} and α_{2i}, and country-specific trends are captured by λ_{1i} and λ_{2i}. Since all variables display unit root process, we estimate cointegrating relationships by using the fully modified OLS (FMOLS) procedure for cointegrated panel proposed by Pedroni [2000].

Estimation of (161a) and (161b) requires data for each sector $j = H, N$ on sectoral value added at constant prices Y^j, sectoral hours worked L^j, sectoral capital stock K^j, sectoral value added deflator P^j, sectoral wage rate W^j and capital rental cost R. Data for sectoral value added Y^H and Y^N, hours worked L^H and L^N, value added price deflators P^H and P^N, and, nominal wages W^H and W^N are taken form the EU KLEMS ([2011], [2017]) and OECD STAN ([2011], [2017]) databases. To construct the national stock of capital K, we use the perpetual inventory method with a fixed depreciation rate taken from Table 7 and the time series of constant prices investment from the OECD Economic

Outlook [2017] Database. Next, following Garofalo and Yamarik [2002], the capital stock is allocated to traded and non-traded industries by using sectoral output shares. Finally, we measure the aggregate rental price of capital R as the ratio of capital income to capital stock. Capital income is derived as nominal value added minus labor compensation. For all aforementioned variables, the sample includes the 17 OECD countries over the period 1970-2017 (except for Japan: 1973-2015).

Employing Monte Carlo experiments, León-Ledesma et al. [2010] compare different approaches for estimating the elasticity of substitution between capital and labor (single equation based on FOCs, system, linear, non-linear and normalization). Their evidence suggests that estimates of both the elasticity of substitution and technical change are close to their true values when the FOC with respect to labor is used. While we take the demand for labor as our baseline model (i.e. eq. (161a)), Table 14 provides FMOLS estimates of σ^j for the demand of both labor and capital. All estimates are positive and statistically significant exception σ^H for Ireland. We replace the inconsistent estimate for σ^j obtained from labor demand with that obtained from the demand of capital. Columns 17-18 of Table 8 report estimates for σ^H and σ^N.

J.7 Estimating the Elasticity of Substitution between Skilled and Unskilled Labor

A large span of the literature, see e.g., Acemoglu [2002], Caselli and Coleman [2006], Jones [2014], assume that skilled and unskilled workers as gross substitutes and choose an elasticity of substitution of 1.5. Havranek et al. [2024] review the estimates documented in empirical studies and report an elasticity of 4, with a minimum value of 2. Our estimates of the elasticity of substitution between skilled and unskilled labor over 1970-2017 for eleven OECD countries of our sample by using cointegration techniques and sectoral data, corroborate the findings by Havranek et al. [2024] as we estimate empirically an elasticity of $\sigma_L^H = 2.88$ for the traded sector and an elasticity of $\sigma_L^H = 3.05$ for the non-traded sector. These values suggest that skilled and unskilled labor are gross substitutes in both the traded and the non-traded sector. In accordance with our estimates, we will assume that skilled and unskilled labor are gross substitutes in the numerical analysis. As unskilled relative to skilled labor-augmenting productivity increases (i.e., as $A^{S,j}(t)/A^{U,j}(t)$ rises), the demand for unskilled labor increases when $\sigma_L^j > 1$ because higher productivity of unskilled lowers their marginal cost. This in turn lowers the share of the skilled labor income share in sector j in line with our evidence. We present below our empirical strategy.

To estimate the elasticity of substitution between capital and labor, σ^j, we draw on Antràs [2004]. We let labor- and capital-augmenting technological change grow at a constant rate:

$$A_t^j = A_0^j e^{a^j t}, \tag{162a}$$

$$B_t^j = B_0^j e^{b^j t}, \tag{162b}$$

where a^j and b^j denote the constant growth rate of labor- and capital-augmenting technical progress and A_0^j and B_0^j are initial levels of technology.

Each sector consists of a large number of identical firms which use labor, L^j, and physical capital (inclusive of capital utilization), $\tilde{K}^j$, according to a technology described by a CES production function:

$$Y_t^j = \left[\gamma^j \left(A_t^j L_t^j\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right)\left(B_t^j \tilde{K}_t^j\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}, \tag{163}$$

where $0 < \gamma^j < 1$ is the weight of labor in the production technology, σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$, and A_t^j and B_t^j are labor- and capital-augmenting efficiency.

Optimal demand for labor and capital:

$$P_t^j \frac{\partial Y_t^j}{\partial L_t^j} = P_t^j \gamma^j \left(A_t^j\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(L_t^j\right)^{-\frac{1}{\sigma^j}} \left(Y_t^j\right)^{\frac{1}{\sigma^j}} = W_t^j, \tag{164a}$$

$$P_t^j \frac{\partial Y_t^j}{\partial K_t^j} = P_t^j \left(1-\gamma^j\right) \left(B_t^j\right)^{\frac{\sigma^j-1}{\sigma^j}} \left(K_t^j\right)^{-\frac{1}{\sigma^j}} \left(Y_t^j\right)^{\frac{1}{\sigma^j}} = R_t^{K,j}. \tag{164b}$$

To estimate the elasticity of substitution σ_L^j between skilled labor (denoted by S_{it}^j), and unskilled labor (denoted by U_{it}^j), we adapt the approach proposed by Antràs [2004]. We let skilled labor- and unskilled labor-augmenting technological change grow at a constant rate:

$$A_t^{S,j} = A_0^{S,j} e^{a^{S,j} t}, \tag{165a}$$

$$A_t^{u,j} = A_0^{U,j} e^{a^{U,j} t}, \tag{165b}$$

where $a^{S,j}$ and $a^{U,j}$ denote the constant growth rate of skilled-labor- and unskilled-labor-augmenting technical progress and $A_0^{S,j}$ and $A_0^{U,j}$ are initial levels of technology.

We assume that efficient labor is a CES aggregator of skilled and unskilled labor:

$$A_t^j L_t^j = \left[\gamma_L^j \left(A_t^{S,j} S_t^j\right)^{\frac{\sigma_L^j-1}{\sigma_L^j}} + \left(1-\gamma_L^j\right) \left(A_t^{U,j} U_t^j\right)^{\frac{\sigma_L^j-1}{\sigma_L^j}}\right]^{\frac{\sigma_L^j}{\sigma_L^j-1}}, \tag{166}$$

where $0 < \gamma_L^j < 1$ is the weight of skilled labor in the efficient labor index, σ_L^j is the elasticity of substitution between skilled and unskilled labor in sector $j = H, N$, and $A_t^{S,j}$ and $A_t^{U,j}$ are skilled labor- and unskilled labor-augmenting efficiency.

Using the fact that $P_t^j \frac{\partial Y_t^j}{\partial L_t^j} = W_t^j$, see eq. (164a), optimal demand for skilled and unskilled labor:

$$P_t^j \frac{\partial Y_t^j}{\partial L_t^j} \frac{\partial L_t^j}{\partial S_t^j} = W_t^j \gamma_L^j \left(\frac{A_t^{S,j}}{A_t^j}\right)^{\frac{\sigma L^j-1}{\sigma_L^j}} \left(S_t^j\right)^{-\frac{1}{\sigma_L^j}} \left(L_t^j\right)^{\frac{1}{\sigma_L^j}} = W_t^{S,j}, \tag{167a}$$

$$P_t^j \frac{\partial Y_t^j}{\partial L_t^j} \frac{\partial L_t^j}{\partial U_t^j} = W_t^j \left(1-\gamma_L^j\right) \left(\frac{A_t^{U,j}}{A_t^j}\right)^{\frac{\sigma L^j-1}{\sigma_L^j}} \left(U_t^j\right)^{-\frac{1}{\sigma_L^j}} \left(L_t^j\right)^{\frac{1}{\sigma_L^j}} = W_t^{U,j}, \tag{167b}$$

Optimal demand for skilled and unskilled labor can be rewritten as follows:

$$\frac{S_t^j}{L_t^j} = \left(\gamma_L^j\right)^{\sigma_L^j} \left(\frac{A_t^{S,j}}{A_t^j}\right)^{-\left(1-\sigma_L^j\right)} \left(\frac{W_t^{S,j}}{W_t^j}\right)^{-\sigma_L^j}, \tag{168a}$$

$$\frac{U_t^j}{L_t^j} = \left(1-\gamma_L^j\right)^{\sigma_L^j} \left(\frac{A_t^{U,j}}{A_t^j}\right)^{-\left(1-\sigma_L^j\right)} \left(\frac{W_t^{U,j}}{W_t^j}\right)^{-\sigma_L^j}, \tag{168b}$$

Inserting first (165a) and (165b) into the demand for labor and capital, taking logarithm and rearranging gives:

$$\text{eq.1} \quad \ln\left(\frac{S_t^j}{L_t^j}\right) = \sigma_L^j \ln \gamma_L^j + \left(\sigma_L^j - 1\right)\left(a_S^j - a^j\right) t - \sigma_L^j \ln\left(\frac{W_t^{S,j}}{W_t^j}\right), \tag{169a}$$

$$\text{eq.2} \quad \ln\left(\frac{U_t^j}{L_t^j}\right) = \sigma_L^j \ln\left(1-\gamma_S^j\right) + \left(\sigma_L^j - 1\right)\left(a_U^j - a^j\right) t - \sigma_L^j \ln\left(\frac{W_t^{U,j}}{W_t^j}\right). \tag{169b}$$

where we estimate a coefficient in front of the ratio of wages $\alpha_3 = -\sigma_L^j$. We have estimated both equations.

Table 15: Elasticity of Substitution between Skilled and Unskilled Labor (σ_L^j)

Country	sector H	sector N
AUT	2.178^a (19.13)	2.844^a (11.32)
BEL	4.350^a (13.26)	4.611^a (9.38)
CAN	2.191^a (7.97)	1.810^a (6.95)
DNK	1.733^a (17.91)	4.417^a (2.86)
ESP	2.546^a (19.03)	2.005^a (10.92)
FIN	2.151^a (10.85)	1.870^a (5.83)
GBR	n.a.	4.123 (1.32)
ITA	n.a.	n.a.
JPN	2.743^a (39.23)	2.812^a (35.88)
NLD	2.998^b (1.99)	2.019^a (3.20)
USA	5.066^a (14.83)	3.991^a (10.63)
Countries	11	
Observations	479	
Data coverage	1970-2017	
Country fixed effects	yes	
Time dummies	no	
Time trend	yes	

Notes: ^{a}, ^{b} and ^{c} denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses. Estimates for tradables for Great-Britain and for both tradables and non-tradables for Italy are not shown as they are negative across all specifications so we leave the cells blank.

Since the first specification, i.e., eq. (169a), gives better results, we restrict attention to the estimates obtained from this equation. Table 15 provides estimates for eleven countries of our sample since data are not available for the rest of the economies. We leave the cells blank when the estimated coefficient is negative. All estimated coefficients are consistent with a value of the elasticity of substitution between skilled and unskilled workers which is larger than one, for both the traded and the non-traded sector. The highest substitutability between skilled and unskilled workers is obtained for the traded sector in the United States.

J.8 Forecast Error Variance Decomposition

Definition of the FEVD. The IRF is just the VMA representation. The structural form of the VAR system is $A(L)Y_t = B\epsilon_t$. Setting $C(L) = A(L)^{-1}B$, leads to $Y_t = C(L)\epsilon_t$.

The forecast error of a variable at time t is the change in the variable that couldn't have been forecast between $t-1$ and t. This is due to the realization of the structural shocks in the system, ϵ_t. We can compute the forecast error over many different horizons, h. The forecast error variance at horizon $h = 0$ for one variable x_t of the 2 variable VAR model is:

$$E_t X_t - E_{t-1} x_t = dx_t = C_{1,1}(0)\epsilon_{1,t} + C_{1,2}(0)\epsilon_{2,t}. \tag{170}$$

The forecast error variances are just the squares of the forecast errors (since the mean forecast error is zero). Using the fact that $Var(ax_t) = a^2 Var(x_t)$, we have:

$$\begin{aligned} Var(dx_t) &= (C_{1,1}(0))^2 Var(\epsilon_{1,t}) + (C_{1,2}(0))^2 Var(\epsilon_{2,t}) + 2C_{1,1}(0)C_{1,2}(0)Cov(\epsilon_{1,t}\epsilon_{2,t}), \\ &= (C_{1,1}(0))^2 Var(\epsilon_{1,t}) + (C_{1,2}(0))^2 Var(\epsilon_{2,t}), \\ \Omega_1 &= (C_{1,1}(0))^2 + (C_{1,2}(0))^2, \end{aligned} \tag{171}$$

where we used the fact that the the shocks have unit variance $Var(\epsilon_{1,t}) = 1$ and shocks are uncorrelated so that the covariance of structural shocks is zero.

The fraction of the forecast error variance of variable x due to shock k at horizon h, denoted $\phi_{k,h}$, is then the above divided by the total forecast error variance:

$$\phi_k(h) = \frac{\sum_h (C_k(h))^2 Var(\epsilon_{k,t})}{\sum_k \sum_h (C_k(h))^2 Var(\epsilon_{k,t})}. \tag{172}$$

Therefore, in our case, $\phi_{k,h}$ is the share of the deviation of utilization-adjusted-TFP caused by an symmetric technology shock which collapses to $1-\eta$ as shown below.

Mapping between η and conditional variance share of symmetric technology shocks. In the model. We define the variance $Var(x_t) = E\left[x_t - E(x_t)\right]^2$ or $Var^{\frac{1}{2}} = \sigma_x = E\left[x_t - E(x_t)\right]$. In the model, aggregate technology has a symmetric and an asymmetric component:

$$Z_t^A = \left(Z_t^{A,S}\right)^{\eta} \left(Z_t^{A,D}\right)^{1-\eta}. \tag{173}$$

The expected value is the mean of the variable which collapses to its steady-state. We denote the steady-state (i.e., the mean) value by dropping the time index. Log-linearizing (173) and subtracting the mean (i.e., the long-run rate of change) leads to:

$$\hat{Z}_t^A - \hat{Z}^A = \eta \left(\hat{Z}_t^{A,S} - \hat{Z}^{A,S}\right) + (1-\eta)\left(\hat{Z}_t^{A,D} - \hat{Z}^{A,D}\right). \tag{174}$$

Dividing both sides by $\hat{Z}_t^A - \hat{Z}^A$, denoting the standard deviation of aggregate technology shocks by σ^Z, the standard deviation of symmetric technology shocks by $\sigma^{Z,S}$, and the standard deviation of asymmetric technology shocks by $\sigma^{Z,D}$, we get:

$$\begin{aligned}
1 &= \eta \frac{\left(\hat{Z}_t^{A,S} - \hat{Z}^{A,S}\right)}{\left(\hat{Z}_t^A - \hat{Z}^A\right)} + (1-\eta) \frac{\left(\hat{Z}_t^{A,D} - \hat{Z}^{A,D}\right)}{\left(\hat{Z}_t^A - \hat{Z}^A\right)}, \\
1 &= \left[\frac{\eta^{1/2}\left(\hat{Z}_t^{A,S} - \hat{Z}^{A,S}\right)}{\left(\hat{Z}_t^A - \hat{Z}^A\right)}\right]^2 \frac{\left(\hat{Z}_t^A - \hat{Z}^A\right)}{\left(\hat{Z}_t^{A,S} - \hat{Z}^{A,S}\right)} + \left[\frac{(1-\eta)^{1/2}\left(\hat{Z}_t^{A,D} - \hat{Z}^{A,D}\right)}{\left(\hat{Z}_t^A - \hat{Z}^A\right)}\right]^2 \frac{\left(\hat{Z}_t^A - \hat{Z}^A\right)}{\left(\hat{Z}_t^{A,S} - \hat{Z}^{A,S}\right)}, \\
1 &= \left[\eta^{1/2}\frac{\sigma^{Z,S}}{\sigma^Z}\right]^2 + \left[(1-\eta)^{1/2}\frac{\sigma^{Z,D}}{\sigma^Z}\right]^2, \\
1 &= \eta + (1-\eta),
\end{aligned} \tag{175}$$

where the last line is obtained by assuming that the persistence of technology shocks does not vary across technology shocks. More specifically aggregate technology shocks, symmetric and asymmetric technology shocks across sectors are governed by the following dynamic processes

$$\hat{Z}_t^A - \hat{Z}^A = \left[e^{-\xi_Z t} - \left(1 - z^A\right) e^{-\chi_Z t}\right], \tag{176a}$$

$$\hat{Z}_t^{A,S} - \hat{Z}^{A,S} = \left[e^{-\xi_{Z,S} t} - \left(1 - z^{A,S}\right) e^{-\chi_{Z,S} t}\right], \tag{176b}$$

$$\hat{Z}_t^{A,D} - \hat{Z}^{A,D} = \left[e^{-\xi_{Z,D} t} - \left(1 - z^{A,D}\right) e^{-\chi_{Z,D} t}\right]. \tag{176c}$$

Assuming that the magnitude of the shock (on impact) as captured by $z^{A,S} \simeq z^A$ and $z^{A,D} \simeq z^A$ and its persistence as captured by $\xi_{Z,S} \simeq \xi_Z$, $\chi_{Z,S} \simeq \chi_Z$, and $\xi_{Z,D} \simeq \xi_Z$, $\xi_{Z,D} \simeq \xi_Z$, $\chi_{Z,D} \simeq \chi_Z$, are similar whether technology improvements are symmetric or asymmetric across sectors, then the dynamic processes of symmetric and asymmetric technology shocks are similar to the dynamic process of aggregate TFP shock

$$\frac{\left(\hat{Z}_t^{A,S} - \hat{Z}^{A,S}\right)}{\left(\hat{Z}_t^A - \hat{Z}^A\right)} \simeq 1, \qquad \frac{\left(\hat{Z}_t^{A,D} - \hat{Z}^{A,D}\right)}{\left(\hat{Z}_t^A - \hat{Z}^A\right)} \simeq 1. \tag{177}$$

Under the assumption that the underlying dynamic process of technology shocks are similar in first approximation, then η collapses to the share of the variance of aggregate technology improvements on impact (i.e., at time $t=0$) driven by symmetric technology shocks across sectors as measured by $\phi_{Z,S}(0)$

$$\begin{aligned}
\phi_{Z,S}(0) &= \frac{(C_{Z,S}(0))^2 Var(\epsilon_{Z,S}(0))}{(C_{Z,S}(0))^2 Var(\epsilon_{Z,S}(0)) + (C_{Z,S}(0))^2 Var(\epsilon_{Z,D}(0))}, \\
&= \frac{(C_{Z,S}(0))^2}{(C_{Z,S}(0))^2 + (C_{Z,D}(0))^2} \\
&= \left(\eta^{1/2}\right)^2 = \eta. \quad (178)
\end{aligned}$$

In the data, we have:

$$\text{VAR}\left(\epsilon^{Z}_{it}\right) = \left(\eta^{1/2}\right)^2 \text{VAR}\left(\epsilon^{Z,S}_{it}\right) + \left((1-\eta)^{1/2}\right)^2 \text{VAR}\left(\epsilon^{Z,D}_{it}\right). \quad (179)$$

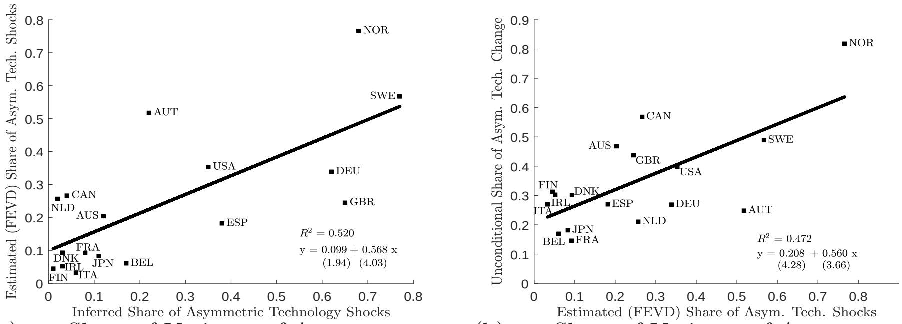
Or alternatively:

$$1 = \eta\left(\frac{\sigma^{Z,S}}{\sigma^{Z}}\right)^2 + (1-\eta)\left(\frac{\sigma^{Z,D}}{\sigma^{Z}}\right)^2. \quad (180)$$

To calibrate our model, we compute the share of technology improvements driven by asymmetric technological change by using eq. (13) that we repeat for convenience, i.e., $\hat{Z}^A(t) = \eta\hat{Z}^A_S(t) + (1-\eta)\hat{Z}^A_D(t)$. More specifically, we calculate the share $1-\eta$ of asymmetric technology shocks so that response of utilization-adjusted-aggregate-TFP we estimate empirically following a 1% permanent increase in $Z^A(t)$ in the long-run collapses to the weighted average of its symmetric and asymmetric components $\eta\hat{Z}^A_S(t) + (1-\eta)\hat{Z}^A_D(t)$ where $\hat{Z}^A_S(t)$ and $\hat{Z}^A_D(t)$ are the endogenous responses of symmetric and asymmetric components of utilization-adjusted-aggregate-TFP.

Estimated share of the conditional FEV of aggregate TFP growth attributable to asymmetric technology shocks vs. inferred share. In Fig. 12(a), we contrast two different measures of the share of aggregate technology improvements driven by asymmetric technology shocks. A standard method to quantify the share of technology shocks driven by the shock to one of its component is to conduct a forecast error variance decomposition (FEVD). We have performed a FEVD for one country at a time (17 OECD countries) by estimating the VAR model which includes utilization-adjusted-TFP of tradables relative to non-tradables, Z^H_t/Z^N_t, utilization-adjusted-aggregate-TFP, Z^A_t, real GDP, $Y_{R,t}$, total hours worked, L_i, the real consumption wage, $W_{C,t}$. Note that we average the share computed on impact (i.e., at $t=0$) and in the long-run (i.e., at $t=10$). We show the share of the variance of aggregate technology improvements driven by asymmetric technology shocks on the vertical axis of Fig. 12(a). We compare these findings with those that we obtain when we infer the share of asymmetric technology shocks in driving aggregate technology improvements by calculating $1-\eta$ so that the weighted average of technology improvements driven by symmetric and asymmetric technology shocks, $\eta\hat{Z}^A_S(t) + (1-\eta)\hat{Z}^A_D(t)$, collapses to the endogenous response of $Z^A(t)$ to an aggregate technology shock. We have performed this exercise for one country at a time. Results are shown on the horizontal axis. Overall, both measures are very close and we find a strong cross country relationship. We number only four countries out of 17 countries where the difference (between the inferred and the estimated share) exceeds plus or minus 20% including Austria (+30%), Canada (-23%), Great Britain (+41%), and the Netherlands (-24%). The cross-country average of the inferred share of asymmetric technology shocks stands at 26% while the cross-country average of the estimated share of asymmetric technology shocks amounts to 24%.

Estimated share of the conditional FEV of aggregate TFP growth attributable to asymmetric technology shocks: Whole period vs. sub-periods and whole sample vs. cross-country analysis. The first row of Table 16 reveals that the conditional FEV of aggregate TFP growth attributable to asymmetric technology shocks amounts to 25% on impact and stands at 23% in the long-run. Importantly, as shown in the second and the third row, when we consider two different sub-periods 1970-1992 and 1993-2017, we find that the conditional FEV of aggregate TFP growth attributable to asymmetric technology shocks has increased dramatically from 7% to 42.5%. In Table 17, we perform



(a) Share of Variance of Aggregate Technology Improvements Driven by Asymmetric Technology Shocks: FEVD vs. Inferred Share

(b) Share of Variance of Aggregate Technology Improvements Driven by Asymmetric Technological Change: Estimated Conditional Share (FEVD) vs. Unconditional Share

Figure 12: Share of Variance of Technology Improvements Driven by Asymmetric Technological Change: Conditional vs. Inferred vs. Unconditional Variance Decomposition. Notes: In Fig. 12(a), we contrast two different measures of the share of aggregate technology improvements driven by asymmetric technology shocks. A standard method to quantify the share of technology shocks driven by the shock to one of its component is to conduct a forecast error variance decomposition (FEVD). We performed a FEVD for each country of our sample (17 OECD countries) and show results on the vertical axis. We compare these findings with those we obtain by calculating the share of asymmetric technology shocks so that response of utilization-adjusted-aggregate-TFP collapses to the weighted average of its symmetric and asymmetric components, $1-\eta$, see eq. (13) that we repeat for convenience, i.e., $\hat{Z}^A(t) = \eta \hat{Z}^A_S(t) + (1-\eta)\,\hat{Z}^A_D(t)$. In Fig. 12(b), we contrast the share of aggregate technological change driven by asymmetric technology improvements which estimated from conditional shocks to utilization-adjusted-TFP and we contrast the conditional share of asymmetric technology shocks with the unconditional share we estimate directly from time series by using eq. (182). Sample: 17 OECD countries, annual data, 1970-2017.

Table 16: The Share of the FEV of Aggregate TFP Growth Attributable to Asymmetric Technology Shocks: 1970-2017 vs. Sub-Periods

	$t=0$	$t=10$
1970 - 2017	0.252	0.232
1970 - 1992	0.074	0.067
1993 - 2017	0.438	0.410

Notes: FEVD: Forecast Error Variance Decomposition. The number in columns denotes the fraction of the total forecast error variance of aggregate TFP growth Z^A attributable to identified asymmetric technology shocks across sectors (Z^H/Z^N). We consider a forecast horizon of 1 and 10 years and compute the FEVs in the five-variable VAR model which includes Z^H/Z^N, Z^A, Y_R, L and W_C, all in growth rate. Sample: 17 OECD countries, 1970-2017, annual data.

the same exercise except that we estimate the share of asymmetric technology shocks driving the FEV of aggregate TFP growth for one country a time. Denmark, Italy and to a lesser extent Japan display a low share of asymmetric technology shocks. At the opposite, Austria, Sweden, Norway display a higher share of asymmetric technology shocks.

J.9 Unconditional Variance Decomposition

The deviation of utilization-adjusted-aggregate-TFP relative to the initial steady-state is a weighted average of the deviation of utilization-adjusted-sectoral-TFP, i.e., $\hat{Z}^A(t) = \nu^{Y,H}\hat{Z}^H(t) + \left(1-\nu^{Y,H}\right)\hat{Z}^N(t)$. This equation can be rearranged so that the productivity growth differential shows up, i.e., $\hat{Z}^A(t) = \hat{Z}^N(t) + \nu^{Y,H}\left(\hat{Z}^H(t) - \hat{Z}^N(t)\right)$. When technology increases by the same amount across sectors, the second term on the RHS vanishes which leads to the following equality have $\hat{Z}^A(t) = \hat{Z}^N(t) = \hat{Z}^H(t)$ where utilization-adjusted-TFP collapses to its symmetric component, i.e., $\hat{Z}^A(t) = \hat{Z}^A_S(t)$.

Plugging the latter equality into the sectoral decomposition of aggregate technology improvement, taking the variance leads to the unconditional variance decomposition of

Table 17: The Share of the FEV of Aggregate TFP Growth Attributable to Asymmetric Technology Shocks: Cross-Country Analysis

	1970 - 2017		1970 - 1992		1993 - 2017	
	$t=0$	$t=10$	$t=0$	$t=10$	$t=0$	$t=10$
AUS	0.229	0.179	0.020	0.238	0.247	0.194
AUT	0.534	0.501	0.060	0.315	0.454	0.344
BEL	0.050	0.071	0.435	0.173	0.131	0.147
CAN	0.259	0.274	0.255	0.360	0.415	0.356
DEU	0.387	0.291	0.212	0.268	0.220	0.203
DNK	0.098	0.089	0.047	0.070	0.124	0.114
ESP	0.130	0.234	0.274	0.183	0.102	0.129
FIN	0.016	0.074	0.190	0.356	0.028	0.418
FRA	0.059	0.125	0.017	0.216	0.455	0.403
GBR	0.231	0.259	0.206	0.166	0.390	0.423
IRL	0.058	0.045	0.139	0.222	0.282	0.222
ITA	0.000	0.066	0.117	0.264	0.002	0.033
JPN	0.020	0.146	0.097	0.209	0.004	0.393
NLD	0.289	0.224	0.590	0.614	0.230	0.259
NOR	0.814	0.718	0.540	0.350	0.572	0.401
SWE	0.578	0.556	0.128	0.709	0.924	0.833
USA	0.380	0.326	0.735	0.457	0.351	0.402
Panel	0.252	0.232	0.074	0.067	0.438	0.410

Notes: FEVD: Forecast Error Variance Decomposition. The number in columns denotes the fraction of the total forecast error variance of aggregate TFP growth Z^A attributable to identified asymmetric technology shocks across sectors (Z^H/Z^N). We consider a forecast horizon of 1 and 10 years and compute the FEVs in the five-variable VAR model which includes Z^H/Z^N, Z^A, Y_R, L and W_C, all in growth rate. Sample: 17 OECD countries, 1970-2017, annual data.

technological change:

$$\begin{aligned}
\text{Var}\left(\hat{Z}^A(t)\right) &= \text{Var}\left(\hat{Z}^A_S(t)\right) + \left(\nu^{Y,H}\right)^2 \text{Var}\left(\hat{Z}^H(t) - \hat{Z}^N(t)\right) + 2\text{Cov}\left(\hat{Z}^A_S(t), \hat{Z}^A_D(t)\right), \\
\text{Var}'\left(\hat{Z}^A(t)\right) &= \text{Var}\left(\hat{Z}^A_S(t)\right) + \left(\nu^{Y,H}\right)^2 \text{Var}\left(\hat{Z}^H(t) - \hat{Z}^N(t)\right), \\
1 &= \frac{\text{Var}\left(\hat{Z}^A_S(t)\right)}{\text{Var}\left(\hat{Z}^A(t)\right)} + \left(\nu^{Y,H}\right)^2 \frac{\text{Var}\left(\hat{Z}^H(t) - \hat{Z}^N(t)\right)}{\text{Var}'\left(\hat{Z}^A(t)\right)}, \qquad (181)
\end{aligned}$$

where Var′ is the variance of aggregate technological change adjusted with the covariance, i.e.,

$$\text{Var}'\left(\hat{Z}^A(t)\right) = \text{Var}\left(\hat{Z}^A(t)\right) - 2\text{Cov}\left(\hat{Z}^A_S(t), \hat{Z}^A_D(t)\right). \qquad (182)$$

Using the fact that $\text{Var}\left(\hat{X}(t)\right) = \left[\hat{X}(t) - \hat{X}\right]^2$ where $X = Z^A, Z^A_S, Z^A_D$, the second term on the RHS of eq. (181) says that the contribution of the variance of asymmetric technology shocks to the variance of technological change is increasing in both the value added share of tradables, $\nu^{H,H}$, and the dispersion in technology improvements between the traded and the non-traded sector

By using time series for utilization-adjusted-TFP of tradables and non-tradables, $Z^H(t)$ and $Z^N(t)$, and utilization-adjusted-aggregate-TFP, $Z^A(t)$, we can compute the share of the variance of aggregate technological change (adjusted with the covariance), $\text{Var}'\left(\hat{Z}^A(t)\right)$, driven by the the variance of asymmetric technological change, $\text{Var}\left(\hat{Z}^H(t) - \hat{Z}^N(t)\right)$:

$$\text{Unconditional Share of Asym. Tech. Change} = \left(\nu^{Y,H}\right)^2 \frac{\text{Var}\left(\hat{Z}^H(t) - \hat{Z}^N(t)\right)}{\text{Var}'\left(\hat{Z}^A(t)\right)}, \qquad (183)$$

where $\nu^{Y,H}$ is the value added share of tradables averaged over 1970-2017.

In Fig. 12(b), we plot the share of asymmetric technological change based on an unconditional decomposition of the variance of the rate of change of utilization-adjusted-aggregate-TFP (vertical axis) against the share of technology improvements driven by asymmetric technology shocks based on the FEVD (horizontal axis). We find a high correlation of the conditional share of asymmetric technology shocks estimated empirically and the unconditional share of asymmetric technological change. Overall, both measures are very close and we find a strong cross country relationship. We quantify some significant differences for seven countries out of 17 countries. More specifically, the difference (between the calculated and the estimated share) exceeds plus or minus 20% for the following countries: Australia (+26%), Austria (-27%), Canada (+30%), Denmark (+21%), Finland (+27%), Ireland (+25%), Great Britain (+41%), and Italy (+24%). The cross-country average of the unconditional share of asymmetric technology shocks stands at 34% while the cross-country average of the estimated share of asymmetric technology shocks amounts to 24%.

J.10 Setting the Dynamics of Factor-Augmenting Efficiency and Capital Utilization Adjustment Costs

Factor-augmenting efficiency. As detailed in section 3.1 (see eq. (7)), factor-augmenting productivity is made up of a symmetric and an asymmetric component across sectors. To set the adjustment of factor-augmenting efficiency, we first recover their dynamics in the data in the same spirit as Caselli and Coleman [2006]. Log-linearizing the demand for labor relative to the demand for capital (10), this equation together with the log-linearized version of the technology frontier (12) can be solved for deviations of $A^j_c(t)$ and $B^j_c(t)$ relative to their initial values (where the subscript $c = S, D$ refers to either the symmetric or asymmetric component):

$$\hat{A}^j_c(t) = \hat{Z}^j_c(t) - \left(1 - s^j_L\right)\left[\left(\frac{\sigma^j}{1-\sigma^j}\right)\hat{S}^j_c(t) - \hat{k}^j_c(t) - \hat{u}^{K,j}_c(t)\right], \tag{184a}$$

$$\hat{B}^j_c(t) = \hat{Z}^j_c(t) + s^j_L\left[\left(\frac{\sigma^j}{1-\sigma^j}\right)\hat{S}^j_c(t) - \hat{k}^j_c(t) - \hat{u}^{K,j}_c(t)\right]. \tag{184b}$$

Plugging estimated values for σ^j and empirically estimated responses for $S^j_c(t) = \frac{s^j_{L,c}(t)}{1-s^j_{L,c}(t)}$, $k^j_c(t)$, $u^{K,j}_c(t)$ (conditional on symmetric, i.e., $c = S$, or asymmetric, i.e., $c = D$, technology improvements) enables us to recover the dynamics for $A^j_c(t)$ and $B^j_c(t)$ consistent with the demand for factors of production (10) and the technology frontier (12). Then we choose values for exogenous parameters x^j_c (for $x = a, b$, $c = S, D$), $\xi^j_{X,c}$ and $\chi^j_{X,c}$ (for $X = A, B$, $c = S, D$) of the continuous time paths (30) within sector $j = H, N$, which are consistent with the estimated paths (32a)-(32b) for $A^j_c(t)$ and $B^j_c(t)$. Once we have generated the dynamics of $A^j_c(t)$ and $B^j_c(t)$, we can infer the dynamics of utilization-adjusted-TFP in sector j by using the technology frontier, i.e., $\hat{Z}^j_c(t) = s^j_L\hat{A}^j_c(t) + \left(1 - s^j_L\right)\hat{B}^j_c(t)$ (see eq. (12)). Table 18 summarizes the values of parameters x^j_c (for $x = a, b$, $c = S, D$), $\xi^j_{X,c}$ and $\chi^j_{X,c}$ (for $X = A, B$, $c = S, D$), the long-run change in factor-augmenting productivity, i.e., $\hat{X}^j_c$, and its change on impact, i.e., $\hat{X}^j_c(0)$.

Capital utilization adjustment costs. Because capital-augmenting productivity has a symmetric and an asymmetric component, capital technology utilization rate must also have both a symmetric and asymmetric component, i.e., $u^{K,j}(t) = \left(u^{K,j}_S(t)\right)^{\eta}\left(u^{K,j}_D(t)\right)^{1-\eta}$, see eq. (8) in the main text, which ensures that symmetric and asymmetric components of TFP are well-defined. At the steady-state $u^{K,j}_c = 1$. Table 19 gives values of parameters to calibrate the dynamic adjustment of capital utilization adjustment costs in the open economy with CES production functions, i.e., $C^{K,j}_c(t) = \xi^j_{1,c}\left(u^{K,j}_c(t) - 1\right) + \frac{\xi^j_{2,c}}{2}\left(u^{K,j}_c(t) - 1\right)^2$, see eq. (20) in the main text. We set the magnitude of the adjustment cost in the capital utilization rate, i.e., $\xi^j_{2,S}$ and $\xi^j_{2,D}$ so as to account for empirical responses of $u^{K,j}_S(t)$ and $u^{K,j}_D(t)$, respectively, conditional on symmetric and asymmetric technology shocks across sectors. We set $\xi^H_{1,S} = \eta\frac{R^{K,H}}{P^H}$, $\xi^H_{1,D} = (1-\eta)\frac{R^{K,H}}{P^H}$, $\xi^N_{1,S} = \eta\frac{R^{K,N}}{P^N}$, $\xi^N_{1,D} = (1-\eta)\frac{R^{K,N}}{P^N}$.

Table 18: Calibration of Dynamics of Symmetric and Asymmetric Technology Shocks

Parameters	Symmetric Technology shock				Asymmetric Technology Shock			
	Tradables		Non-Tradables		Tradables		Non-Tradables	
	$A_S^H(t)$	$B_S^H(t)$	$A_S^N(t)$	$B_S^N(t)$	$A_D^H(t)$	$B_D^H(t)$	$A_D^N(t)$	$B_D^N(t)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Exogenous technology shock, x_c^j	-0.03	-0.70	-0.78	3.18	-8.20	14.46	-0.42	-1.12
Impact effect, $\hat{X}_c^j(0)$	1.68	0.00	1.84	0.00	-4.64	14.79	-1.20	1.00
Long-run effect, $\hat{X}_c^j$	1.71	0.70	2.62	-3.18	3.56	0.33	-0.78	2.12
Persistence and shape of $\hat{X}^j(t)$, $\xi_{X,c}^j$	0.38	0.38	0.50	0.50	0.19	0.20	0.10	0.10
Persistence and shape of $\hat{X}^j(t)$, $\chi_{X,c}^j$	0.41	0.35	0.51	0.50	0.18	0.24	0.10	0.10

Notes: Denoting the factor-augmenting efficiency by $X_c^j = A_c^j, B_c^j$ for technology shock $c = S, D$ in sector j, the adjustment of $X_c^j(t)$ toward its long-run level expressed in percentage deviation from initial steady-state is governed by the following continuous time process: $\hat{X}_c^j(t) = \hat{X}_c^j + e^{-\xi_{X,c}^j t} - \left(1 - x_c^j\right) e^{-\chi_{X,c}^j t}$. The first row is an exogenous parameter which determines the magnitude of the change in $X_c^j(t)$ on impact (see the second row) given its rate of change in the long-run $\hat{X}_c^j$ (see the third row). The last two rows display the values of parameters $\xi_{X,c}^j$ and $\chi_{X,c}^j$ which determines the shape and the persistence of the technology shock.

Table 19: Baseline Parameters (Representative OECD Economy): Capital Utilization Adjustment Costs Parameters

Parameter	Tradables		Non-Tradables	
	Symmetric	Asymmetric	Symmetric	Asymmetric
	(1)	(2)	(3)	(4)
	$\xi_{1,S}^H$	$\xi_{1,D}^H$	$\xi_{1,S}^N$	$\xi_{1,D}^N$
Value of $\xi_{1,c}^j$	0.05285	0.03524	0.04329	0.02886
	$\xi_{2,S}^H$	$\xi_{2,D}^H$	$\xi_{2,S}^N$	$\xi_{2,D}^N$
Value of $\xi_{2,c}^j$	0.5	0.03	0.6	0.5

Notes: Table 19 gives values of parameters to calibrate the dynamic adjustment of capital utilization adjustment costs in the open economy with CES production functions, i.e., $C_c^{K,j}(t) = \xi_{1,c}^j \left(u_c^{K,j}(t) - 1\right) + \frac{\xi_{2,c}^j}{2} \left(u_c^{K,j}(t) - 1\right)^2$, see eq. (20) in the main text. Note that at the steady-state $u_c^{K,j} = 1$.

J.11 Calibration to the Data

In Table 18, we show the values we choose to set the dynamic processes of symmetric and asymmetric components of factor-augmenting technology shocks. Because in the empirical part, we estimate the dynamics of utilization-adjusted-TFP, we have to ensure that the dynamics of $Z_c^j(t)$ generated numerically are in line with those estimated empirically. The first two rows of Fig. 13 show responses following a symmetric technology shock. Rows 3-4 show responses following an asymmetric technology shock. We attribute a value of 0.6 to the share of symmetric technology shocks and generate the dynamics of technology variables for an aggregate technology improvement which is a combination of symmetric and asymmetric technology shocks, as shown in the last two rows. While the blue line displays responses we estimate empirically, the black line with squares plots theoretical responses we generate by assuming that labor- and capital-augmenting technological change is governed by dynamic equation (30) while the log-linearized version of the technology frontier allows us to recover the law of motion of utilization-adjusted-TFP. The first column shows that the model reproduces well the adjustment of technology improvements in the traded and the non-traded sector.

In Table 19, we show the values we choose to set the dynamic adjustment of the capital utilization adjustment costs in the traded and the non-traded sector conditional on symmetric and asymmetric technology shocks. The second column of Fig. 13 plots empirical responses of the capital utilization rate for the traded and the non-traded sector shown in blue lines. Black lines with squares plot theoretical responses for $u_t^{K,H}$ and $u_t^{K,N}$. The confidence bounds indicate that none of the responses are statistically significant, except for $u^{K,H}(t)$ after an asymmetric technology shock.[12] Inspection of the second column reveals that our model reproduces well the dynamics of the capital utilization rate. First, as shown in the first two rows, the capital utilization rates increase slightly following a symmetric technology shock (but the responses are not statistically significant) because technological change is biased toward capital which increases the return on capital and thus rental rate. By contrast, an asymmetric technology shock leads to a dramatic fall in $u^{K,H}(t)$ because technological change is strongly biased toward labor in the traded sector which drives down the return on capital. As shown in Fig. 13(q), our model reproduces well the dynamic adjustment of the capital utilization rate for non-tradables while Fig. 13(n) indicates that the model tends to somewhat overstate the response of $u^{K,H}$, especially in the short-term.

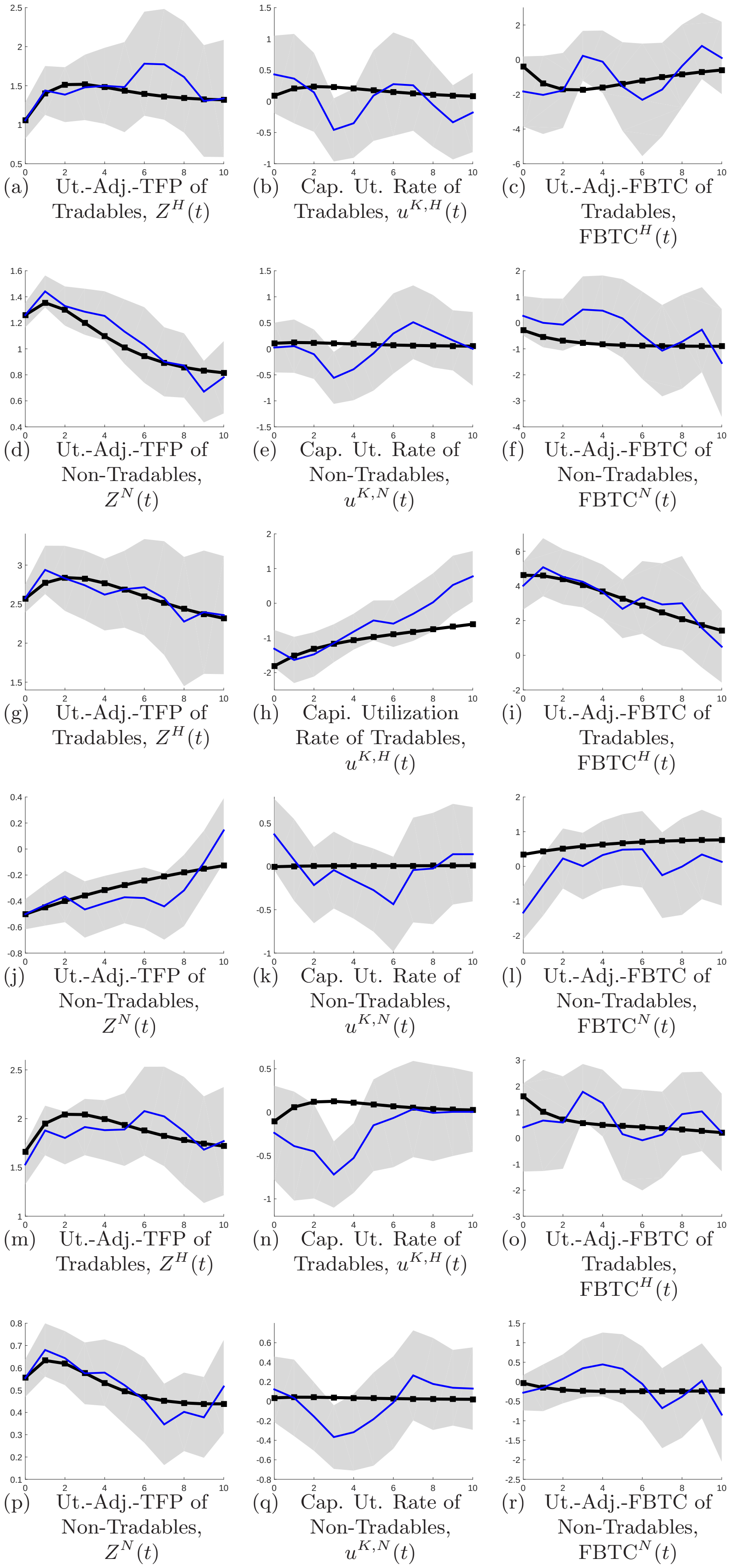
The last column of Fig. 13 plots empirical responses of FBTC in the traded and the non-traded sector. As mentioned above, symmetric technology shocks are biased toward capital while asymmetric technology shocks are biased toward labor. As shown in the last two rows, our model reproduces well the dynamics of FBTC following an aggregate technology improvement.

J.12 Calibration of the Model to Generate the Time-Varying Effect

Strategy. Our main objective in the paper is to account for the vanishing decline in hours after a technology shock we document for OECD countries in the main text in section 4.4. Fig. 2.6 shows that the decline in hours shrinks from -0.26% the first thirty years of our sample to -0.11% the last thirty years. These values are displayed by column 3 of Table 20. According to our assumption, the gradual disappearance of the decline in hours after a technology shock is driven by the increasing share of technological change which is explained by asymmetric technology shock between sectors.

Calibration of the model to generate time-varying effects. To test our hypothesis, we keep all model's parameters discussed in the main text in section 4.1 unchanged and we lower the share of symmetric technology shocks. We take values we have computed in the empirical part, see Fig. 4(d), by estimating the share of the variations in technology improvements explained by asymmetric technology shocks. Column 2 of Table 20 shows the values of the share of symmetric technology shocks which have been estimated on the corresponding sub-period shown in column 1. We simulate the same model nineteen times

[12] The reason is that there exists a wide cross-country dispersion in the movement of the capital utilization rates across countries in terms of both direction and magnitude.



(a) Ut.-Adj.-TFP of Tradables, $Z^H(t)$ (b) Cap. Ut. Rate of Tradables, $u^{K,H}(t)$ (c) Ut.-Adj.-FBTC of Tradables, $\text{FBTC}^H(t)$

(d) Ut.-Adj.-TFP of Non-Tradables, $Z^N(t)$ (e) Cap. Ut. Rate of Non-Tradables, $u^{K,N}(t)$ (f) Ut.-Adj.-FBTC of Non-Tradables, $\text{FBTC}^N(t)$

(g) Ut.-Adj.-TFP of Tradables, $Z^H(t)$ (h) Capi. Utilization Rate of Tradables, $u^{K,H}(t)$ (i) Ut.-Adj.-FBTC of Tradables, $\text{FBTC}^H(t)$

(j) Ut.-Adj.-TFP of Non-Tradables, $Z^N(t)$ (k) Cap. Ut. Rate of Non-Tradables, $u^{K,N}(t)$ (l) Ut.-Adj.-FBTC of Non-Tradables, $\text{FBTC}^N(t)$

(m) Ut.-Adj.-TFP of Tradables, $Z^H(t)$ (n) Cap. Ut. Rate of Tradables, $u^{K,H}(t)$ (o) Ut.-Adj.-FBTC of Tradables, $\text{FBTC}^H(t)$

(p) Ut.-Adj.-TFP of Non-Tradables, $Z^N(t)$ (q) Cap. Ut. Rate of Non-Tradables, $u^{K,N}(t)$ (r) Ut.-Adj.-FBTC of Non-Tradables, $\text{FBTC}^N(t)$

Figure 13: Dynamics of Technology Variables: Theoretical vs. Empirical Responses. Notes: The solid blue line displays point estimate from local projections with shaded areas indicating 90% confidence bounds. The thick solid black line with squares displays model predictions in the baseline scenario with capital and technology utilization together with FBTC, while the dashed red line shows predictions of a model with Cobb-Douglas production functions and abstracting from capital and technology utilization. Fig. 13 plots the dynamic effects of a 1% permanent technology improvement on utilization-adjusted-TFP, the capital utilization rate and utilization-adjusted-FBTC for tradables and non-tradables. The fist two rows show the effects of a symmetric technology shock across sectors while rows 3-4 display the effects of an asymmetric technology shock. The last two rows shows the effects following a technology shock.

Table 20: Calibration of the Model to Generate the Time-Varying Impact Effects of a Technology Shock

Subperiod (30 years) (1)	Share of symmetric shocks (η) (2)	Impact Response of Hours Empirical (3)	Numerical (4)
1970 - 1999	0.902	-0.257	-0.285
1971 - 2000	0.868	-0.243	-0.248
1972 - 2001	0.838	-0.233	-0.260
1973 - 2002	0.811	-0.243	-0.259
1974 - 2003	0.787	-0.255	-0.261
1975 - 2004	0.766	-0.218	-0.254
1976 - 2005	0.748	-0.217	-0.209
1977 - 2006	0.731	-0.223	-0.227
1978 - 2007	0.716	-0.228	-0.228
1979 - 2008	0.703	-0.197	-0.183
1980 - 2009	0.692	-0.189	-0.149
1981 - 2010	0.682	-0.168	-0.122
1982 - 2011	0.673	-0.147	-0.119
1983 - 2012	0.664	-0.150	-0.128
1984 - 2013	0.657	-0.157	-0.138
1985 - 2014	0.651	-0.136	-0.120
1986 - 2015	0.645	-0.120	-0.093
1987 - 2016	0.640	-0.113	-0.095
1988 - 2017	0.636	-0.115	-0.078

Notes: Column 2 displays the values for the share of symmetric technology shocks (η) we choose numerically. In column 3, we show impact responses that we estimate empirically by means of local projections (sample: 17 OECD countries, 1970-2017, annual data). Column 4 shows impact effects we estimate numerically in the baseline model which allows for endogenous capital utilization rate, CES production functions and FBTC.

by feeding the model with the value of the share of symmetric technology shocks shown in column 2. Column 4 displays the impact responses of hours after a technology shock of 1% we estimate numerically. While Fig. 6(a) contrasts the impact responses of hours after a permanent technology shock we estimate empirically (blue line) with those we estimated numerically (lack line) by using values of η displayed by column 2 in Table 20 to simulate the open economy model, empirical and numerical estimates are shown in columns 3 and 4 of the Table.

Additional comments on the strategy. It is worth mentioning that the share of symmetric component of technology improvements is not modelled as a shock but as a structural parameter which shapes the composition of technology improvements, i.e., the mix of symmetric and asymmetric technology shocks. It is not a model's parameter because η does not determine the shape of labor demand nor labor supply. Instead, the gradual change in the value of η over the last 50 years captures time-increasing biasedness of technology improvements toward the traded sector.

K More Numerical Results

For reasons of space, we relegate to the online appendix a number of numerical results we refer to in the main text. These results include the effects of symmetric and asymmetric technology shocks across restricted variants of the baseline model.

K.1 Impact Effects across Restricted Versions of the Baseline Model: Symmetric vs. Asymmetric Technology Shocks

For reasons of space, in the main text, we restrict the discussion to the effects of symmetric and asymmetric technology shocks in the baseline model. In this section, we discuss the effects of symmetric and asymmetric technology shocks by considering the restricted versions of the baseline model and show that all variants fail to account for the effects we estimate empirically.

Symmetric technology improvements across sectors. When home- and foreign-produced traded goods are perfect substitutes, as considered in columns 9 and 12, a technology improvement which is evenly spread across sectors leads to a dramatic decline in total hours worked. Intuitively, a technology improvement produces a positive wealth effect which increases consumption in both traded and non-traded goods. Because home- and foreign-produced traded goods are perfect substitutes, households find it optimal to borrow from abroad (see panel E) to consume more foreign goods and increase leisure. As shown in panel B, total hours fall dramatically by -0.88% when we assume perfect mobility of inputs (see column 12) and by -0.67% under the assumption of imperfect mobility of inputs (see column 9). While the technology improvement drives down both traded and non-traded hours worked (see the second and the third row of panel B), the hours worked share of tradables falls (see the last row of panel B) which enters in contradiction with our empirical results which show that labor shifts away from non-traded industries and toward traded industries on impact.

In contrast, when home- and foreign-produced traded goods are assumed to be imperfect substitutes which is the scenario considered in columns 3 and 6, a symmetric technology improvement shifts labor away from non-traded and toward traded industries in accordance with the evidence we document in the empirical section 2. Intuitively, a symmetric technology shock across sectors lowers the marginal cost in both sectors which leads both traded and non-traded firms to cut prices. By increasing exports and mitigating the rise in imports, the terms of trade depreciation reduces considerably the current account deficit as shown in panel E. In addition, because traded and non-traded goods are gross complements (i.e., $\phi < 1$), the excess supply on the non-traded goods market lowers the non-tradable content of expenditure (see the second row of panel D) which leads labor to shift toward the traded sector in line with our evidence. As can be seen in panel E, since households are reluctant to substitute foreign for domestic goods, the current account deficit shrinks from -0.43 ppt of GDP in the restricted model to -0.06 ppt of GDP in the baseline model. To meet higher demand for home-produced traded goods, households must mitigate their appetite for leisure which curbs the fall in hours worked. As shown in columns 3 and 6, a model assuming endogenous terms of trade produces a decline in hours worked ranging from 0.40% to 0.46% which squares well with the decline in hours worked by 0.47% we estimate empirically. The reallocation of labor toward the traded sector and the reduction in the consumption of leisure mitigates substantially the fall in traded hours worked, i.e., from -0.49 ppt of total hours worked (see column 12) to -0.11 ppt (see column 3), and leaves the value added share of tradables at constant prices, $\nu^{Y,H}$ essentially unchanged (see the first row of panel D).

Asymmetric technology improvements across sectors. While symmetric technology improvements drive down hours worked in the data, we find empirically that asymmetric technology shocks across sectors do the opposite and increase total hours worked by 0.31%. Importantly, only the baseline model can account for the magnitude of the response of hours worked to a technology improvement. If we consider a restricted version of the model shown in column 13, the model generates a decline in hours worked by 0.38% instead of an increase. Intuitively, when technology improvements are concentrated toward traded industries, non-traded firms set higher prices to compensate for lower productivity gains. Because traded and non-traded goods have low substitutability, the tradable content of expenditure declines (see the second row of panel D). Labor thus shifts away from the traded sector which leads the traded goods-sector share of total hours worked by 0.51 ppt of total hours worked (see the last row of panel B). Because home- and foreign-produced traded goods are perfect substitutes, households import goods from abroad and increase leisure time. While labor supply falls, the rise in the hours worked share of non-tradables is large enough to produce additional units of non-traded goods. As shown in column 10, when we put frictions into the movement of inputs, the reallocation of labor toward the non-traded sector is less and and total hours worked is almost unchanged. The reason is that labor

Table 21: Impact Labor Effects of a Technology Improvement: Baseline vs. Restricted Models

	Data	CES: FBTC and uK			CD: IM & TOT			CD: IML& IMK			CD: PM		
	LP	AGG	SYM	ASYM	AGG	SYM	ASYM	AGG	SYM	ASYM	AGG	SYM	ASYM
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
A.Technology													
Aggregate technology, $dZ^A(t)$	0.93	0.94	1.19	0.58	0.95	1.19	0.58	0.95	1.19	0.58	0.95	1.19	0.58
T technology, $dZ^H(t)$	1.53	1.66	1.06	2.57	1.66	1.06	2.57	1.66	1.06	2.58	1.66	1.06	2.58
NT technology, $dZ^N(t)$	0.55	0.56	1.26	-0.50	0.56	1.26	-0.50	0.56	1.26	-0.50	0.56	1.26	-0.50
T capital utilization, $du^{K,H}(t)$	-0.24	-0.11	0.09	-1.81	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
NT capital utilization, $du^{K,N}(t)$	0.12	0.03	0.11	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
B.Hours													
Hours, $dL(t)$	-0.15	-0.07	-0.40	0.28	-0.26	-0.47	0.05	-0.42	-0.67	-0.01	-0.70	-0.88	-0.38
Traded Hours, $dL^H(t)$	-0.04	-0.03	-0.11	-0.02	-0.15	-0.11	-0.19	-0.28	-0.29	-0.26	-0.57	-0.49	-0.64
Non-Traded Hours, $dL^N(t)$	-0.11	-0.05	-0.30	0.29	-0.12	-0.35	0.23	-0.14	-0.39	0.25	-0.13	-0.39	0.26
Hours Share of Tradables, $d\nu^{L,H}(t)$	0.01	-0.00	0.03	-0.11	-0.06	0.04	-0.21	-0.14	-0.06	-0.26	-0.33	-0.20	-0.51
C.Relative Prices													
Relative price of NT, $d(P^N/P^H)(t)$	1.05	1.63	-0.43	4.69	1.56	-0.50	4.69	2.11	0.25	4.88	1.15	-0.15	3.12
Terms of trade, $dP^H(t)$	-1.15	-1.09	-0.44	-1.99	-0.93	-0.47	-1.68	0.00	0.00	0.00	0.00	0.00	0.00
D.VA Shares													
VA share of T (constant prices) $d\nu^{Y,H}(t)$	0.18	0.23	-0.02	0.47	0.22	-0.01	0.57	0.14	-0.09	0.50	-0.08	-0.24	0.17
VA share of N (current prices) $d\omega^{Y,N}(t)$	0.05	0.13	-0.07	0.57	0.13	-0.10	0.47	0.34	0.14	0.59	0.34	0.20	0.53
E.Current Account													
Current Account, $dCA(t)$	n.a.	-0.02	-0.06	0.04	-0.02	-0.04	0.01	-0.18	-0.26	-0.04	-0.38	-0.43	-0.27

Notes: This table shows impact effects of a 1% permanent increase in government consumption in the baseline model (columns 2-4) and in restricted versions of the model (columns 5-13). 'T' refers to traded industries while 'NT' refers to non-tradables. Panel A shows the impact effects for technology variables, panel B displays the impact effects for hours worked, panel C shows the relative price effects while panel D reports the change on impact in the current account (in percentage point of GDP). Across all scenarios, we consider a 1% permanent increase in utilization-adjusted-aggregate-TFP. In column 1, we show impact responses of the corresponding variables. Columns 2, 5, 8, 11 show numerical results following a technology improvement which increases the utilization-adjusted-aggregate-TFP by 1% in the long-run. Columns 3, 6, 9, 12 show numerical results following a symmetric technology shock across sectors which increases the utilization-adjusted-aggregate-TFP by 1% in the long-run. Columns 4, 7, 10, 123 shows numerical results following an asymmetric technology shock across sectors which increases the utilization-adjusted-aggregate-TFP by 1% in the long-run. In Columns 11-13 show numerical results for an open economy model with tradables and non-tradables with capital adjustment costs, perfect mobility of labor and capital, perfect substitutability between home- and foreign-produced traded goods. In columns 8-10, we augment the previous model with imperfect mobility of labor and capital. In columns 5-7, we augment the previous model with imperfect substitutability between home- and foreign-produced traded goods so that terms of trade are endogenous. In columns 2-4, we consider the baseline model which allows for endogenous capital utilization rate and assumes that sectoral goods are produced by means of CES production functions and we let technological change to be factor-biased.

mobility costs lead non-traded firms to pay higher wages to encourage workers to shift away from traded industries. Because the non-tradable content of the labor compensation share of non-tradables is two-third, higher non-traded wages push the aggregate wage index up. The higher wage rate produces a substitution effect which almost offsets the positive wealth effect.

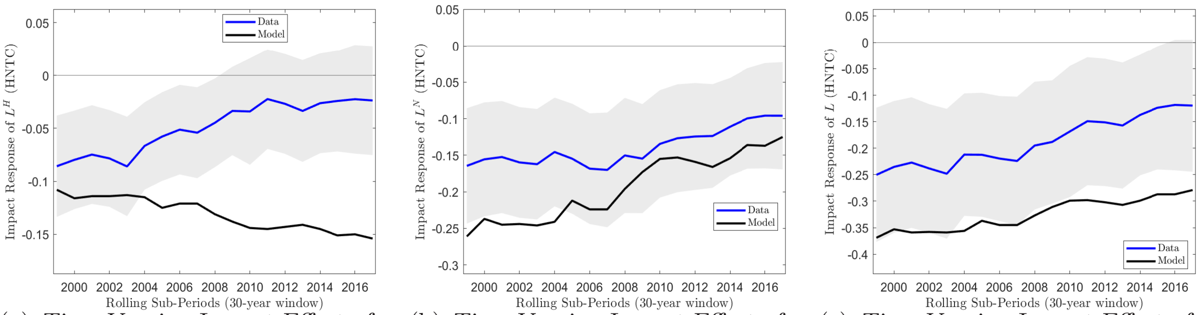
While labor mobility costs has a positive impact on hours worked by putting upward pressure on wages, adding imperfect substitutability between home- and foreign-produced traded goods allows the model to produce an increase in hours worked by 0.05% (see the first row of panel B in column 7). Intuitively, when technology improvements are concentrated in traded industries and traded goods are price-elastic, traded firms find it optimal to lower their prices which leads to a current account surplus (see panel E). Because imports increase less than if terms of trade were exogenous, households must increase their labor supply to produce home-produced traded goods units. However, the rise in total hours worked by 0.05% remains significantly below what we estimate. It is only once we allow for FBTC and endogenous capital utilization at a sectoral level that the open economy model can account for the magnitude of the rise in hours worked we estimate. Intuitively, our empirical evidence reveals that technology improvements in the traded sector are associated with technological change biased toward labor. By making the production in the traded sector more labor intensive, technological change biased toward labor increases wages and further increases labor supply. However, by increasing labor demand in the traded relative to the non-traded sector, the positive FBTC differential between tradables and non-tradables reduces the magnitude of the decline in the hours worked share of tradables. To account for the impact response of hours worked to asymmetric technology shocks and the shift of labor toward the non-traded sector, we have to allow for endogenous capital utilization. Because technological change biased toward labor lowers the demand for capital in the traded sector, it is profitable to reduce in the intensity in the use of physical capital in this sector. The fall in the capital utilization rate of tradables lowers the traded wage rate which amplifies the shift of labor toward the non-traded sector and generates an increase in labor supply by 0.28% close to what we estimate empirically.

K.2 Time-Varying Effects on Hours Worked in a Model Imposing Hicks-Neutral Technological Change (HNTC)

As highlighted in the main text, one key ingredient of our model is FBTC. Without this ingredient, the model cannot generate an increase in total hours worked which is in line with the evidence after an asymmetric technology shock. In addition, as mentioned in section 4.4, technological change is key to giving rise to a time-increasing impact response of traded and non-traded hours worked. As can be seen in Fig. 14, abstracting from technological change biased toward labor by assuming Cobb-Douglas production functions leads the model to fail to account for the evidence. First, as shown in Fig. 14(a), a model imposing HNTC produces a time-decreasing impact response of traded hours worked (see the black line) while according to the evidence, the contractionary effect of a technology improvement on traded hours shrinks over time. The inability of a model abstracting from FBTC to produce the time-increasing impact response of $L^H(t)$ is that asymmetric technology shocks have a strong expansionary effect on non-traded hours worked at the expense of traded hours worked because such shocks strongly appreciate non-traded goods prices and increase the share of non-tradables. In contrast, by assuming that technological change is significantly biased toward labor in the traded sector in line with the evidence, the baseline model with FBTC can reproduce very well the time-increasing impact responses of $L^H(t)$. Second, when technological change biased toward labor is absent, the model overstates the decline in hours worked.

L More Empirical Results and Robustness Checks

In this section, we conduct some robustness checks. Our identification of aggregate technology shocks and their decomposition into symmetric and asymmetric technology shocks is



(a) Time-Varying Impact Effect of Technology on Traded Hours Worked

(b) Time-Varying Impact Effect of Technology on Non-Traded Hours Worked

(c) Time-Varying Impact Effect of Technology on Total Hours Worked

Figure 14: Time-Varying Impact Effects of a Technology Shock on Sectoral Hours Worked.
Notes: The figure shows impact responses of traded and non-traded hours worked to a 1% permanent increase in utilization-adjusted aggregate TFP. The solid blue line shows the impact response we estimate empirically on rolling sub-periods by using Jordà's [2005] single-equation method. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. The solid black line shows the impact response we compute numerically by considering a restricted version of our baseline model where we shut down FBTC by assuming $\sigma^j = 1$ and we abstract from endogenous capital utilization by letting ξ_2^j tend toward infinity. Note that we have normalized the rise in utilization-adjusted aggregate TFP to 1% on impact as we focus on The horizontal axis shows the end year of the period of the sub-sample and the vertical line displays the point estimate of the impact effect of technology on total hours worked.

based on the assumption that time series for utilization-adjusted-aggregate-TFP together with the utilization-adjusted-TFP of tradables relative to non-tradables follow a unit root process. Because in the main text, all variables enter the VAR model in growth rate, subsection L.1 shows panel unit tests for all variables considered in the empirical analysis. Because one major contribution of our paper is to show that that the vanishing decline in hours is caused by a the changing nature of technology shocks and not by switching regime, we have run panel unit root tests on utilization-adjusted-TFP and hours by allowing for potential structural breaks where the date of the structural break is endogenously determined.

Due to data availability, we use annual data for eleven 1-digit ISIC-rev.3 industries that we classify as tradables or non-tradables. At this level of disaggregation, the classification is somewhat ambiguous because some broad sectors are made-up of heterogenous sub-industries, a fraction being tradables and the remaining industries being non-tradables. Since we consider a sample of 17 OECD countries over a period running from 1970 to 2017, the classification of some sectors may vary across time and countries. Industries such as 'Finance Intermediation' classified as tradables, 'Hotels and Restaurants' classified as non-tradables display intermediate levels of tradedness which may vary considerably across countries but also across time. Subsection L.2 deals with this issue and conducts a robustness check to investigate the sensitivity of our empirical results to the classification of industries as tradables or non-tradables.

Since we split the gross capital stock into traded and non-traded industries by using sectoral valued added shares, in subsection L.3, we conduct a robustness check by considering time series for capital stock per industry from KLEMS which are available for a limited number of countries.

Our dataset covers eleven industries which are classified as tradables or non tradables. The traded sector is made up of five industries and the non-traded sector of six industries. In subsection L.4, we conduct our empirical analysis at a more disaggregated level. The objective is twofold. First, we investigate whether all industries classified as tradables or non-tradables behave homogeneously or heterogeneously. Second, we explore empirically which industry drives the responses of broad sectors following a rise in government spending by 1% of GDP.

In subsection L.5, we document evidence about the drivers of asymmetric technology shocks. We find that only asymmetric technology shocks increase significantly the stock of R&D and only in the traded sector. We find that the share of asymmetric technology shocks is larger in countries where the R&D intensity of traded output is higher. In subsection L.6, we contrast empirically the adjustment of total hours with the adjustment at the intensive margin following an exogenous increase in utilization-adjusted-aggregate-TFP by 1% in the long-run. In subsection L.7, we estimate and plot time-varying impact responses of hours worked to symmetric and asymmetric technology shocks which are estimated over rolling sub-samples.

In subsection L.8, we calculate the correlation of technology shocks across OECD countries and find that shocks are uncorrelated. We estimate a VAR model in panel format and assume that the response of hours to a technology shock is homogenous across countries. In subsection L.9, we test the validity of the homogeneity assumption in estimating the dynamic response of hours to a technology shock in panel format. In the main text, we adopt a two-step method where we identify first technology shocks which are used as regressors in the second step. While Pagan [1984] presents a formal confirmation of the robustness of the two-step method, in subsection L.10, we further test this approach by adopting a one-step approach based on local projections as suggested by Ramey and Zubairy [2018] who apply this approach to estimate the effects of government spending shocks. Since we estimate both the VAR model and local projections in panel format by allowing for time dummies which capture common macroeconomic shocks, in subsection L.11, we test the sensitivity of our results to the inclusion of time dummies.

In subsection L.12, we re-estimate the effects of a technology shock by by generating impulse response functions to the identified technology shocks from the SVAR model. We further test our assumption of the changing nature of technology shocks and constancy of model's parameters by running a series of tests in panel format to detect the potential presence of structural breaks in the relationship between technology and hours in subsection L.13. In subsection L.14, we conduct an empirical analysis to identify the key factors driving international differences in the response of hours and the current account to a technology shock.

L.1 Panel Unit Root Tests

Short description of the four panel unit root test. When estimating alternative VAR specifications, all variables enter in growth rates. In order to support our assumption of I(1) variables, we ran panel unit root tests displayed by Table 22. We consider four panel unit root tests among the most commonly used in the literature: Levin, Lin and Chu ([2002], hereafter LLC), Breitung [2000], Im, Pesaran and Shin ([2003], hereafter IPS), and Hadri [2000]. All tests, with the exception of Hadri [2000], consider the null hypothesis of a unit root against the alternative that some members of the panel are stationary. Additionally, they are designed for cross sectionally independent panels. LLC and IPS are based on the use of the Augmented Dickey-Fuller test (ADF hereafter) to each individual series of the form $\Delta x_{i,t} = \alpha_i + \rho_i x_{i,t-1} + \sum_{j=1}^{q_i} \theta_{i,j} \Delta x_{i,t-j} + \varepsilon_{i,t}$, where $\varepsilon_{i,t}$ are assumed to be i.i.d. (the lag length q_i is permitted to vary across individual members of the panel). Under the homogenous alternative the coefficient ρ_i in LLC is required to be identical across all units ($\rho_i = \rho$, $\forall i$). IPS relax this assumption and allow for ρ_i to be individual specific under the alternative hypothesis. We also apply the pooled panel unit root test developed by Breitung [2000] which does not require bias correction factors when individual specific trends are included in the ADF type regression. This is achieved by an appropriate variable transformation. As a sensitivity analysis, we also employ the test developed by Hadri [2000] which proposes a panel extension of the Kwiatkowski et al. [1992] test of the null that the time series for each cross section is stationary against the alternative of a unit root in the panel data. Breitung' and Hadri's tests, like LLC's test, are pooled tests against the homogenous alternative.[13]

Empirical results: macroeconomic variables considered in the empirical part are all integrated of order one. As noted above, IPS test allows for heterogeneity of the autoregressive root, accordingly, we will focus intensively on these tests when testing for unit roots. Across all variables the null hypothesis of a unit root against the alternative of trend stationarity cannot be rejected at conventional significance levels, suggesting that the set of variables of interest are integrated of order one. When considering the Hadri's test for which the null hypothesis implies stationary against the alternative of a unit root in the panel data, we reach the same conclusion and conclude again that all series are nonstationary. Taken together, unit root tests applied to our variables of interest show that

[13] In all aforementioned tests and for all variables of interest, we allow for individual deterministic trends and country-fixed effects. Conclusions of unit root tests are robust whether there are individual trends in regressions or not. Appropriate lag length q_i is determined according to the Akaike criterion.

Table 22: Panel Unit Root Tests

	LLC		Breitung		IPS		Hadri	
	Stat.	p-value	Stat.	p-value	Stat.	p-value	Stat.	p-value
Z^A_{adjK}	2.584	0.995	3.782	1.000	1.368	0.914	49.802	0.000
Z^H_{adjK}/Z^N_{adjK}	5.075	1.000	2.721	0.997	1.677	0.953	38.462	0.000
Z^H_{adjK}	5.512	1.000	3.069	0.999	3.288	0.999	46.085	0.000
Z^N_{adjK}	3.542	1.000	2.105	0.982	-1.784	0.037	40.995	0.000
Z^A	2.770	0.997	2.555	0.995	3.650	1.000	51.528	0.000
Z^H	5.580	1.000	2.626	0.996	5.725	1.000	50.884	0.000
Z^N	3.259	0.999	1.533	0.937	1.180	0.881	43.072	0.000
Z^H/Z^N	3.773	1.000	2.375	0.991	1.237	0.892	38.231	0.000
Y_R	5.999	1.000	4.783	1.000	0.831	0.797	32.188	0.000
I	8.106	1.000	3.977	1.000	-1.657	0.049	27.022	0.000
NX/Y	7.388	1.000	-1.317	0.094	-1.892	0.029	26.619	0.000
L	1.895	0.971	-2.132	0.016	-0.624	0.266	42.163	0.000
W_C	5.027	1.000	3.921	1.000	1.367	0.914	46.474	0.000
Y^H	5.760	1.000	4.343	1.000	1.369	0.915	34.095	0.000
Y^N	4.652	1.000	5.276	1.000	-0.491	0.312	34.677	0.000
Y^H/Y	4.116	1.000	0.950	0.829	0.778	0.782	35.765	0.000
Y^N/Y	4.206	1.000	0.951	0.829	0.854	0.804	36.350	0.000
L^H	3.777	1.000	3.102	0.999	-0.405	0.343	39.294	0.000
L^N	2.652	0.996	3.223	0.999	-1.481	0.069	35.428	0.000
L^H/L	6.378	1.000	3.411	1.000	0.197	0.578	29.488	0.000
L^N/L	3.173	0.999	3.069	0.999	3.110	0.999	49.082	0.000
W^H_C	5.511	1.000	3.957	1.000	2.361	0.991	48.366	0.000
W^N_C	4.372	1.000	4.375	1.000	-0.323	0.373	40.834	0.000
W^H/W	5.655	1.000	1.159	0.877	0.035	0.514	34.592	0.000
W^N/W	5.605	1.000	1.186	0.882	-0.393	0.347	40.573	0.000
W^N/W^H	5.911	1.000	1.195	0.884	0.200	0.579	38.036	0.000
P^N/P^H	4.711	1.000	3.281	0.999	1.036	0.850	37.766	0.000
P^H/P^{H*}	3.697	0.000	-0.015	0.494	-2.845	0.002	49.728	0.000
P^N/P^{H*}	0.930	0.824	0.971	0.834	0.835	0.798	47.444	0.000
s^A_L	7.545	1.000	0.733	0.768	0.479	0.684	29.691	0.000
s^H_L	7.845	1.000	1.280	0.900	-0.778	0.218	28.716	0.000
s^N_L	5.371	1.000	0.302	0.619	0.003	0.501	37.364	0.000
k^A	2.744	0.997	4.505	1.000	-0.965	0.167	36.339	0.000
k^H	4.212	1.000	4.162	1.000	0.200	0.579	34.524	0.000
k^N	3.384	1.000	5.396	1.000	-1.099	0.136	33.419	0.000
$FBTC^H$	7.896	1.000	3.048	0.999	-0.571	0.284	30.124	0.000
$FBTC^N$	4.960	1.000	1.718	0.957	0.661	0.746	37.112	0.000
$FBTC^H_{adjK}$	8.227	1.000	2.862	0.998	-0.610	0.271	28.090	0.000
$FBTC^N_{adjK}$	5.723	1.000	1.612	0.947	0.283	0.612	37.668	0.000

Notes: For LLC, Breitung and IPS, the null of a unit root is not rejected if p-value ≥ 0.05 at a 5% significance level. For Hadri, the null of stationarity is rejected if p-value ≤ 0.05 at a 5% significance level. All tests (with the exception of Breitung) include a linear trend and, for LLC, Breitung and IPS, four lags in the Augmented Dickey-Fuller regressions.

non stationarity is pervasive, suggesting that all variables should enter in the VAR models in growth rate.

Panel unit root tests with structural breaks. So far, we have run the panel unit root tests by abstracting from structural breaks. We now run panel unit root tests developed by Karavias and Tzavalis [2014] who allow for potential structural breaks where the date of the structural break is endogenously determined. We focus on two important variables, say, utilization-adjusted-TFP and total hours worked. Results summarized in Table 23 reveal that both utilization-adjusted-TFP and total hours worked are integrated of order one and no structural breaks have been detected.

L.2 Classification of Industries as Tradables vs. Non-Tradables

This section explores the robustness of our findings to the classification of the eleven 1-digit ISIC-rev.3 industries as tradables or non tradables.

Following De Gregorio et al. [1994], we define the tradability of an industry by con-

Table 23: Karavias and Tzavalis [2014] Panel Unit Root Tests with Structural Breaks

Variable	Test statistic	Value	Critical-value	$p-value$	Trend	Estimated breaks
L_{it}	$\min\mathcal{Z}$	2.3135	-9.1839	1.0000	Yes	None
Z_{it}^A	$\min\mathcal{Z}$	2.1208	-9.3052	1.0000	Yes	None

Notes: The null hypothesis of a unit root is not rejected if $p-value > 0.05$. The test includes a linear trend. The dates of the breaks are unknown and are endogenously determined from the data. The number of bootstrap replications is set to 100. Sample: 17 OECD countries, 1970-2017, annual data.

structing its openness to international trade given by the ratio of total trade (imports + exports) to gross output. Data for trade and output are provided by the World Input-Output Databases ([2013], [2016]). Table 24 gives the openness ratio (averaged over 1995-2014) for each industry in all countries of our sample. Unsurprisingly, "Agriculture, Hunting, Forestry and Fishing", "Mining and Quarrying", "Total Manufacturing" and "Transport, Storage and Communication" exhibit high openness ratios (0.54 in average if "Mining and Quarrying", due to its relatively low weight in GDP, is not considered). These four sectors are consequently classified as tradables. At the opposite, "Electricity, Gas and Water Supply", "Construction", "Wholesale and Retail Trade" and "Community Social and Personal Services" are considered as non tradables since the openness ratio in this group of industries is low (0.07 on average). For the three remaining industries "Hotels and Restaurants", "Financial Intermediation", "Real Estate, Renting and Business Services" the results are less clearcut since the average openness ratio amounts to 0.18 which is halfway between the two aforementioned averages. In the benchmark classification, we adopt the standard classification of De Gregorio et al. [1994] by treating "Real Estate, Renting and Business Services" and "Hotels and Restaurants" as non traded industries. Given the dramatic increase in financial openness that OECD countries have experienced since the end of the eighties, we allocate "Financial Intermediation" to the traded sector. This choice is also consistent with the classification of Jensen and Kletzer [2006] who categorize "Finance and Insurance" as tradable. They use locational Gini coefficients to measure the geographical concentration of different sectors and classify sectors with a Gini coefficient below 0.1 as non-tradable and all others as tradable (the authors classify activities that are traded domestically as potentially tradable internationally).

Table 24: Openness Ratios per Industry: 1995-2014 Averages

	Agri.	Minig	Manuf.	Elect.	Const.	Trade	Hotels	Trans.	Finance	Real Est.	Public
AUS	0.242	0.721	0.643	0.007	0.005	0.025	0.255	0.247	0.054	0.051	0.054
AUT	0.344	2.070	1.152	0.178	0.075	0.135	0.241	0.491	0.302	0.221	0.043
BEL	1.198	13.374	1.414	0.739	0.067	0.186	0.389	0.536	0.265	0.251	0.042
CAN	0.304	0.821	0.966	0.098	0.002	0.030	0.338	0.211	0.169	0.121	0.038
DEU	0.553	2.594	0.868	0.115	0.037	0.072	0.139	0.266	0.101	0.086	0.017
DNK	0.470	0.786	1.329	0.214	0.014	0.092	0.021	0.832	0.138	0.131	0.027
ESP	0.386	4.699	0.680	0.021	0.003	0.044	0.008	0.206	0.130	0.149	0.022
FIN	0.228	2.899	0.796	0.117	0.006	0.094	0.131	0.280	0.153	0.256	0.021
FRA	0.280	3.632	0.815	0.049	0.004	0.048	0.001	0.224	0.068	0.070	0.014
GBR	0.360	0.853	0.958	0.017	0.010	0.024	0.148	0.209	0.233	0.147	0.041
IRL	0.298	1.384	1.127	0.154	0.013	0.652	0.772	0.285	1.014	0.988	0.049
ITA	0.300	4.130	0.603	0.041	0.013	0.087	0.035	0.150	0.095	0.082	0.012
JPN	0.158	3.923	0.293	0.004	0.000	0.067	0.021	0.159	0.034	0.020	0.005
NLD	0.988	1.496	1.259	0.082	0.076	0.106	0.011	0.562	0.245	0.405	0.114
NOR	0.391	0.837	0.995	0.146	0.024	0.097	0.009	0.354	0.146	0.143	0.058
SWE	0.294	2.263	0.969	0.119	0.020	0.163	0.019	0.392	0.274	0.256	0.026
USA	0.207	0.541	0.428	0.012	0.001	0.055	0.003	0.109	0.066	0.052	0.008
OECD	0.412	2.766	0.900	0.124	0.022	0.116	0.150	0.324	0.205	0.202	0.035
H/N	*H*	*H*	*H*	*N*	*N*	*N*	*N*	*H*	*H*	*N*	*N*

Notes: the complete designations for each industry are as follows (EU KLEMS codes are given in parentheses). "Agri.": "Agriculture, Hunting, Forestry and Fishing" (AtB), "Minig": "Mining and Quarrying" (C), "Manuf.": "Total Manufacturing" (D), "Elect.": "Electricity, Gas and Water Supply" (E), "Const.": "Construction" (F), "Trade": "Wholesale and Retail Trade" (G), "Hotels": "Hotels and Restaurants" (H), "Trans.": "Transport, Storage and Communication" (I), "Finance": "Financial Intermediation" (J), "Real Est.": "Real Estate, Renting and Business Services" (K), "Public": "Community Social and Personal Services" (LtQ). The openness ratio is the ratio of total trade (imports + exports) to gross output (source: World Input-Output Databases ([2013], [2016]).

We conduct below a sensitivity analysis with respect to the three industries (”Real Estate, Renting and Business Services”, ”Hotels and Restaurants” and ”Financial Intermediation”) which display some ambiguity in terms of tradedness to ensure that the benchmark classification does not drive the results. In order to address this issue, we re-estimate the dynamic responses to a permanent tchnology shock for the main variables of interest using local projections for different classifications in which one of the three above industries initially marked as tradable (non tradable resp.) is classified as non-tradable (tradable resp.), all other industries staying in their original sector. In doing so, the classification of only one industry is altered, allowing us to see if the results are sensitive to the inclusion of a particular industry in the traded or the non-traded sector.

As an additional robustness check, we also exclude the industry ”Community Social and Personal Services” from the non-tradable industries' set. This robustness analysis is based on the presumption that among the industries provided by the EU KLEMS and STAN databases, this industry is government-dominated and its removal allows us to assess whether it influences or not our results related to the effects of a permanent technology improvement. The baseline and the four alternative classifications considered in this exercise are shown in Table 25. The last line provides the matching between the color line (when displaying IRFs below) and the classification between tradables and non tradables.

Table 25: Robustness check: Classification of Industries as Tradables or Non Tradables

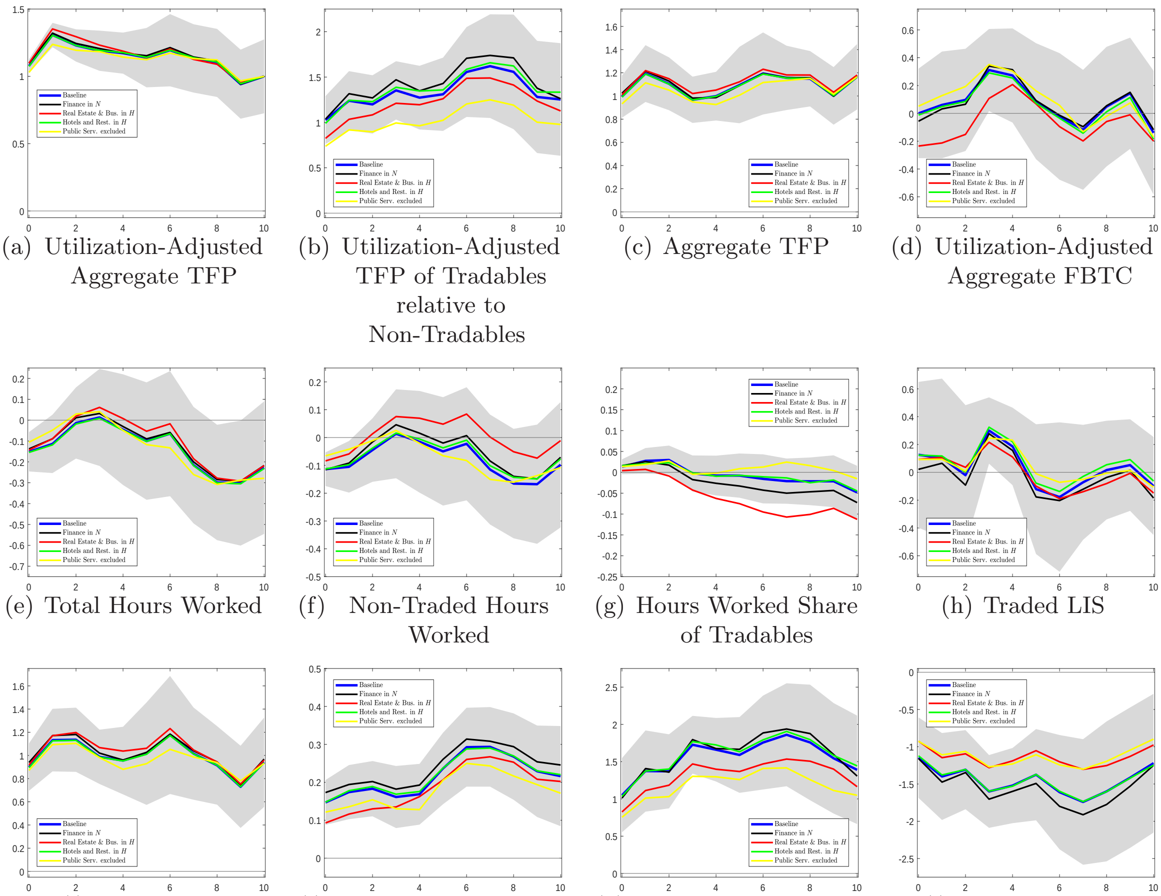
	KLEMS	Classification				
	code	Baseline	#1	#2	#3	#4
Agriculture, Hunting, Forestry and Fishing	AtB	H	H	H	H	H
Mining and Quarrying	C	H	H	H	H	H
Total Manufacturing	D	H	H	H	H	H
Electricity, Gas and Water Supply	E	N	N	N	N	N
Construction	F	N	N	N	N	N
Wholesale and Retail Trade	G	N	N	N	N	N
Hotels and Restaurants	H	N	N	N	**H**	N
Transport, Storage and Communication	I	H	H	H	H	H
Financial Intermediation	J	H	**N**	H	H	H
Real Estate, Renting and Business Services	K	N	N	**H**	N	N
Community Social and Personal Services	LtQ	N	N	N	N	**neither H or N**
Color line in Figure 15		blue	red	black	green	yellow

Notes: H stands for the Traded sector and N for the Non traded sector.

Fig. 15 reports the effects of a permanent technology improvement by 1% in the long-run on selected variables shown in Fig. 2 in the main text. The green line and the red line show results when 'Hotels and restaurants' and 'Real Estate, Renting and Business Services' are treated as tradables, respectively. The black line shows results when 'Financial intermediation' is classified as non-tradables. Finally, the yellow line displays results when Public services ('Community Social and Personal Services') is excluded.

In each panel, the shaded area corresponds to the 90% confidence bounds for the baseline. For aggregate variables shown in the first column, including aggregate utilization-adjusted-aggregate-TFP, total hours worked and real GDP, the responses are remarkably similar across the baseline and alternative classifications. As shown in the yellow line which displays the response for the market sector only, the response of total hours worked is little sensitive to the inclusion or not of the public services. Inspection of the first row reveals that the classification of industries as tradables or non-tradables has an impact on the utilization-adjusted-TFP of tradables relative to non-tradables. In particular, the removal of the non-market sector (classification #4 and shown in the yellow line) mitigates the rise in traded relative to non-traded technology. But the shape of the dynamic adjustment is similar to the benchmark classification and the alternative IRF lies within the confidence bounds of the baseline classification. Aggregate TFP and FBTC are not sensitive to the classification.

The second row of Fig. 15 contrasts the responses of total hours worked, non-traded hours worked (i.e., L^N), the hours worked share of tradables (i.e., $\nu^{L,H}$), and the labor income share of tradables (i.e., s_L^H). Moving 'Real Estate, Renting and Business Services' in the traded sector results in a decline in non-traded hours worked which is less pronounced



(a) Utilization-Adjusted Aggregate TFP
(b) Utilization-Adjusted TFP of Tradables relative to Non-Tradables
(c) Aggregate TFP
(d) Utilization-Adjusted Aggregate FBTC
(e) Total Hours Worked
(f) Non-Traded Hours Worked
(g) Hours Worked Share of Tradables
(h) Traded LIS
(i) Real GDP
(j) Value Added Share of Tradables
(k) Relative Price of Non-Tradables
(l) Terms of Trade

Figure 15: Labor Market Effects of a Technology Shock: Robustness Check w.r.t. the Classification of Industries as Tradable or Non-Tradable. Notes: The solid blue line shows the response of aggregate and sectoral variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. To estimate the dynamic responses to a technology shock, we adopt a two-step method. In the first step, we estimate a VAR model that includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage and the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the second step, we estimate the effects by using Jordà's [2005] single-equation method. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. The green line and the red line show results when 'Hotels and restaurants' and 'Real Estate, renting and business services' are treated as tradables, respectively. The black line shows results when 'Financial intermediation' is classified as non-tradables. Finally, the yellow line displays results when Public services ('Community Social and Personal Services') is excluded. Sample: 17 OECD countries, 1970-2017, annual data.

which in turn amplifies the deindustrialization trend, as displayed by Fig. 15(g). Across all scenarios, the traded LIS exhibits a similar dynamic adjustment following a technology improvement.

The third row of Fig. 15 contrasts the responses of real GDP, the value added share of tradables ($\nu^{Y,H}$), the relative price of non-tradables (P^N/P^H), and the terms of trade ($P^H/P^{H,\star}$) for the baseline classification with those obtained for alternative classifications of industries as tradables or non-tradables. Alternative responses are fairly close to those estimated for the baseline classification as they lie within the confidence interval (for the baseline classification) for all the selected horizons. The dynamic adjustment of the relative price of non-tradables displays some differences across the baseline and the four alternative classifications: the appreciation is less pronounced when the public sector is excluded (classification #4 and the yellow line) because Z^H/Z^N increases less which mitigates the excess demand for non-traded goods. We also note some differences for the terms of trade which depreciate more when 'Financial intermediation" is moved to the non-traded sector (classification #2 and the black line) because technology improvements are more pronounced in the traded sector which results in a larger excess supply of traded goods. One can notice that the discrepancy in the estimated effect between the benchmark and the alternative classifications are not statistically significant

In conclusion, our main findings hold and remain unsensitive to the classification of one specific industry as tradable or non-tradable. In this regard, the specific treatment of "Hotels and Restaurants", "Real Estate, Renting and Business Services", "Financial

Intermediation" or "Community Social and Personal Services" does not drive the results.

L.3 Robustness Check to the Construction of Sectoral Physical Capital Time Series

In the main text, due to data availability, we construct time series for sectoral capital by computing the overall capital stock by adopting the perpetual inventory approach and then by splitting the gross capital stock into traded and non-traded industries by using sectoral valued added shares. In this Appendix, we investigate whether the effects on utilization-adjusted-TFP and utilization-adjusted-FBTC we estimate empirically are driven by our assumption about the construction of time series for sectoral capital stock. To conduct this robustness check, we contrast below empirical responses when sectoral capital stocks are measured by adopting the Garofalo and Yamarik's [2002] methodology (our benchmark) with those obtained by using sectoral data on K^j provided by EU KLEMS [2011], [2017] databases. Due to data availability, our results in the latter case include a sample of thirteen OECD countries which provide time series on sectoral capital of reasonable length. In this regard, Belgium, Germany, Ireland and Sweden are removed from the sample due to a lack of data over a reasonable time length to construct K^H and K^N. To be consistent, our benchmark excludes these four countries and thus focuses on thirteen countries only. Our estimates below show that our empirical findings are unsensitive to the way the sectoral capital stocks are constructed in the data.

The methodology by Garofalo and Yamarik's [2002] is based on the assumption of perfect mobility of capital across sectors and a small discrepancy in the LIS across sectors, i.e., $s_L^H \simeq s_L^N$. The assumption of perfect capital mobility implies that the marginal revenue product of capital must equalize across sectors:

$$P_t^H \left(1 - s_L^H\right) \frac{Y_t^H}{K_t^H} = P_t^N \left(1 - s_L^N\right) \frac{Y_t^N}{K_t^N}. \tag{185}$$

Using the resource constraint for capital, $K = K^H + K^N$, dividing the numerator and the denominator in the LHS of (185) by GDP, Y, and denoting by $\omega_t^{Y,j} = \frac{P_t^j Y_t^j}{Y_t}$ the share of value added of sector j in GDP at current prices (at time t), eq. (185) can be solved for the K^H/K:

$$\frac{K_t^H}{K_t} = \frac{\omega_t^{Y,H}\left(1 - s_L^H\right)}{\left(1 - s_L^N\right)\left(1 - \omega_t^{Y,H}\right) + \left(1 - s_L^H\right)\omega_t^{Y,H}}. \tag{186}$$

Assuming that $s_L^H \simeq s_L^N$ leads to the rule we apply to split the aggregate stock of capital into tradables and non tradables:

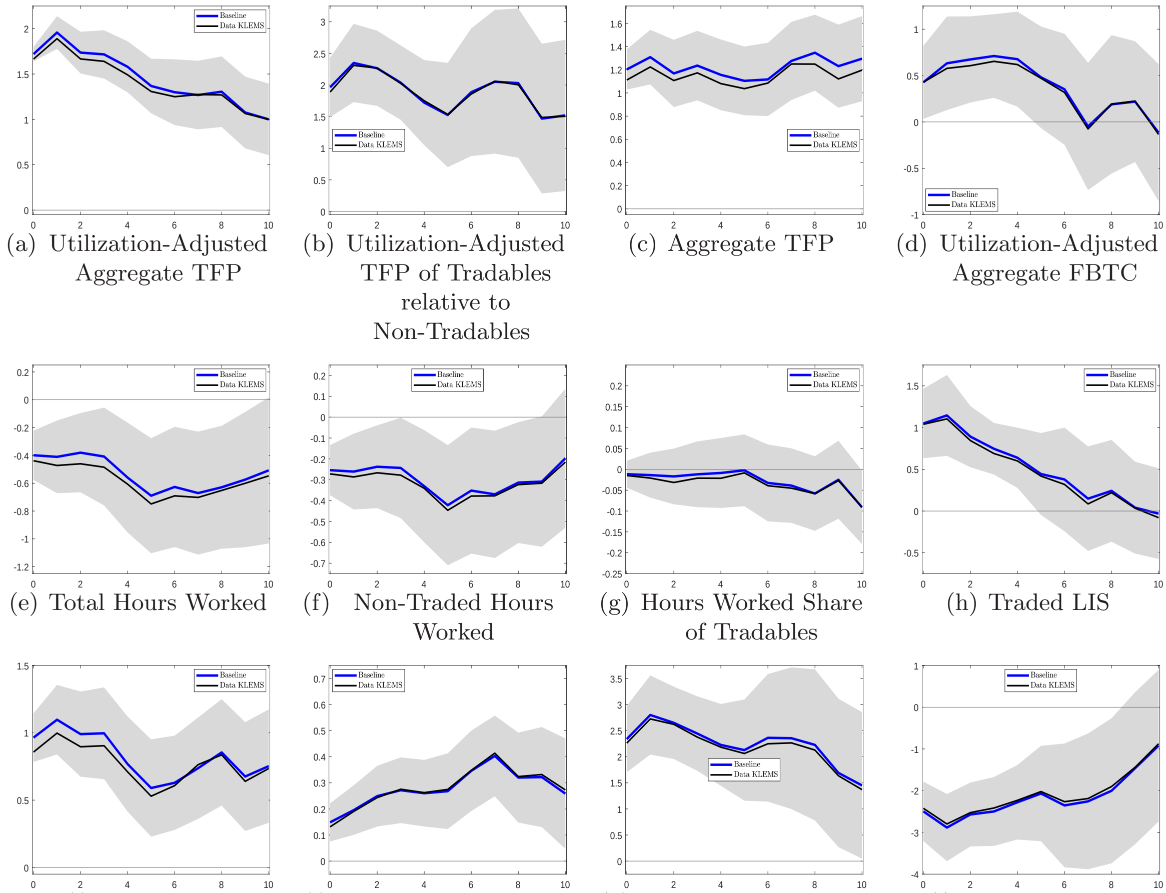
$$\frac{K_t^H}{K_t} = \omega_t^{Y,H}. \tag{187}$$

In the baseline, we adopt the methodology of Garofalo and Yamarik [2002] to split the national gross capital stock into traded and non-traded industries by using sectoral value added shares at current prices. Let $\omega^{Y,j}$ be the share of sector j's value added (at current prices) $P^j Y^j$ for $j = H, N$ in overall output (at current prices) $Y \equiv P^H Y^H + P^N Y^N$, the allocation of the national capital stock to sector j is given by the rule:

$$K_{GY}^j = \omega^{Y,j} K = \frac{P^j Y^j}{Y} K, \tag{188}$$

where we denote the sectoral stock of capital obtained with the decomposition by Garofalo and Yamarik [2002] by K_{GY}^j. National capital stocks are estimated from the perpetual inventory approach. Following Garofalo and Yamarik [2002], the gross capital stock is then allocated to traded and non-traded industries by using sectoral value added shares according to eq. (188). Once the series for K_{GY}^j are obtained, we can construct the sectoral capital-labor ratios, $k_{GY}^j = K_{GY}^j / L^j$, sectoral capital utilization rates, $u_{GY}^{K,j}$, sectoral utilization-adjusted-TFPs, Z_{GY}^j, and sectoral utilization-adjusted-FBTC (see section F).

Sample. As a robustness check, we alternatively take capital stock series from the EU KLEMS [2011] and [2017] and STAN [2017] and [2017] databases which provide disaggregated capital stock data (at constant prices) at the 1-digit ISIC-rev.3 level for up to 11 industries, but only for thirteen countries of our sample which include Australia (1970-2007), Austria (1976-2017), Canada (1970-2016), Denmark (1970-2017), Spain (1970-2016), Finland (1970-2017), France (1978-2017), the United Kingdom (1970-2015), Italy (1970-2017), Japan (1973-2015), the Netherlands (1970-2017), Norway (1970-2017) and the United States (1970-2016). In efforts to have time series of a reasonable length, we exclude Belgium (1995-2017), Germany (1991-2017), Ireland (1985-2017) and Sweden (1993-2016) because the period is too short.



(a) Utilization-Adjusted Aggregate TFP (b) Utilization-Adjusted TFP of Tradables relative to Non-Tradables (c) Aggregate TFP (d) Utilization-Adjusted Aggregate FBTC

(e) Total Hours Worked (f) Non-Traded Hours Worked (g) Hours Worked Share of Tradables (h) Traded LIS

(i) Real GDP (j) Value Added Share of Tradables (k) Relative Price of Non-Tradables (l) Terms of Trade

Figure 16: Labor Market Effects of a Technology Shock: Robustness Check w.r.t. the Construction of Sectoral Capital Stocks Notes: The solid blue line shows the response of aggregate and sectoral variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. To estimate the dynamic responses to a technology shock, we adopt a two-step method. In the first step, we estimate a VAR model that includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage and the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the second step, we estimate the effects by using Jordà's [2005] single-equation method. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. The black line reports responses when we use the EU KLEMS [2011] and [2017] databases to construct sectoral capital stocks series K^j. Sample: 13 OECD countries, 1970-2017, annual data.

Results. In Fig. 16, we compare the responses of selected variables displayed by Fig. 2 in the main text. Note that because we consider new time series for K^j, we have reconstructed time series for sectoral TFPs and the capital utilization rates. The blue line shows the dynamic effects of a 1% permanent increase in utilization-adjusted-aggregate-TFP when the sectoral capital stock is measured by adopting the methodology by Garofalo and Yamarik [2002] while the black line shows the dynamic effects when the capital stock is obtained directly from KLEMS (black line). For comparison purposes and to ensure consistency, we compare the results by considering the same sample, i.e. the restricted sample that includes 13 OECD countries over the period 1970-2017. As it stands out, the construction of capital stocks does not affect the results as we cannot detect any difference, even for the utilization-adjusted-TFP, TFP, or FBTC. In conclusion, our main findings are robust and unsensitive to the way the sectoral capital stocks are constructed in the data. While the responses of capital-labor ratios are not reproduced, one can observe that a discrepancy in the results in the short-run only. To conclude, the dynamic effects of a technology improvement are similar across the two methods as they are both qualitatively and quantitatively similar since the solid black line lies within the original confidence bounds of those obtained when K^j is constructed with the use of the methodology of Garofalo and Yamarik [2002]. In particular, one can observe that the discrepancy in the results is small and not statistically significant at conventional level.

L.4 How Technology at Industry Level Responds to Aggregate Technology Improvements: A Disaggregated Approach

Empirical analysis at a disaggregate sectoral level. Our dataset covers eleven industries which are classified as tradables or non-tradables. The traded sector is made up of five industries and the non-traded sector of six industries. To conduct a decomposition of the sectoral effects at a sub-sector level, we estimate the responses of sub-sectors to the same identified technology shock by adopting the two-step approach detailed in the main text. More specifically, indexing countries with i, time with t, sectors with j, and sub-sectors with k, we first identify the permanent technology shock, by estimating a VAR model which includes utilization-adjusted-aggregate-TFP, Z^A_{it}, real GDP, total hours worked, the real consumption wage (all quantities are divided by the working age population and all variables are in rate of growth) and next we estimate the dynamic effects by using the Jordà's [2005] single-equation method. The local projection method amounts to running a series of regression of each variable of interest on the structural identified shock for each horizon $h = 0, 1, 2, ...$:

$$x^{k,j}_{i,t+h} = \alpha^{k,j}_{i,h} + \alpha^{k,j}_{t,h} + \psi^{k,j}_h (L)\, z_{i,t-1} + \gamma^{k,j}_h \,.\epsilon^{ZA}_{i,t} + \eta^{k,j}_{i,t+h}, \tag{189}$$

where $x = \text{TFP}^{k,j}_{i,t}, L^{k,j}_{i,t}$. To express the results in meaningful units, i.e., we multiply the responses of TFP of sub-sector k by the share of industry k in the value added of the broad sector j (at current prices), i.e., $\omega^{Y,k,j} = \frac{P^{k,j}Y^{k,j}}{P^jY^j}$. We multiply the responses of hours worked within the broad sector j by its labor compensation share, i.e., $\alpha^{L,k,j} = \frac{W^{k,j}L^{k,j}}{W^jL^j}$. We detail below the mapping between the responses of broad sector's variables and responses of variables in sub-sector k of one broad sector j.

The response of $L^{k,j}$ to a technology shock is the percentage deviation of hours worked in sub-sector $k \in j$ relative to initial steady-state: $\ln L^{k,j}_t - \ln L^{k,j} \simeq \frac{dL^{k,j}_t}{L^{k,j}} = \hat{L}^{k,H}_t$ where $L^{k,j}$ is the initial steady-state. We assume that hours worked of the broad sector is an aggregate of sub-sector hours worked which are imperfect substitutes. Therefore, the response of hours worked in the broad sector $\hat{L}^j_t$ is a weighted average of the responses of hours worked $\frac{W^{k,j}L^{k,j}}{W^jL^j}\hat{L}^{k,j}_t$ where $\frac{W^{k,j}L^{k,j}}{W^jL^j}$ is the share of labor compensation of sub-sector k in labor compensation of the broad sector j:

$$\begin{aligned} \hat{L}^j_t &= \sum_{k\in j} \frac{W^{k,j}L^{k,j}}{W^jL^j}\hat{L}^{k,j}_t, \\ \frac{W^jL^j}{WL}\hat{L}^j_t &= \sum_{k\in j} \frac{W^{k,j}L^{k,j}}{WL}\hat{L}^j_t, \\ \alpha^{L,j}\hat{L}^j_t &= \sum_{k\in j} \alpha^{L,k}\hat{L}^{k,j}_t, \end{aligned} \tag{190}$$

where $\sum_j \sum_k \alpha^{L,k} = 1$. Above equation breaks down the response of hours worked in broad sector j into the responses of hours worked in sub-sectors $k \in j$ weighted by their labor compensation share $\alpha^{L,k} = \frac{W^{k,j}L^{k,j}}{W^jL^j}$ averaged over 1970-2017. In multiplying $\hat{L}^{k,j}_t$ by $\alpha^{L,k}$, we express the response of hours worked in sub-sector $k \in j$ in percentage point of hours worked in the broad sector $j = H, N$.

The response of TFP in the broad sector j is a weighted average of responses $\text{TFP}^{k,j}_t$ of TFP in sub-sector $k \in j$ where the weight collapses to the value added share of sub-sector

k:

$$\begin{aligned}
\text{TFP}_t^{k,j} &= \sum_{k\in j} \frac{P^{k,j}Y^{k,j}}{P^jY^j}\hat{\text{TFP}}_t^{k,j}, \\
\text{TFP}_t^{j} &= \sum_{k\in j} \frac{P^{k,j}Y^{k,j}}{P^jY^j}\hat{\text{TFP}}_t^{k,j}, \\
\text{TFP}_t^{j} &= \sum_{k\in j} \omega^{Y,k,j}\hat{\text{TFP}}_t^{k,j}, \qquad (191)
\end{aligned}$$

where $\omega^{Y,k,j} = \frac{P^{k,j}Y^{k,j}}{P^jY^j}$ averaged over 1970-2017 is the value added share at current prices of sub-sector $k \in j$ which collapses (at the initial steady-state) to the value added share at constant prices as prices at the base year are prices at the initial steady-state. Note that $\sum_k \sum_{k\in j} \omega^{Y,k,j} = 1$.

Aggregate technology shock. The first column of Fig. 17 shows responses of TFP and hours worked of sub-sectors classified in the traded sector and the non-traded sector to a permanent technology improvement of 1% in the long-run. When we consider an aggregate technology shock, all industries behave as the broad sector as they all experience a permanent technology improvement, except 'Mining' shown in the black line for which the rise in TFP vanishes in the long-run. More interestingly, the rise in traded TFP is driven by technology improvement in 'Manufacturing' because this sector accounts for the greatest value added share of the traded sector and also experiences significant increases in TFP. With regard to non-traded industries, 'Real Estate, Renting, and Business Services' drives the rise in non-traded TFP followed by 'Wholesale and Retail Trade' and 'Community Social and Personal Services' (i.e., the public sector which also includes health and education services). When we focus on traded and non-traded hours worked, we find that all industries experience a decline in hours worked except 'Construction'. One explanation to this lies in the shift of labor away from traded and toward non-traded industries. As we shall see, this sector experiences a dramatic increase in its hours worked following an asymmetric technology shock.

Symmetric technology shock. The second column of Fig. 17 shows responses of TFP and hours worked of sub-sectors classified in the traded sector and the non-traded sector to a permanent technology improvement of 1% which is evenly spread between the traded and non-traded sectors. Like for an aggregate technology shock, the rise in traded TFP is driven by the technology improvement in 'Manufacturing' while 'Real Estate, Renting, and Business Services' drives the rise in non-traded TFP. All traded industries experience a decline in hours worked on impact while only 'Agriculture' and 'Manufacturing' experience a fall in the long-run. All non-traded industries experience a decline in hours worked on impact while only 'Real Estate, Renting, and Business Services' experiences a persistent decline in its hours worked below trend.

Asymmetric technology shock. The third column of Fig. 17 shows responses of TFP and hours worked of sub-sectors classified in the traded sector and the non-traded sector to a permanent technology improvement of 1% which is concentrated toward traded industries. As it stands out, the rise in traded TFP is driven by a technology improvement in 'Manufacturing' and the gap with other sectors is even more pronounced than after an aggregate technology shock. We can notice that the contribution of 'Mining' is substantial given its small weight in the traded sector. When we turn to the non-traded TFP, we find that 'Real Estate, Renting, and Business Services' together with 'Community Social and Personal Services' (i.e., the public sector which also includes health and education services) drive the fall in non-traded TFP. Traded industries such as 'Manufacturing', 'Financial Intermediation', 'Transport and Communication' drive the rise in traded hours worked following an asymmetric technology shock. All non-traded industries experience an increase in hours worked. The rise in non-traded hours worked is driven by the rise in labor in 'Construction' and 'Community Social and Personal Services' followed by 'Real Estate, Renting, and Business Services' and 'Wholesale and Retail Trade'. The diversity of industries which experience a rise in labor can explain why both skilled and unskilled labor shift away from traded industries and toward non-traded industries following an asymmetric technology

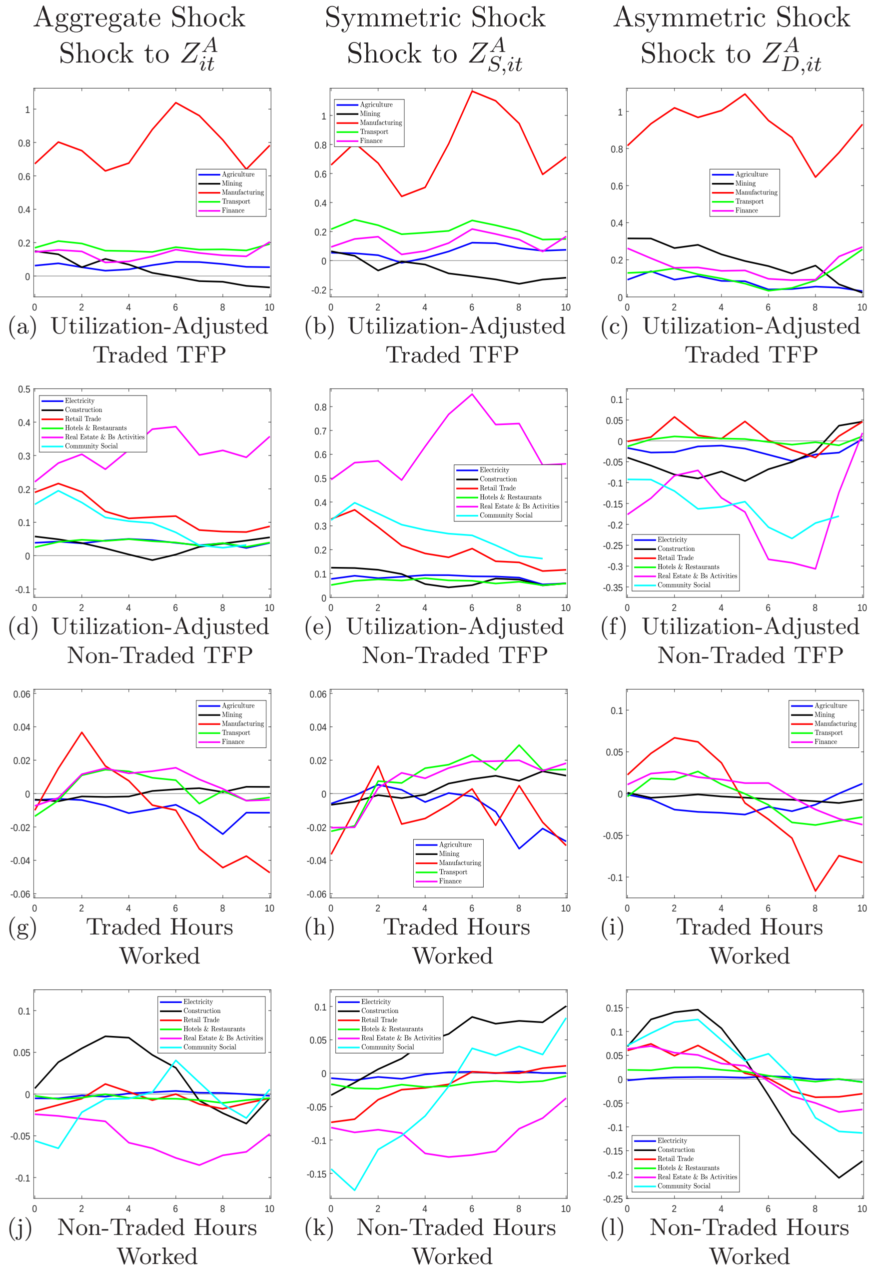


Figure 17: Effects of Technology Shocks on Eleven Sub-Sectors. Notes: Because the traded and non-traded sector are made up of industries, we conduct a decomposition of the sectoral effects at a sub-sector level following a an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. To estimate the dynamic responses to a technology shock, we adopt a two-step method. In the first step, we estimate a VAR model that includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage and the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the second step, we estimate the effects by using Jordà's [2005] single-equation method. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. To express the results in meaningful units, i.e., total hours worked units, we multiply the responses of hours worked sub-sector k by its labor compensation share (in the traded sector of traded industries or in the non-traded sector for non-traded industries), i.e., $\frac{W^{k,j}L^{j,j}}{W^j L^j}$. Column 1-3 display the responses of technology and hours in traded and non-traded industries to aggregate, symmetric and asymmetric technology shocks across sectors, respectively. For tradable industries: the blue line shows results for 'Agriculture', the black line for 'Mining and Quarrying', the red line for 'Manufacturing', the green line for 'Transport and Communication', and the purple line for 'Financial Intermediation'. The second/fourth columns show results for sub-sectors classified in the non-traded sector. For non-tradable industries: the blue line shows results for 'Electricity, Gas and Water Supply', the black line for 'Construction', the red line for 'Wholesale and Retail Trade', the green line for 'Hotels and Restaurants', and the cyan line for 'Community Social and Personal Services'. Sample: 17 OECD countries, 11 industries, 1970-2017, annual data.

shock.

L.5 Do both Symmetric and Asymmetric Technology Shocks Stimulate Innovation?

In this subsection, we further investigate the drivers behind symmetric and asymmetric technology shocks and if these two shocks are different. We must acknowledge that the literature on technology shocks is silent about the factors driving technology improvements except Shea [1999] and Alexopoulos [2011]. Shea [1999] employs direct measures of technological change based on research and R&D expenditure and patent activities in a VAR to identify technology shocks. Using annual panel data for 19 U.S. manufacturing industries from 1959 to 1991, the author estimates VARs to determine the dynamic impact of shocks to two observable indicators of technological change: R&D spending (measures the amount of input devoted to innovative activity), and patent applications (measure innovation). The author finds that favorable technology shocks tend to increase input use, especially labor, in the short run, but to reduce inputs in the long run. Alexopoulos [2011] presents new measures of technical change based on new book titles in the field of technology from 1955-1997. Results show that technology shocks driven by book publications in the area of technology increases R&D and employment.

Effects of symmetric and asymmetric technology shocks on R&D. First, we identify asymmetric and symmetric technology shocks by estimating a VAR model which includes the ratio of traded to non-traded technology measure, aggregate technology measure, real GDP, total hours worked and real consumption wage and then we estimate the dynamics effects of aggregate, symmetric and asymmetric technology improvements on the stock of R&D of tradables and non-tradables at constant prices. Table 26 and Table 27 present the point estimate at horizons $t = 0...8$ which measures the increase in percentage in the stock of R&D in the traded and the non-traded sectors after an aggregate, asymmetric and symmetric technology shocks, respectively. Our sample includes 13 OECD countries over 1995-2017. The evidence reveals that only asymmetric technology shocks have a positive and a statistically significant impact in the stock of R&D and only in the traded sector.

Do asymmetric technology shocks increase innovation? Asymmetric technology shocks are technology improvements which are concentrated toward traded industries. As discussed above, only these shocks give rise to a significant and positive increase in the stock of R&D which reflects cumulated investment devoted to innovative activity. As shown below when we estimate the elasticity of utilization-adjusted-TFP w.r.t. the stock of R&D, the latter has a significant impact on utilization-adjusted-TFP of tradables only as it has virtually no impact on non-traded technology. Therefore, accumulation of R&D investment can generate innovation since according to our FMOLS estimates, an increase in the stock of R&D in the traded sector by 1% improves technology of tradables by 0.23%. This evidence thus underlines that technology improvements concentrated in traded industries, i.e., asymmetric technology shocks, are shocks which increase innovation. In contrast, symmetric technology shocks do not increase the stock of R&D significantly and may capture improvements in work organization within the firm and/or better management practices.

Effects of technology shocks on labor: shocks to the stock of R&D vs. shocks to utilization-adjusted-TFP. Shea [1999] and Alexopoulos [2011] find that technology shocks driven by innovation increase employment. In this paper, we show that symmetric technology shocks lower dramatically hours worked while asymmetric technology shocks increase significantly labor. Since asymmetric technology shocks are driven by innovation, our work can reconcile the labor effects of technology shocks reported by the literature and the evidence documented by Shea [1999] and Alexopoulos [2011] who focus on shocks to innovation and find that innovation-driven technology shocks increase employment.

To further investigate the discrepancy in the effects on hours caused by shocks to innovation or driven by technology shocks reflecting mainly technology adoption of better worker organizations, we estimate a SVAR which includes the aggregate stock of R&D at constant prices, utilization-adjusted-aggregate-TFP, real GDP, total hours worked and the real consumption wage, all variables entering the VAR model in growth rates. Our identification strategy lies in long-run restrictions. We identify innovation shocks as shocks which increase permanently the stock of R&D while we identify technology improvements not driven by innovative activities as technology shocks which increase permanently the

Table 26: IRF of the Stock of R&D in the Traded Sector After Technology Shocks

Horizon	AGG	ASYM	SYM
0	−0.025	0.148	−0.163
2	0.381	0.511^b	0.187
4	0.328	0.639^b	0.009
6	−0.015	0.461	−0.416
8	0.332	1.213^a	−0.349

Notes: ^{a}, ^{b} and ^{c} denote significance at 1%, 5% and 10% levels. The number in columns denotes the impulse response function (estimated with local projections) of the stock of R&D in the traded sector after an aggregate technology shock (column AGG), an asymmetric technology shock (column ASYM) and an symmetric technology shock (column SYM). Sample: 12 OECD countries, 1995-2017, annual data.

Table 27: IRF of the Stock of R&D in the Non Traded Sector After Technology Shocks

Horizon	AGG	ASYM	SYM
0	0.086	0.134	0.029
2	0.310	0.388	0.173
4	0.224	0.109	0.273
6	−0.103	−0.006	−0.161
8	0.085	0.291	−0.120

Notes: ^{a}, ^{b} and ^{c} denote significance at 1%, 5% and 10% levels. The number in columns denotes the impulse response function (estimated with local projections) of the stock of R&D in the non traded sector after an aggregate technology shock (column AGG), an asymmetric technology shock (column ASYM) and an symmetric technology shock (column SYM). Sample: 12 OECD countries, 1995-2017, annual data.

utilization-adjusted-aggregate-TFP. We find that innovation shocks do not drive down hours on impact and instead increase labor in the long-run. In contrast, technology shocks which are not driven by innovative industries lower persistently hours worked.

Table 28: Stocks of Capital from KLEMS and sectoral R&D series: Data Availability

	data on K from KLEMS	data on R&D
AUS	1970-2007	no data
AUT	1976-2017	1995-2017
BEL	1995-2017	1995-2017
CAN	1970-2016	no data
DEU	1991-2017	1995-2017
DNK	1970-2017	1995-2017
ESP	1970-2016	1995-2016
FIN	1970-2017	1995-2017
FRA	1978-2017	1995-2017
GBR	1970-2017	1995-2017
IRL	1985-2017	no data
ITA	1970-2017	1995-2017
JPN	1973-2015	1995-2015
NLD	1970-2017	1995-2017
NOR	1970-2017	no data
SWE	1993-2016	1995-2016
USA	1970-2016	1995-2017

Elasticity of technology w.r.t. the stock of R&D. One key parameter is ν^j which measures the impact of 1% increase in the stock of R&D in sector j on utilization-adjusted-TFP in sector j. In an earlier version of the paper, we have laid out a model, we extend

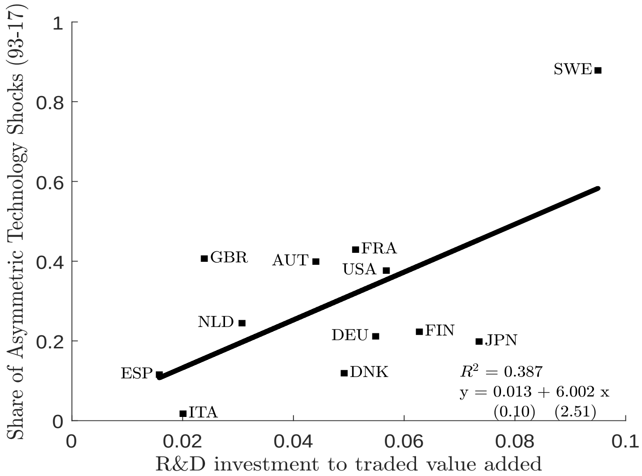


Figure 18: Cross-Country Relationship between Investment in R&D (% of Value Added in the Traded Sector) and the Share of FEV of Technological Change Driven by Asymmetric Technology Improvements. Notes: The horizontal axis shows the R&D investment to value added ratio for the traded sector. To measure the intensity of the traded sector in investment in R&D, we take data from EU KLEMS, Stehrer et al. [2019], see Table 28 for data coverage. Sample: 12 OECD countries, 1995-2017. On the vertical axis, we show the share of FEV of technological change attributed to asymmetric technology shocks over the period 1993-2017 to fit the period over which data on R&D is available. The share of asymmetric technology shocks is an average of the share at time $t = 0$ and $t = 10$. Sample: 12 OECD countries, 1993-2017.

Table 29: Elasticity of Utilization-Adjusted-TFP w.r.t. the Stock of R&D

	Z^H	Z^N	Z^W
	(1)	(2)	(3)
$\mathcal{Z}^H$	0.1499^a (5.88)	n.a.	0.077^a (4.71)
$\mathcal{Z}^N$	n.a.	0.0007^b (1.66)	-0.002^b (-2.13)
$\mathcal{Z}^A$			0.019 (0.42)

Notes: ^{a}, ^{b} and ^{c} denote significance at 1%, 5% and 10% levels. Heteroskedasticity and autocorrelation consistent t-statistics are reported in parentheses. Denoting utilization-adjusted-TFP in sector j by $\mathcal{Z}^j_{it}$ is We run the regression of utilization adjusted TFP on the stock of R&D at constant prices in sector j in panel format on annual data:

$$\ln \mathcal{Z}^j_{it} = \alpha_i + \alpha_t + \beta_i t + \gamma^j \ln Z^j_t + \eta_{it},$$

where we include country fixed effects, time dummies, country-specific linear time trend and we estimate $\gamma^j = \nu^j \zeta^j$. Because ζ^j is the domestic component of country-level-utilization-adjusted-TFP we obtain from the principal component analysis, we can infer $\nu^j = \frac{\gamma^j}{\zeta^j}$. Since our estimates for 17 countries by adopting an ACP reveals that $\zeta^H = 0.631$ and $\zeta^N = 0.695$, and our FMOLS estimates show that $\gamma^H = 0.1499$ and $\gamma^N = 0.0007$, we can recover $\nu^H = 0.238$ and $\nu^N = 0.001$. In column 3, we construct the international stock of knowledge as a geometric weighted average of trade partners' aggregate stock of R&D at constant prices for country i, i.e., $Z^W_{it} = \Pi^{12}_{k=1} (Z_{kt})^{\alpha^M_{ik}}$ where α^M_k is the share of imports of home country i from the trade partner k. Sample: 13 OECD countries, 1970-2017, annual data.

the setup by Corhay et al. [2020] to a two-sector open economy where households decide about investment in tangible and intangible assets and the stocks of physical capital and R&D are allocated across sectors in accordance to their return.

Households decide about investment in R&D which gives rise to an aggregate stock of knowledge $Z^A(t)$. Households stand ready to supply the stock of knowledge to firms in the traded and the non-traded sectors. Because intangible assets are imperfect substitutes, they pay different returns. Given sector-specific rental rates on intangible assets denoted by $R^j_Z(t)$, traded and non-traded firms choose the amount of intangible assets $Z^H(t)$ and $Z^N(t)$ according to the following optimal rules:

$$\frac{P^j(t)}{\mu^j}\zeta^j\nu^j\left(Z^j(t)\right)^{\zeta^j\nu^j-1}\left(Z^W(t)\right)^{\left(1-\zeta^j\right)\nu^j}\left(L^j(t)\right)^{\theta^j}\left(\tilde{K}^j(t)\right)^{1-\theta^j} = R^j_Z(t),$$

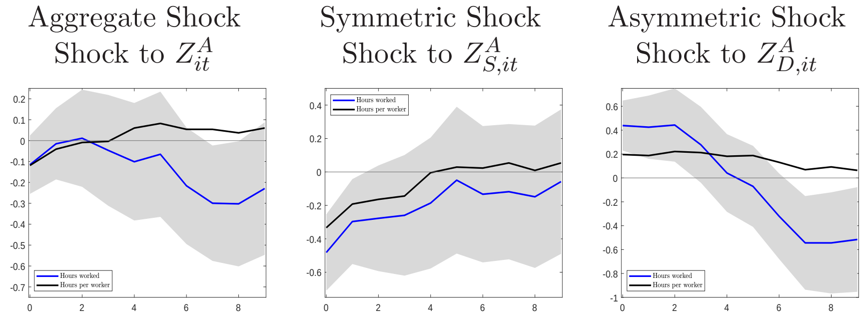
where P^j is the price of the final good in sector $j = H, N$. This equation shows that an increase in international stock of knowledge $Z^W(t)$ raises the marginal revenue product of investing in intangible assets and thus has a positive impact on $Z^j(t)$. Higher levels in both international Z^W and domestic $Z^j(t)$ stock of knowledge have a positive impact on utilization-adjusted-TFP.

Using data from Stehrer et al. [2019] (EU KLEMS database) we construct time series for both gross fixed capital formation and capital stock in R&D in the traded and non-traded sectors. Data are available for thirteen countries over 1995-2017, see Table 28. We have run the regression of the logged utilization-adjusted-TFP in sector j on the logged stock of R&D at constant prices by using cointegration techniques. As shown in Table 29, we find a FMOLS estimated value of the long-term elasticity of utilization-adjusted-TFP w.r.t. the stock of R&D of 0.1499 for the traded sector and 0.0007 for the non-traded sector. Once we have estimated the elasticity γ^j of utilization-adjusted-TFP in sector j w.r.t the stock of knowledge in sector j, we have to recover the parameter ν^H and ν^N by using values of parameters ζ^H and ζ^N. By adopting a principal component analysis, we have estimated the common component of utilization-adjusted-TFP which stands at $1 - \zeta^H = 0.369$ for tradables and $1 - \zeta^N = 0.305$ for non-tradables. These values lead to $\nu^H = \gamma^H/\zeta^H = 0.238$ and $\nu^N = \gamma^N/\zeta^N = 0.001$. These values suggest that increasing the domestic or the international stock of knowledge have little impact on utilization-adjusted-TFP of non-tradables and instead have a significant impact on utilization-adjusted-TFP of tradables. These values fit the data which indicates that utilization-adjusted-TFP has increased by 0.2% per year while technology improves by 1.6% on average per year in the traded sector over 1995-2017.

L.6 Intensive vs. Extensive Margin

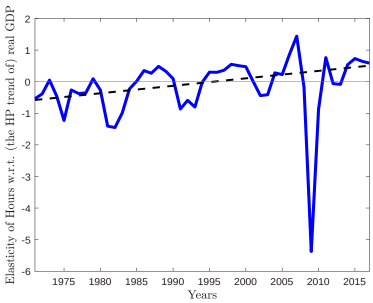
Responses of hours to a technology shock: intensive vs. extensive margin. Because total hours can be decomposed in employment and hours per worker, we contrast empirically the adjustment of total hours (shown in the solid blue line) with the adjustment at the intensive margin (shown in the solid black line) following an exogenous increase in utilization-adjusted-aggregate-TFP by 1% in the long-run. In Fig. 19, we consider the effects of an aggregate technology shock in column 1 and the effects of symmetric and asymmetric technology shocks in columns 2 and 3. Like Thomet and Wegmuller [2021] who use a panel of fourteen OECD countries, we find that the movements in the intensive margin are the dominant channel of adjustment in total hours after an aggregate technology shock. While most of the variations in total hours are driven by changes in hours per worker after a symmetric technology shock, the intensive margin is predominant only in the short-run after an asymmetric technology shock.

Elasticity of hours w.r.t. real GDP: Structural but gradual change. Fig. 20(a), the elasticity of hours worked w.r.t. real GDP has substantially increased over time, moving from negative to positive values from the mid-nineties. More specifically, the blue line shows the ratio of the rate of change in hours worked in (17) OECD countries to the trend rate of growth of real GDP. The trend (dashed black) line which neutralizes short-run fluctuations reveals that the elasticity of hours worked w.r.t. (the trend of) real GDP has increased from -0.58 to 0.51 from 1970 to 2017. As documented by Galí and

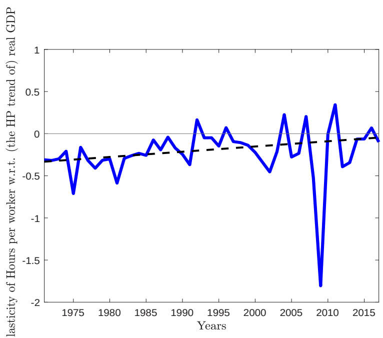


(a) Agg. Tech. Shock: Total Hours vs. Hours per Worker
(b) Sym. Tech. Shock: Total Hours vs. Hours per Worker
(c) Asym. Tech. Shock: Total Hours vs. Hours per Worker

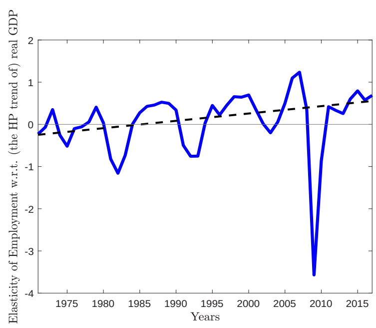
Figure 19: Effects of Technology Shocks on Total Hours: Extensive. Intensive Margin Notes: Because total hours can be decomposed in employment and hours per worker, we contrast empirically the adjustment of total hours (shown in the solid blue line) with the adjustment at the intensive margin (shown in the solid black line) following an exogenous increase in utilization-adjusted-aggregate-TFP by 1% in the long-run. We show the effects of an aggregate technology shock in column 1 and the effects of symmetric and asymmetric technology shocks in columns 2 and 3. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. Sample: 17 OECD countries, 1970-2017, annual data.



(a) Elasticity of Total Hours w.r.t. Real GDP



(b) Elasticity of Hours per Worker w.r.t. Real GDP

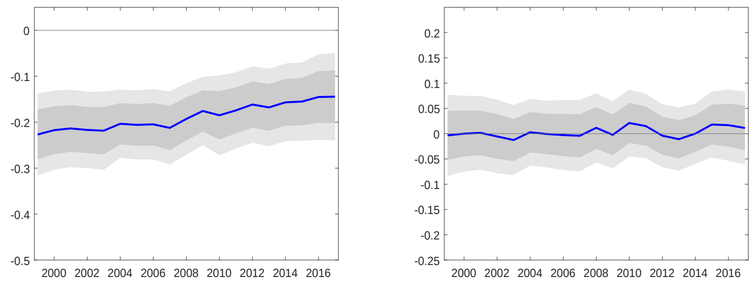


(c) Elasticity of Employment w.r.t. Real GDP

Figure 20: Structural Change in the Elasticity of Hours w.r.t. Real GDP: Intensive vs. Extensive Margin. Notes: In Fig. 20(b), the blue line shows the ratio of the rate of change in hours per worker to the (Hodrick-Prescott) trend rate of growth of real GDP. In Fig. 20(c), the blue line shows the ratio of the rate of change in employment to the (Hodrick-Prescott) trend rate of growth of real GDP. Both employment and real GDP are divided by the working age population. We apply a Hodrick-Prescott filter with a smoothing parameter of 100 as we are using annual data to obtain the trend rate of growth for real GDP. In estimating the trend growth rate, we added a dummy for the 2009 year. Sample: 17 OECD countries, annual data, 1970-2017.

Gambetti [2009], one potential explanation to this structural change lies in the change in the relationship between hours and technology. Because changes in hours worked can be driven by variations at the intensive margin (i.e., by the change in hours per worker) and at the extensive margin (i.e., by the change in employment), it is useful to disentangle these two components. We thus decompose the elasticity of hours worked w.r.t. real GDP into the elasticity of hours per worker and the elasticity of employment. Inspection of Fig. 20(b) and Fig. 20(c) reveals that the rise in the elasticity of hours w.r.t. real GDP is driven by the rise in the elasticity of hours per worker and the elasticity of employment.

Impact response of hours to a technology shock on rolling sub-samples. In section 2.6, we investigate whether the contractionary effect of a permanent technology improvements on hours varies across time. Our empirical analysis on rolling sub-samples



(a) Response of Hours per Worker (b) Response of Employment

Figure 21: Time-Varying Impact Response of Hours to a Technology Shock: Intensive vs. Extensive Margin. Notes: Fig. 21(a) and Fig. 21(b) show the time-varying impact response of hours per worker and employment to a 1% permanent technology improvement. We have estimated impact responses over rolling windows of fixed length. While the vertical axis of Fig. 21(a) (Fig. 21(b)) shows the point estimate, i.e., γ_0, for the impact response of hours per worker (employment) to a 1% permanent increase in utilization-adjusted-aggregate-TFP obtained from estimating eq. (5) on rolling subs-samples, the horizontal axis shows the end year of the corresponding window. Light (dark) shaded areas represent 90 (68) percent confidence intervals based on Newey-West standard errors. Sample: 17 OECD countries, annual data, 1970-2017.

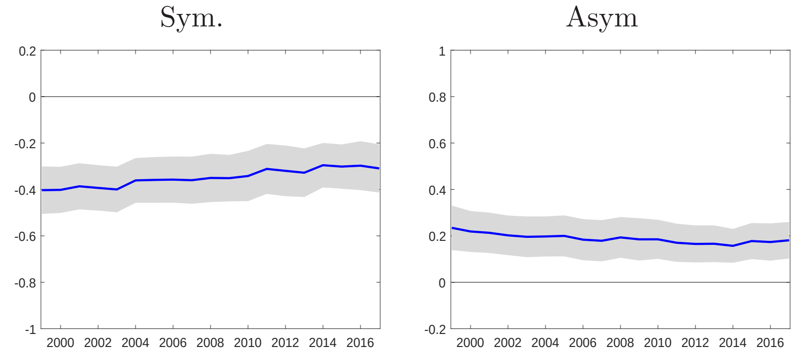
reveals that the impact response of hours to a technology shock shrinks over time. In Fig. 21, we decompose the impact response of hours worked estimated on rolling subsamples into an extensive and an intensive margin. Dividing employment by the working age population and hours by employment, we estimate the impact response of hours per worker (employment) to a 1% permanent increase in utilization-adjusted-aggregate-TFP obtained from estimating eq. (5) on rolling sub-samples. As shown in Fig. 21(b), employment is muted on impact to a technology shock because it is a state variable which responds only gradually. The variation of employment does not drive the shrinking contractionary effect we document empirically and therefore a reduction in hiring costs cannot account for our evidence. In contrast, Fig. 21(a) reveals that the decline in hours per worker shrinks over time and thus the time-increasing impact response of hours to a technology shock only operates at the intensive margin.

L.7 Time-Varying Hours Effects: Symmetric vs. Asymmetric Technology Shocks

Our hypothesis that the time-increasing response of total hours worked to a technology improvement is driven by the growing share of asymmetric technology shocks is valid as long as the elasticity of hours worked to symmetric and asymmetric technology shocks remains stable over time. To clarify this point, we decompose the impact response of total hours worked to an aggregate technology shock into impact responses of hours to symmetric and asymmetric technology shocks, i.e.,

$$\gamma_0 = \eta \gamma_{S,0} + (1 - \eta)\, \gamma_{D,0}, \tag{192}$$

where $\gamma_0 = \frac{\hat{L}_0}{\hat{Z}_0^A}$ and $\gamma_{X,0} = \frac{\hat{L}_{X,0}}{\hat{Z}_{X,0}^A}$ with $X = S, D$. According to our hypothesis, the time-declining share η of symmetric technology shocks leads γ_0 to move from larger to smaller negative values over time while $\gamma_{S,0}$ and $\gamma_{D,0}$ are assumed to remain constant over time. In column 2 of Fig. 22, we plot the impact responses of hours worked to symmetric and asymmetric technology shocks which are estimated over rolling sub-samples. Two conclusions emerge. The first conclusion is that as discussed in the next subsection, symmetric technology shocks exert a strong negative impact on hours worked while asymmetric technology shocks increase hours worked on impact. The second conclusion which emerges from the inspection of Fig. 22(a) is that the elasticity of labor to symmetric technology shocks is increasing over time which could potentially rationalize smaller negative values of γ_0. However, as displayed by Fig. 22(b), asymmetric technology shocks tend to produce smaller positive effects on total hours worked which thus lead to larger negative values of γ_0.



(a) Time-Varying Impact Effect of Symmetric Technology Shocks on Hours Worked

(b) Time-Varying Impact Effect of Asymmetric Technology Shocks on Hours Worked

Figure 22: Time-Varying Impact Response of Hours Worked to a Symmetric vs. Asymmetric Technology Shock. Notes: In columns 1 and 2, we estimate the impact response of total hours worked to a 1% permanent increase in utilization-adjusted aggregate TFP driven by symmetric technology shocks (Fig. 22(a)) while in Fig. 22(b), we consider a rise in utilization-adjusted aggregate TFP driven by asymmetric technology shocks. To identify symmetric vs. asymmetric technology shocks, we estimate the VAR model $[\hat{Z}^H_{it} - \hat{Z}^N_{it}, \hat{Z}^A_{it}, \hat{Y}_{R,it}, \hat{L}_{it}, \hat{W}_{C,it}]$. We impose long-run restrictions such that both symmetric and asymmetric technology shocks increase permanently Z^A_{it} while only asymmetric technology shocks increase permanently Z^H_{it}/Z^N_{it} in the long-run. Once we have identified technology shocks, we estimate the effects of a 1% permanent increase in utilization-adjusted aggregate TFP on hours worked by using Jordà's [2005] single-equation method. We run the regression (5) in rolling sub-samples by considering a fixed window length of thirty years. Because we are interested in the impact effect of technology on hours worked, we consider an horizon $h = 0$ into (5). The horizontal axis shows the end year of the period of the sub-sample and the vertical line displays the point estimate of the impact effect of technology on total hours worked. Sample: 17 OECD countries, 1970-2017, annual data.

L.8 Correlation of Technology Shocks between OECD Countries

We estimate a VAR model in panel format which has the advantage to increase substantially the number of observations. One first key feature of panel VAR is that we control for common macroeconomic shocks. Although we stack up the time series, the second key feature is that the technology shocks are estimated for each country. The country-level technology shocks have a country-specific component (determined by management practices, the structure of production organization, the ability to transform R&D expenditure into innovation) and an international component which also remains country-specific because the ability to take advantage of foreign ideas to innovate domestically will depend on the number of factors such as the absorptive capacity and human capital.

Because we estimate error terms for each country of our sample, it is straightforward to calculate the correlation of shocks across OECD countries, as displayed by Table 30. We find a cross-country mean of -0.048 and the mean amounts to 0.18 when we take the absolute values for country pair correlation. The correlation of technology shocks between OECD countries is thus low because technology improvements depend on country-specific factors and also because the share of asymmetric technology shocks across sectors varies substantially across countries. It is worth mentioning that our empirical approach serves our purpose as the nature of technology shocks are allowed to vary between space and time while the effect of a technology shock on hours is captured by parameters which display some homogeneity between countries.

L.9 Homogeneity Assumption in Estimating the Dynamic Effects

Nature of technology shocks varying across time and space and the homogeneity assumption to estimate the panel VAR model. Our paper stresses the importance of the variations in the share of asymmetric technology shocks across time and space and we show that hours worked decline after a technology shock in an average OECD economy because symmetric technology shocks are predominant but the decline in hours after a technology shocks progressively vanishes over time as technological change is increasingly driven by technology shocks which are concentrated within traded industries. Our panel SVAR approach let the share of asymmetric technology shocks vary across time and countries and assume that the effect of a technology shock on hours is homogenous across countries, i.e., the structural parameters of the model such the Frisch elasticity of labor supply and other parameters display some homogeneity across countries. Besides the fact that this assumption increases the accuracy of estimates by economizing the degrees of freedom (as the

Table 30: Country-pair correlation of identified technology shocks (ϵ^{ZA})

	AUS	AUT	BEL	CAN	DEU	DNK	ESP	FIN	FRA	GBR	IRL	ITA	JPN	NLD	NOR	SWE	USA
AUS	1	0.057	-0.024	0.237	-0.207	-0.171	0.293	-0.371	0.014	-0.293	-0.058	-0.305	-0.264	-0.146	0.174	-0.204	0.015
AUT		1	-0.103	0.173	0.199	-0.040	0.035	-0.136	0.140	-0.015	-0.395	-0.111	0.058	0.200	-0.075	-0.065	-0.050
BEL			1	-0.104	0.154	-0.290	0.029	0.009	0.248	-0.443	-0.130	0.390	0.039	-0.014	-0.085	-0.279	-0.129
CAN				1	-0.376	-0.096	-0.058	-0.534	0.066	-0.126	-0.081	-0.222	-0.369	-0.258	0.247	-0.210	0.457
DEU					1	-0.029	0.096	0.251	0.118	-0.186	-0.196	0.466	0.220	0.156	-0.359	-0.040	-0.225
DNK						1	-0.095	-0.005	0.023	0.181	-0.289	-0.120	0.313	0.137	0.111	-0.057	0.009
ESP							1	-0.046	0.109	-0.225	-0.111	0.186	0.106	0.010	-0.229	-0.335	-0.268
FIN								1	0.038	0.195	-0.190	0.225	0.398	0.126	-0.433	0.295	-0.131
FRA									1	-0.292	-0.302	0.205	0.285	0.029	-0.347	-0.050	-0.284
GBR										1	-0.179	-0.352	0.068	0.012	0.030	0.210	0.356
IRL											1	0.044	-0.243	-0.323	-0.046	0.204	-0.125
ITA												1	0.125	-0.067	-0.371	-0.058	-0.490
JPN													1	-0.038	-0.603	0.278	-0.211
NLD														1	0.032	-0.191	-0.188
NOR															1	-0.391	0.143
SWE																1	-0.054
USA																	1

Notes: the element (i, j) of the Table denotes the correlation between ϵ^{Z}_{AGG} of country i and ϵ^{Z}_{AGG} of country j, over the period 2010-2017 (annual data).

homogeneity assumption implies that we estimate less parameters), this approach is in line with our modelling strategy where we assume that the response of hours to a technology shock varies across time (and potentially across countries) as a result of the time-varying importance of asymmetric technology shocks.

Testing the homogeneity assumption. To test the validity of the homogeneity assumption in estimating the dynamic response of hours to a technology shock in panel format, we proceed as follows. We estimate the same VAR model but for one country at a time. Fig. 23 contrasts the dynamic response of hours to a technology shock when we adopt a panel approach shown in the blue line with the dynamic response when we estimate the same VAR model but for one country at a time and estimate the dynamic effect by using local projections. The red line shows the country mean of point estimates while the black line shows the median estimate when we estimate the dynamic effect for one country at a time. We consider four cases by estimating the technology shocks in panel format (first row), by estimating the technology shocks separately for one country at a time (second row), by adding time dummies in local projections (second step to plot the dynamic response of hours) as shown in the first column, or by dropping the time dummies in both the panel SVAR and local projections as shown in the second column.

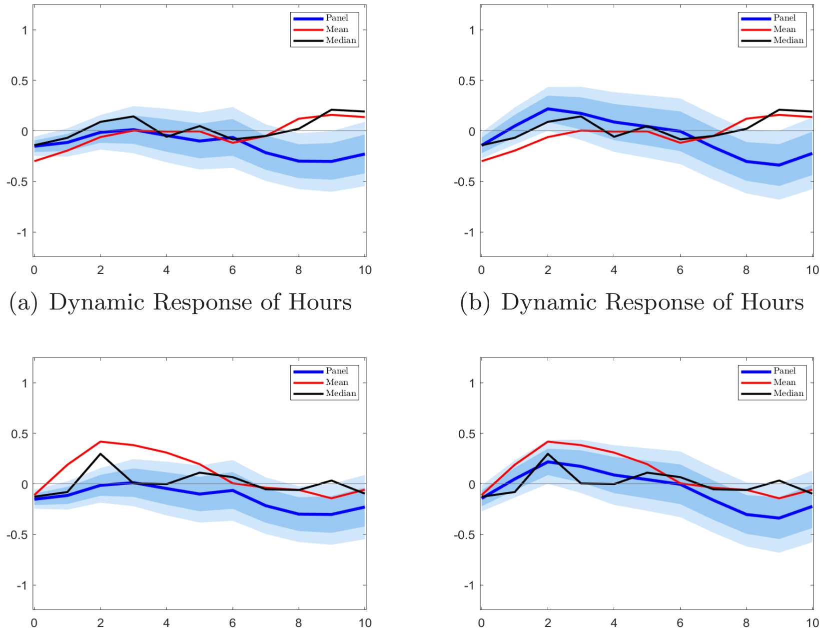
The first observation is that adding time dummies to estimate the panel SVAR and local projections (blue line in Fig. 23(a)), or to estimate only local projections (blue line in Fig. 23(c)) or dropping time dummies (second column of Fig. 23) does not affect the response of hours. What matters is whether the technology shocks are estimated in the first step from a panel SVAR (first row) or instead technology shocks are estimated in the first step for one country a time (second row). As it stands out, the second row of Fig. 23 shows that the dynamic responses of hours are essentially identical when the technology shocks are estimated for one country at a time whether the dynamic response is estimated in panel format (blue line) or for one country at a time (black and red lines). In other words, the second row of Fig. 23 reveals that imposing the homogeneity when estimating the response of hours to a technology shock in local projections (blue line), i.e., in the second step, leads to the same results when we estimate the dynamic response of hours for one country at a time (black and red line). As shown in the first row, when technology shocks are identified in the panel format across all scenarios and we contrast the response of hours estimated in panel format (blue line) or for one country at a time (black and red line), we don't find a discrepancy which is statistically different until year 8. Quantitatively, in the baseline model shown in the blue line of Fig. 23(a), hours decline by -0.15% on impact; when we estimate the dynamic response of hours by relaxing the homogeneity assumption and by estimating the response for one country at a time, the decline in hours amounts to -0.10% for the median and -0.25% for the mean.

Precision-weighted estimator. As stressed in the main text, we first identify the technology shock by estimating a panel SVAR and then in a second step, we use local projections to estimate the dynamic response of hours to a technology shock. To further test our homogeneity assumption, we use the mean-group estimator which amounts to estimating the dynamic response of hours to a technology shock for each country and aggregating the response by using a weighted average where the more precise estimators gives us better information and thus receive a higher weight. In Fig. 24, we contrast the panel OLS fixed effect estimator when the coefficient is assumed bo be homogenous across countries (see the solid blue line) with the precision-weighted average of individual estimates (see the solid red line). As it stands out, the discrepancy in the point estimate between the panel OLS fixed effect estimator and the precision-weighted-estimator is small and insignificant. These empirical findings provide an additional piece of evidence confirming the validity of the homogeneity assumption.

L.10 One Step vs Two-Step Method

In the main text, we adopt a two-step approach where we first identify the exogenous shock to utilization-adjusted-TFP by estimating a panel SVAR which includes utilization-adjusted-TFP, real GDP, total hours worked, the real consumption wage and assume that technology shocks are shocks which increase permanently utilization-adjusted-TFP. Once

With time dummies | Without time dummies



(a) Dynamic Response of Hours

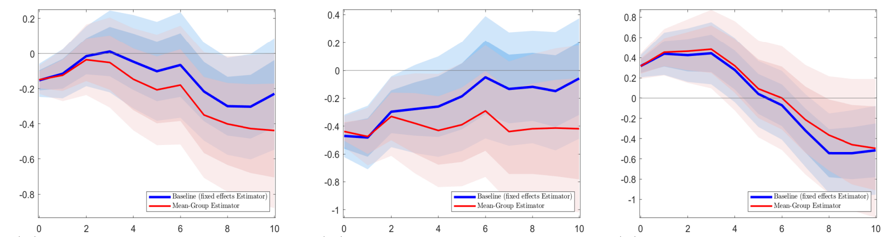
(b) Dynamic Response of Hours

(c) Dynamic Response of Hours

(d) Dynamic Response of Hours

Figure 23: Dynamic Response of Hours to a Technology Shock and Homogeneity Assumption Notes The solid lines show the dynamic responses to an exogenous increase in utilization-adjusted-aggregate-TFP by 1%. In the first row, we estimate the dynamic response of hours to a technology shock in panel format (blue line) and for one country at a time. In the latter case, the black line shows the median of estimates while the red line displays the country mean. Across all scenarios, we have estimated the error terms and thus the technology shocks in panel format and we relax the homogeneity assumption only in the second step, i.e., when we estimate the dynamic effect of a technology shock on hours by using local projections. In Fig. 23(a), we estimate the VAR model in panel format and local projections with time dummies (blue line) while in Fig. 23(b), we estimate the VAR model in panel format and local projections without time dummies (blue line). In the second row, we adopt the same approach except that in the first step, we identify the technology shocks for one country at a time. While solid lines represent point estimates, light (dark) shaded areas represent 90 (68) percent confidence intervals based on Newey-West standard errors. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Sample: 17 OECD countries, 1970-2017, annual data.

Aggregate Technology Shock | Sym. Technology Shock | Asym. Technology



(a) Dynamic Response Hours to a Technology Shock

(b) Dynamic Response Hours to a Symmetric Technology Shock

(c) Dynamic Response Hours to an Asymmetric Technology Shock

Figure 24: Dynamic Response of Hours after a Technology Shock: OLS Fixed Effect Estimator vs. Mean-Group Estimator Notes: The solid blue line shows the dynamic response of hours we estimate by assuming that the coefficient is homogenous across countries while the red line displays the dynamic response when the point estimate is computed a weighted average of cross-country point estimates. Light (dark) Shaded areas represent 90 (68) percent confidence intervals based on Newey-West standard errors. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Sample: 17 OECD countries, 1970-2017, annual data.

we have identified the technology shock, we estimate the dynamic effects by using the local projection method which simply requires estimation of a series of regressions for each horizon h for each variable of interest on the identified shock (see eq. (5) in the main text):

$$x_{i,t+h} = \alpha_{i,h} + \alpha_{t,h} + \psi_h(L)\, y_{i,t-1} + \gamma_h \varepsilon^Z_{i,t} + \eta_{i,t+h}. \tag{193}$$

In the main text, baseline control variables collected in y, includes past values of utilization-adjusted-TFP and of the variable of interest.

One-step approach. Ramey and Zubairy [2018] adopt a one-step approach (to ensure a straightforward comparison of results with estimates from defense news variables) by replacing the shock with current government spending in the single-equation method. We adapt their approach to our case and thus we run a series of regressions for each horizon h for each variable of interest in rate of growth on the rate of growth of the considered technology variable:

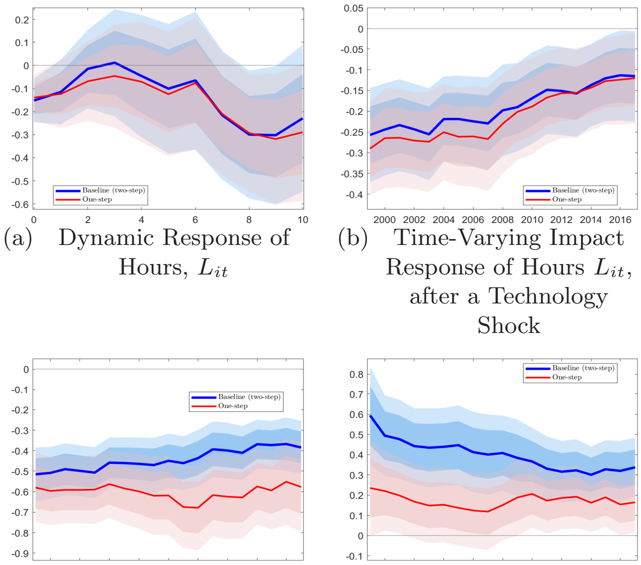
$$\Delta x_{i,t+h} = \alpha_{i,h} + \alpha_{t,h} + \psi_h(L)\, y_{i,t-1} + \gamma_h \Delta z_{it} + \eta_{i,t+h}, \tag{194}$$

where x is the (logged) variable of interest and z is the (logged) technology variable; $\Delta x_{i,t+h}$ represents the accumulated growth of the dependent variable from $t-1$ to $t+h$. We consider three types of technology improvements: i) a technology improvement by considering the time series for logged utilization-adjusted-TFP, ii) a technology improvement which is asymmetric between sectors by using $z^A_{D,it} = z^H_{it} - z^N_{it}$, i.e., the differential between traded and non-traded utilization-adjusted-TFP, iii) a technology improvement which is symmetric between sectors by constructing $z^A_{S,it} = \log Z^A_{S,it}$ where $Z^A_{S,it} = Z^A_{it} - \nu^{Y,H}_i Z^A_{D,it}$, see eq. (3) in the main text, where Z^A is utilization-adjusted-TFP, $\nu^{Y,H}_i$ the value added share of tradables, and $Z^A_{D,it}$ the ratio of utilization-adjusted-TFP of tradables to non-tradables.

Robustness of the two-step method. Pagan [1984] provides a complete treatment of the econometric problems arising when generated variables appear in a regression equation. In particular, the author explores the situation when generated residuals are used as regressors. It is found that the coefficient and its standard error from an OLS program would be a consistent estimator of the true coefficient and the true standard error for the coefficient of the unanticipated variable. In other words, running a regression with structural technology shocks recovered from the estimation of utilization-adjusted-TFP over a set of regressors is equivalent to running a regression where the regressor is utilization-adjusted-TFP itself.

Contrasting the effect of a technology improvement on hours from the two-step with that obtained from the one-step method. Fig. 25(a) contrasts the dynamic response of hours to a technology shock when we adopt the two-step approach detailed in the main text (shown in the solid blue line) with the dynamic response of hours to a permanent technology improvement when we adopt the one-step approach (shown in the solid red line). As it stands out, the difference between the two methods is insignificant. Fig. 25(b) displays the impact response of hours to a permanent technology improvement normalized to one 1%. The response is estimated on rolling windows of fixed length of thirty years. Again, the difference between the two approaches is insignificant. These empirical findings reveal that the two-step and the one-step method are equivalent and thus identifying the technology shock in the first step by estimating a panel VAR and running the regression of hours on the identified shock could be replaced with a one step approach where we estimated directly the effect of a permanent technology improvement on hours by using raw series of utilization-adjusted-TFP.

Advantage of the the two-step over the one-step method. While the discrepancy between the two methods is insignificant when we consider a standard technology shock reflected by a permanent increase in utilization-adjusted-TFP, the second row of Fig. 25 reveals that the two-step approach is more suited when it comes to decomposing the technology shock into a symmetric and an asymmetric component. More specifically, when we use the two-step method and impose in the VAR model that symmetric technology shocks are shocks which increase permanently utilization-adjusted TFP while leaving unchanged the ratio Z^H_{it}/Z^N_{it}, this approach cancels any productivity differential. In contrast, the one-step method cannot neutralize the productivity differential in the short-run as there is no simultaneous identification of symmetric and asymmetric technology shocks. The effects of an asymmetric technology shock display much less difference.



(a) Dynamic Response of Hours, L_{it}

(b) Time-Varying Impact Response of Hours L_{it}, after a Technology Shock

(c) Time-Varying Impact Response of Hours L_{it}, after a Symmetric Technology Shock

(d) Time-Varying Impact Response of Hours L_{it}, after an Asymmetric Technology Shock

Figure 25: Effects of a Technology Shock on Hours: One-Step vs Two-Step Method. Notes: The blue line in Fig. 25(a) shows the dynamic response of hours to a technology shock by adopting a two-step approach where we identify the technology shock by estimating a VAR model which includes utilization-adjusted-TFP and macroeconomic variables in the first step and in the second step, we estimate the dynamic effect of the identified technology shock on hours on rolling windows. Alternatively, we estimate the dynamic effect of a permanent increase in utilization-adjusted-TFP on hours by adopting a one-step approach. In the latter case, we estimate the impact response of a permanent technology improvement on hours by mans of local projections by using directly time series for utilization-adjusted-TFP. The blue line in Fig. 25(b) shows the point estimate (i.e., γ_0) for the impact response of hours (L_{it}) to a 1% permanent increase in utilization-adjusted-aggregate-TFP obtained from an estimation on rolling sub-samples, the horizontal axis shows the end year of the corresponding window. Light (dark) shaded areas represent 90 (68) percent confidence intervals based on Newey-West standard errors. In Fig. 25(c), we show impact responses of hours to a technology improvement which is symmetric across sectors. In Fig. 25(d), we show impact responses of hours to a technology improvement which is asymmetric across sectors. Impact responses are estimated on rolling sub-samples. Sample: 17 OECD countries, 1970-2017, annual data.

L.11 Inclusion of Time Dummies

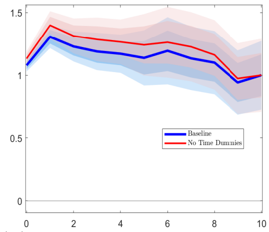
Our empirical strategy. We include time effects when we estimate the VAR model in panel format to identify technology shocks and in the second step when we run a series of regressions of each variable of interest on the identified technology shock for each horizon $h = 0, 1, 2, ...$

$$x_{i,t+h} = \alpha_{i,h} + \alpha_{t,h} + \psi_h(L) z_{i,t-1} + \gamma_h \varepsilon^Z_{i,t} + \eta_{i,t+h}, \tag{195}$$

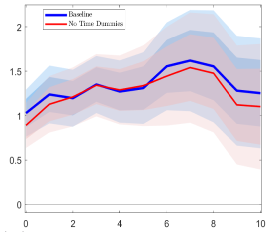
where $\alpha_{i,h}$ are country fixed effects and $\alpha_{t,h}$ are time dummies. Time effects should be included when we estimate the VAR model and local projections as we have to control for the shocks which are common across countries such as oil price shocks or the 2008 financial crisis. In addition, it is recommended to include time dummies as it enures that the responses of variables reflect the deviations relative to the sample average.

What time dummies capture and do not capture. The time effects do not capture or remove the technology shocks which are symmetric or asymmetric across sectors because both the symmetric and asymmetric components are country-specific. The time dummies might capture the common component of technology improvements across countries, i.e., the progression of the international stock of ideas. However, the impact of the world stock of ideas on country-level TFP is country-specific because the absorptive capacity of technology, the structure of production and technology adoption costs vary substantially across countries. Therefore, time dummies should not remove the impact of the international stock of knowledge.

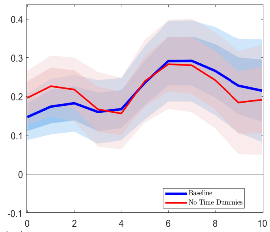
Dynamic effects with vs. without time dummies. In Fig. 26, we contrast the dynamic responses to a technology shock we obtain when we include time dummies (shown in the solid blue line) and when we exclude time dummies from the VAR model and local projections (shown in the solid red line). Note that the blue line shows the responses we estimate in the main text, see Fig. 2. We have chosen the set of macroeconomic variables displayed by Fig. 2. While Fig. 26(e) shows the dynamic response of hours to a technology shock, Fig. 27(b) and Fig. 27(c) show the dynamic responses to a symmetric and an



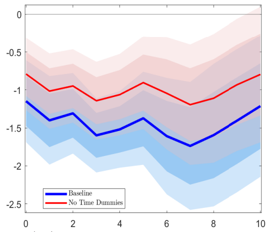
(a) Utilization-Adjusted Aggregate TFP



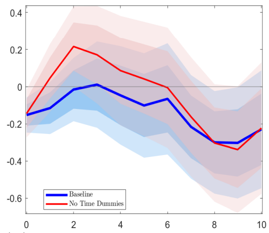
(b) Utilization-Adjusted TFP of Tradables relative to Non-Tradables



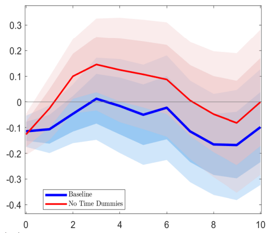
(c) Value Added Share of Tradables



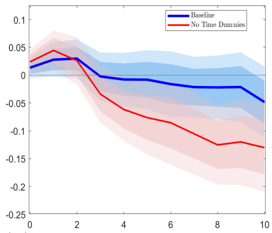
(d) Terms of Trade



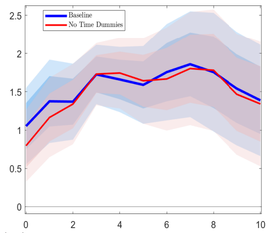
(e) Total Hours Worked



(f) Non-Traded Hours Worked

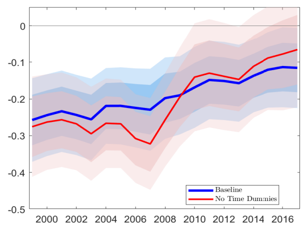


(g) Hours Worked Share of Tradables

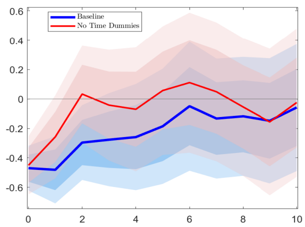


(h) Relative Price of Non-Tradables

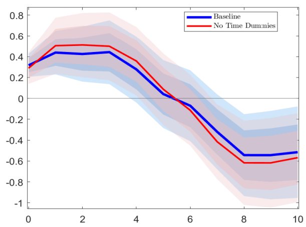
Figure 26: Dynamic Effects of a Technology Shock on Hours: With and Without Time Dummies. Notes: The blue line shows the dynamic response of hours to a technology shock by adopting a two-step approach where we identify the technology shock by estimating a VAR model which includes utilization-adjusted-TFP and macroeconomic variables in the first step and in the second step, we estimate the dynamic effect of the identified technology shock on hours on rolling windows. In the baseline scenario shown in the blue line, we include time dummies when we estimate the VAR model (first step) and local projections (second step). In the solid red line, we show the point estimate when we exclude time dummies from the VAR model and local projections. Light (dark) shaded areas represent 90 (68) percent confidence intervals based on Newey-West standard errors. Sample: 17 OECD countries, 1970-2017, annual data.



(a) Time-Varying Impact Response of Hours L_{it}, after a Technology Shock



(b) Dynamic Response of Hours, L_{it}, to a Symmetric Technology Shock



(c) Dynamic Response of Hours, L_{it}, to an Asymmetric Technology Shock

Figure 27: Impact Effects of a Technology Shock on Hours over Sub-Periods: With and Without Time Dummies. Notes: The blue line in Fig. 27(b) and Fig. 27(c) shows the dynamic response of hours to a technology shock by adopting a two-step approach where we identify symmetric and asymmetric technology shocks by estimating a VAR model which includes the ratio of traded to non-traded utilization-adjusted-TFP, utilization-adjusted-TFP, and macroeconomic variables in the first step and in the second step, we estimate the dynamic effect of the identified (symmetric or asymmetric) technology shock on hours on rolling windows. In the baseline scenario shown in the blue line, we include time dummies when we estimate the VAR model (first step) and local projections (second step). In the solid red line, we show the point estimate when we exclude time dummies from the VAR model and local projections. The solid lines in Fig. 27(a) show the point estimate (i.e., γ_0) for the impact response of hours (L_{it}) to a 1% permanent increase in utilization-adjusted-aggregate-TFP obtained from an estimation on rolling sub-samples, the horizontal axis shows the end year of the corresponding window. Light (dark) shaded areas represent 90 (68) percent confidence intervals based on Newey-West standard errors. Sample: 17 OECD countries, 1970-2017, annual data.

asymmetric technology shock. Fig. 27(a) contrasts the impact response of hours estimated on rolling sub-samples. Overall, we do not detect any significant discrepancy. Inspection of Fig. 26 and Fig. 27 reveals that the dynamic responses of variables lie within the confidence interval of the baseline. Therefore, whether we include or not time dummies, the difference is not statistically significant.

L.12 SVAR vs Local Projections

In the main text, we adopt a two-step approach and estimate the dynamic effects by using local projections in the second step. The reason is that we want to shed some light on the multi-sector aspect of the transmission mechanism of technology shocks and by decoupling the shock identification and the estimate of the dynamic responses, we ensure that the variables respond to the same shock. In this subsection, we re-estimate the effects of a technology shock we show in the main text by using a one-step approach, say by imposing long-run restrictions when estimating the SVAR model to identify structural shocks and next by generating impulse response functions to the identified technology shocks from the SVAR model.

Advantages of Local Projections over SVAR. Jordà's [2005] local projection method has several advantages over the VAR methodology. First, when estimating the dynamic adjustment of variables to the technology shock, it considerably reduces the number of coefficients and thus is particularly suited when estimating the effects over overlapping subperiods of fixed length. The second advantage is that it does not impose the dynamic restrictions implicitly embedded in VARs and can accommodate non-linearities in the response function, see Jordà [2005]. By imposing fewer restrictions, impulse responses obtained by using the local projection method might be erratic. The third advantage is that we are interested in shedding some light about the transmission mechanism of technology shocks which leads us to estimate the dynamic effects on a set of aggregate and sectoral variables. If we estimate several VAR models, we have to identify new technology shocks which might slightly differ from the previous VAR model. One way to circumvent this obstacle is to estimate one unique VAR model to identify once and for all the technology shock and then to estimate the dynamic effects of identified technology shock on a set of variables by using local projections.

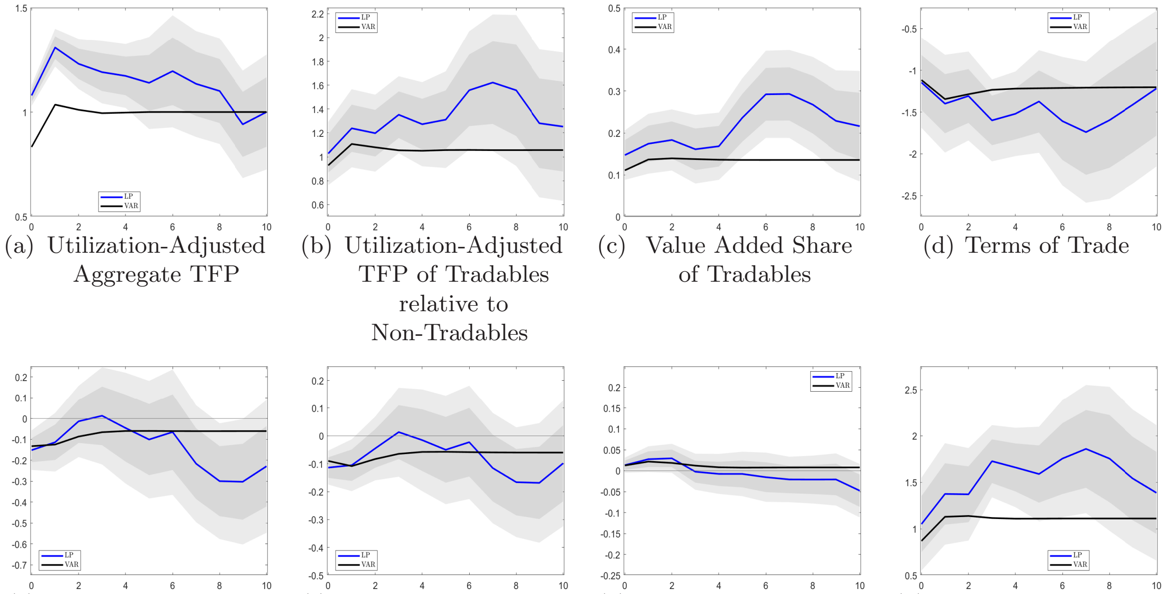
SVAR vs. Local Projections. Fig. 28 contrasts the dynamic responses generated from the VAR model (shown in the black line) with the baseline displayed by the solid blue line. We consider the same set of variables as in the main text, see Fig. 2. Overall, we do not detect any significant discrepancy.

Inspection of Fig. 28, reveals that both methods lead to very similar results, especially on impact, and even at a longer time horizon, as responses lie within the confidence interval of the baseline case (i.e., associated with the point estimate from local projections). We may notice some quantitative differences because local projections are based on sequential regressions of the endogenous variable shifted several steps ahead,. In particular, the responses generated from local projections can account for the non-monotonic adjustment of macroeconomic variables after a technology shock such as utilization-adjusted-TFP, the ratio of utilization-adjusted-TFP of tradables relative to non-tradables, the relative price of non-tradables, the terms of trade or hours worked.

Fig. 29 contrasts the impact response of hours to a technology estimated on rolling windows. While we do not detect any statistical significant difference because the responses from the VAR model lies with the confidence international, as stressed above, time-varying estimates are more reliable and consistent since in estimating the dynamic effects, the technology shock for every year remains unchanged from one sub-period to another.

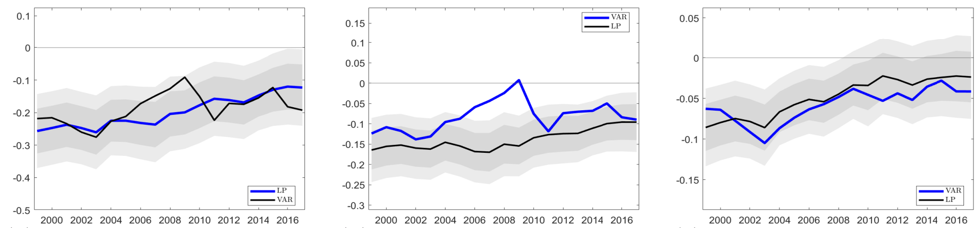
L.13 Testing the Presence of Structural Breaks in the Relationship between Hours and Technological Change

Empirical strategy. The main objective of the paper is to provide an explanation to the vanishing decline in hours after a technology shock we document for OECD countries. The explanation we put forward is based on the rising share of technological change explained by exogenous asymmetric technology shocks. More specifically, according to our hypothesis, the gradual disappearance of the fall in labor is driven by the changing nature of technology shocks and is not the result of a change in the structural model's parameters such as the Frisch elasticity of labor supply, the degree of labor mobility between sectors, or the substitutability across goods. In accordance with this hypothesis, in the empirical part, we estimate the VAR model in panel format by assuming that the coefficients in the VAR model are constant over time. Once we have identified the structural shocks, we estimate the dynamic response of hours to the exogenous technology shock on rolling sub-samples and find that the decline in hours shrinks over time from -0.26% the first thirty of our sample to -0.11% the last thirty years of our sample. The changing nature of technology shocks over time is assumed to drive the shrinking contractionary effect of technology shocks on hours. In other words, the decline in hours after a technology shock gradually vanishes over time not because the elasticity of labor supply takes smaller values over time but instead because the composition of technology improvements gradually changes over time as it tends



(a) Utilization-Adjusted Aggregate TFP
(b) Utilization-Adjusted TFP of Tradables relative to Non-Tradables
(c) Value Added Share of Tradables
(d) Terms of Trade
(e) Total Hours Worked
(f) Non-Traded Hours Worked
(g) Hours Worked Share of Tradables
(h) Relative Price of Non-Tradables

Figure 28: Dynamic Effects of a Technology Shock. Notes: The solid lines shows the dynamic responses to an exogenous increase in utilization-adjusted-aggregate-TFP by 1% in the long-run. While solid lines represent point estimates, light (dark) shaded areas represent 90 (68) percent confidence intervals based on Newey-West standard errors. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. The solid blue line shows the dynamic adjustment when we estimate the dynamic effects by using local projections while the solid black line displays the dynamic effects when we generate the dynamic responses from the VAR model. Sample: 17 OECD countries, 1970-2017, annual data.



(a) Time-Varying Response of L_{it}
(b) Time-Varying Response of L_{it}^{N}
(c) Time-Varying Response of L_{it}^{H}

Figure 29: Time-Varying Effects of a Technology Shock. Notes: While the vertical axis of Fig. 29(a) shows the point estimate (i.e., γ_0) for the impact response of hours (L_{it}) to a 1% permanent increase in utilization-adjusted-aggregate-TFP obtained from estimating eq. (5) on rolling subs-samples, the horizontal axis shows the end year of the corresponding window. Light (dark) shaded areas represent 90 (68) percent confidence intervals based on Newey-West standard errors. Fig. 29(b) and Fig. 29(c) show time-varying impact responses of non-traded (L_{it}^{N}) and traded (L_{it}^{H}) hours worked to an aggregate technology shock, both re-scaled by the labor compensation share so that the sum response of sectoral hours worked are expressed in percentage point of total hours. The solid blue line shows the dynamic adjustment when we estimate the dynamic effects by using local projections while the solid black line displays the dynamic effects when we generate the dynamic responses from the VAR model. Sample: 17 OECD countries, 1970-2017, annual data.

to become more concentrated toward industries. We test our hypothesis by developing and simulating a model with tradables and non-tradables. In computing numerically the impact response of hours to a technology shock, we increase the share of technology improvements driven by asymmetric technology shocks between sectors by assuming that the model's parameters remain unchanged. We feed the model with the share of asymmetric technology shocks between sectors we estimate in the data by computing the forecast error variance decomposition over rolling sub-periods and we find that the model can account for the vanishing decline in hours after a technology shock we document empirically.

The test for potential structural breaks in the estimated relationship. While the quantitative exercise we conduct corroborates our hypothesis, we further test our assumption of the changing nature of technology shocks and constancy of model's parameters by running a series of tests in panel format to detect the potential presence of structural breaks in the relationship between technology and hours. In section L.1, we have investigated the potential presence breaks in the time series for hours and utilization-adjusted-TFP. Both variables are found to be integrated of order one and no structural breaks have been detected. Although time series do not contain structural breaks, we cannot reject the assumption of the presence of structural breaks in the relationship between hours and technology. We apply the test developed by Ditzen et al. [2024] for detecting multiple structural breaks in panel data to the relationship we are interested in, i.e. the relationship between total hours worked and the identified technology shocks ε^Z where Z can be either aggregate (AGG), asymmetric (ASYM) or symmetric (SYM) between sectors. We run the regression of the logged total hours worked on the identified technology shocks ε^Z and a set of controls which are lagged values of the dependent variable and utilization-adjusted-TFP:

$$\ln L_{i,t} = \alpha_i + \gamma \varepsilon^Z_{i,t} + \left(\beta_1 \ln L_{i,t-1} + \beta_2 \ln L_{i,t-2} + \beta_3 \ln Z^A_{i,t-1} + \beta_4 \ln Z^A_{i,t-2}\right) + \eta_{i,t}, \quad (196)$$

where we allow for two lags on control variables. Equation (196) collapses to the equation we estimate in the main text by using local projections by considering a time horizon $h = 0$; therefore γ captures the impact effect of a technology shock on hours. The coefficient γ associated with the regressor $\varepsilon^Z_{i,t}$ is potentially subject to structural breaks while the coefficients β_j for $j = 1, \ldots, 4$ are supposed to be unaffected by the breaks. To detect potential structural breaks, the authors test the null of s structural breaks against the alternative of $s + 1$ structural breaks consecutively in order to estimate the true number of structural breaks. Due to the homogeneity assumption, the break dates are common for all countries in our sample. According to Ditzen et al. [2024], this assumption is common and is reasonable in panels where the frequency of the data is not too high. To account for potential heteroskedasticity and autocorrelation we use robust (HAC) standard errors.

Results: no structural breaks in the estimated relationship between hours and technology. The test proposed by Ditzen et al. [2024] is aimed at testing directly the presence of structural breaks that could affect the impact effect of technological shocks on total hours worked. Columns 1-3 of Table 31 report the test value $F(s|s+1)$; $F(s|s+1)$ is the F-statistic for testing the null hypothesis H_0 where there are s breaks versus hypothesis H_1 with $s+1$ breaks. The critical values of the test are shown in columns 4-6. When the F statistic is lower that the critical value, then we cannot reject assumption H_0. As shown in the first row, we accept H_0 of $s = 0$ structural break. Therefore, there is no structural breaks in the relationship between hours and technology we estimate in the main text.

According to the test $F(1|0)$, the hypothesis of 0 breaks against at least 1 break is not rejected for the three identified shocks. The same conclusion holds for the consecutive tests. By and large, we therefore cannot reject the null of no breaks at the 1% level, suggesting that the local projection regressions we estimated are not subject to structural breaks.

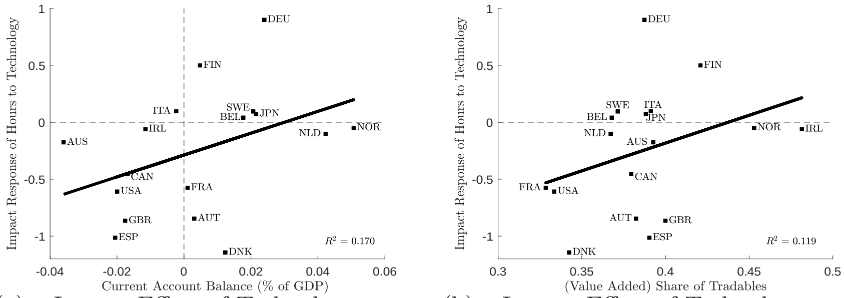
L.14 Cross-Country Variations

In this paper, we put forward international openness to generate a negative link between technology and hours worked. When the country is open to international trade and world capital markets, the open economy will find it optimal to import consumption and investment goods from abroad by running a current account deficit. By increasing imports, the home country can meet a higher domestic demand for goods and thus households can enjoy

Table 31: Ditzen et al. [2024] Test for Detecting One or More Structural Breaks

	eq. (196)			Critical Values		
	AGG (1)	ASYM (2)	SYM (3)	1% (4)	5% (5)	10% (6)
$F(1\|0)$	0.58	0.13	0.14	12.29	8.58	7.04
$F(2\|1)$	0.65	0.24	5.47	13.89	10.13	8.51
$F(3\|2)$	1.09	1.70	1.62	14.80	11.14	9.41
$F(4\|3)$	2.07	1.56	2.49	15.28	11.83	10.04
$F(5\|4)$	1.02	1.53	0.63	15.76	12.25	10.58

Notes: AGG refers to aggregate technology shocks. ASYM refers to asymmetric technology shocks. SYM refers to symmetric technology shocks. Columns 1-3 of Table 31 report the test value $F(s|s+1)$. $F(s|s+1)$ is the F-statistic for testing the null hypothesis H_0: s breaks versus H_1: $s+1$ breaks. The critical values of the test are shown in columns 4-6. When the F statistic is lower that the critical value, then we cannot reject assumption H_0 of s structural breaks. Sample: 17 OECD countries, 1970-2017, annual data.



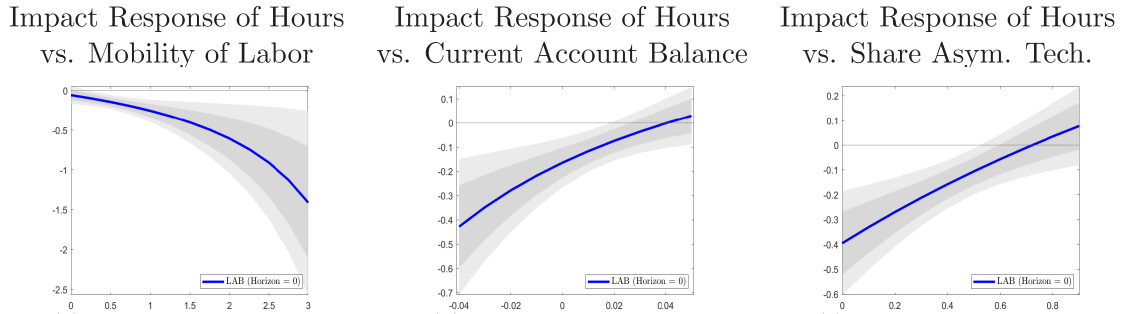
(a) Impact Effect of Technology on Hours vs. Current Account Balance

(b) Impact Effect of Technology on Hours vs. Tradable Share

Figure 30: Impact Responses of Hours to a Permanent Technology Improvement: Financial Openness and Tradable Share. Notes: Fig. 30(a) and Fig. 30(b) show the impact response of total hours worked to a 1% permanent increase in utilization-adjusted-aggregate-TFP. We first identify the permanent technology shock by estimating a VAR model which includes utilization-adjusted-aggregate-TFP together with a set of variables and impose long-run restrictions. Then in a second step, we estimate the impact response of hours worked by means of local projections. In Fig. 30(a), we plot impact responses of hours worked (on vertical axis) against the current account balance (as a percentage of GDP) averaged over 1970-2017. Data for the current account balance are taken from Lane and Milesi-Ferretti [2007]. In Fig. 30(b), we plot impact responses of hours (on vertical axis) against the value added share of tradables (as a percentage of GDP) averaged over 1970-2017. Data are taken from EU KLEMS. Sample: 17 OECD countries, annual data, 1970-2017.

leisure. In line with our hypothesis, we find that OECD countries run a current account (or a trade balance) deficit on impact, see Fig. 2(c) in the main text. We have to keep in mind that empirical estimates capture the reaction of an average OECD economy. More specifically, as shown below, there exists a substantial cross-country dispersion in the response of hours as some countries will not decide to run a current account deficit.

Cross-country dispersion in the impact response of hours. In Fig. 30(a), we plot impact responses of hours to a permanent technology improvement against the (unconditional) averaged current balance (in % of GDP) for the seventeen OECD countries over 1970-2017. Because estimates are made for one country at a time, the limited number of observations implies a great amount of uncertainty surrounding the point estimate of the response of hours. The economies (mostly English-speaking and Spain) which borrow from abroad (located in the south-west part) experience a decline in hours worked. The economies (mostly Scandinavian, Japan and Germany) which lend to abroad (located in the North-east part) do not experience a decline in hours worked. As shown in the numerical part of the paper, barriers to factors' mobility and imperfect substitutability between home- and foreign-produced traded goods reduce considerably the current account deficit. For countries with low mobility costs, such as English-speaking countries, it is optimal to import goods from abroad (and run a current account deficit) and meet higher demand for non-traded goods by shifting productive resources away from traded and toward non-traded industries. Conversely, factors' mobility costs have a positive influence on the current account and labor supply. Scandinavian countries tend to have a low degree of labor



(a) Hours vs. Mobility (b) Hours vs. Current Account (c) Hours vs. Share of Asym. Tech. Change

Figure 31: Impact Response of Hours after a Technology Shock against the degree of mobility of labor across sectors and the current account balance. Notes: We have estimated the impact response of hours to a technology shock by using local projections. We add an interaction term which involves the degree of labor mobility across sectors, ϵ_L, and plot $\gamma_{1,0} + \gamma_{2,0} \times \epsilon_{L,i}$ in Fig. 31(a). The values for ϵ_L are taken from our own estimates which are used to calibrate the model. We add an interaction term which involves the averaged current account balance in percentage of GDP, denoted by ca and plot $\gamma_{1,0} + \gamma_{2,0} \times \text{ca}_i$ in Fig. 32(b). Data for the current account balance are taken from Lane and Milesi-Ferretti [2007]. In Fig. 32(b), we plot the coefficient associated with the interaction term $\gamma_{1,0} + \gamma_{2,0} \times \text{asym share}_i$. Light (dark) shaded areas represent 90 (68) percent confidence intervals based on Newey-West standard errors. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Sample: 17 OECD countries, 1970-2017, annual data.

mobility between sectors and thus they have low incentives to borrow from abroad as the cost of moving resources away from the traded sector and toward the non-traded sector is prohibitive, thus explaining why the group of countries in the north-east part of Fig. 30(a) does not experience a current account deficit and a fall in hours.

An alternative way to visualize the role of the degree of labor mobility across sectors in determining the response of hours to a technology shock is to re-estimate the dynamic effect of a technology shock on hours by adding an interaction term between the technology shock and the degree of labor mobility across sectors, i.e., we run the regression:

$$x_{i,t+h} = \alpha_{i,h} + \alpha_{t,h} + \psi_h(L)\, y_{i,t-1} + \gamma_{1,h}\,.\varepsilon^Z_{i,t} + \gamma_{2,h}\,.\varepsilon^Z_{i,t} \times \epsilon_{L,i} + \eta_{i,t+h}, \tag{197}$$

where $\alpha_{i,h}$ are country fixed effects, $\alpha_{t,h}$ are time dummies; x is the logarithm of the variable of interest, y is a vector of control variables (i.e., past values of utilization-adjusted-TFP and of the variable of interest), $\psi_h(L)$ is a polynomial (of order two) in the lag operator. Since we are interested in the impact effect of a technology shock, we focus on the horizon $h = 0$. The coefficient $\gamma_{1,0}$ gives the response of x at time $t + h$ to the identified technology shock $\varepsilon^Z_{i,t}$ at time t if labor were immobile across sectors while $\gamma_{2,0}$ captures the effect of a technology shock on hours conditional on the degree of labor mobility. Formally, in Fig. 31(a), we plot the impact response of hours to a technology shock (vertical axis)

$$\frac{\partial x_{i,t}}{\partial \varepsilon^Z_{i,t}} = \gamma_{1,0} + \gamma_{2,0} \times \epsilon_{L,i}, \tag{198}$$

against $\epsilon_{L,i}$ (horizonal axis). According to our model's predictions, we expect $\gamma_{1,0}+\gamma_{2,0}\times\epsilon_{L,i}$ to be negative. Intuitively, as the degree of labor mobility between sectors increases, because it is less costly to move labor, the open economy will be more inclined to increase imports from abroad to meet the demand for traded goods and will shift more labor toward the non-traded sector to meet the demand for non-traded goods. Therefore, households will lower significantly labor supply. Fig. 31(a) corroborates our model's predictions. More specifically Fig. 31(a) reveals that hours decline dramatically for values of ϵ_L larger than one.

As shown by Rothert and Short [2023] and in line with our model's predictions, all factors which mitigate the shift of productive resources away from the traded and toward the non-traded sector will reduce the amount of capital inflows. Therefore, countries which are on average borrowers such as English-speaking countries which are characterized by a lower amount of frictions in the movements of factors between sectors should borrow more after a technology shock and thus should experience a greater decline in hours. Conversely, countries such as Scandinavian countries will tend to be lenders as they are characterized by larger costs of factors' mobility because their structure of production is less diversified.

Other countries such as Germany will run a current account surplus as a result of trade-oriented government policies. An additional important factor which is highlighted in our numerical analysis is imperfect substitutability between home- and foreign-produced traded goods. As home- and foreign-produced traded goods are more differentiated, households will import less goods produced from abroad which will results in a lower current account deficit. Taking time series for the current account balance from Lane and Milesi-Ferretti [2007], we have replaced ϵ_L with the current account balance as a share of GDP, denoted by ca, in eq. (199). In Fig. 31(b), we plot the impact response of hours to a technology shock measured by (on the vertical axis)

$$\frac{\partial x_{i,t}}{\partial \varepsilon^{Z}_{i,t}} = \gamma_{1,0} + \gamma_{2,0} \times \mathrm{ca}_i, \tag{199}$$

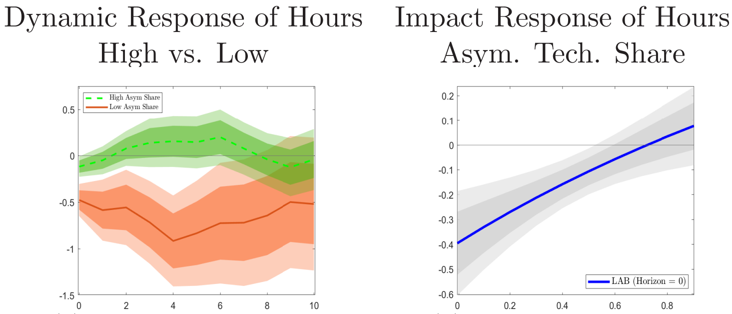
against the current account balance as a percentage of GDP (horizontal axis). According to our model's predictions, we expect $\gamma_{1,0} + \gamma_{2,0} \times \mathrm{ca}_i$ to be positive. Intuitively, borrowers (i.e., $ca < 0$) will experience a dramatic decline in hours after a technology shock while hours will not decrease after a technology shock in countries which lend to abroad (i.e., $ca > 0$). In line with our hypothesis, Fig. 31(b) shows that there exists a strong positive relationship between the response of hours to a technology shock and the current account balance. The decline in hours tend to be larger in countries which are more prone to borrow from abroad while the decline in hours is less in countries which are more inclined to lend to abroad.

Hours vary across countries due to international differences in the share of asymmetric technology improvements between sectors. As displayed by Fig. 30(b) which plots impact responses of hours to a technology shock against the (value added) share of tradables, a greater contribution of exporting industries to GDP is associated with an increase in hours worked following a permanent technology improvement. Intuitively, a greater share of tradables implies that the variations in utilization-adjusted-aggregate-TFP are further driven by technological change in traded industries. Because technological change is more pronounced in traded than in non-traded industries, aggregate technological change tends to be more asymmetric across sectors. Because the value added share of tradables, i.e., $\nu^{Y,H}$, is only an approximation of the share of asymmetric technological change, we conduct below a deeper investigation of the role of share of asymmetric technology improvements in driving technological change.

We have split our sample into two groups of countries on the basis of the share of the (unconditional) variance of technological change driven by its asymmetric component (between sectors). As shown in Online Appendix J.9, the share of the (unconditional) variance of the rate of growth of utilization-adjusted-aggregate-TFP, $\hat{\mathrm{TFP}}^A(t)$, driven by its asymmetric component (between sectors), $\hat{\mathrm{TFP}}^A_D(t)$, reads:

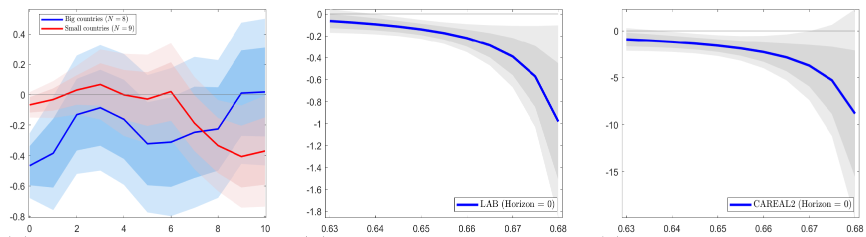
$$\frac{\mathrm{Var}\left(\hat{\mathrm{TFP}}^A_D(t)\right)}{\mathrm{Var}'\left(\hat{\mathrm{TFP}}^A(t)\right)} = \left(\nu^{Y,H}\right)^2 \frac{\mathrm{Var}\left(\hat{\mathrm{TFP}}^H(t) - \hat{\mathrm{TFP}}^N(t)\right)}{\mathrm{Var}'\left(\hat{\mathrm{TFP}}^A(t)\right)}, \tag{200}$$

where $\mathrm{Var}'\left(\hat{\mathrm{TFP}}^A(t)\right)$ denotes the variance of aggregate technological change adjusted with the covariance of symmetric and asymmetric components. Eq. (200) reveals that the contribution of asymmetric technology improvements to the variance of technological change is increasing in both the value added share of tradables, $\nu^{Y,H}$, and the dispersion in technology improvement between the traded and the non-traded sector, $\frac{\mathrm{Var}\left(\hat{\mathrm{TFP}}^H(t) - \hat{\mathrm{TFP}}^N(t)\right)}{\mathrm{Var}'\left(\hat{\mathrm{TFP}}^A(t)\right)}$. Fig. 32(a) suggests that the share of asymmetric technology improvements is a major driver of the response of hours. More specifically, the figure reveals that in the group of countries where the share of asymmetric technology improvements is lower than 30% (with a mean of 22%), as shown in the orange line, hours decline by -0.48% on impact, while in the group of countries where the share of asymmetric shocks is higher than 30% (with a mean of 46%), the response of hours is muted at all time horizons (see the dashed green line). This finding is important because our estimates also reveal that (only) asymmetric



(a) Dynamic Response of Hours: High vs. Share of Asymmetric Technological Change (b) Impact Response of Hours vs. Share of Asymmetric Technological Change

Figure 32: Response of Hours to Technology Shocks: Low vs. High Share of Asymmetric Technological Change Notes: Fig. 32(a) plots the response of hours to a 1% permanent increase in utilization-adjusted-TFP for countries with low (orange line) and high (dashed green line) variance share attributable to asymmetric technology improvements ('Share of Asym. Tech. Change'). We perform a country-split on the basis of the share of the (unconditional) variance of utilization-adjusted-TFP growth driven by asymmetric technology improvements across sectors which is calculated for each country by using eq. (200). We have eight countries with a share of technological change driven by asymmetric technology improvements lower than 30% (including continental European countries and Japan) and nine countries with a share higher than 30% (including English-speaking and Scandinavian countries). Fig. 32(b) plot the estimated coefficient which includes an interaction term, i.e., $\gamma_{1,0} + \gamma_{2,0} \times \text{asym share}_i$, against the share of the (unconditional) variance of utilization-adjusted-TFP growth driven by asymmetric technology improvements across sectors.



(a) Dynamic Response of Hours: Big vs Small Countries (b) Impact Response of Hours vs. Country's Size (c) Impact Response of Current Account vs. Country's Size

Figure 33: Response of Hours to a Technology Shock: Big vs. Small Countries Notes: 'CA' refers to the current account. Fig. 33(a) contrasts the response of hours to a 1% permanent increase in utilization-adjusted-TFP between small (dashed red line) and large (solid blue line) countries. We split the sample into small (nine) and big (eight) countries by using the median for the working age population. Solid and dashed lines represent point estimates and light (dark) shaded areas represent 90 (68) percent confidence intervals. Vertical axis measures deviation from the pre-shock trend/level in percent. Fig. 33(b) and Fig. 33(c) plot the estimated coefficient which includes an interaction term, i.e., $\gamma_{1,0} + \gamma_{2,0} \times \text{size}_i$, which measures the impact response of hours and the impact response of the current account conditional on the country's size, respectively, against the country'size which is measured by the working age population.

technology improvements are shocks which are associated with innovation (concentrated in traded industries).

In Fig. 32(b), we plot the impact response of hours to a technology shock measured by (on the vertical axis)

$$\frac{\partial x_{i,t}}{\partial \varepsilon^Z_{i,t}} = \gamma_{1,0} + \gamma_{2,0} \times \text{asym share}_i, \tag{201}$$

against the share of asymmetric technological change which is measured by using (200) (horizontal axis). According to our model's predictions, we expect $\gamma_{1,0} + \gamma_{2,0} \times \text{asym share}_i$ to be positive. Intuitively, when technological change is concentrated toward specific industries, this creates a dispersion in technology improvement between sectors. Because asymmetric technology improvements have a positive impact on labor supply, the impact response of hours to a a technology is expected to be increasing in the share of technological change driven by asymmetric technological change. In line with our hypothesis, Fig. 32(b) shows that there exists a strong positive relationship between the response of hours to a technology shock and the share of technological change which is explained by asymmetric technology improvements.

Small vs. big countries. Because we divide quantities by the working age population, each country receives the same weight in the empirical analysis. Therefore, the size of the country does not drive our findings. But small vs. large countries will have a different production structure which shapes the reaction of the current account balance and the response of hours to a technology shock. Because small countries have a production structure which is less diversified and biased toward exports, smaller countries will tend to run smaller current account deficits or a current account surplus and will experience a smaller decline in hours after a technology shock. In Fig. 33(a), we split the sample into two-samples by using the median of the working age population. There are nine small countries and eight large countries. The figure contrasts the response of hours to a 1% permanent increase in utilization-adjusted-TFP between small (dashed red line) and big (solid blue line) countries. In line with our hypothesis, larger countries (blue line) experience a greater decline in hours on impact because mobility costs between sectors are smaller, the substitutability between home- and foreign-produced traded goods is larger and the share of asymmetric technology shocks is lower.

In Fig. 33(b) and Fig. 33(c), we plot the impact response of hours and the impact response of the current account, respectively, to a technology shock (see the vertical axis)

$$\frac{\partial x_{i,t}}{\partial \varepsilon^Z_{i,t}} = \gamma_{1,0} + \gamma_{2,0} \times \text{size}_i, \tag{202}$$

against the country's size(horizontal axis) which is measured by means of the working age population (in % of the total population in our sample). According to our model's predictions, we expect $\gamma_{1,0} + \gamma_{2,0} \times \text{size}_i$ to be increasing in the size of the country for both hours and the current account. Intuitively, countries with a greater size have lower mobility cots, a greater substitutability between home- and foreign-produced traded goods and a smaller value added share of tradables so that the share of asymmetric technological change is smaller. These large countries have greater incentives to borrow from abroad which in turn allow households to further reduce labor supply. In line with our hypothesis, Fig. 33(b) (Fig. 33(c)) shows that there exists a strong negative relationship between the response of hours (the current account) to a technology shock and the country's size.

Do all countries experience a current account deficit? Our sample includes seventeen OECD countries. Among these seventeen OECD countries, using the time series for the current account balance as a percentage of GDP constructed by Lane and Milesi-Ferretti [2007], our sample consists of nine net lenders (such as Germany, Scandinavian countries) and eight net borrowers (such as English-speaking countries) as shown in Fig. 30(a). In line with our model's predictions, countries with low mobility costs across sectors are more likely to borrow from aborad than countries with high mobility costs. When we estimate the response of the current account to our identified technology shock, we find that nine countries borrow from abroad (i.e., experience a current account deficit) and eight countries lend to abroad (i.e., experience a current account surplus).

While in an average OECD economy, a technology shock generates a current account deficit and a decline in hours worked, there are some international differences. Obviously, our sample cannot be viewed as a closed economy on its own, i.e., the sum of the current account surplus of lenders plus the sum of the current account deficits of borrowers won't be equal to zero because Asian countries and oil exporting countries are big lenders to industrialized countries, including the United States.

M Addressing the SVAR Critique

The SVAR methodology allows researchers to estimate the dynamic adjustment of macroeconomic variables conditional on a shock. We run VARs on the actual data and impose identification assumptions to identify a specific shock and trace out the dynamic responses of variables to this shock. Then we calibrate the macroeconomic model and compare the theoretical responses with empirical responses in order to determine which model is more suited to rationalize the SVAR evidence.

The identification of technology shocks by adopting the SVAR methodology has been subject to criticism. As summarized by Dupaigne, Fève, and Matheron [2007], the distortions in a DSVAR may originate from several sources: (i) hours are over-differenced (Erceg, Gust and Guerrieri [2005]) (ii) average labor productivity is a poor proxy for total factor productivity at business cycle frequencies (Chang and Hong [2006]); (iii) the estimation of

DSVARs is subject to small-sample biases, especially with long-run restrictions (see Faust and Leeper [1997]); (iv) a structural VAR with a finite number of lags may poorly approximate the dynamics of DSGE models (Chari, Kehoe and McGrattan [2008]). Whilst SVAR models might be subject to potential biases, nevertheless, the information they produce can effectively complement analyses conducted with dynamic macroeconomic models, help to point out the dimensions where these models fail, and provide stylized facts and predictions which can improve the realism of macroeconomic models.

In this section, we address the SVAR critique. In section M.1, we investigate if our identification of permanent technology improvements is contaminated by non-technology shocks. In section M.2, we conduct a robustness check w.r.t. to the number of lags. In section M.3, we consider alternative measures of technology. In section M.4, we employ the Maximum FEV share approach. In section M.5, we use a two-step procedure proposed by Fève and Guay [2010] to identify technology shocks so that a VAR model with a finite number of lags can more easily approximate the true underlying dynamics of the data. In section M.6, we replace the country-level utilization-adjusted-aggregate-TFP with its world counterpart.

M.1 Are Utilization-Adjusted-Technology Shocks Contaminated by Non-Technology Shocks?

In the lines of Francis and Ramey [2005], we assess below the validity of the technology shocks identified using long-run restrictions by subjecting the model to exogeneity tests.

Mertens and Ravn [2011] find that permanent changes in income tax rates induce permanent changes in hours worked as well as in labor productivity which leads to a violation of the standard long-run identification strategy for technology shocks. The importance of controlling for tax changes was raised earlier by Uhlig [2004] who points out that changes in capital income tax rates may give rise to long-lasting changes in labor productivity, thus leading to a violation of the identifying assumption for technology shocks. Because Gali [1999] uses labor productivity, the shocks identified could include capital income tax rate shocks. As stressed by Francis and Ramey [2005], permanent shifts in government spending have permanent effects on wages, and hours, but not on labor productivity (because the capital-labor ratio remains unaffected). However, as shown by Chaudourne, Fève and Guay [2014], permanent or long-lasting non-technology shocks can contaminate the SVAR identification of technology shocks as they impinge on hours worked and thus on labor productivity.

Because our measure of productivity is utilization-adjusted-TFP, the technology shocks we identified in the main text should not be contaminated by non-technology shocks. The reason is twofold. One advantage of using TFP is that labor productivity is presumably affected in more important ways by business cycle fluctuations than TFP. More specifically, total factor productivity is a measure of technological change purified from changes in the capital labor-ratio. Second, we consider a 'purified' measure of technology as recommended by BKF [2006] and Chaudourne, Fève and Guay [2014] which ensures that technology shocks are less likely to be contaminated by non-technology shocks, such as shocks to taxation, monetary policy and government spending. To confirm this assumption, we closely follow Francis and Ramey [2005].

Exogeneity tests. The identified technology shock should not in principle be correlated with other exogenous non-technology shifts nor with lagged endogenous variables. To investigate whether the identified shows are really technology shocks is to test whether non-technology variables are correlated with the shocks. We consider three types of non-technology shocks: unanticipated temporary changes in taxation, in government spending, and in monetary policy. We identify three types of shocks by considering two different VAR models. Our identification of government spending shocks follows Blanchard and Perotti [2002] and our identification of monetary policy shocks follows from Christiano et al. [2005]. We estimate a Vector Autoregression (VAR) which includes government consumption, real GDP, total hours worked, the real consumption wage, utilization-adjusted aggregate total factor productivity, and the short-term interest rate. For consistency reasons, we adjust the nominal interest rate with foreign prices as foreign goods and services are the numeraire in our model. All quantities are divided by the working age population. All variables enter the VAR model in log level except the interest rate which is in level. Like Blanchard and Perotti [2002], we base the identification scheme on the assumption that there are some delays inherent to the legislative system which prevents government spending from responding endogenously to contemporaneous output developments. We thus order government consumption before the other variables which amounts to adopting the standard Cholesky decomposition pioneered by Blanchard and Perotti [2002]. Like Christiano et al. [2005], we identify monetary policy shocks as the innovation to the federal funds rate under a recursive ordering, with the policy rate ordered last. The ordering of the variables embodies the key identifying assumptions according to which the variables do not respond contemporaneously to a monetary policy shock.

Source: Government final consumption expenditure (CGV), OECD Economic Outlook Database [2017]. The short-term interest rate based on three-month money market rates taken from OECD Economic Outlook Database. The nominal interest rate deflated by the price of foreign goods which is the numeraire in our model and thus we subtract the rate of change of the weighted average of the traded value added deflators of trade partners of the country i from the nominal interest rate denoted by R_{it}.

To identify shocks to tax rates, denoted by ϵ_{it}^{T}, we estimate a VAR model which includes net taxes defined as taxes minus security social benefits paid by general government (deflated using the GDP deflator), real GDP, total hours worked, the real consumption wage, and utilization-adjusted aggregate TFP. Following Blanchard and Perotti [2002], we identify shocks to taxation by assuming that net taxes do not respond within the year to the other variables includes in the VAR model.

Empirical strategy and results. As in the main text, we identify technology shocks by estimating a VAR which includes utilization-adjusted-aggregate-TFP, real GDP, total hours worked, the real consumption wage and identify technology shocks as shocks which increase permanently utilization-adjusted aggregate TFP. We run the regression, in panel format on annual data, of identified technology shocks, ϵ_{it}^{ZA}, on three different structural shocks:

$$\epsilon_{it}^{Z} = d_i + d_t + \beta_G \epsilon_{it}^{G} + \beta_R \epsilon_{it}^{R} + \beta_T \epsilon_{it}^{T} + \nu_{it}. \tag{203}$$

where ν_{it} is an i.i.d. error term; country fixed effects are captured by country dummies, d_i, and common macroeconomic shocks by year dummies, d_t. Note that in estimating eq. (203), we add lagged values (we consider four lags) on non-technology shocks which allow us to take into account for the persistence of non-technology shocks. As detailed in the next section, we consider a 'purified' measure of technology as recommended by BKF [2006] and Chaudourne, Fève and Guay [2014] which ensures that technology shocks are less likely to be contaminated by non-technology shocks. To show this point, we re-estimate the VAR model by replacing utilization-adjusted aggregate TFP with the Solow residual and identify technology shocks as shocks which increase permanent aggregate TFP. As pointed out above, TFP is a better measure than labor productivity to identify technology shocks. To test this statement, we estimate a VAR model which includes labor productivity (calculated as the ratio of real GDP to total hours worked), total hours worked, and the real consumption wage. We omit real GDP which collapses to the product of labor productivity with total hours worked.

If our identification is correct, we should observe that non-technology shocks are correlated with demand shocks or tax shocks. To test this assumption, we run the regression of non-technology shocks which are shocks to real GDP denoted by ϵ_{it}^{YR} on the set of three shocks shown on the RHS of eq. (203) and thus replace ϵ_{it}^{Z} with ϵ_{it}^{YR}.

Panel data estimations are shown in Table 32. We test the null hypothesis that all of the coefficients on explanatory variables are jointly equal to zero. If p-value ≥ 0.05 at a 5% significance level, the variables are not significant in explaining the identified technology shock ϵ_{it}^{Z} or the identified non-technology shock ϵ_{it}^{YR}. The first row of Table 32 runs the regression (203) by considering our baseline measure of technology shocks and two alternative measures based on the Solow residual and labor productivity on the three sets of shocks. The p-value of 0.136 for the F-test shows that none of the variables is significant in explaining our identified technology shocks. By contrast, the p-value is lower than 0.05 for both technology shocks identified on the basis of the Solow residual and labor productivity.

In contrast, we expect non-technology shocks we identify by estimating the VAR model with long-run restrictions to be correlated with the set of non-technology variables. To test this assumption, we run the same regression as above, i.e., eq. (203) where ϵ_{it}^{Z} is replaced with the shock denoted by ϵ_{it}^{YR} which increases permanently real GDP but have no permanent effect on utilization-adjusted TFP. As shown in the second row of Table 32, the p-value is lower than 0.05 which thus reveals that non-technology shocks are correlated with demand shocks and tax shocks.

Table 32: Identified Shocks: Exogeneity Tests

	TFP variable used in the VAR		
p-value for Exogeneity Test	adjusted TFP	Solow residual	Labor productivity
Identified Aggregate Technology Shocks (ϵ_{it}^{Z})	0.136	0.009	0.023
Identified Non-Technology Shocks ($\epsilon_{it}^{Y_R}$)	0.000	0.000	-

Notes: The exogeneity F-test is based on a regression of the identified aggregate technology shock ϵ_{it}^{Z} (shown in the first row) or non-technology shocks ϵ_{it}^{YR} shown in the second row, on fixed effects, time dummies and current and four lags of government spending shocks (ϵ_{it}^{G}), monetary shocks (ϵ_{it}^{R}) and tax shocks (ϵ_{it}^{T}). The null hypothesis is that all of the coefficients on explanatory variables are jointly equal to zero. If p-value ≥ 0.05 at a 5% significance level, the variables are not significant in explaining the identified technology shock ϵ_{it}^{Z} or the identified non-technology shock ϵ_{it}^{YR}.

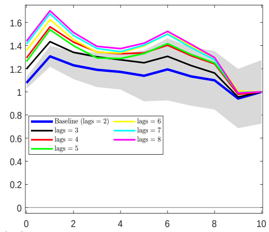
M.2 Robustness Check w.r.t. lags

Erceg, Gust and Guerrieri [2005] find that a four-variable SVAR with four lags (as the authors use quarterly data) performs well in recovering the true responses from DGP. More specifically, the SVAR predicts correctly the sign and the pattern of responses but some empirical IRFs are biased as the SVAR tends to understate the rise in labor productivity and real GDP. The source of bias, called the lag-truncation bias arises because the VAR allows for a limited number of lags which provides an approximation of the true dynamics implied by the model which considers an infinite number of lags. Erceg, Gust and Guerrieri [2005] find that the truncation bias appears negligible for each variable considered by the authors. Thus a short-ordered VAR provides a good approximation of the true dynamics.

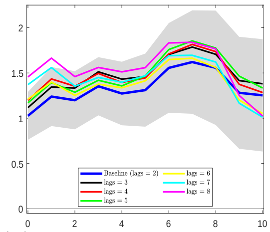
In the baseline VAR model, we consider 2 lags. Because Chari et al. [2008] find that increasing the number of lags implies that empirical IRF is a good approximation of theoretical IRF, as a robustness check, we increase the number of lags from 2 to 8 to estimate all VAR models. Chaudourne, Fève and Gay [2014] also indicate that the bias can be reduced by increasing the number of lags in the DSVAR. De Graeve and Westermark [2013] perform Monte Carlo experiments and find that raising the number of lags may be a viable strategy to reduce the severity of the problem. We document below that the results are robust with respect to using a smaller number of lags.

In Fig. 34, we re-estimate the VAR model of the main text and generate impulse response functions by increasing the number of lags (for both the SVAR and local projections). Note that the SVAR critique focuses on the identification of technology shocks and thus only the number of lags in the VAR model should affect estimation of the response of hours worked. For consistency purposes, we set the same number of lags to estimate local projections.

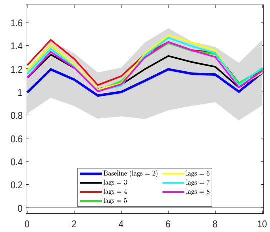
The baseline VAR model which allows for two lags as we use annual data is displayed by the solid blue line. In the black line, we allow for three lags; in the red line, we allow for four lags, in the green line, we allow for five lags; in the yellow line, we allow for six lags; in the cyan line, we allow for seven lags and in the magenta line, we allow for eight lags. Overall, all responses lie within the 90% confidence bounds of the original VAR model. We may notice some quantitative differences. We can notice the decline in non-traded hours worked and thus in total hours is somewhat amplified because the technology improvement is larger on impact. Most importantly, the dynamic adjustment of sectoral variables remains little sensitive to the increase in the number of lags.



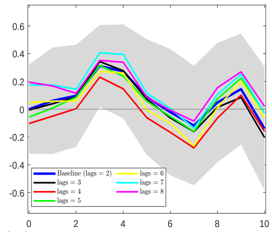
(a) Utilization-Adjusted Aggregate TFP



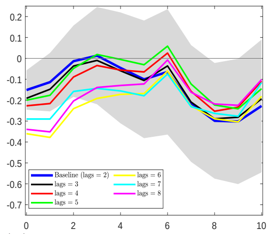
(b) Utilization-Adjusted TFP of Tradables relative to Non-Tradables



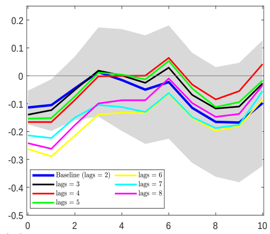
(c) Aggregate TFP



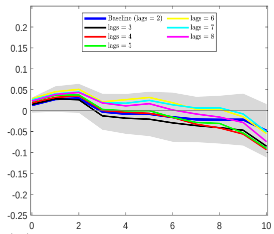
(d) Utilization-Adjusted Aggregate FBTC



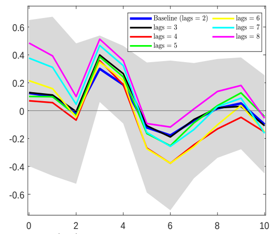
(e) Total Hours Worked



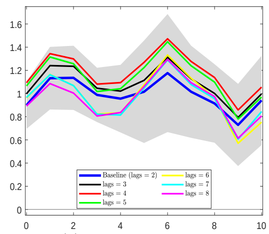
(f) Non-Traded Hours Worked



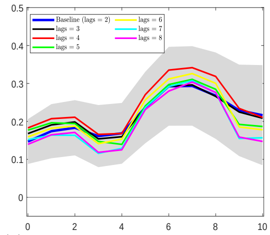
(g) Hours Worked Share of Tradables



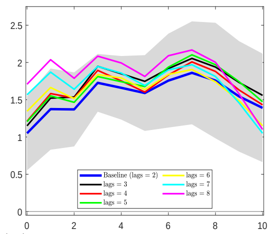
(h) Traded LIS



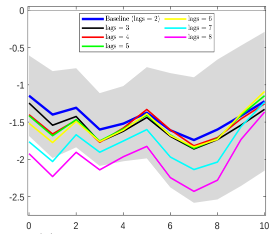
(i) Real GDP



(j) Value Added Share of Tradables



(k) Relative Price of Non-Tradables



(l) Terms of Trade

Figure 34: Labor Market Effects of a Technology Shock: Robustness Check w.r.t. Lags Notes: The solid blue line shows the response of aggregate and sectoral variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. To estimate the dynamic responses to a technology shock, we adopt a two-step method. In the first step, we estimate a VAR model that includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage and the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permnanent increase in utilization-adjusted aggregate TFP. In the second step, we estimate the effects by using Jordà's [2005] single-equation method. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. The baseline VAR model which allows for two lags is displayed by the solid blue line. Whilst in the red line we allow for one lag, in the green line we allow for three lags; in the cyan line, we allow for four lags; in the magenta line, we allow for five lags and in the yellow line, we allow for six lags; in the solid black line, we allow for seven lags and in the dashed black line, we allow for eight lags. Sample. Sample: 17 OECD countries, 1970-2017, annual data.

M.3 Alternative Measures of Utilization-Adjusted-TFP: Basu [1996], BKF [2006], HLPN [2023] vs. Imbs [1999]

'Purified' TFP eliminates biases in estimating the effects of technology shocks. Chaudourne, Fève and Guay [2014] analyze the properties of estimators and IRF to a permanent technology shock when technological change is measured by means of labor productivity, TFP, 'purified' TFP. The authors show that the estimated responses from the DSVAR model are biased in a finite sample if technological change is measured by labor productivity. This bias comes from the fact that both the technology and the non-technology shocks have a permanent effect on labor productivity when hours worked follow a persistent process. The authors also demonstrate that the bias is considerably reduced when the econometrician uses the TFP to measure technological change and the bias is completely eliminated when TFP is purified, i.e., adjusted with factor utilization rate. In addition to eliminating the potential bias in empirical IRFs, Basu, Fernald and Kimball [2006] show that correcting for unobserved input utilization can avoid understating TFP changes when technology improves because utilization falls.

To measure technology, in line with the recommendation of Basu, Fernald and Kimball (BFK henceforth) [2006], we adjust aggregate and sectoral TFPs with the utilization rate. Because time series for utilization-adjusted TFP are only available for the United States at an aggregate level, we have constructed time series for the capital utilization rate for the 17 OECD countries of our sample and at a sectoral level by adopting the methodology proposed by Imbs [1999].

To check whether our purified measure of efficiency reflects technology, we conduct below a robustness check where we use alternative measures to ours and we also propose a set of factors that can rationalize our findings. Note that in contrast to existing methods which 'purify' TFP measure from variations in the utilization rate, our method has two advantages over others: first, we are able to construct time series at a sectoral level in line with our classification T/N for our sample of seventeen OECD countries over 1970-2017 and second we adapt the existing methodology to CES production functions where the labor income share is variable over time.

We conduct a robust check by considering three different approaches. The first approach by BFK [2006] is thinner than ours because the authors construct a measure of aggregate technology change, controlling for varying utilization of capital and labor, non-constant returns to scale, and imperfect competition. HLPN [2023] construct time series for utilization-adjusted TFP for a sample of 29 OECD countries, 30 sectors and up to 37 years (1970-2007). The authors control for the capital utilization rate, the labor utilization rate (or worker's efforts), hours per worker, by adapting the approach initiated by BFK 2006. While the authors allow for non-constant returns to scale, their estimations indicate that returns to scale are close to constant. They show that hours per worker are not always an ideal proxy for unobserved utilization. The third approach by Basu [1996] has the advantage of controlling for unobserved changes in both capital utilization and intensity of worker effort while we control for the intensity in the use of capital only by adapting Imbs's [1999] method. Basu's [1996] approach is based on the ingenious idea that intermediate inputs do not have an extra effort or intensity dimension and thus variations in the use of intermediate inputs relative to measured capital and labor are an index of unmeasured capital and labor input.

Because time series for utilization-adjusted TFP at a sectoral level are not available for the countries in our sample over 1970-2017, we conduct a third robustness check where we construct time series of utilization-adjusted TFP measure at a sectoral level for all OECD countries by adopting the methodology developed by Basu [1996] and we compare the responses of utilization-adjusted TFP based on Basu [1996] methodology with the responses of utilization-adjusted TFP based on Imbs [1999] approach. See Online Appendix Q.3 of Cardi and Restout [2023] who detail the steps of derivation of the utilization rate. Assuming that intermediate inputs and value added are complements implies that the capacity utilization rate can be calculated as follows:

$$\hat{u}_Y^j = \hat{M}^j - s_L^j \hat{L}^j - \left(1 - s_L^j\right) \hat{K}^j, \tag{204}$$

where M^j are intermediate inputs (i.e., intermediate consumption) at constant prices, L^j hours worked, K^j the capital stock at constant prices, s_L^j is the LIS. We use (204) to measure the intensity in the use of capital and labor at a sectoral level (i.e., for each industry) and adjust the Solow residual with this measure to construct time series for the utilization-adjusted TFP in sector $j = H, N$:

$$\hat{Z}^j = \hat{\text{TFP}}^j - \hat{u}_Y^j. \tag{205}$$

Source: Time series for intermediate inputs at constant prices are taken from EU KLEMS. Data coverage: 1970-2017 for 17 OECD countries except for JPN (1973-2017). Table 33 provides the information about data availability for our four measures of utilization-adjusted-TFP.

Table 33: Alternative Meaasures of Technology: Data Availability

	Imbs [1999]	Basu [1996]	HLPN [2023]	BFK [2006]
AUS	1970-2017	1970-2007	1970-2007	1970-2007
AUT	1970-2017	1970-2017	1976-2007	1976-2007
BEL	1970-2017	1970-2017	1970-2006	1970-2006
CAN	1970-2017	1970-2007	1970-2007	1970-2007
DEU	1970-2017	1970-2017	1970-2007	1970-2007
DNK	1970-2017	1970-2017	1970-2007	1970-2007
ESP	1970-2017	1970-2007	1970-2007	1970-2007
FIN	1970-2017	1970-2017	1970-2007	1970-2007
FRA	1970-2017	1970-2017	1970-2007	1970-2007
GBR	1970-2016	1970-2007	1970-2007	1970-2007
IRL	1970-2017	1970-2007	1988-2007	1988-2007
ITA	1970-2017	1970-2017	1970-2007	1970-2007
JPN	1973-2015	1973-2015	1973-2006	1973-2006
NLD	1970-2017	1970-2017	1970-2007	1970-2007
NOR	1970-2017	1970-2017	no data	no data
SWE	1970-2017	1970-2017	1993-2007	1993-2007
USA	1970-2017	1970-2017	1977-2007	1977-2007

Results. Fig. 35 contrasts the effects of a technology shock by considering our baseline measure of technology shown in the blue line where we adjust the TFP with the capital utilization rate constructed by adapting the method proposed by Imbs [1999] and three alternative measures. We have constructed an alternative measure of technology where we adjust the Solow residual with the capacity utilization rate constructed by following the approach proposed by Basu [1996] shown in the yellow line. To further test our approach, we also consider two different time series, i.e., the utilization-adjusted-TFP constructed by Levchenko et al. [2023] shown in the green line, and that constructed by Basu et al. [2006] which is displayed by the brown line. While in the baseline case, we estimate the VAR model with two lags, we alternatively allow for four lags, as displayed by the black line, and eight lags, as displayed by the red line.

The first column shows the dynamic effects of a technology shock on utilization-adjusted-aggregate-TFP, total hours worked, traded hours worked, non-traded hours worked, and the hours worked share of tradables. Overall, a technology improvement produces similar effects across measures of technology. Importantly, the adjustment of utilization-adjusted-aggregate TFP is very close whether we adjust the Solow residual with the capital utilization rate or with alternative methods. We may notice some quantitative differences as alternative measures of technology tend to produce a larger decline in total hours worked and in non-traded hours worked. The second and the third columns show the effects following an asymmetric and a symmetric technology shock. While our measure of technology controls for the intensity in the use of capital only, columns 2 and 3 reveal that the controlling for the both capital and labor utilization rate does not modify the results, as can be see in the yellow line where we consider the Basu's [1996] approach. Increasing the lags tend to produce a larger decline in hours worked following symmetric technology shocks and a

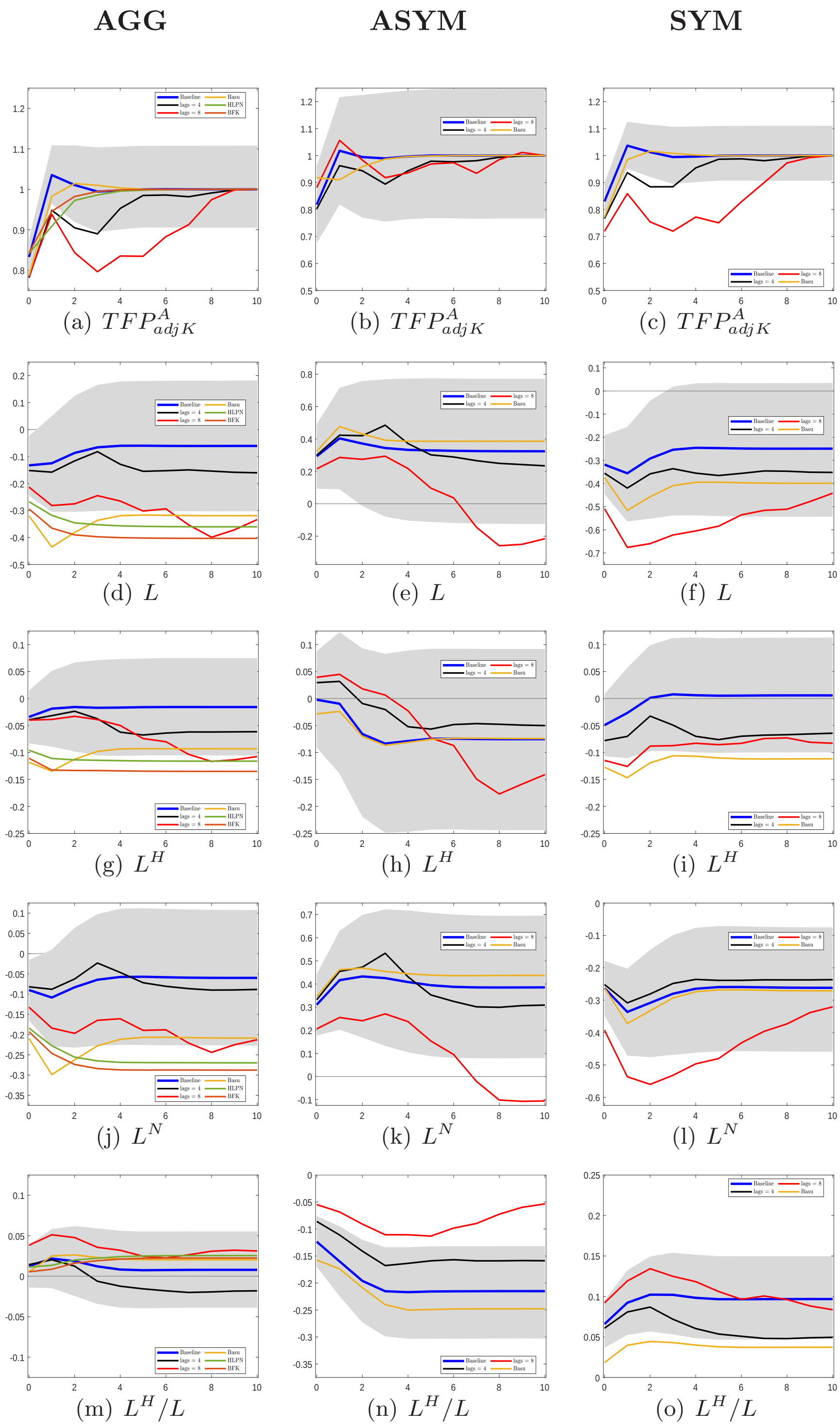


Figure 35: Labor Market Effects of a Technology Shock: Country-Level vs. World Technology Shock Notes: Robustness Check w.r.t. the Measure of Technology Notes: The solid blue line shows the response of aggregate and sectoral variables to an exogenous increase in the country level utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. We estimate a VAR model which includes the country-level utilization-adjusted-aggregate-TFP, total hours worked, traded hours worked, non-traded hours worked, the hours worked share of tradables, all variables entering the VAR model in rate of growth. While in the baseline case, we estimate the VAR model with two lags, we alternatively allow for four lags, as displayed by the black line, and eight lags, as displayed by the red line. Because in our measure of technology, we adjust the Solow residual with the capital utilization rate constructed by adapting the methodology proposed by Imbs [1999], we alternatively adopt the approach of Basu [1996]. The yellow line shows the response of TFP based on the Solow residual adjusted with the time series for the capacity utilization rate by using Basu's [1996] method. To further test our approach, we also consider two different time series, i.e., the utilization-adjusted-TFP constructed by Levchenko et al. [2023] shown in the green line, and that constructed by Basu et al. [2006] which is displayed by the brown line. Sample: 17 OECD countries, 1970-2017, annual data.

smaller in crease in hours worked after asymmetric technology shocks. In conclusion, our results are robust to the measure of technology.

M.4 Max Share Identification

Advantages of Max share over LR identification of technology shocks. One key difference between the empirical and the theoretical model is that the former imposes a small number of lags whilst the latter allows for an infinite number of lags. Erceg, Gust and Guerrieri [2005], Chari et al. [2008] argue that it causes a lag-truncation bias which lead estimated IRFs to be biased, in magnitude for the former and in sign for the latter. Francis et al. [2014] offer an alternative approach to identification with the intent of addressing the aforementioned shortcoming associated with long-run restriction in small-sample estimation. Instead of imposing long-run restrictions, Francis et al. [2014] identify the technology shock by maximizing the forecast error variance share of productivity at long, finite horizons. This method has two major advantages over the standard long-run identification which assumes that the technology shock is the sole contributor of long-run productivity shifts, all other structural innovations having transitory effects on productivity. First, in place of the restriction that the unit root in productivity is driven exclusively by technology, their approach imposes a weaker restriction that the forecast-error variance in productivity at long horizons is dominated by the technology shock. This allows other shocks to influence productivity at finite horizon. Second, the max share approach considers a finite horizon which is more suited to estimate $B_k A_0$ (see section G, eq. (85)). Intuitively, as shown by Uhlig [2004], there is no horizon at which technology shocks alone explain productivity. Thus, neither short-run, medium-run, nor long-run identification will exactly identify the technology shock. He finds however that medium-run identification works better than the other two.

Using data simulated from a RBC model and a standard medium-scale DSGE model with sticky prices, Francis et al. [2014] find that the Max Share approach exhibits less bias (measured by the deviation between the median response and the theoretical response) and less uncertainty (measured by the width of the 68 percent error bands) than the LR approach. In addition to the responses to the shocks, when the authors compare the model-generated and the estimated technology shocks, they find a high correlation (of 0.81) for the Max share shocks with the true shocks generated by RBC and NK models whilst the correlation is lower for technology shocks from the LR model.

Advantages of max share identification. As mentioned in section G where we detail formally the long-run identification of asymmetric technology shocks across sectors, we consider a specification where all variables enter the VAR model in growth rate, we order utilization-adjusted-aggregate-TFP first, and identify technology shocks as shocks that increase permanently utilization-adjusted-aggregate-TFP (at an infinite horizon). We consider below two VAR specifications to estimate the labor effects of a permanent technology improvement. In addition to utilization-adjusted-aggregate-TFP, the baseline VAR model includes real GDP, total hours worked, the real consumption wage, while the alternative VAR model includes traded and non-traded hours worked (all variables in rate of growth).

Instead of imposing long-run restrictions, Francis et al. [2014] identify the technology shock by maximizing the forecast error variance share of productivity at long, finite horizons. In the Max Share identification, all variables including utilization-adjusted-TFP enter the VAR in log levels. As mentioned above, instead of estimating the long-run cumulative matrix $B(1)A_0$, the max share approach amounts to estimating $B_k A_0$ at a finite horizon. The Maximum Forecast Error Variance approach extracts the shock that best explains the FEV at a long but finite horizon of utilization-adjusted-TFP.

LR model vs. Max share: One country at a time. In Fig. 36-39, we generate the empirical responses from the VAR model estimated for one country at a time. We have estimated the same VAR model for the seventeen OECD countries of our sample. The blue line shows responses obtained by imposing LR restrictions to identify asymmetric technology shocks across sectors. The black line shows results when we estimate the aforementioned VAR model and use the max share identification developed by Francis et al. [2014] to estimate the effects of a permanent increase in utilization-adjusted-aggregate-TFP by 1% in the long-run. As it stands out, for almost all countries (except Austria, Belgium, Germany) and almost all variables, the LR model generates empirical responses which lie within the confidence bounds associated with the baseline VAR model estimated with long-run restrictions.

Overall, the responses of hours worked generated by applying the Max share (black line) identification lie within the confidence bounds associated with the LR model (blue line)

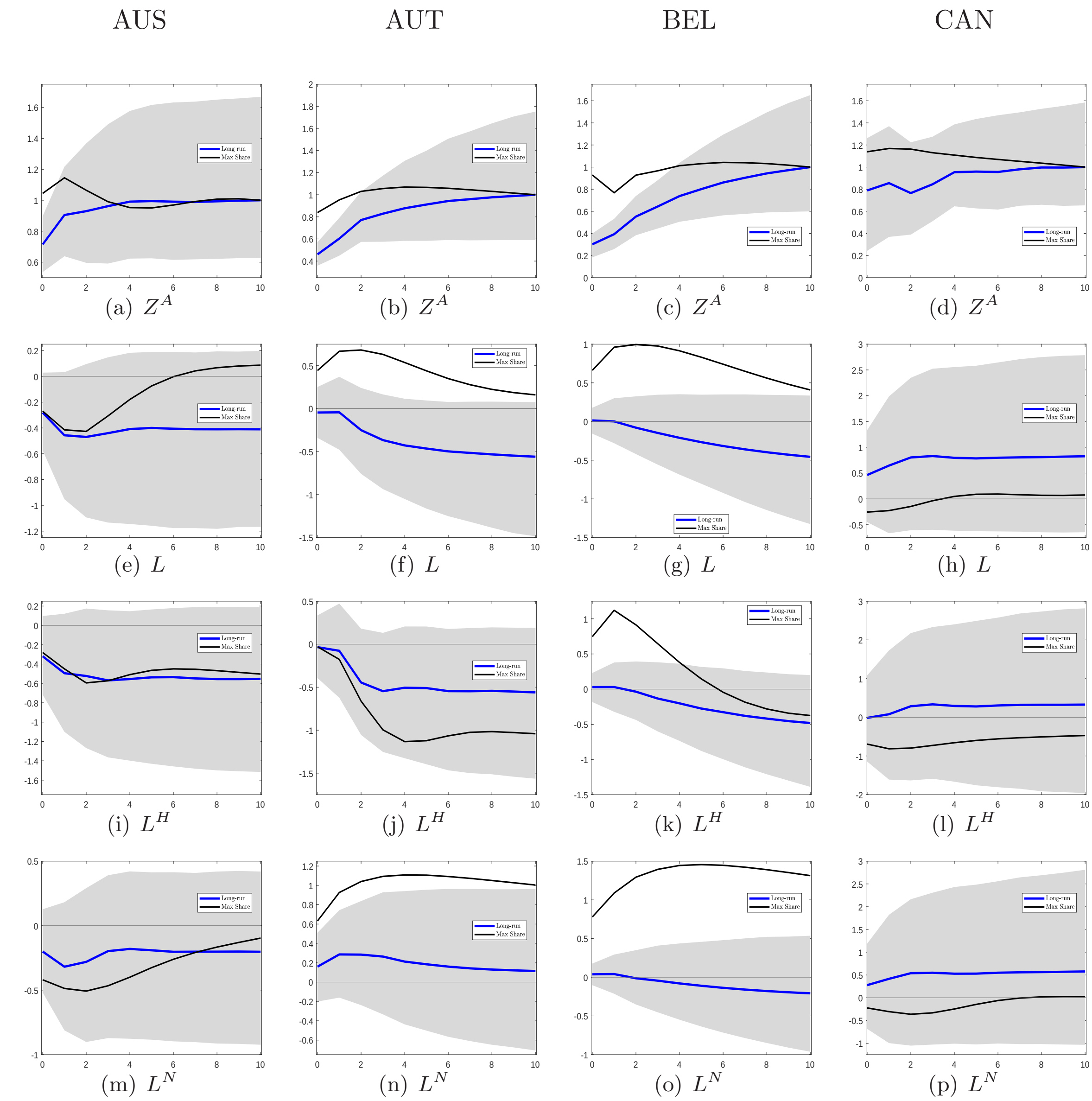


Figure 36: Responses of Hours to a Technology Shock: Max Share (solid black line) vs. Long-Run Restriction (solid blue line) Identification for Australia, Austria, Belgium, Canada. Notes: The solid lines show the responses of aggregate variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent con¯dence bounds obtained by bootstrap sampling. We compare the dynamic effects of two identification methods. In both cases, we estimate a VAR model which includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage. In the baseline shown in the blue line, the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the alternative identification method, we employ the Max Share approach. Instead of imposing long-run restrictions, Francis et al. [2014] identify the technology shock by maximizing the forecast error variance share of productivity at long, finite horizons. In the Max Share identification, all variables including utilization-adjusted aggregate TFP enter the VAR in log levels. The black line shows the median of the responses. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Sample: Australia, Austria, Belgium, Canada, 1970-2017, annual data.

except for three countries (Austria, Belgium, Germany) out of seventeen in our sample. We may notice some quantitative differences however. The LR model generates a gradual increase in utilization-adjusted-TFP while the Max share produces a larger technology improvement on impact. This overshooting may produce a larger increase in traded relative to non-traded technology that would explain why in Austria, Belgium, Germany, non-traded hours worked increases instead of falling or being muted.

LR model vs. Max share: Median estimates. So far, we have compared the responses to technology shocks across countries by considering the Max share (black line) approach and the LR model (blue line). To ease the comparison between the two approaches, it is convenient to compare one single IRF of one variable between the LR model and the Max share identification by considering the median of estimates for both methods. Fig. 40 shows the responses for the VAR model which includes aggregate technology, Z_{it}^A,

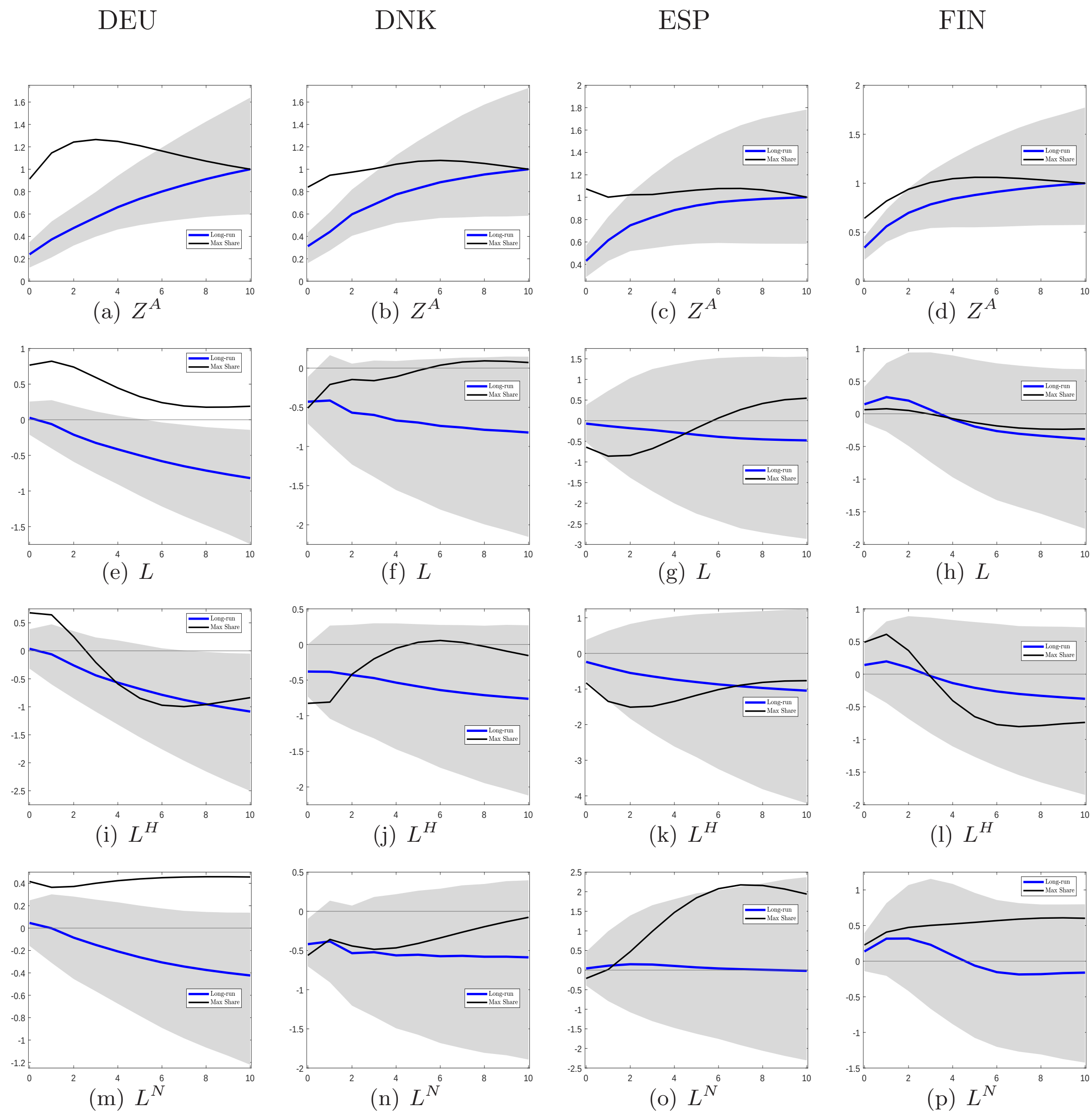


Figure 37: Responses of Hours to a Technology Shock: Max Share (solid black line) vs. Long-Run Restriction (solid blue line) Identification for Germany, Denmark, Spain, Finland.
Notes: The solid lines show the responses of aggregate variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent con¯dence bounds obtained by bootstrap sampling. We compare the dynamic effects of two identification methods. In both cases, we estimate a VAR model which includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage. In the baseline shown in the blue line, the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the alternative identification method, we employ the Max Share approach. Instead of imposing long-run restrictions, Francis et al. [2014] identify the technology shock by maximizing the forecast error variance share of productivity at long, finite horizons. In the Max Share identification, all variables including utilization-adjusted aggregate TFP enter the VAR in log levels. The black line shows the median of the responses. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Sample: Germany, Denmark, Spain, Finland, 1970-2013, annual data.

real GDP, hours worked and the real consumption wage. Overall the responses to the Max share lie within the confidence bounds of the baseline LR model although the Max share predicts a smaller decline in hours on impact and a greater increase in real GDP.

M.5 Two-Step SVARs-Based Procedure to Identify Technology Shocks

Why should hours be removed from the SVAR? Evidence documented by Christiano et al. [2006] from their simulation experiments suggests using other variables than hours worked which are less sensitive to the volatility of non-technology shocks and/or contain a sizeable part of technology shocks. The reason is that they show that when the model is more properly estimated, the standard error of the non-technology shocks is half the standard error of the technology shock. In such a case, the bias in SVARs with labour

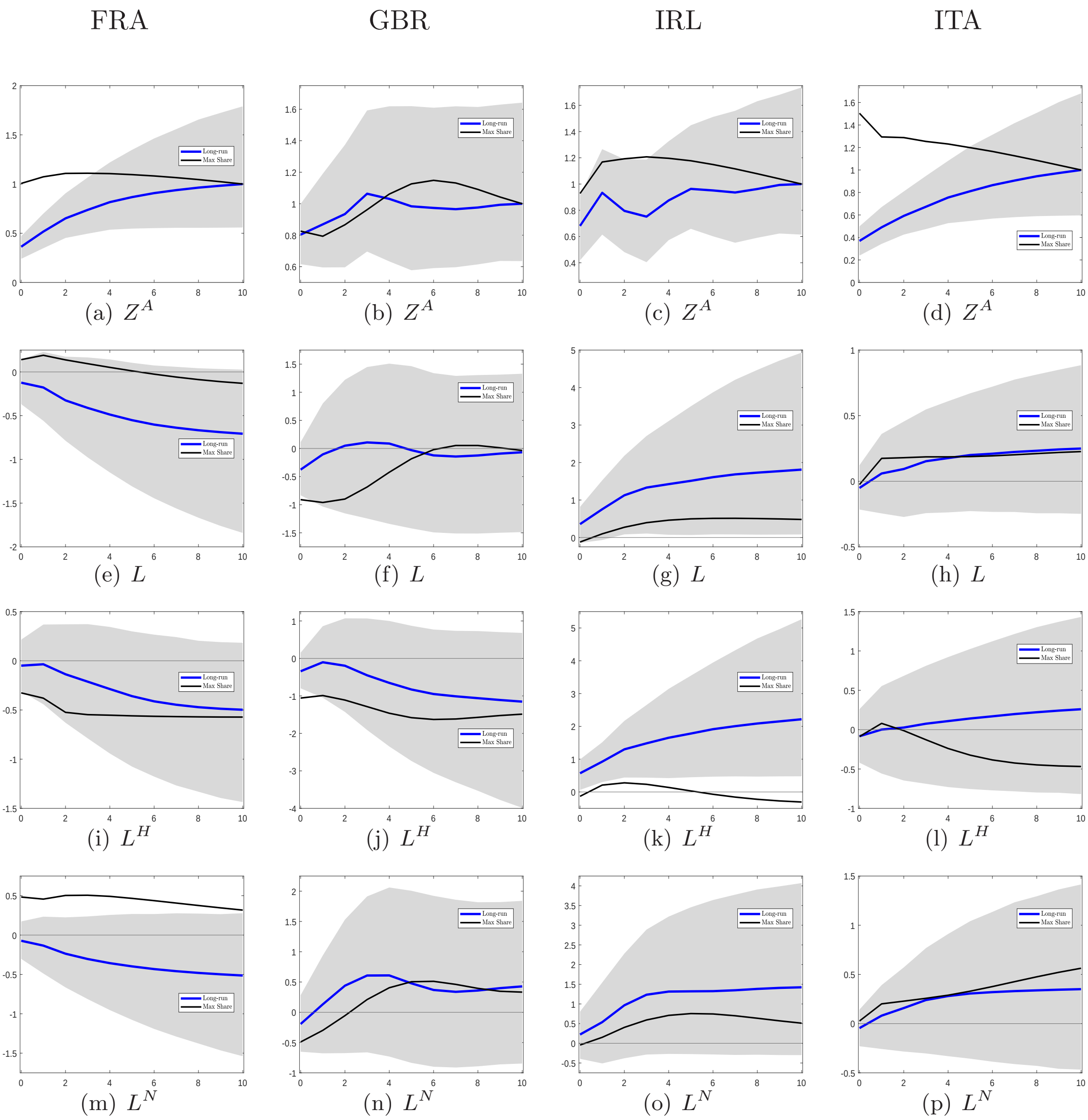


Figure 38: Responses of Hours to a Technology Shock: Max Share (solid black line) vs. Long-Run Restriction (solid blue line) Identification for France, the United Kingdom, Ireland, Italy. Notes: The solid lines show the responses of aggregate variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent con¯dence bounds obtained by bootstrap sampling. We compare the dynamic effects of two identification methods. In both cases, we estimate a VAR model which includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage. In the baseline shown in the blue line, the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the alternative identification method, we employ the Max Share approach. Instead of imposing long-run restrictions, Francis et al. [2014] identify the technology shock by maximizing the forecast error variance share of productivity at long, finite horizons. In the Max Share identification, all variables including utilization-adjusted aggregate TFP enter the VAR in log levels. The black line shows the median of the responses. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Sample: France, the United Kingdom, Ireland, Italy, 1970-2013, annual data.

productivity and hours is strongly reduced. In light of the above findings, Fève and Guay [2010] argue that SVARs can deliver accurate results if more efforts are made over the choice of the stationary variables. More precisely, hours (or other highly persistent variables subject to empirical controversies about their stationarity) must be excluded from SVARs and replaced with any variable which presents better stochastic properties. The introduction of a highly persistent variable as hours worked in the SVARs confounds the identification of the permanent and transitory shocks and thus contaminates the corresponding Impulse Response Functions (IRFs). Following the previously mentioned contributions, the selected variable must satisfy the following stochastic properties. First, the variable must display less controversy over its stationarity. Second, the variable must behave more as a capital (or state) variable than hours worked do, so that a VAR model with a finite number of lags can more easily approximate the true underlying dynamics of the data. Third, the vari-

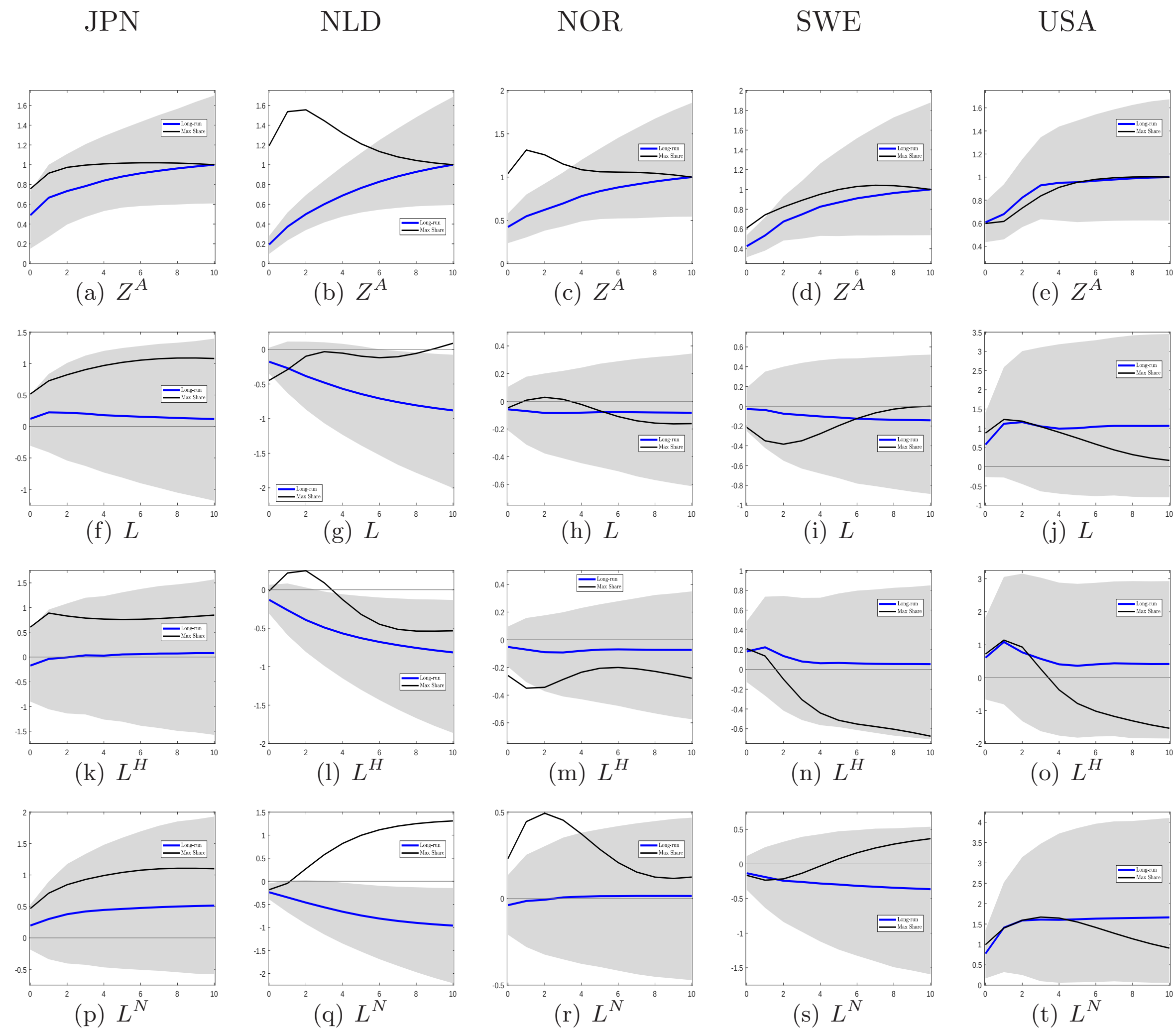
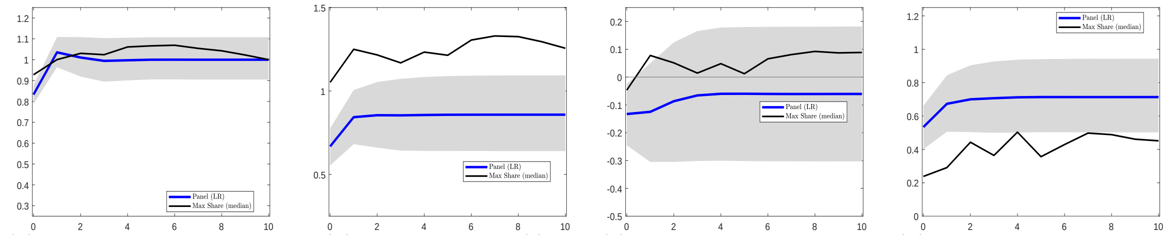


Figure 39: Responses of Hours to a Technology Shock: Max Share (solid black line) vs. Long-Run Restriction (solid blue line) Identification for Japan, the Netherlands, Norway, Sweden, the United States. Notes: The solid lines show the responses of aggregate variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent con¯dence bounds obtained by bootstrap sampling. We compare the dynamic effects of two identification methods. In both cases, we estimate a VAR model which includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage. In the baseline shown in the blue line, the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the alternative identification method, we employ the Max Share approach. Instead of imposing long-run restrictions, Francis et al. [2014] identify the technology shock by maximizing the forecast error variance share of productivity at long, finite horizons. In the Max Share identification, all variables including utilization-adjusted aggregate TFP enter the VAR in log levels. The black line shows the median of the responses. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Sample: Japan, the Netherlands, Norway, Sweden, the United States, 1970-2017, annual data.

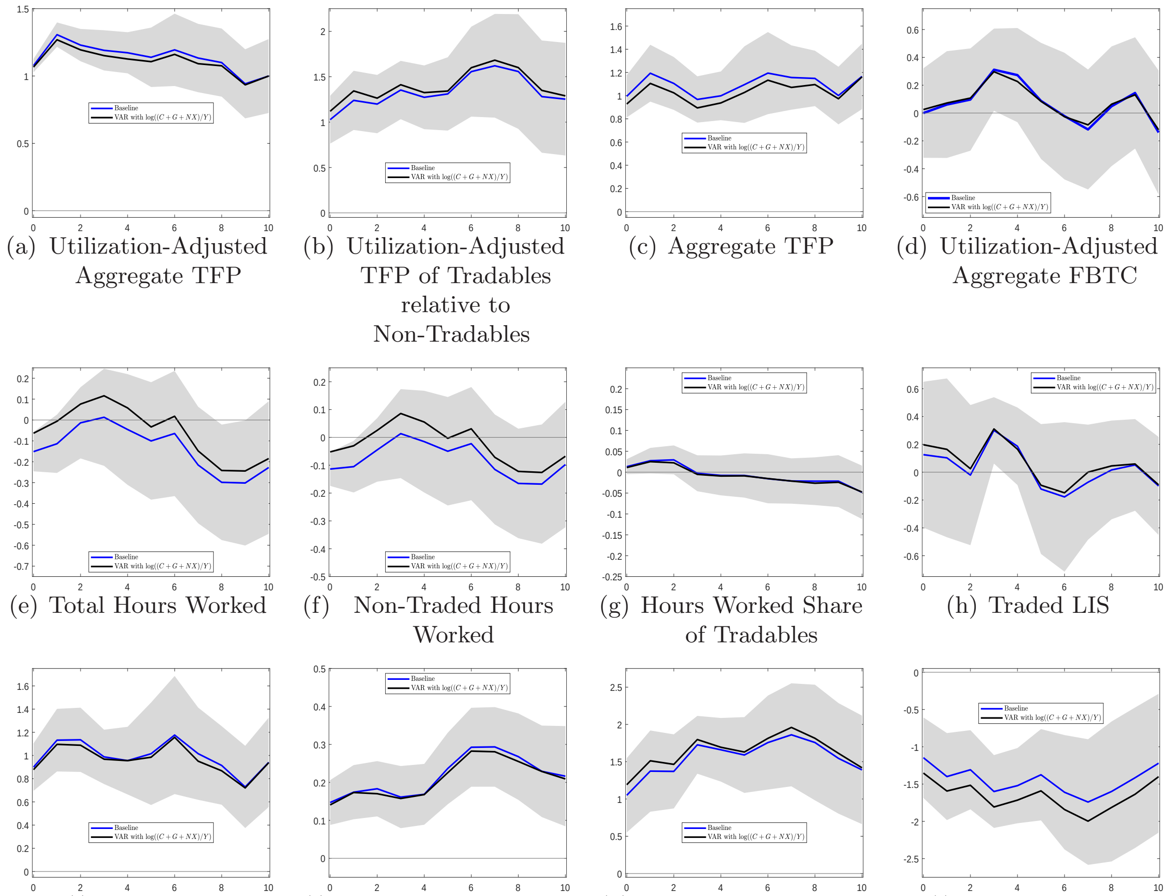
able must contain a sizeable technology component and present less sensitivity to highly persistent non-technology shocks. According to Fève and Guay [2010], the consumption to output ratio (in logs) is a promising candidate for fulfilling these three requirements as it is stationary and consequently displays less persistence than hours worked, it represents a better approximation of the state variables than hours worked and appears less sensitive to transitory shocks.

Two-step approach. The proposed approach by Fève and Guay [2010] consists in two steps. In the first step, a SVAR model which includes utilization adjusted aggregate TFP Z^A_{it} and the consumption to GDP ratio $\omega_{C,it}$ is considered to consistently estimate technology shocks using a long-run restriction. Note that consumption includes both private and government consumption. Because we consider an open economy model, for the purposes of consistency, we augment the broad measure of consumption with net exports which has the advantage to isolate the demand for domestic goods. In the second step, the IRFs of hours (or any other aggregate variable under interest) at different horizons are obtained by a simple (univariate or multivariate) regression of hours on the estimated technology shock.



(a) Utilization-Adjusted Aggregate TFP, $Z^A(t)$ (b) Real GDP, $Y_R(t)$ (c) Total Hours Worked, $L(t)$ (d) Real Consumption Wage, $L(t)$

Figure 40: Labor Market Effects of a Technology Shock: Robustness Check w.r.t. Lags
Notes: The solid lines show the responses of aggregate variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent con¯dence bounds obtained by bootstrap sampling. We compare the dynamic effects of two identification methods. In both cases, we estimate a VAR model which includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage. In the baseline shown in the blue line, the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the alternative identification method, we employ the Max Share approach. Instead of imposing long-run restrictions, Francis et al. [2014] identify the technology shock by maximizing the forecast error variance share of productivity at long, finite horizons. In the Max Share identification, all variables including utilization-adjusted aggregate TFP enter the VAR in log levels. The black line shows the median of the responses. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend. Sample. Sample: 17 OECD countries, 1970-2017, annual data.



(a) Utilization-Adjusted Aggregate TFP (b) Utilization-Adjusted TFP of Tradables relative to Non-Tradables (c) Aggregate TFP (d) Utilization-Adjusted Aggregate FBTC

(e) Total Hours Worked (f) Non-Traded Hours Worked (g) Hours Worked Share of Tradables (h) Traded LIS

(i) Real GDP (j) Value Added Share of Tradables (k) Relative Price of Non-Tradables (l) Terms of Trade

Figure 41: Labor Market Effects of a Technology Shock: Robustness Check w.r.t. Lags Notes: The solid blue line shows the response of aggregate and sectoral variables to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run in the baseline case. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. In the first step, we estimate a VAR model that includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage and the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permnanent increase in utilization-adjusted aggregate TFP. In the second step, we estimate the effects by using Jordà's [2005] single-equation method. Horizontal axes indicate years. In the lines of Fève and Guay [2010], we estimate in the first step a VAR model which includes the measure of technology, i.e., utilization-adjusted aggregate TFP, and real GDP both in log differences and the ratio of the sum of consumption, government spending and net exports to GDP in log level. Results are shown in the black line. Vertical axes measure percentage deviation from trend. Sample. Sample: 17 OECD countries, 1970-2017, annual data.

The VAR we estimate, i.e., $[\hat{Z}^A_{it}, \log \omega_{C,it}]$, includes utilization adjusted aggregate TFP is in growth rate and ω_C is in log as in Blanchard and Quah where they consider a VAR model which includes the rate of change in real GDP and the unemployment rate (which is in level). In Fève and Guay ω_C enters the VAR model in log level (and not in level). In the second step, we estimate the dynamic effects on total hours worked by using local

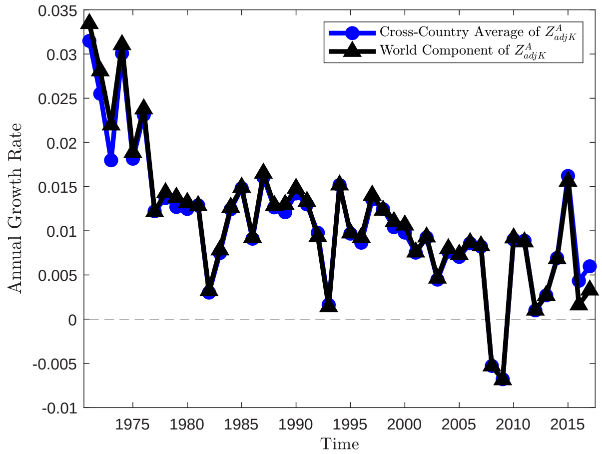


Figure 42: Rate of Growth of the Ratio of World TFP of Tradables Relative to Non-Tradable Notes: We run the regression of the growth rate of TFP in sector j at time t in country i on country and year effects, see eq. (206), and interpret estimated coefficients for time dummies as the rate of growth of sectoral TFP which is common to the seventeen OECD countries of our sample. The solid blue line with circles plots the world productivity growth against time. Alternatively, we calculate a world productivity growth by averaging logged sectoral TFP across countries which is displayed by the black line with triangles. The two measures give similar results. Sample: 17 OECD countries, 1970-2017, annual data.

projection methods.

Fig. 41 reveals that the two-step approach (black line) leads to empirical results which are very close to our baseline estimates shown in the blue line. Because the two-step approach should considerably mitigate the likelihood for technology shocks to be contaminated by long-lasting demand shocks, these results corroborate the robustness of our approach.

M.6 Shock to World TFP

Motivation. In this subsection, we conduct a third empirical test of the robustness of our SVAR results. Because labor productivity growth depends on adjustment of the capital stock which adjusts sluggishly and through this channel non-technology shocks can contaminate the 'true' identification of technology shocks, Dupaigne and Fève [2009] find that each country's average productivity of labor reflect all the shocks in the model, including those which materialize in the other countries.

Because SVARs on country-level data fail to properly disentangle the permanent technology shock common to all countries from the country-specific stationary shocks, Dupaigne and Fève propose to replace the country-level measure of productivity with an aggregate measure of country-level productivity. Because world permanent productivity shocks are not affected by country-specific persistent non-technology shocks, identifying technology shocks by using productivity growth common to all countries can eliminate the problem of identification raised by Erceg, Gust and Guerrieri [2005], Chari, Kehoe and McGrattan [2008]. Dupaigne and Fève [2009] find empirically that when they use the G7 labor productivity instead of country-level labor productivities, there is almost no discrepancy between the responses of employment evaluated at the country and G7 level.

Estimating the importance of the world component for utilization-adjusted-TFP growth. Building on the ingenious idea of Dupaigne and Fève [2009], we replace the country-level utilization-adjusted TFP with the 'world' stock of knowledge. We consider a first measure which has the advantage to reflect the common component of the stock ideas across countries and to allow us to assess the share of aggregate, traded and non-traded technological change driven by the world component. By using the time series for the country-level utilization-adjusted-TFP, we run the regression of the growth rate of utilization-adjusted-TFP in sector j at time t in country i on country and year effects:

$$\hat{Z}^j_{it} = d_i + d_t + \eta_{it}, \tag{206}$$

where d_i captures the country fixed effects, d_t are time dummies, and η_{it} are the i.i.d. error terms. We interpret estimates of time dummies as the growth rate of utilization-adjusted-TFP which is common to the seventeen OECD countries. We denote the world

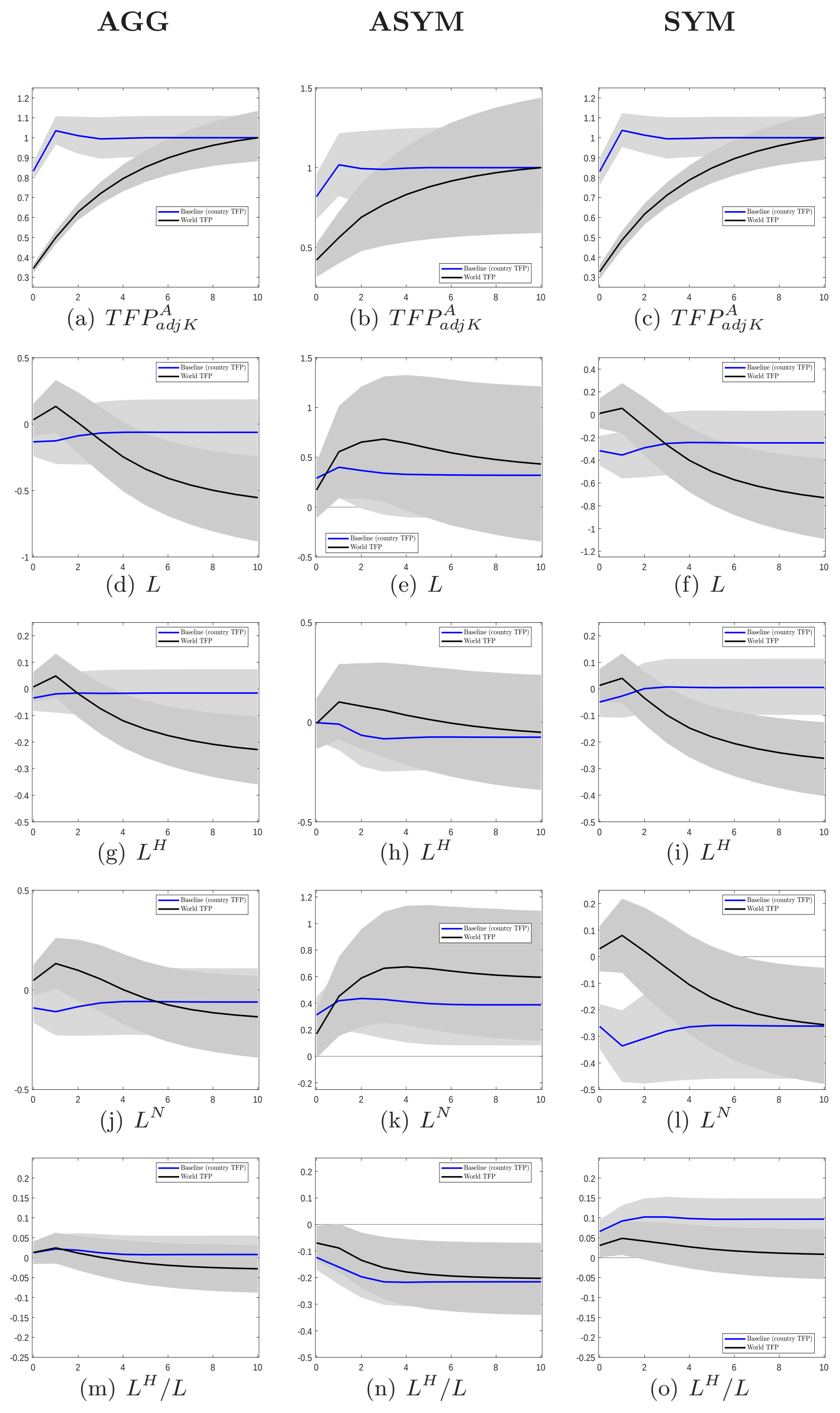


Figure 43: Labor Market Effects of a Technology Shock: Country-Level vs. World Technology Shock Notes: The solid blue line shows the response of aggregate and sectoral variables to an exogenous increase in the country level utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. We estimate a VAR model which includes the country-level utilization-adjusted-aggregate-TFP, total hours worked, traded hours worked, non-traded hours worked, the hours worked share of tradables, all variables entering the VAR model in rate of growth. The black line shows the dynamic effects of hours worked when the country-level utilization-adjusted-aggregate-TFP is replaced with the world component of TFP. The world stock of knowledge or world technology is constructed as an import-share-geometric-weighted-average of TFP of trade partners of country i, i.e., $Z^W_{i,t} = \Pi_{k=1}^{16}\left(Z^A_{k,t}\right)^{\alpha^k_M}$ where $Z_{k,t}$ is the utilization-adjusted-TFP of country i's trade partner (i.e., country k). Sample: 17 OECD countries, 1970-2017, annual data.

Table 34: The Share of Variance of TFP Growth Attributable to World TFP Growth (in %)

	Total Variance (1)	Variance World (2)	Contribution in % World (3)	Country-level (4)	Sub-periods 1970-1992 (5)	1993-2017 (6)
Agg. Technology	0.0043	0.0014	32.2	67.8	0.0015 (35.7%)	0.0013 (37.9%)
H-Technology	0.0125	0.0046	36.9	63.1	0.0041 (36.6%)	0.0060 (49.0%)
N-Technology	0.0032	0.0010	30.5	69.5	0.0015 (34.5%)	0.0006 (32.7%)
H/N Technology	0.0138	0.0052	37.7	62.3	0.0044 (34.7%)	0.0069 (48.6%)

Notes: We run a principal component analysis to extract the common component to all country-level-adjusted-aggregate-TFP growth that we interpret as the world component. In columns 1 and 2, we show the variance of the rate of growth of country-level-adjusted-TFP and its common component, respectively. The figure in columns 3-4 denotes the fraction of the variance of country-level TFP growth attributable to the world component and country-specific component, respectively. In columns 5 and 6, we show the variance of the rate of growth of world adjusted-TFP. Numbers in parentheses denote shares of the country-level-adjusted-TFP. Sample: 17 OECD countries, 1970-2017, annual data.

component of sectoral utilization-adjusted-TFP in sector j by $Z_{it}^{W,j}$ and the world component of utilization-adjusted-aggregate-TFP by Z_{it}^{W}. Fig. 42 plots the world productivity growth in the black line with triangles. In the blue line with circles, we plot the growth rate of utilization-adjusted-aggregate-TFP which is constructed as a cross-country average of country-level utilization-adjusted-TFP growth. Because the blue and the black line are hardly distinguishable, we can conclude that estimating the world component of productivity gives very similar results to averaging utilization-adjusted-TFP.

Contribution of world TFP component to rate of growth of domestic TFP. One interesting question to ask is to what extent the world component of utilization-adjusted-TFP contributes to the rate of growth of the country-level utilization-adjusted-TFP. Column 1 of Table 34 shows the variance of the growth rate of utilization-adjusted-TFP. We consider four measures: utilization-adjusted-aggregate-TFP, utilization-adjusted-traded-TFP, utilization-adjusted-non-traded-TFP and the ratio of traded to non-traded utilization-adjusted-TFP. Column 2 of Table 34 shows the variance of the rate of growth of world utilization-adjusted-TFP. Column 3 gives the contribution of the world component to the rate of growth of the country-level of utilization-adjusted-TFP. The first row reveals that over the period 1970-2017, the common component to the seventeen OECD countries of the rate of growth of aggregate TFP contributes 32% to the rate of growth of the country-level aggregate TFP. As can be seen in the second and third row, as expected, the world component of utilization-adjusted-traded-TFP is larger than the world component of non-traded utilization-adjusted-non-traded-TFP since traded firms are more prone to benefit from international innovations as they are more open to trade and investment more in R&D. Importantly, the analysis over sub-periods reveals that the intensity of traded technology in the world component has increased from 36% to 49%.

Empirical strategy and results. Fig. 43 contrasts the effects of a technology improvement in the baseline scenario where we estimate a VAR model which includes the country-level utilization-adjusted-aggregate-TFP, total hours worked, traded hours worked, non-traded hours worked, the hours worked share of tradables, all variables entering the VAR model in rate of growth. The black line shows the dynamic effects of hours worked when the country-level utilization-adjusted-aggregate-TFP is replaced with the world component of TFP. The world stock of knowledge or world technology is constructed as an import-share-geometric-weighted-average of utilization-adjusted-TFP of trade partners of country i, i.e., $Z_{i,t}^{W} = \Pi_{k=1}^{16}\left(Z_{k,t}^{A}\right)^{\alpha_M^k}$ where $Z_{k,t}$ is the utilization-adjusted-TFP of country i's trade partner. We use this index in running our estimates in order to use the panel SVAR methodology which leads to higher accuracy of estimated values. We may notice a discrepancy in the adjustment of utilization-adjusted-aggregate-TFP. When we use the international stock of knowledge, we find that technology improves gradually. Our interpretation is that taking advantage of existing technologies from abroad might generate adoption technology costs which result in a gradual increase in Z_{it}^{A}.

Overall, world technology shocks do not lower labor on impact. Our interpretation is that world technology shocks are mostly driven by asymmetric technology shocks and symmetric technology shocks play a minor role. As shown in column 2, world technology shocks produce very similar effects to those following country-level technology shocks once we consider asymmetric technology shocks. More specifically, we find that a technology improvement which is concentrated within traded industries generates an increase in non-traded hours worked while traded hours worked are unresponsive, thus leading to a gradual decline in the hours worked share of tradables. As can be seen in the second row of column 2, the response of total hours worked following an asymmetric world technology shock is very similar to that following an asymmetric country-level technology shock. In contrast, the effects of symmetric technology shocks are somewhat different from our baseline when we approximate the stock of knowledge with the international stock of ideas. The reason is that while we impose in the long-run that the ratio of traded to non-traded utilization-adjusted-TFP is fixed, in the short-run, technology improves in the traded relative to the non-traded sector which appreciates the relative price of non-tradables and thus has an expansionary effect non non-traded hours worked on impact. However, when we consider an aggregate technology shock, overall, the discrepancy in the labor market effects are not statistically different when we consider the baseline measure of technology or the international stock of knowledge.

N Semi-Small Open Economy Model

This Appendix puts forward an open economy version of the neoclassical model with tradables and non-tradables, imperfect mobility of labor and capital across sectors, capital adjustment costs, endogenous intensity in the use of physical capital and endogenous terms of trade. This section illustrates in detail the steps we follow in solving this model. We assume that production functions take a Cobb-Douglas form since this economy is the reference model for our calibration as we normalize CES productions by assuming that the initial steady state of the Cobb-Douglas economy is the normalization point.

Households supply labor, L, and must decide on the allocation of total hours worked between the traded sector, L^H, and the non-traded sector, L^N. They consume both traded, C^T, and non-traded goods, C^N. Traded goods are a composite of home-produced traded goods, C^H, and foreign-produced foreign (i.e., imported) goods, C^F. Households also choose investment which is produced using inputs of the traded, J^T, and the non-traded good, J^N. As for consumption, input of the traded good is a composite of home-produced traded goods, J^H, and foreign imported goods, J^F. The numeraire is the foreign good whose price, P^F, is thus normalized to one.

N.1 Households

At each instant of time, the representative household consumes traded and non-traded goods denoted by C^T and C^N, respectively, which are aggregated by means of a CES function:

$$C(t) = \left[\varphi^{\frac{1}{\phi}} \left(C^T(t)\right)^{\frac{\phi-1}{\phi}} + (1-\varphi)^{\frac{1}{\phi}} \left(C^N(t)\right)^{\frac{\phi-1}{\phi}}\right]^{\frac{\phi}{\phi-1}}, \tag{207}$$

where $0 < \varphi < 1$ is the weight of the traded good in the overall consumption bundle and ϕ corresponds to the elasticity of substitution between traded goods and non-traded goods. The index C^T is defined as a CES aggregator of home-produced traded goods, C^H, and foreign-produced traded goods, C^F:

$$C^T(t) = \left[\left(\varphi^H\right)^{\frac{1}{\rho}} \left(C^H(t)\right)^{\frac{\rho-1}{\rho}} + (1-\varphi_H)^{\frac{1}{\rho}} \left(C^F(t)\right)^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}}, \tag{208}$$

where $0 < \varphi_H < 1$ is the weight of the home-produced traded good in the overall traded consumption bundle and ρ corresponds to the elasticity of substitution between home-produced traded goods goods and foreign-produced traded goods.

As in De Cordoba and Kehoe [2000], the investment good is produced using inputs of the traded good and the non-traded good according to a constant-returns-to-scale function which is assumed to take a CES form:

$$J(t) = \left[\iota^{\frac{1}{\phi_J}} \left(J^T(t)\right)^{\frac{\phi_J-1}{\phi_J}} + (1-\iota)^{\frac{1}{\phi_J}} \left(J^N(t)\right)^{\frac{\phi_J-1}{\phi_J}}\right]^{\frac{\phi_J}{\phi_J-1}}, \tag{209}$$

where ι is the weight of the investment traded input ($0 < \iota < 1$) and ϕ_J corresponds to the elasticity of substitution in investment between traded and non-traded inputs. The index J^T is defined as a CES aggregator of home-produced traded inputs, J^H, and foreign-produced traded inputs, J^F:

$$J^T(t) = \left[\left(\iota_H\right)^{\frac{1}{\rho_J}} \left(J^H(t)\right)^{\frac{\rho_J-1}{\rho_J}} + (1-\iota_H)^{\frac{1}{\rho_J}} \left(J^F(t)\right)^{\frac{\rho_J-1}{\rho_J}}\right]^{\frac{\rho_J}{\rho_J-1}}, \tag{210}$$

where $0 < \iota_H < 1$ is the weight of the home-produced traded in input in the overall traded investment bundle and ρ_J corresponds to the elasticity of substitution between home- and foreign-produced traded inputs.

Following Horvath [2000], we assume that hours worked in the traded and the non-traded sectors are aggregated by means of a CES function:

$$L(t) = \left[\vartheta_L^{-1/\epsilon_L} \left(L^H(t)\right)^{\frac{\epsilon_L+1}{\epsilon_L}} + (1-\vartheta_L)^{-1/\epsilon_L} \left(L^N(t)\right)^{\frac{\epsilon_L+1}{\epsilon_L}}\right]^{\frac{\epsilon_L}{\epsilon_L+1}}, \tag{211}$$

where $0 < \vartheta_L < 1$ is the weight of labor supply to the traded sector in the labor index $L(.)$ and ϵ_L measures the ease with which hours worked can be substituted for each other and thereby captures the degree of labor mobility across sectors.

Like labor, we generate imperfect capital mobility by assuming that traded $K^H(t)$ and non-traded $K^N(t)$ capital stock are imperfect substitutes:

$$K(t) = \left[\vartheta_K^{-1/\epsilon_K} \left(K^H(t)\right)^{\frac{\epsilon_K+1}{\epsilon_K}} + (1-\vartheta_K)^{-1/\epsilon_K} \left(K^N(t)\right)^{\frac{\epsilon_K+1}{\epsilon}}\right]^{\frac{\epsilon_K}{\epsilon_K+1}}, \tag{212}$$

where $0 < \vartheta_K < 1$ is the weight of capital supply to the traded sector in the aggregate capital index $K(.)$ and ϵ_K measures the ease with which sectoral capital can be substituted for each other and thereby captures the degree of capital mobility across sectors.

Households choose the level of capital utilization in sector j, denoted by $u^{K,j}(t)$. The capital utilization rate collapses to one at the steady-state. Capital utilization adjustment costs are assumed to be an increasing and convex function of the capital utilization rate:

$$C^{K,j}(t) = \xi_1^j \left(u^{K,j}(t) - 1\right) + \frac{\xi_2^j}{2} \left(u^{K,j}(t) - 1\right)^2. \tag{213}$$

The representative agent is endowed with one unit of time, supplies a fraction $L(t)$ as labor, and consumes the remainder $1 - L(t)$ as leisure. At any instant of time, households derive utility from their consumption and experience disutility from working and maximizes the following objective function:

$$\mathcal{U} = \int_0^\infty \Lambda\left(C(t), L(t)\right) e^{-\beta t} \mathrm{d}t, \tag{214}$$

where $\beta > 0$ is the discount rate and we consider the utility specification proposed by Shimer [2009]:

$$\Lambda\left(C, L\right) \equiv \frac{C^{1-\sigma} V(L)^\sigma - 1}{1-\sigma}, \quad \text{if} \quad \sigma \neq 1, \quad V(L) \equiv \left(1 + (\sigma - 1)\gamma \frac{\sigma_L}{1+\sigma_L} L^{\frac{1+\sigma_L}{\sigma_L}}\right), \tag{215}$$

subject to the flow budget constraint:[14]

$$\begin{aligned} \dot{N}(t) &\quad + P_C(t)C(t) + P_J(t)J(t) + \sum_{j=H,N} P^j(t) C^{K,j}(t) \nu^{K,j}(t) K(t) \\ &= \quad r^\star N(t) + W(t)L(t) + R^K(t)K(t) \sum_{j=H,N} \alpha_K^j(t) u^{K,j}(t) - T(t), \end{aligned} \tag{216}$$

and capital accumulation which evolves as follows:

$$\dot{K}(t) = I(t) - \delta_K K(t), \tag{217}$$

where I is investment and $0 \leq \delta_K < 1$ is a fixed depreciation rate. We assume that capital accumulation is subject to increasing and convex cost of net investment, $I(t) - \delta_K K(t)$:

$$J(t) = I(t) + \frac{\kappa}{2} \left(\frac{I(t)}{K(t)} - \delta_K\right)^2 K(t), \tag{218}$$

Partial derivatives of total investment expenditure are:

$$\frac{\partial J(t)}{\partial I(t)} = 1 + \kappa \left(\frac{I(t)}{K(t)} - \delta_K\right), \tag{219a}$$

$$\frac{\partial J(t)}{\partial K(t)} = -\frac{\kappa}{2} \left(\frac{I(t)}{K(t)} - \delta_K\right) \left(\frac{I(t)}{K(t)} + \delta_K\right). \tag{219b}$$

[14] we denote the share of sectoral capital in the aggregate capital stock by $\nu^{K,j}(t) = K^j(t)/K(t)$ and the capital and labor compensation share in sector $j = H, N$ by $\alpha_K^j(t) = \frac{R^j(t)K^j(t)}{R^K(t)K(t)}$ and $\alpha_L^j(t) = \frac{W^j(t)L^j(t)}{W(t)L(t)}$.

Denoting the co-state variables associated with (216) and (217) by λ and Q', respectively, the first-order conditions characterizing the representative household's optimal plans are:

$$C(t)^{-\sigma}V(t)^{\sigma} = P_C(t)\lambda(t), \tag{220a}$$

$$C(t)^{1-\sigma}V(t)^{\sigma}\gamma L(t)^{\frac{1}{\sigma_L}} = \lambda(t)W(t), \tag{220b}$$

$$Q(t) = P_J(t)\left[1+\kappa\left(\frac{I(t)}{K(t)}-\delta_K\right)\right], \tag{220c}$$

$$\dot{\lambda}(t) = \lambda\left(\beta - r^{\star}\right), \tag{220d}$$

$$\dot{Q}(t) = \left(r^{\star}+\delta_K\right)Q(t) - \left\{\sum_{j=H,N}\alpha_K^j(t)u^{K,j}(t)R^K(t) - \sum_{j=H,N}P^j(t)C^{K,j}(t)\nu^{K,j}(t) - P_J(t)\frac{\partial J(t)}{\partial K(t)}\right\}, \tag{220e}$$

$$\frac{R^j(t)}{P^j(t)} = \xi_1^j + \xi_2^j\left(u^{K,j}(t)-1\right), \quad j = H,N, \tag{220f}$$

and the transversality conditions $\lim_{t\to\infty}\bar{\lambda}N(t)e^{-\beta t}=0$ and $\lim_{t\to\infty}Q(t)K(t)e^{-\beta t}=0$; to derive (220c) and (220e), we used the fact that $Q(t)=Q'(t)/\lambda(t)$. We drop the time index below when it does not cause confusion.

Given the above consumption indices, we can derive appropriate price indices. With respect to the general consumption index, we obtain the consumption-based price index P_C:

$$P_C = \left[\varphi\left(P^T\right)^{1-\phi} + (1-\varphi)\left(P^N\right)^{1-\phi}\right]^{\frac{1}{1-\phi}}, \tag{221}$$

where the price index for traded goods is:

$$P^T = \left[\varphi_H\left(P^H\right)^{1-\rho} + (1-\varphi_H)\right]^{\frac{1}{1-\rho}}. \tag{222}$$

Given the consumption-based price index (221), the representative household has the following demand of traded and non-traded goods:

$$C^T = \varphi\left(\frac{P^T}{P_C}\right)^{-\phi}C, \tag{223a}$$

$$C^N = (1-\varphi)\left(\frac{P^N}{P_C}\right)^{-\phi}C. \tag{223b}$$

Given the price indices (221) and (222), the representative household has the following demand of home-produced traded goods and foreign-produced traded goods:

$$C^H = \varphi\left(\frac{P^T}{P_C}\right)^{-\phi}\varphi_H\left(\frac{P^H}{P^T}\right)^{-\rho}C, \tag{224a}$$

$$C^F = \varphi\left(\frac{P^T}{P_C}\right)^{-\phi}(1-\varphi_H)\left(\frac{1}{P_T}\right)^{-\rho}C. \tag{224b}$$

As will be useful later, the percentage change in the consumption price index is a weighted average of percentage changes in the price of traded and non-traded goods in terms of foreign goods:

$$\hat{P}_C = \alpha_C\hat{P}^T + (1-\alpha_C)\hat{P}^N, \tag{225a}$$

$$\hat{P}^T = \alpha_H\hat{P}^H, \tag{225b}$$

where α_C is the tradable content of overall consumption expenditure and α^H is the home-produced goods content of consumption expenditure on traded goods:

$$\alpha_C = \varphi \left(\frac{P^T}{P_C}\right)^{1-\phi}, \tag{226a}$$

$$1 - \alpha_C = (1-\varphi)\left(\frac{P^N}{P_C}\right)^{1-\phi}, \tag{226b}$$

$$\alpha^H = \varphi_H \left(\frac{P^H}{P^T}\right)^{1-\rho}, \tag{226c}$$

$$1 - \alpha^H = (1-\varphi_H)\left(\frac{1}{P^T}\right)^{1-\rho}. \tag{226d}$$

Given the CES aggregator functions above, we can derive the appropriate price indices for investment. With respect to the general investment index, we obtain the investment-based price index P_J:

$$P_J = \left[\iota \left(P_J^T\right)^{1-\phi_J} + (1-\iota)\left(P^N\right)^{1-\phi_J}\right]^{\frac{1}{1-\phi_J}}, \tag{227}$$

where the price index for traded goods is:

$$P_J^T = \left[\iota^H \left(P^H\right)^{1-\rho_J} + \left(1-\iota^H\right)\right]^{\frac{1}{1-\rho_J}}. \tag{228}$$

Given the investment-based price index (227), we can derive the demand for inputs of the traded good and the non-traded good:

$$J^T = \iota \left(\frac{P_J^T}{P_J}\right)^{-\phi_J} J, \tag{229a}$$

$$J^N = (1-\iota)\left(\frac{P^N}{P_J}\right)^{-\phi_J} J. \tag{229b}$$

Given the price indices (227) and (228), we can derive the demand for inputs of home-produced traded goods and foreign-produced traded goods:

$$J^H = \iota \left(\frac{P_J^T}{P_J}\right)^{-\phi_J} \iota^H \left(\frac{P^H}{P_J^T}\right)^{-\rho_J} J, \tag{230a}$$

$$J^F = \iota \left(\frac{P_J^T}{P_J}\right)^{-\phi_J} \left(1-\iota^H\right)\left(\frac{1}{P_J^T}\right)^{-\rho_J} J. \tag{230b}$$

As will be useful later, the percentage change in the investment price index is a weighted average of percentage changes in the price of traded and non-traded inputs in terms of foreign inputs:

$$\hat{P}_J = \alpha_J \hat{P}_J^T + (1-\alpha_J)\hat{P}^N, \tag{231a}$$

$$\hat{P}_J^T = \alpha_J^H \hat{P}^H, \tag{231b}$$

where α_J is the tradable content of overall investment expenditure and α_J^H is the home-produced goods content of investment expenditure on traded goods:

$$\alpha_J = \iota \left(\frac{P_J^T}{P_J}\right)^{1-\phi_J}, \tag{232a}$$

$$1-\alpha_J = (1-\iota)\left(\frac{P^N}{P_J}\right)^{1-\phi_J}, \tag{232b}$$

$$\alpha_J^H = \iota^H \left(\frac{P^H}{P_J^T}\right)^{1-\rho_J}, \tag{232c}$$

$$1-\alpha_J^H = \left(1-\iota^H\right)\left(\frac{1}{P_J^T}\right)^{1-\rho_J}. \tag{232d}$$

The aggregate wage index, W, associated with the labor index defined above (211) is:

$$W = \left[\vartheta_L \left(W^H\right)^{\epsilon_L+1} + (1-\vartheta_L)\left(W^N\right)^{\epsilon_L+1}\right]^{\frac{1}{\epsilon_L+1}}, \tag{233}$$

where W^H and W^N are wages paid in the traded and the non-traded sectors, respectively. The aggregate capital rental rate, R, associated with the aggregate capital index defined above (212) is:

$$R = \left[\vartheta_K \left(R^H\right)^{\epsilon_K+1} + (1-\vartheta_K)\left(R^N\right)^{\epsilon_K+1}\right]^{\frac{1}{\epsilon_K+1}}, \tag{234}$$

where R^H and R^N are capital rental rates paid in the traded and the non-traded sectors, respectively.

Given the aggregate wage index and the aggregate capital rental rate, the allocation of aggregate labor supply and the aggregate capital stock to the traded and the non-traded sector reads:

$$L^H = \vartheta_L \left(\frac{W^H}{W}\right)^{\epsilon_L} L, \quad L^N = (1-\vartheta_L)\left(\frac{W^N}{W}\right)^{\epsilon_L} L, \tag{235a}$$

$$K^H = \vartheta_K \left(\frac{R^H}{R}\right)^{\epsilon_K} K, \quad K^N = (1-\vartheta_K)\left(\frac{R^N}{R}\right)^{\epsilon_K} K, \tag{235b}$$

As will be useful later, the percentage change in the aggregate return index on labor and capital is a weighted average of percentage changes in sectoral wages and sectoral capital rental rates:

$$\hat{W} = \alpha_L \hat{W}^H + (1-\alpha_L)\hat{W}^N, \quad \hat{R} = \alpha_K \hat{R}^H + (1-\alpha_K)\hat{R}^N, \tag{236}$$

where α_L and α_K are the tradable content of aggregate labor and capital compensation:

$$\alpha_L = \vartheta_L \left(\frac{W^H}{W}\right)^{1+\epsilon_L}, \quad 1-\alpha_L = (1-\vartheta_L)\left(\frac{W^N}{W}\right)^{1+\epsilon_L}, \tag{237a}$$

$$\alpha_K = \vartheta_K \left(\frac{R^H}{R}\right)^{1+\epsilon_K}, \quad 1-\alpha_K = (1-\vartheta_K)\left(\frac{R^N}{R}\right)^{1+\epsilon_K}. \tag{237b}$$

N.2 Firms

Both the traded and non-traded sectors use physical capital, $\tilde{K}^j = u^{K,j}K^j$, and labor, L^j, according to constant returns to scale production functions $Y^j = Z^j F^j\left(\tilde{K}^j, L^j\right)$ which are assumed to take a Cobb-Douglas form:

$$Y^j = Z^j \left(L^j\right)^{\theta^j}\left(\tilde{K}^j\right)^{1-\theta^j}, \quad j = H, N \tag{238}$$

where θ^j is the labor income share in sector j and Z^j corresponds to the total factor productivity. Both sectors face two cost components: a capital rental cost equal to R^j, and a labor cost equal to the wage rate, i.e., W^j.

Both sectors are assumed to be perfectly competitive and thus choose capital and labor by taking prices as given:

$$\max_{\tilde{K}^j, L^j} \Pi^j = \max_{\tilde{K}^j, L^j} \left\{P^j Y^j - W^j L^j - R^j \tilde{K}^j\right\}. \tag{239}$$

Since capital can move freely between the two sectors, the value of marginal products in the traded and non-traded sectors equalizes while costly labor and capital mobility implies a capital rental rate and wage rate differential across sectors:

$$P^j Z^j \left(1-\theta^j\right)\left(L^j\right)^{\theta^j}\left(\tilde{K}^j\right)^{-\theta^j} = R^j, \tag{240a}$$

$$P^j Z^j \theta^j \left(L^j\right)^{1-\theta^j}\left(\tilde{K}^j\right)^{1-\theta^j} = W^j. \tag{240b}$$

N.3 Short-Run Solutions

Consumption and Labor

Before linearizing, we have to determine short-run solutions. Totally differentiating first-order conditions (220a) and (220b), i.e., $\Lambda_C = \bar{\lambda} P_C$ and $-\Lambda_L = \bar{\lambda} W$, respectively, leads to:

$$\frac{\Lambda_{CC}}{\Lambda_C} dC + \frac{\Lambda_{CL}}{\Lambda_C} dL = \frac{d\bar{\lambda}}{\bar{\lambda}} + \frac{\alpha_C \alpha^H}{P^H} dP^H + \frac{(1-\alpha_C)}{P^N} dP^N, \tag{241a}$$

$$\frac{\Lambda_{LC}}{\Lambda_C} dC + \frac{\Lambda_{LL}}{\Lambda_C} dL = \frac{d\bar{\lambda}}{\bar{\lambda}} + \alpha_L \frac{dW^H}{W^H} + (1-\alpha_L) \frac{dW^N}{W^N} \tag{241b}$$

where we used (236) and (225). By applying the implicit functions theorem, (220a) and (220b) can be solved for consumption and aggregate labor supply which of course must hold at any point of time:

$$C = C\left(\bar{\lambda}, P^N, P^H, W^H, W^N\right), \quad L = L\left(\bar{\lambda}, P^N, P^H, W^H, W^N\right). \tag{242}$$

Inserting first the solution for consumption (242) into (223a)-(224b) allows us to solve for C^g (with $g = H, N, F$)

$$C^g = C^g\left(\bar{\lambda}, P^N, P^H, W^H, W^N\right), \tag{243}$$

where we used the fact that

$$\hat{C}^N = -\phi \alpha_C \hat{P}^N + \phi \alpha_C \alpha^H \hat{P}^H + \hat{C}, \tag{244a}$$

$$\hat{C}^H = -\left[\rho\left(1-\alpha^H\right) + \phi\left(1-\alpha_C\right)\alpha^H\right] \hat{P}^H + \left(1-\alpha_C\right)\phi \hat{P}^N + \hat{C}, \tag{244b}$$

$$\hat{C}^F = \alpha^H \left[\rho - \phi\left(1-\alpha_C\right)\right] \hat{P}^H + \left(1-\alpha_C\right)\phi \hat{P}^N + \hat{C}. \tag{244c}$$

Inserting first the solution for labor (242) into (235a) allows us to solve for L^j (with $j = H, N$):

$$L^j = L^j\left(\bar{\lambda}, P^N, P^H, W^H, W^N\right), \tag{245}$$

with partial derivatives given by:

$$\hat{L}^H = \epsilon_L \left(1-\alpha_L\right) \hat{W}^H - \left(1-\alpha_L\right) \epsilon_L \hat{W}^N + \hat{L}, \tag{246a}$$

$$\hat{L}^N = \epsilon_L \alpha_L \hat{W}^N - \alpha_L \epsilon_L \hat{W}^H + \hat{L}. \tag{246b}$$

The decision to allocate capital between to the traded and the non-traded sectors (235b) allows us to solve for K^H and K^N:

$$K^H = K^H\left(K, R^H, R^N\right), \quad K^N = K^N\left(K, R^H, R^N\right), \tag{247}$$

with partial derivatives given by:

$$\hat{K}^H = \epsilon_K \left(1-\alpha_K\right) \hat{R}^H - \left(1-\alpha_K\right) \epsilon_K \hat{R}^N + \hat{K}, \tag{248a}$$

$$\hat{K}^N = \epsilon_K \alpha_K \hat{R}^N - \alpha_K \epsilon_K \hat{R}^H + \hat{K}. \tag{248b}$$

Sectoral Wages and Sectoral Capital Rental Rates

Plugging the short-run solutions for L^H, L^N, K^H, K^N, given by (245)-(247) into the demand for capital and labor (240a)-(240b), the system of four equations can be solved for sectoral wages W^j and sectoral capital rental rates R^j. Log-differentiating (240a)-(240b) yields in matrix form:

$$\begin{pmatrix} -\left[\left(1-\theta^H\right)\frac{L^H_{W^H}}{L^H}+\frac{1}{W^H}\right] & -\left(1-\theta^H\right)\frac{L^H_{W^N}}{L^H} & \left(1-\theta^H\right)\frac{K^H_{R^H}}{K^H} & \left(1-\theta^H\right)\frac{K^H_{R^N}}{K^H} \\ -\left(1-\theta^N\right)\frac{L^N_{W^N}}{L^N} & -\left[\left(1-\theta^N\right)\frac{L^N_{W^N}}{L^N}+\frac{1}{W^N}\right] & \left(1-\theta^N\right)\frac{K^N_{R^H}}{K^N} & \left(1-\theta^N\right)\frac{K^N_{R^N}}{K^N} \\ \theta^H\frac{L^H_{W^H}}{L^H} & \theta^H\frac{L^H_{W^N}}{L^H} & -\left[\theta^H\frac{K^H_{R^H}}{K^H}+\frac{1}{R^H}\right] & \theta^H\frac{K^H_{R^N}}{K^H} \\ \theta^N\frac{L^N_{W^H}}{L^N} & \theta^N\frac{L^N_{W^N}}{L^N} & \theta^N\frac{K^N_{R^H}}{K^N} & -\left[\theta^N\frac{K^N_{R^N}}{K^N}+\frac{1}{R^N}\right] \end{pmatrix}$$
$$\times\begin{pmatrix} dW^H \\ dW^N \\ dR^H \\ dR^N \end{pmatrix}$$
$$= \begin{pmatrix} \left(1-\theta^H\right)\frac{L^H_{P^N}}{L^H}dP^N+\left[\left(1-\theta^H\right)\frac{L^H_{P^H}}{L^H}-\frac{1}{P^H}\right]dP^H-\left(1-\theta^H\right)\frac{K^H_K}{K^H}dK-\hat{Z}^H-\left(1-\theta^H\right)du^{K,H} \\ \left[\left(1-\theta^N\right)\frac{L^N_{P^N}}{L^N}-\frac{1}{P^N}\right]dP^N+\left(1-\theta^N\right)\frac{L^N_{P^H}}{L^N}dP^H-\left(1-\theta^N\right)\frac{K^N_K}{K^N}dK-\hat{Z}^N-\left(1-\theta^N\right)du^{K,N} \\ -\theta^H\frac{L^H_{P^H}}{L^H}dP^N-\left[\theta^H\frac{L^H_{P^H}}{L^H}+\frac{1}{P^H}\right]dP^H+\theta^H\frac{K^H_K}{K^H}dK-\hat{Z}^H+\theta^H du^{K,H} \\ -\left[\theta^N\frac{L^N_{P^N}}{L^N}+\frac{1}{P^N}\right]dP^N-\theta^N\frac{L^N_{P^H}}{L^N}dP^H+\theta^N\frac{K^N_K}{K^N}dK-\hat{Z}^N+\theta^N du^{K,N} \end{pmatrix} \quad (249)$$

The short-run solutions for sectoral wages and sectoral capital rental rates are:

$$W^j = W^j\left(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N, u^{K,H}, u^{K,N}\right), \quad R^j = R^j\left(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N, u^{K,H}, u^{K,N}\right). \quad (250)$$

Inserting first sectoral wages and capital rental rates (250) into intermediate solutions for sectoral hours worked (245) and sector capital capital (247), these equations can be solved as functions of the aggregate capital stock, the price of non-traded goods in terms of foreign goods, P^N, the terms of trade, and the sectoral capital utilization rates:

$$L^j = L^j\left(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N, u^{K,H}, u^{K,N}\right), \quad K^j = K^j\left(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N, u^{K,H}, u^{K,N}\right), \quad (251)$$

Finally, plugging solutions for sectoral labor (251) and sector capital-labor ratios (250), production functions (238) can be solved for sectoral value added:

$$Y^j = Y^j\left(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N, u^{K,H}, u^{K,N}\right). \quad (252)$$

Capital Utilization Rates, $u^{K,j}(t)$

Inserting firm's optimal decision for capital (240a) in sector j in the optimal intensity in the use of physical capital (220f) leads to:

$$\frac{R^j(t)}{P^j(t)} = \xi^j_1 + \xi^j_2\left(u^{K,j}(t)-1\right) = Z^j(t)\left(1-\theta^j\right)\left(L^j(t)\right)^{\theta^j}\left(\tilde{K}^j(t)\right)^{-\theta^j}. \quad (253)$$

Inserting intermediate solutions (251) for sectoral hours worked and sectoral capital into (253) and log-differentiating leads to in a matrix form:

$$\begin{pmatrix} \left[\frac{\xi^H_2}{\xi^H_1}+\theta^H+\theta^H\frac{K^H_{u^{K,H}}}{K^H}\right]-\theta^H\frac{L^H_{u^{K,H}}}{L^H} & \theta^H\frac{K^H_{u^{K,N}}}{K^H}-\theta^H\frac{L^H_{u^{K,N}}}{L^H} \\ \theta^N\frac{K^N_{u^{K,H}}}{K^N}-\theta^N\frac{L^N_{u^{K,H}}}{L^N} & \left[\frac{\xi^N_2}{\xi^N_1}+\theta^N+\theta^N\frac{K^N_{u^{K,N}}}{K^N}\right]-\theta^N\frac{L^N_{u^{K,N}}}{L^N} \end{pmatrix}\begin{pmatrix} \hat{u}^{K,H} \\ \hat{u}^{K,N} \end{pmatrix}$$
$$= \begin{pmatrix} \left[\theta^H\frac{L^H_X}{L^H}-\theta^H\frac{K^H_X}{K^H}\right]dX+\hat{Z}^H \\ \left[\theta^N\frac{L^N_X}{L^N}-\theta^N\frac{K^N_X}{K^N}\right]dX+\hat{Z}^N \end{pmatrix}, \quad (254)$$

where $X = K, P^H, P^N, Z^H, Z^N$

The short-run solutions for capital utilization rates are:

$$u^{K,j} = u^{K,j}\left(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N\right). \tag{255}$$

Intermediate Solutions for R^j, W^j, K^j, L^j, Y^j

Plugging back solutions for the capital utilization rates (255) into the intermediate solutions for the sectoral wage rates and the capital rental rates (250), for sectoral hours worked and sectoral capital stocks (251), and for sectoral value added (252) leads to intermediate solutions for sectoral wages, sectoral capital rental rates, sectoral hours worked, sectoral capital stocks, sectoral value added:

$$W^j, R^j, L^j, K^j, Y^j\left(\bar{\lambda}, K, P^N, P^H, Z^H, Z^N\right). \tag{256}$$

Optimal Investment Decision, I/K

Eq. (220c) can be solved for the investment rate:

$$\frac{I}{K} = v\left(\frac{Q}{P_I\left(P^T, P^N\right)}\right) + \delta_K, \tag{257}$$

where

$$v\left(.\right) = \frac{1}{\kappa}\left(\frac{Q}{P_J} - 1\right), \tag{258}$$

with

$$v_Q = \frac{\partial v(.)}{\partial Q} = \frac{1}{\kappa}\frac{1}{P_J} > 0, \tag{259a}$$

$$v_{P^H} = \frac{\partial v(.)}{\partial P^H} = -\frac{1}{\kappa}\frac{Q}{P_J}\frac{\alpha_J \alpha_J^H}{P^H} < 0, \tag{259b}$$

$$v_{P^N} = \frac{\partial v(.)}{\partial P^N} = -\frac{1}{\kappa}\frac{Q}{P_J}\frac{\left(1-\alpha_J\right)}{P^N} < 0. \tag{259c}$$

Inserting (257) into (218), investment including capital installation costs can be rewritten as follows:

$$\begin{aligned} J &= K\left[\frac{I}{K} + \frac{\kappa}{2}\left(\frac{I}{K} - \delta_K\right)^2\right], \\ &= K\left[v(.) + \delta_K + \frac{\kappa}{2}\left(v(.)\right)^2\right]. \end{aligned} \tag{260}$$

Eq. (260) can be solved for investment including capital installation costs:

$$J = J\left(K, Q, P^N, P^H\right), \tag{261}$$

where

$$J_K = \frac{\partial J}{\partial K} = \frac{J}{K}, \tag{262a}$$

$$J_X = \frac{\partial J}{\partial X} = \kappa v_X\left(1 + \kappa v(.)\right) > 0, \tag{262b}$$

with $X = Q, P^H, P^N$.

Substituting (261) into (229b), (230a), and (230b) allows us to solve for the demand of non-traded, home-produced traded, and foreign inputs:

$$J^N = J^N\left(K, Q, P^N, P^H\right), \quad J^H = J^H\left(K, Q, P^N, P^H\right), \quad J^F = J^F\left(K, Q, P^N, P^H\right), \tag{263}$$

with partial derivatives given by

$$\hat{J}^N = -\alpha_J\phi_J\hat{P}^N + \phi_J\alpha_J\alpha_J^H\hat{P}^H + \hat{J}, \tag{264a}$$

$$\hat{J}^H = -\left[\rho_J\left(1-\alpha_J^H\right) + \alpha_J^H\phi_J\left(1-\alpha_J\right)\right]\hat{P}^H + \phi_J\left(1-\alpha_J\right)\hat{P}^N + \hat{J}, \tag{264b}$$

$$\hat{J}^F = \alpha_J^H\left[\rho_J - \phi_J\left(1-\alpha_J\right)\right]\hat{P}^H + \phi_J\left(1-\alpha_J\right)\hat{P}^N + \hat{J}, \tag{264c}$$

where

$$\begin{aligned} \hat{J} &= \hat{K} + \frac{Q}{P_J}\frac{\left(1+\kappa v(.)\right)}{J}\hat{Q} - \frac{Q}{P_J}\frac{\left(1+\kappa v(.)\right)}{J}\left(1-\alpha_J\right)\hat{P}^N \\ &\quad -\alpha_J\alpha_J^H\frac{Q}{P_J}\frac{\left(1+\kappa v(.)\right)}{J}\hat{P}^H. \end{aligned}$$

N.4 Market Clearing Conditions

Finally, we have to solve for non-traded good prices and the terms of trade. The role of the price of non-traded goods in terms of foreign goods is to clear the non-traded goods market:

$$Y^N = C^N + G^N + J^N + C^{K,N} K^N. \tag{265}$$

The role of the price of home-produced goods in terms of foreign-produced goods or the terms of trade is to clear the home-produced traded goods market:

$$Y^H = C^H + G^H + J^H + X^H + C^{K,H} K^H, \tag{266}$$

where X^H stands for exports which are negatively related to the terms of trade:

$$X^H = \varphi_X \left(P^H\right)^{-\phi_X}, \tag{267}$$

with ϕ_X is the elasticity of exports with respect to the terms of trade. The rationale behind (267) comes from the fact that exports are the sum of foreign demand for the domestically produced tradable consumption goods and investment inputs denoted by $C^{F,\star}$ and $J^{F,\star}$, respectively:

$$\begin{aligned} X^H(t) &= C^{F,\star}(t) + J^{F,\star}(t), \\ &= \varphi \left(\frac{P^{T,\star}}{P_C^\star}\right)^{-\phi} (1-\varphi_H^\star) \left(\frac{P^H(t)}{P_T^\star}\right)^{-\rho^\star} C^\star + \iota \left(\frac{P_J^{T,\star}}{P_J^\star}\right)^{-\phi_J} (1-\iota_H^\star) \left(\frac{P^H(t)}{P_J^{T,\star}}\right)^{-\rho_J^\star} J^\star, \end{aligned}$$

where we assume that the rest of the world have similar preferences with the same elasticities elasticities (i..e, $\rho^\star = \rho$ and $\rho_J^\star = \rho_J$) between foreign and domestic tradable goods. To keep things simple, we assume that technology is fixed abroad. Therefore foreign prices denoted with a star remain constant and thus domestic exports are decreasing in the terms of trade, $P^H(t)$.

As shall be useful to write formal expressions in a compact form, we set

$$\Delta^H_{P^H} = Y^H_{P^H} - C^H_{P^H} - J^H_{P^H} - X^H_{P^H} - \xi_1^H u^{K,H}_{P^H}, \tag{268a}$$

$$\Delta^H_{P^N} = Y^H_{P^N} - C^H_{P^N} - J^H_{P^N} - \xi_1^H u^{K,H}_{P^N}, \tag{268b}$$

$$\Delta^H_{K} = Y^H_{K} - C^H_{K} - J^H_{K} - \xi_1^H u^{K,H}_{K}, \tag{268c}$$

$$\Delta^H_{Z^j} = Y^H_{Z^j} - C^H_{Z^j} - \xi_1^H u^{K,H}_{Z^j}, \tag{268d}$$

$$\Delta^N_{P^H} = Y^N_{P^H} - C^N_{P^H} - J^N_{P^H} - \xi_1^N u^{K,N}_{P^H} > 0, \tag{268e}$$

$$\Delta^N_{P^N} = Y^N_{P^N} - C^N_{P^N} - J^N_{P^N} - \xi_1^N u^{K,N}_{P^H}, \tag{268f}$$

$$\Delta^N_{K} = Y^N_{K} - C^N_{K} - J^N_{K} - \xi_1^N u^{K,N}_{K}, \tag{268g}$$

$$\Delta^N_{Z^j} = Y^N_{Z^j} - C^N_{Z^j} - \xi_1^N u^{K,N}_{Z^j}, \tag{268h}$$

where $X^H_{P^H} = \frac{\partial X^H}{\partial P^H} < 0$.

Totally differentiating the market clearing conditions (265)-(266) leads to in a matrix form:

$$\begin{pmatrix} \Delta^H_{P^H} & \Delta^H_{P^N} \\ \Delta^N_{P^H} & \Delta^N_{P^N} \end{pmatrix} \begin{pmatrix} dP^H \\ dP^N \end{pmatrix} = \begin{pmatrix} -\Delta^H_K dK + J^H_Q dQ - \sum_j \Delta^H_{Z^j} dZ^j \\ -\Delta^N_K dK + J^N_Q dQ - \sum_j \Delta^N_{Z^j} dZ^j \end{pmatrix}. \tag{269}$$

Applying the implicit functions theorem leads to the short-run solutions for the terms of trade and non-traded good prices:

$$P^H, P^N \left(\bar{\lambda}, K, Q, Z^H, Z^N\right). \tag{270}$$

Plugging back the solutions for sectoral prices into (255) and (256) allow us to find the final versions of solutions of the capital utilization rate, sectoral wages, sectoral capital rental rates, sectoral hours worked, sectoral capital stocks, sectoral value added:

$$u^{K,j}, W^j, R^j, L^j, K^j, Y^j \left(\bar{\lambda}, K, Q, Z^H, Z^N\right). \tag{271}$$

Inserting the solutions for prices into the intermediate solutions for consumption (243) and investment (263) leads to:

$$C^g, J^g \left(K, Q, Z^H, Z^N, \bar{\lambda}\right), \tag{272}$$

where $g = H, N, F$.

N.5 Solving the Model

Remembering that the non-traded input J^N used to produce the capital good is equal to $(1-\iota)\left(\frac{P^N}{P_J}\right)^{-\phi_J} J$ (see eq. (229b)) with $J = I + \frac{\kappa}{2}\left(\frac{I}{K} - \delta_K\right)^2 K$, using the fact that $J^N = Y^N - C^N - G^N - C^{K,N}K^N$ and inserting $I = \dot{K} + \delta_K$, the capital accumulation equation reads as follows:

$$\dot{K} = \frac{Y^N - C^N - G^N - C^{K,N}K^N}{(1-\iota)\left(\frac{P^N}{P_J}\right)^{-\phi_J}} - \delta_K K - \frac{\kappa}{2}\left(\frac{I}{K} - \delta_K\right)^2 K. \tag{273}$$

Inserting short-run solutions for the capital utilization rate and value added, i.e., (271) , investment and consumption in non-tradables (272), into the physical capital accumulation equation (273), and plugging the short-run solution for the return on domestic capital (271) into the dynamic equation for the shadow value of capital stock (220e), the dynamic system reads as follows:[15]

$$\dot{K} \equiv \Upsilon\left(K, Q, Z^H, Z^N\right) = \frac{E^N\left(K, Q, Z^H, Z^N\right)}{(1-\iota)\left\{\frac{P^N(.)}{P_J[P^H(.), P^N(.)]}\right\}^{-\phi_J}} - \delta_K K - \frac{K}{2\kappa}\left\{\frac{Q}{P_J\left[P^H(.), P^N(.)\right]} - 1\right\}^2 \tag{274a}$$

$$\begin{aligned}
\dot{Q} \equiv \Sigma\left(K, Q, Z^H, Z^N\right) &= (r^\star + \delta_K) Q - \left[\frac{\sum_j R^j\left(K, Q, Z^H, Z^N\right)\tilde{K}^j\left(K, Q, Z^H, Z^N\right)}{K}\right. \\
&- \sum_j C^{K,j}\left(u^{K,j}\left(K, Q, Z^H, Z^N\right)\right]\frac{K^j\left(K, Q, Z^H, Z^N\right)}{K} \\
&+ \left. P_J \frac{\kappa}{2} v(.)\left(v(.) + 2\delta_K\right)\right],
\end{aligned} \tag{274b}$$

where $E^N = Y^N - C^N - G^N - C^{K,N}K^N$

To facilitate the linearization, it is useful to break down the capital accumulation into two components:

$$\hat{K} = J - \delta_K K - \frac{\kappa}{2}\left(\frac{I}{K} - \delta_K\right)^2 K. \tag{275}$$

The first component is J. Using the fact that $J = \frac{J^N}{(1-\iota)\left(\frac{P^N}{P_J}\right)^{-\phi_J}}$ and log-linearizing gives:

$$\hat{J} = \hat{J}^N + \phi_J \alpha_J \hat{P}^N - \phi_J \alpha_J \alpha_J^H \hat{P}^H \tag{276}$$

where we used the fact that $\hat{P}_J = \alpha_J \alpha_J^H \hat{P}^H + (1-\alpha_J)\hat{P}^N$. Using (275) and the fact that $J^N = Y^N - C^N - G^N - C^{K,N}u^{K,N}$, linearizing (275) in the neighborhood of the steady-state gives:

$$\begin{aligned}
\dot{K} &= \frac{J}{J^N}\left[dY^N(t) - dC^N(t) - \xi_1^N du^{K,N}(t)\right] + \phi_J \frac{J}{P^N}\alpha_J dP^N(t) \\
&- \phi_J \frac{J}{P^H}\alpha_J \alpha_J^H dP^H(t) - \delta_K dK(t),
\end{aligned} \tag{277}$$

where $J = I = \delta_K K$ in the long-run.

As will be useful, let us denote by Υ_K, Υ_Q, and Υ_{Z^j} the partial derivatives evaluated at the steady-state of the capital accumulation equation w.r.t. K, Q, and Z^j, respectively. Using (277), these elements of the Jacobian matrix are given by:

$$\Upsilon_K \equiv \frac{\partial \dot{K}}{\partial K} = \frac{J}{J^N}E_K^N + \alpha_J \phi_J J\left(\frac{P_K^N}{P^N} - \alpha_J^H \frac{P_K^H}{P^H}\right) - \delta_K \gtrless 0, \tag{278a}$$

$$\Upsilon_Q \equiv \frac{\partial \dot{K}}{\partial Q} = \frac{J}{J^N}E_Q^N + \alpha_J \phi_J J\left(\frac{P_Q^N}{P^N} - \alpha_J^H \frac{P_Q^H}{P^H}\right) > 0, \tag{278b}$$

$$\Upsilon_{Z^j} \equiv \frac{\partial \dot{K}}{\partial Z^j} = \frac{J}{J^N}E_{Z^j}^N + \alpha_J \phi_J J\left(\frac{P_{Z^j}^N}{P^N} - \alpha_J^H \frac{P_{Z^j}^H}{P^H}\right), \tag{278c}$$

[15] We omit the shadow value of wealth from short-run solutions for clarity purposes as λ remains constant over time.

where $J = \delta_K K$ in the long run and $E^N_X = Y^N_X - C^N_X - \xi^N_1 u^{K,N}_X$ with $X = K, Q, Z^j$,

Let us denote by Σ_K, Σ_Q, and Σ_{Z^j} the partial derivatives evaluated at the steady-state of the dynamic equation for the marginal value of an additional unit of capital w.r.t. K, Q, and Z^j, respectively:

$$\Sigma_K \equiv \frac{\partial \dot{Q}}{\partial K} = -\left[-\frac{R}{K} + \frac{\Delta_K}{K} + P_J \kappa v_K \delta_K\right] > 0, \tag{279a}$$

$$\Sigma_Q \equiv \frac{\partial \dot{Q}}{\partial Q} = (r^\star + \delta_K) - \left[\frac{\Delta_Q}{K} + P_J \kappa v_Q \delta_K\right] > 0, \tag{279b}$$

$$\Sigma_{Z^j} \equiv \frac{\partial \dot{Q}}{\partial Z^j} = -\left[\frac{\Delta_{Z^j}}{K} + P_J \kappa v_{Z^j} \delta_K\right]. \tag{279c}$$

where $\Delta_K = \sum_j K^j R^j_K + R^j K^j_K + R^j K^j u^{K,j}_K$, $\Delta_Q = \sum_j K^j R^j_Q + R^j K^j_Q + R^j K^j u^{K,j}_Q$, $\Delta_{Z^j} = \sum_j K^j R^j_{Z^j} + R^j K^j_{Z^j} + R^j K^j u^{K,j}_{Z^j}$.

Assuming that the saddle-path stability condition is fulfilled, and denoting the negative eigenvalue by ν_1 and the positive eigenvalue by ν_2, the general solutions for K and Q are:

$$K(t) - \tilde{K} = D_1 e^{\nu_1 t} + D_2 e^{\nu_2 t}, \quad Q(t) - \tilde{Q} = \omega^1_2 D_1 e^{\nu_1 t} + \omega^2_2 D_2 e^{\nu_2 t}, \tag{280}$$

where K_0 is the initial capital stock and $\left(1, \omega^i_2\right)'$ is the eigenvector associated with eigenvalue ν_i:

$$\omega^i_2 = \frac{\nu_i - \Upsilon_K}{\Upsilon_Q}. \tag{281}$$

Because $\nu_1 < 0$, $\Upsilon_K > 0$ and $\Upsilon_Q > 0$, we have $\omega^1_2 < 0$, regardless of sectoral capital intensities, which implies that the shadow value of investment and the stock physical capital move in opposite direction along a stable path (i.e., $D_2 = 0$).

N.6 Current Account Equation and Intertemporal Solvency Condition

To determine the current account equation, we use the following identities and properties:

$$P_C C = P^H C^H + C^F + P^N C^N, \tag{282a}$$

$$P_J J = P^H J^H + J^F + P^N J^N, \tag{282b}$$

$$T = G = P^H G^H + G^F + P^N G^N, \tag{282c}$$

$$W L + R\tilde{K} = \left(W^H L^H + R^H \tilde{K}^H\right) + \left(W^N L^N + R^N \tilde{K}^N\right) = P^H Y^H + P^N Y^N, \tag{282d}$$

where (282d) follows from Euler theorem. Using (282d), inserting (282a)-(282c) into (216) and invoking market clearing conditions for non-traded goods (265) and home-produced traded goods (266) yields:

$$\begin{aligned} \dot{N} &= r^\star N + P^H \left(Y^H - C^H - G^H - J^H - C^{K,H} K^H\right) - \left(C^F + J^F + G^F\right), \\ &= r^\star N + P^H X^H - M^F, \end{aligned} \tag{283}$$

where $X^H = Y^H - C^H - G^H - J^H - C^{K,H} K^H$ stands for exports of home goods and we denote by M^F imports of foreign consumption and investment goods:

$$M^F = C^F + G^F + J^F. \tag{284}$$

Inserting appropriate solutions, the current account equation reads:

$$\begin{aligned} \dot{N} &\equiv r^\star N + \Xi\left(K, Q, Z^H, Z^N\right), \\ &= r^\star N + P^H\left(K, Q, Z^H, Z^N\right) X^H\left(K, Q, Z^H, Z^N\right) - M^F\left(K, Q, Z^H, Z^N\right). \end{aligned} \tag{285}$$

Let us denote by Ξ_K, Ξ_Q, and Ξ_{Z^j} the partial derivatives evaluated at the steady-state of the dynamic equation for the current account w.r.t. K, Q, and Z^j, respectively:

$$\Xi_K \equiv \frac{\partial \dot{N}}{\partial K} = \left(1 - \phi_X\right) X^H P^H_K - M^F_K, \tag{286a}$$

$$\Xi_Q \equiv \frac{\partial \dot{N}}{\partial Q} = \left(1 - \phi_X\right) X^H P^H_Q - M^F_Q, \tag{286b}$$

$$\Xi_{Z^j} \equiv \frac{\partial \dot{N}}{\partial Z^j} = \left(1 - \phi_X\right) X^H P^H_{Z^j} - M^F_{Z^j}. \tag{286c}$$

where we used the fact that $P^H X^H = \varphi_X \left(P^H\right)^{1-\phi_X}$ (see eq. (267)).

Linearizing (285) in the neighborhood of the steady-state, making use of (286a) and (286b), inserting solutions for $K(t)$ and $Q(t)$ given by (280) and solving yields the general solution for the net foreign asset position:

$$N(t) = N + \left[(N_0 - N) - \Psi_1 D_1 - \Psi_2 D_2\right] e^{r^\star t} + \Psi_1 D_1 e^{\nu_1 t} + \Psi_2 D_2 e^{\nu_2 t}, \tag{287}$$

where N_0 is the initial stock of traded bonds and we set

$$E_i = \Xi_K + \Xi_Q \omega_2^i, \tag{288a}$$

$$\Psi_i = \frac{E_i}{\nu_i - r^\star}. \tag{288b}$$

Invoking the transversality condition leads to the linearized version of the nations's intertemporal solvency condition:

$$N - N_0 = \Psi_1 \left(K - K_0\right), \tag{289}$$

where K_0 is the initial stock of physical capital.

N.7 Derivation of the Accumulation Equation of Non Human Wealth

Remembering that the stock of financial wealth $A(t)$ is equal to $N(t)+Q(t)K(t)$, differentiating w.r.t. time, i.e., $\dot{A}(t) = \dot{N}(t) + \dot{Q}(t)K(t) + Q(t)\dot{K}(t)$, plugging the dynamic equation for the marginal value of capital (220e), inserting the accumulation equations for physical capital (217) and traded bonds (216), yields the accumulation equation for the stock of financial wealth or the dynamic equation for private savings:

$$\dot{A}(t) = \tag{290}$$

where we assume that the government levies lump-sum taxes, T, to finance purchases of foreign-produced, home-produced and non-traded goods, i.e., $T = G = \left(G^F + P^H(.)G^H + P^N(.)G^N\right)$.

Solving for $C = C\left(K, Q, Z^H, Z^N\right)$ by inserting the solutions for sectoral prices (270) into the optimal decision for consumption (220a), inserting solutions for W^j, L^j, into (256) allows us to write the financial wealth accumulation equation as follows:

$$\begin{aligned} \dot{A} &\equiv r^\star A + \Lambda\left(K, Q, Z^H, Z^N\right), \\ &= r^\star A + \sum_j W^j\left(K, Q, Z^H, Z^N\right) L^j\left(K, Q, Z^H, Z^N\right) - G\left(K, Q, Z^H, Z^N\right) \\ &- P_C\left[P^H(.), P^N(.)\right] C\left(K, Q, Z^H, Z^N\right), \end{aligned} \tag{291}$$

where P^N and P^H are given by (270).

Let us denote by Λ_K, Λ_Q, and Λ_{Z^j} the partial derivatives evaluated at the steady-state of the dynamic equation for the non human wealth w.r.t. K, Q, and Z^j, respectively:

$$\Lambda_K \equiv \frac{\partial \dot{A}}{\partial K} = \left(W_K L + W L_K\right) - G_K - \left(\frac{\partial P_C}{\partial K} C + P_C C_K\right), \tag{292a}$$

$$\Lambda_Q \equiv \frac{\partial \dot{A}}{\partial Q} = \left(W_Q L + W L_Q\right) - G_Q - \left(\frac{\partial P_C}{\partial Q} C + P_C C_Q\right), \tag{292b}$$

$$\Lambda_{Z^j} \equiv \frac{\partial \dot{A}}{\partial Z^j} = \left(W_{Z^j} L + W L_{Z^j}\right) - G_{Z^j} - \left(\frac{\partial P_C}{\partial Z^j} C + P_C C_{Z^j}\right). \tag{292c}$$

Linearizing (291) in the neighborhood of the steady-state, making use of (292a) and (292b), inserting solutions for $K(t)$ and $Q(t)$ given by (280) and solving yields the general solution for the stock of non human wealth:

$$A(t) = A + \left[(A_0 - A) - \Delta_1 D_1 - \Delta_2 D_2\right] e^{r^\star t} + \Delta_1 D_1 e^{\nu_1 t} + \Delta_2 D_2 e^{\nu_2 t}, \tag{293}$$

where A_0 is the initial stock of financial wealth and we set

$$M_i = A_K + A_Q \omega_2^i, \tag{294a}$$

$$\Delta_i = \frac{M_i}{\nu_i - r^\star}. \tag{294b}$$

The linearized version of the representative household's intertemporal solvency condition is:

$$A - A_0 = \Delta_1 \left(K - K_0\right), \tag{295}$$

where A_0 is the initial stock of non human wealth.

O Semi-Small Open Economy Model with CES Production Functions

In section N, we have laid out a model with Cobb-Douglas production functions. The steady-state of this model is used to normalize CES production functions. This section extends the model with Cobb-Douglas production functions in two directions. First, in the baseline model we allow for CES production functions and factor-biased technological change (FBTC henceforth). Second, we assume that factor-augmenting efficiency has both a symmetric and an asymmetric component. The first order conditions from households' maximization problem detailed in subsection N.1 remain almost identical and we emphasize only the main changes.

O.1 Households

Households choose the level of capital utilization in sector j, which includes both a symmetric and an asymmetric component, denoted by $u_S^{K,j}(t)$ and $u_D^{K,j}(t)$:

$$u^{K,j}(t) = \left(u_S^{K,j}(t)\right)^{\eta} \left(u_D^{K,j}(t)\right)^{1-\eta}. \tag{296}$$

Both components of the capital utilization rate collapse to one at the steady-state. The capital utilization adjustment costs are assumed to be an increasing and convex function of the capital utilization rate:

$$C_S^{K,j}(t) = \xi_{1,S}^j \left(u_S^{K,j}(t) - 1\right) + \frac{\xi_{2,S}^j}{2} \left(u_S^{K,j}(t) - 1\right)^2, \tag{297a}$$

$$C_D^{K,j}(t) = \xi_{1,S}^j \left(u_D^{K,j}(t) - 1\right) + \frac{\xi_{2,D}^j}{2} \left(u_D^{K,j}(t) - 1\right)^2, \tag{297b}$$

where $\xi_{2,S}^j > 0$, $\xi_{2,D}^j > 0$, are free parameters which indicate the extent of the cost of adjusting the intensity in the use of capital. When we let $\xi_{2,c}^j \to \infty$ $(c = S, D)$, capital utilization is fixed at unity and TFP growth collapses to technological change.

The dynamic equation of the shadow price of capital (220e) and the optimal decision about the capital utilization rate (220f) are modified as follows:

$$\dot{Q}(t) = \left(r^\star + \delta_K\right) Q(t) - \Bigg\{ \sum_{j=H,N} \alpha_K^j(t) u^{K,j}(t) R^K(t) - \sum_{j=H,N} P^j(t) \left(C_S^{K,j}(t) + C_D^{K,j}(t)\right) \nu^{K,j}(t) - P_J(t) \frac{\partial J(t)}{\partial K(t)} \Bigg\}, \tag{298a}$$

$$\frac{R^j(t)}{P^j(t)} \eta \frac{u^{K,j}(t)}{u_S^{K,j}(t)} = \xi_{1,S}^j + \xi_{2,S}^j \left(u_S^{K,j}(t) - 1\right), \quad j = H, N, \tag{298b}$$

$$\frac{R^j(t)}{P^j(t)} (1-\eta) \frac{u^{K,j}(t)}{u_D^{K,j}(t)} = \xi_{1,D}^j + \xi_{2,D}^j \left(u_D^{K,j}(t) - 1\right), \quad j = H, N, \tag{298c}$$

where η is the share of aggregate technology shocks driven by symmetric technology improvements.

O.2 Firms

Both the traded and non-traded sectors use physical capital, $\tilde{K}^j$, and labor, L^j, according to constant returns to scale production functions which are assumed to take a CES form:

$$Y^j(t) = \left[\gamma^j \left(A^j(t)L^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right)\left(B^j(t)\tilde{K}^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}, \tag{299}$$

where γ^j and $1-\gamma^j$ are the weight of labor and capital in the production technology, σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$, A^j and B^j are labor- and capital-augmenting efficiency. Both sectors face two cost components: a capital rental cost equal to R^j, and a labor cost equal to the wage rate W^j.

Factor-augmenting productivity is made up of a symmetric component (across sectors) denoted by the subscript S and an asymmetric component denoted by the subscript D:

$$A^j(t) = \left(A^j_S(t)\right)^\eta \left(A^j_D(t)\right)^{1-\eta}, \qquad B^j(t) = \left(B^j_S(t)\right)^\eta \left(B^j_D(t)\right)^{1-\eta}, \tag{300}$$

where the elasticity of factor-augmenting productivity w.r.t. to its symmetric component is denoted by η which is assumed to be symmetric across sectors. As we shall see below, this parameter determines the share of technology improvements which are symmetric across sectors.

Firms rent capital $\tilde{K}^j(t)$ and labor $L^j(t)$ services from households. We assume that the movements in capital and labor across sectors are subject to frictions which imply that the capital rental cost equal to $R^j(t)$, and the wage rate $W^j(t)$, are sector-specific. Both sectors are assumed to be perfectly competitive and thus choose capital services and labor by taking prices P^j as given:

$$\max_{\tilde{K}^j(t),L^j(t)} \Pi^j(t) = \max_{\tilde{K}^j(t),L^j(t)} \left\{P^j(t)Y^j(t) - W^j(t)L^j(t) - R^j(t)\tilde{K}^j(t)\right\}. \tag{301}$$

We drop the time index when it does not cause confusion. Costly labor and capital mobility implies a labor and capital cost differential across sectors:

$$P^j(t)\gamma^j\left(A^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}}\left(L^j(t)\right)^{-\frac{1}{\sigma^j}}\left(Y^j(t)\right)^{\frac{1}{\sigma^j}} \equiv W^j(t), \tag{302a}$$

$$P^j(t)\left(1-\gamma^j\right)\left(B^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}}\left(u^{K,j}(t)K^j(t)\right)^{-\frac{1}{\sigma^j}}\left(Y^j(t)\right)^{\frac{1}{\sigma^j}} = R^j(t). \tag{302b}$$

Some Useful Results

Multiplying both sides of (302a)-(302b) by L^j and $\tilde{K}^j$, respectively, and dividing by sectoral value added leads to the labor and capital income share:

$$s^j_L = \gamma^j\left(\frac{A^j}{y^j}\right)^{\frac{\sigma^j-1}{\sigma^j}}, \quad 1-s^j_l = \gamma^j\left(\frac{B^j u^{K,j} k^j}{y^j}\right)^{\frac{\sigma^j-1}{\sigma^j}}, \tag{303}$$

where

$$y^j = \left[\gamma^j\left(A^j\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right)\left(B^j u^{K,j} k^j\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}. \tag{304}$$

Dividing eq. (303) by eq. (304), the ratio of the labor to the capital income share denoted by $S^j = \frac{s^j_L}{1-s^j_L}$ reads as follows:

$$S^j = \frac{\gamma^j}{1-\gamma^j}\left(\frac{B^j u^{K,j} K^j}{A^j L^j}\right)^{\frac{1-\sigma^j}{\sigma^j}}. \tag{305}$$

Dividing (302a) by (302b) leads to a positive relationship between the relative cost of labor and the capital-labor ratio in sector j:

$$\frac{W^j}{R^j} = \frac{\gamma^j}{1-\gamma^j}\left(\frac{B^j}{A^j}\right)^{\frac{1-\sigma^j}{\sigma^j}}\left(\frac{\tilde{K}^j}{L^j}\right)^{\frac{1}{\sigma^j}}. \tag{306}$$

To determine the conditional demands for both inputs, we make use of (306) which leads to:

$$L^j = \tilde{K}^j \left(\frac{\gamma^j}{1-\gamma^j}\right)^{\sigma^j} \left(\frac{B^j}{A^j}\right)^{1-\sigma^j} \left(\frac{W^j}{R^j}\right)^{-\sigma^j}, \tag{307a}$$

$$\tilde{K}^j = L^j \left(\frac{1-\gamma^j}{\gamma^j}\right)^{\sigma^j} \left(\frac{B^j}{A^j}\right)^{\sigma^j-1} \left(\frac{W^j}{R^j}\right)^{\sigma^j}. \tag{307b}$$

Inserting eq. (307b) (eq. (307a) resp.) in the CES production function and solving for L^j ($\tilde{K}^j$ resp.) leads to the conditional demand for labor (capital resp.):

$$L^j = Y^j \left(A^j\right)^{\sigma^j-1} \left(\frac{\gamma^j}{W^j}\right)^{\sigma} \left(X^j\right)^{\frac{\sigma^j}{1-\sigma^j}}, \quad \tilde{K}^j = Y^j \left(B^j\right)^{\sigma^j-1} \left(\frac{1-\gamma^j}{R^j}\right)^{\sigma^j} \left(X^j\right)^{\frac{\sigma^j}{1-\sigma^j}}, \tag{308}$$

where X^j is given by:

$$X^j = \left(\gamma^j\right)^{\sigma^j} \left(A^j\right)^{\sigma^j-1} \left(W^j\right)^{1-\sigma^j} + \left(1-\gamma^j\right)^{\sigma^j} \left(B^j\right)^{\sigma^j-1} \left(R^j\right)^{1-\sigma^j}. \tag{309}$$

Total cost is equal to the sum of the labor and capital cost:

$$C^j = W^j L^j + R^j K^j. \tag{310}$$

Inserting conditional demand for inputs (307) into total cost (310), we find C^j is homogenous of degree one with respect to the level of production

$$C^j = c^j Y^j, \quad \text{with} \quad c^j = \left(X^j\right)^{\frac{1}{1-\sigma^j}}. \tag{311}$$

Using the fact that $\left(c^j\right)^{1-\sigma^j} = X^j$, conditional demand for labor (307a) can be rewritten as $L^j = Y^j \left(A^j\right)^{\sigma^j-1} \left(\frac{\gamma^j}{W^j}\right) \left(c^j\right)^{\sigma^j}$ which gives the labor income share denoted by s_L^j:

$$s_L^j = \frac{W^j L^j}{P^j Y^j} = \left(\gamma^j\right)^{\sigma^j} \left(\frac{W^j}{A^j}\right)^{1-\sigma^j} \left(c^j\right)^{\sigma^j-1}, \tag{312a}$$

$$1 - s_L^j = \frac{R^j \tilde{K}^j}{P^j Y^j} = \left(1-\gamma^j\right)^{\sigma^j} \left(\frac{R^j}{B^j}\right)^{1-\sigma^j} \left(c^j\right)^{\sigma^j-1}. \tag{312b}$$

O.3 Short-Run Solutions

Sectoral Wages and Capital-Labor Ratios

Plugging the short-run solutions for L^H, L^N, K^H, K^N, given by (245)-(247) into the demand for capital and labor (302a)-(302b), the system of four equations can be solved for sectoral wages W^j and sectoral capital rental rates R^j. Log-differentiating (302a)-(302b)yields in matrix form:

$$\begin{pmatrix}
-\left[\left(\frac{1-s_L^H}{\sigma^H}\right)\frac{L^H_{W^H}}{L^H} + \frac{1}{W^H}\right] & -\left(\frac{1-s_L^H}{\sigma^H}\right)\frac{L^H_{W^N}}{L^H} & \left(\frac{1-s_L^H}{\sigma^H}\right)\frac{K^H_{R^H}}{K^H} & \left(\frac{1-s_L^H}{\sigma^H}\right)\frac{K^H_{R^N}}{K^H} \\
-\left(\frac{1-s_L^N}{\sigma^N}\right)\frac{L^N_{W^N}}{L^N} & -\left[\left(\frac{1-s_L^N}{\sigma^N}\right)\frac{L^N_{W^N}}{L^N} + \frac{1}{W^N}\right] & \left(\frac{1-s_L^N}{\sigma^N}\right)\frac{K^N_{R^H}}{K^N} & \left(\frac{1-s_L^N}{\sigma^N}\right)\frac{K^N_{R^N}}{K^N} \\
\frac{s_L^H}{\sigma^H}\frac{L^H_{W^H}}{L^H} & \frac{s_L^H}{\sigma^H}\frac{L^H_{W^N}}{L^H} & -\left[\frac{s_L^H}{\sigma^H}\frac{K^H_{R^H}}{K^H} + \frac{1}{R^H}\right] & \frac{s_L^H}{\sigma^H}\frac{K^H_{R^N}}{K^H} \\
\frac{s_L^N}{\sigma^N}\frac{L^N_{W^H}}{L^N} & \frac{s_L^N}{\sigma^N}\frac{L^N_{W^N}}{L^N} & \frac{s_L^N}{\sigma^N}\frac{K^N_{R^H}}{K^N} & -\left[\frac{s_L^N}{\sigma^N}\frac{K^N_{R^N}}{K^N} + \frac{1}{R^N}\right]
\end{pmatrix}
\times \begin{pmatrix} dW^H \\ dW^N \\ dR^H \\ dR^N \end{pmatrix}$$

$$= \begin{pmatrix}
\left(\frac{1-s_L^H}{\sigma^H}\right)\frac{L^H_{P^N}}{L^H}dP^N + \left[\left(\frac{1-s_L^H}{\sigma^H}\right)\frac{L^H_{P^H}}{L^H} - \frac{1}{P^H}\right]dP^H - \left(\frac{1-s_L^H}{\sigma^H}\right)\frac{K^H_K}{K^H}dK - \left(\frac{1-s_L^H}{\sigma^H}\right)du^{K,H} - \left[\frac{\left(\sigma^H-1\right)+s_L^H}{\sigma^H}\right]\hat{A}^H - \left(\frac{1-s_L^H}{\sigma^H}\right)\hat{B}^H \\
\left[\left(\frac{1-s_L^N}{\sigma^N}\right)\frac{L^N_{P^N}}{L^N} - \frac{1}{P^N}\right]dP^N + \left(\frac{1-s_L^N}{\sigma^N}\right)\frac{L^N_{P^H}}{L^N}dP^H - \left(\frac{1-s_L^N}{\sigma^N}\right)\frac{K^N_K}{K^N}dK - \left(\frac{1-s_L^N}{\sigma^N}\right)du^{K,N} - \left[\frac{\left(\sigma^N-1\right)+s_L^N}{\sigma^N}\right]\hat{A}^N - \left(\frac{1-s_L^N}{\sigma^N}\right)\hat{B}^N \\
-\frac{s_L^H}{\sigma^H}\frac{L^H_{P^H}}{L^H}dP^N - \left[\frac{s_L^H}{\sigma^H}\frac{L^H_{P^H}}{L^H} + \frac{1}{P^H}\right]dP^H + \frac{s_L^H}{\sigma^H}\frac{K^H_K}{K^H}dK + \frac{s_L^H}{\sigma^H}du^{K,H} - \left(\frac{\sigma^H-s_L^H}{\sigma^H}\right)\hat{B}^H - \left(\frac{s_L^H}{\sigma^H}\right)\hat{A}^H \\
-\left[\frac{s_L^N}{\sigma^N}\frac{L^N_{P^N}}{L^N} + \frac{1}{P^N}\right]dP^N - \frac{s_L^N}{\sigma^N}\frac{L^N_{P^H}}{L^N}dP^H + \frac{s_L^N}{\sigma^N}\frac{K^N_K}{K^N}dK + \frac{s_L^N}{\sigma^N}du^{K,N} - \left(\frac{\sigma^N-s_L^N}{\sigma^N}\right)\hat{B}^N - \left(\frac{s_L^N}{\sigma^N}\right)\hat{A}^N
\end{pmatrix} \tag{313}$$

From eq. (296), i.e., $u^{K,j}(t) = \left(u_S^{K,j}\right)^{\eta} \left(u_D^{K,j}\right)^{1-\eta}$, the capital utilization rate is a function of its symmetric and asymmetric components:

$$u^{K,j} = u^{K,j}\left(u_S^{K,j}, u_D^{K,j}\right), \tag{314}$$

where

$$\frac{\partial u^{K,j}}{\partial u_S^{K,j}} = \eta, \qquad \frac{\partial u^{K,j}}{\partial u_D^{K,j}} = 1 - \eta. \tag{315}$$

By using the implicit function theorem, eq. (313) together with eq. (314) leads to the short-run solutions for sectoral wages

$$W^j = W^j\left(\bar{\lambda}, K, P^j, A^j, B^j, u_S^{K,j}, u_D^{K,j}\right), \quad j = H, N, \tag{316}$$

and capital rental rates

$$R^j = R^j\left(\bar{\lambda}, K, P^j, A^j, B^j, u_S^{K,j}, u_D^{K,j}\right), \quad j = H, N. \tag{317}$$

Inserting sectoral wages (316) into (245), sectoral hours worked can be solved as functions of the shadow value of wealth, the capital stock, the price of non-traded goods in terms of foreign goods, P^N, the terms of trade, factor-augmenting productivity and capital utilization rates:

$$L^j = L^j\left(\bar{\lambda}, K, P^j, A^j, B^j, u_S^{K,j}, u_D^{K,j}\right), \quad j = H, N. \tag{318}$$

Inserting capital rental rates (317) into (247), sectoral capital stock can be solved as functions of the shadow value of wealth, the aggregate capital stock, the price of non-traded goods in terms of foreign goods, P^N, the terms of trade, factor-augmenting productivity and capital utilization rates:

$$K^j = K^j\left(\bar{\lambda}, K, P^N, P^H, A^j, B^j, u_S^{K,j}, u_D^{K,j}\right). \quad j = H, N. \tag{319}$$

Finally, plugging solutions for sectoral hours worked (318) and sectoral capital stock (319), and using (296), production functions (299) can be solved for sectoral value added:

$$Y^j = Y^j\left(\bar{\lambda}, K, P^j, A^j, B^j, u_S^{K,j}, u_D^{K,j}\right), \quad j = H, N. \tag{320}$$

Symmetric and Asymmetric Components of Capital Utilization Rates, $u_S^{K,j}(t)$ and $u_D^{K,j}(t)$

Inserting firm's optimal decision for capital (302b) in sector j in the optimal intensity in the use of physical capital (298b) leads to:

$$\eta \frac{u^{K,j}(t)}{u_S^{K,j}(t)} = \xi_{1,S}^j + \xi_{2,S}^j\left(u_S^{K,j}(t) - 1\right) = \left(1 - \gamma^j\right)\left(B^j(t)\right)^{\frac{\sigma^j - 1}{\sigma^j}} \left(u^{K,j}(t) K^j(t)\right)^{-\frac{1}{\sigma^j}} \left(Y^j(t)\right)^{\frac{1}{\sigma^j}}. \tag{321}$$

Inserting intermediate solutions (318) for sectoral hours worked and (319) for sectoral capital into (321) and log-differentiating leads to in a matrix form:

$$\begin{pmatrix} a_{11} & a_{12} & -\frac{s_L^H}{\sigma^H}\frac{L^H_{u_S^{K,N}}}{L^H} + \frac{s_L^H}{\sigma^H}\frac{K^H_{u_S^{K,N}}}{K^H} & -\frac{s_L^H}{\sigma^H}\frac{L^H_{u_D^{K,N}}}{L^H} + \frac{s_L^H}{\sigma^H}\frac{K^H_{u_D^{K,N}}}{K^H} \\ a_{21} & a_{22} & -\frac{s_L^H}{\sigma^H}\frac{L^H_{u_S^{K,N}}}{L^H} + \frac{s_L^H}{\sigma^H}\frac{K^H_{u_S^{K,N}}}{K^H} & -\frac{s_L^H}{\sigma^H}\frac{L^H_{u_D^{K,N}}}{L^H} + \frac{s_L^H}{\sigma^H}\frac{K^H_{u_D^{K,N}}}{K^H} \\ -\frac{s_L^N}{\sigma^N}\frac{L^N_{u_S^{K,H}}}{L^N} + \frac{s_L^N}{\sigma^N}\frac{K^N_{u_S^{K,H}}}{K^N} & -\frac{s_L^N}{\sigma^N}\frac{L^N_{u_D^{K,H}}}{L^N} + \frac{s_L^N}{\sigma^N}\frac{K^N_{u_D^{K,H}}}{K^N} & a_{33} & a_{34} \\ -\frac{s_L^N}{\sigma^N}\frac{L^N_{u_S^{K,H}}}{L^N} + \frac{s_L^N}{\sigma^N}\frac{K^N_{u_S^{K,H}}}{K^N} & -\frac{s_L^N}{\sigma^N}\frac{L^N_{u_D^{K,H}}}{L^N} + \frac{s_L^N}{\sigma^N}\frac{K^N_{u_D^{K,H}}}{K^N} & a_{43} & a_{44} \end{pmatrix}$$

$$\times \begin{pmatrix} \hat{u}_S^{K,H} \\ \hat{u}_D^{K,H} \\ \hat{u}_S^{K,N} \\ \hat{u}_D^{K,N} \end{pmatrix}$$

$$= \begin{pmatrix} \sum_{X^j = A^j, B^j, P^j, j=H,N} \left(\frac{s_L^H}{\sigma^H}\frac{L^H_{X^j}}{L^H} - \frac{s_L^H}{\sigma^H}\frac{K^H_{X^j}}{K^H}\right) dX^j + \left(\frac{s_L^H}{\sigma^H}\frac{L^H_K}{L^H} - \frac{s_L^H}{\sigma^H}\frac{K^H_K}{K^H}\right) dK + \frac{s_L^H}{\sigma^H}\hat{A}^H - \left(\frac{\sigma^H - s_L^H}{\sigma^H}\right)\hat{B}^H \\ \sum_{X^j = A^j, B^j, P^j, j=H,N} \left(\frac{s_L^H}{\sigma^H}\frac{L^H_{X^j}}{L^H} - \frac{s_L^H}{\sigma^H}\frac{K^H_{X^j}}{K^H}\right) dX^j + \left(\frac{s_L^H}{\sigma^H}\frac{L^H_K}{L^H} - \frac{s_L^H}{\sigma^H}\frac{K^H_K}{K^H}\right) dK + \frac{s_L^H}{\sigma^H}\hat{A}^H - \left(\frac{\sigma^H - s_L^H}{\sigma^H}\right)\hat{B}^H \\ \sum_{X^j = A^j, B^j, P^j, j=H,N} \left(\frac{s_L^N}{\sigma^N}\frac{L^N_{X^j}}{L^N} - \frac{s_L^N}{\sigma^N}\frac{K^N_{X^j}}{K^N}\right) dX^j + \left(\frac{s_L^N}{\sigma^N}\frac{L^N_K}{L^N} - \frac{s_L^N}{\sigma^N}\frac{K^N_K}{K^N}\right) dK + \frac{s_L^N}{\sigma^N}\hat{A}^N - \left(\frac{\sigma^N - s_L^N}{\sigma^N}\right)\hat{B}^N \\ \sum_{X^j = A^j, B^j, P^j, j=H,N} \left(\frac{s_L^N}{\sigma^N}\frac{L^N_{X^j}}{L^N} - \frac{s_L^N}{\sigma^N}\frac{K^N_{X^j}}{K^N}\right) dX^j + \left(\frac{s_L^N}{\sigma^N}\frac{L^N_K}{L^N} - \frac{s_L^N}{\sigma^N}\frac{K^N_K}{K^N}\right) dK + \frac{s_L^N}{\sigma^N}\hat{A}^N - \left(\frac{\sigma^N - s_L^N}{\sigma^N}\right)\hat{B}^N \end{pmatrix}, \tag{322}$$

where $X^j =, P^H, P^N, Z^H, Z^N$ and

$$a_{11} = \left[\frac{\xi^H_{2,S}}{\xi^H_{1,S}} + \eta\frac{s^H_L}{\sigma^H} + (1-\eta)\right] - \frac{s^H_L}{\sigma^H}\frac{L^H_{u^{K,H}_S}}{L^H} + \frac{s^H_L}{\sigma^H}\frac{K^H_{u^{K,H}_S}}{K^H}, \tag{323a}$$

$$a_{12} = -\left(\frac{\sigma^H - s^H_L}{\sigma^H}\right)(1-\eta) - \frac{s^H_L}{\sigma^H}\frac{L^H_{u^{K,H}_D}}{L^H} + \frac{s^H_L}{\sigma^H}\frac{K^H_{u^{K,H}_D}}{K^H}, \tag{323b}$$

$$a_{21} = -\left(\frac{\sigma^H - s^H_L}{\sigma^H}\right)\eta - \frac{s^H_L}{\sigma^H}\frac{L^H_{u^{K,H}_S}}{L^H} + \frac{s^H_L}{\sigma^H}\frac{K^H_{u^{K,H}_S}}{K^H}, \tag{323c}$$

$$a_{22} = \left[\frac{\xi^H_{2,D}}{\xi^H_{1,D}} + (1-\eta)\frac{s^H_L}{\sigma^H} + \eta\right] - \frac{s^H_L}{\sigma^H}\frac{L^H_{u^{K,H}_D}}{L^H} + \frac{s^H_L}{\sigma^H}\frac{K^H_{u^{K,H}_D}}{K^H}, \tag{323d}$$

$$a_{33} = \left[\frac{\xi^N_{2,S}}{\xi^N_{1,S}} + \eta\frac{s^N_L}{\sigma^N} + (1-\eta)\right] - \frac{s^N_L}{\sigma^N}\frac{L^N_{u^{K,N}_S}}{L^N} + \frac{s^N_L}{\sigma^N}\frac{K^N_{u^{K,N}_S}}{K^N}, \tag{323e}$$

$$a_{34} = -\left(\frac{\sigma^N - s^N_L}{\sigma^N}\right)(1-\eta) - \frac{s^N_L}{\sigma^N}\frac{L^N_{u^{K,N}_D}}{L^N} + \frac{s^N_L}{\sigma^N}\frac{K^N_{u^{K,N}_D}}{K^N}, \tag{323f}$$

$$a_{43} = -\left(\frac{\sigma^N - s^N_L}{\sigma^N}\right)\eta - \frac{s^N_L}{\sigma^N}\frac{L^N_{u^{K,N}_S}}{L^N} + \frac{s^N_L}{\sigma^N}\frac{K^N_{u^{K,N}_S}}{K^N}, \tag{323g}$$

$$a_{44} = \left[\frac{\xi^N_{2,D}}{\xi^N_{1,D}} + \eta\frac{s^N_L}{\sigma^N} + (1-\eta)\right] - \frac{s^N_L}{\sigma^N}\frac{L^N_{u^{K,N}_D}}{L^N} + \frac{s^N_L}{\sigma^N}\frac{K^N_{u^{K,N}_D}}{K^N}. \tag{323h}$$

The short-run solutions for capital and technology utilization rates are:

$$u^{K,j}_c = u^{K,j}_c\left(\bar{\lambda}, K, P^j, A^j, B^j\right), \quad c = S, D, \quad j = H, N. \tag{324}$$

Intermediate Solutions for R^j, W^j, K^j, L^j, Y^j

Plugging back solutions for the capital utilization rates (324) into the intermediate solutions for the sectoral wage rates (316) and the capital rental rates (317), for sectoral hours worked (318) and sectoral capital stocks (319), and for sectoral value added (320) leads to intermediate solutions for sectoral wages, sectoral capital rental rates, sectoral hours worked, sectoral capital stocks, sectoral value added:

$$W^j, R^j, L^j, K^j, Y^j\left(\bar{\lambda}, K, P^N, P^H, A^H, B^H, A^N, B^N\right). \tag{325}$$

O.4 Market Clearing Conditions

Finally, we have to solve for non-traded good prices and the terms of trade. The role of the price of non-traded goods in terms of foreign goods is to clear the non-traded goods market:

$$Y^N = C^N + G^N + J^N + \left(C^{K,N}_S + C^{K,N}_D\right)K^N. \tag{326}$$

The role of the price of home-produced goods in terms of foreign-produced goods or the terms of trade is to clear the home-produced traded goods market:

$$Y^H = C^H + G^H + J^H + X^H + \left(C^{K,H}_S + C^{K,H}_D\right)K^H. \tag{327}$$

As shall be useful to write formal expressions in a compact form, we wet

$$\Delta^H_{P^H} = Y^H_{P^H} - C^H_{P^H} - J^H_{P^H} - X^H_{P^H} - \xi^H_{1,S}\frac{\partial u^{K,H}_S}{\partial P^H} - \xi^H_{1,D}\frac{\partial u^{K,H}_D}{\partial P^H}, \tag{328a}$$

$$\Delta^H_{P^N} = Y^H_{P^N} - C^H_{P^N} - J^H_{P^N} - \xi^H_{1,S}\frac{\partial u^{K,H}_S}{\partial P^N} - \xi^H_{1,D}\frac{\partial u^{K,H}_D}{\partial P^H}, \tag{328b}$$

$$\Delta^H_K = Y^H_K - C^H_K - J^H_K - \xi^H_{1,S}\frac{\partial u^{K,H}_S}{\partial K} - \xi^H_{1,D}\frac{\partial u^{K,H}_D}{\partial K}, \tag{328c}$$

$$\Delta^H_{A^j} = Y^H_{A^j} - C^H_{A^j} - \xi^H_{1,S}\frac{\partial u^{K,H}_S}{\partial A^j} - \xi^H_{1,D}\frac{\partial u^{K,H}_D}{\partial A^j}, \quad j = H, N, \tag{328d}$$

$$\Delta^H_{B^j} = Y^H_{B^j} - C^H_{B^j} - \xi^H_{1,S}\frac{\partial u^{K,H}_S}{\partial B^j} - \xi^H_{1,D}\frac{\partial u^{K,H}_D}{\partial B^j}, \quad j = H, N, \tag{328e}$$

$$\Delta^N_{P^j} = Y^N_{P^j} - C^N_{P^j} - J^N_{P^j} - \xi^N_{1,S}\frac{\partial u^{K,N}_S}{\partial P^j} - \xi^N_{1,D}\frac{\partial u^{K,N}_D}{\partial P^j}, \quad j = H, N, \tag{328f}$$

$$\Delta^N_K = Y^N_K - C^N_K - J^N_K - \xi^N_{1,S}\frac{\partial u^{K,N}_S}{\partial K} - \xi^N_{1,D}\frac{\partial u^{K,N}_D}{\partial K}, \tag{328g}$$

$$\Delta^N_{A^j} = Y^N_{A^j} - C^N_{A^j} - J^N_{A^j} - \xi^N_{1,S}\frac{\partial u^{A^j,N}_S}{\partial A^j} - \xi^N_{1,D}\frac{\partial u^{A^j,N}_D}{\partial A^j}, \quad j = H, N, \tag{328h}$$

$$\Delta^N_{B^j} = Y^N_{B^j} - C^N_{B^j} - J^N_{B^j} - \xi^N_{1,S}\frac{\partial u^{B^j,N}_S}{\partial B^j} - \xi^N_{1,D}\frac{\partial u^{B^j,N}_D}{\partial B^j}, \quad j = H, N. \tag{328i}$$

Totally differentiating the market clearing conditions (326)-(327) leads to in a matrix form:

$$\begin{pmatrix} \Delta^H_{P^H} & \Delta^H_{P^N} \\ \Delta^N_{P^H} & \Delta^N_{P^N} \end{pmatrix} \begin{pmatrix} dP^H \\ dP^N \end{pmatrix} = \begin{pmatrix} -\Delta^H_K dK + J^H_Q dQ - \sum_{j=H,N}\Delta^H_{A^j} dA^j - \sum_{j=H,N}\Delta^H_{B^j} dB^j \\ -\Delta^N_K dK + J^N_Q dQ - \sum_{j=H,N}\Delta^N_{A^j} dA^j - \sum_{j=H,N}\Delta^N_{B^j} dB^j \end{pmatrix}. \tag{329}$$

Applying the implicit functions theorem leads to the short-run solutions for the terms of trade and non-traded good prices:

$$P^H, P^N \left(\bar{\lambda}, K, Q, A^H, B^H, A^N, B^N\right). \tag{330}$$

Plugging back the solutions (330) for sectoral prices into (324) and (325) allow us to find the final versions of solutions of capital utilization rates, sectoral wages, sectoral capital rental rates, sectoral hours worked, sectoral capital stocks, sectoral value added:

$$u^{K,j}_S, u^{K,j}_D, W^j, R^j, L^j, K^j, Y^j \left(\bar{\lambda}, K, Q, A^H, B^H, A^N, B^N\right). \tag{331}$$

Inserting the solutions for prices into the intermediate solutions for consumption (243) and investment (263)

$$C^g, Q^g \left(\bar{\lambda}, K, Q, A^H, B^H, A^N, B^N\right). \tag{332}$$

where $g = H, N, F$.

Using the fact that factor-augmenting efficiency X^j (with $X = A, B$, $j = H, N$) has both a symmetric S and an asymmetric D component across sectors,

$$X^j = X^j\left(X^j_S, X^j_D\right). \tag{333}$$

where

$$X^j_{X^j_S} = \frac{\partial X^j}{\partial X^j_S} = \eta\frac{X^j}{X^j_S}, \qquad X^j_{X^j_D} = \frac{\partial X^j}{\partial X^j_D} = (1-\eta)\frac{X^j}{X^j_D}, \tag{334}$$

and inserting (333) into (330), (331) and (332) leads to the following solutions for capital utilization rate, sectoral wages, sectoral capital rental rates, sectoral hours worked, sectoral capital stocks, sectoral value added:

$$P^j, u^{K,j}_S, u^{K,j}_D, W^j, R^j, L^j, K^j, Y^j \left(\bar{\lambda}, K, Q, X^j_c\right), \quad j = H, N, \tag{335}$$

and for consumption and investment in good $g = H, N, F$:

$$C^g, Q^g \left(\bar{\lambda}, K, Q, X^j_c\right), \tag{336}$$

where $X = A, B$, $j = H, N$, $c = S, D$.

O.5 Solving the Model

In our model, there are nine state variables, namely K, X_c^j where $X = A,,$ $j = H, N$, $c = S, D$, and one control variable, Q. The capital accumulation equation reads as follows:

$$\dot{K} = \frac{Y^N - C^N - G^N - \left(C_S^{K,N} + C_D^{K,N}\right) K^N}{(1-\iota)\left(\frac{P^N}{P_J}\right)^{-\phi_J}} - \delta_K K - \frac{\kappa}{2}\left(\frac{I}{K} - \delta_K\right)^2 K. \tag{337}$$

Inserting short-run solutions for value added and the capital utilization rate (335), investment and consumption in non-tradables (336), into the physical capital accumulation equation (337), and plugging the short-run solution for the return on domestic capital (335) into the dynamic equation for the shadow value of capital stock (298a), the dynamic system reads as follows:[16]

$$\dot{K} \equiv \Upsilon\left(K, Q, X_c^j\right) = \frac{E^N\left(K, Q, X_c^j\right)}{(1-\iota)\left\{\frac{P^N(.)}{P_J\left[P^H(.), P^N(.)\right]}\right\}^{-\phi_J}} - \delta_K K - \frac{K}{2\kappa}\left\{\frac{Q}{P_J\left[P^H(.), P^N(.)\right]} - 1\right\}^2, \tag{338a}$$

$$\begin{aligned}\dot{Q} \equiv \Sigma\left(K, Q, X_c^j\right) &= (r^\star + \delta_K)\, Q - \Bigg[\frac{\sum_j R^j\left(K, Q, X_c^j\right) K^j\left(K, Q, X_c^j\right)\left(u_S^{K,j}\left(K, Q, X_c^j\right)\right)^\eta \left(u_D^{K,j}\left(K, Q, X_c^j\right)\right)^{1-\eta}}{K} \\ &- \sum_j \left[C_S^{K,j} u_S^{K,j}\left(K, Q, X_c^j\right) + C_D^{K,j} u_D^{K,j}\left(K, Q, X_c^j\right)\right] \frac{K^j\left(K, Q, X_c^j\right)}{K} \\ &+ P_J\left[P^H(.), P^N(.)\right] \frac{\kappa}{2} v(.)\left(v(.) + 2\delta_K\right)\Bigg],\end{aligned} \tag{338b}$$

where $E^N = Y^N - C^N - G^N - \left(C_S^{K,N} + C_D^{K,N}\right) K^N$

O.6 Current Account Equation and Intertemporal Solvency Condition

Following the same steps as in subsection N.6, the current account reads as:

$$\dot{N} = r^\star N + P^H X^H - M^F, \tag{339}$$

where $X^H = Y^H - C^H - G^H - J^H$ stands for exports of home goods and we denote by M^F imports of foreign consumption and investment goods:

$$M^F = C^F + G^F + J^F. \tag{340}$$

Substituting first solutions for sectoral prices P^j given by (335) into export function (267) and substituting solutions for consumption and investment (336) into (340) allows us to write the current account equation as follows:

$$\begin{aligned}\dot{N} &\equiv r^\star N + \Xi\left(\bar{\lambda}, K, Q, X_c^j\right), \\ &= r^\star N + P^H\left(\bar{\lambda}, K, Q, X_c^j\right) X^H\left(\bar{\lambda}, K, Q, X_c^j\right) \\ &\quad -M^F\left(\bar{\lambda}, K, Q, X_c^j\right).\end{aligned} \tag{341}$$

O.7 CES Technology Frontier

We assume that firms in sector j choose labor and capital efficiency along the technology frontier which is assumed to take a CES form:

$$\left[\gamma_Z^j\left(A^j(t)\right)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}} + \left(1 - \gamma_Z^j\right)\left(B^j(t)\right)^{\frac{\sigma_Z^j - 1}{\sigma_Z^j}}\right]^{\frac{\sigma_Z^j}{\sigma_Z^j - 1}} \leq Z^j(t), \tag{342}$$

where $Z^j > 0$ is the height of the technology frontier, $0 < \gamma_Z^j < 1$ is the weight of labor efficiency in technology and $\sigma_Z^j > 0$ corresponds to the elasticity of substitution between

[16] We omit the shadow value of wealth from short-run solutions for clarity purposes as λ remains constant over time.

labor and capital efficiency. Performing the minimization of the unit cost for producing (53) subject to the technology frontier (342) leads to:

$$\frac{\gamma_Z^j}{1-\gamma_Z^j}\left(\frac{A^j}{B^j}\right)^{\frac{\sigma_Z^j-1}{\sigma_Z^j}} = \frac{s_L^j}{1-s_L^j}, \tag{343}$$

where we used the fact that $\left(\gamma^j\right)^{\sigma^j}\left(\frac{W^j(t)}{A^j(t)}\right)^{1-\sigma^j}\left(c^j(t)\right)^{\sigma^j-1} = s_L^j(t)$, see eq. (312a), and $\left(1-\gamma^j\right)^{\sigma^j}\left(\frac{R^j(t)}{B^j(t)}\right)^{1-\sigma^j}\left(c^j(t)\right)^{\sigma^j-1} = 1-s_L^j(t)$, see eq. (312b). As shall be useful later, we solve eq. (343) for s_L^j:

$$\begin{aligned} s_L^j &= \frac{\gamma_Z^j\left(A^j\right)^{\frac{\sigma_Z^j-1}{\sigma_Z^j}}}{\gamma_Z^j\left(A^j\right)^{\frac{\sigma_Z^j-1}{\sigma_Z^j}}+\left(1-\gamma_Z^j\right)\left(B^j\right)^{\frac{\sigma_Z^j-1}{\sigma_Z^j}}}, \\ &= \gamma_Z^j\left(\frac{A^j}{Z^j}\right)^{\frac{\sigma_Z^j-1}{\sigma_Z^j}}, \end{aligned} \tag{344}$$

where we made use of (342) to obtain the last line.

Log-linearizing (342) in the neighborhood of the initial steady-state and making use of eq. (344) leads to:

$$\begin{aligned} \hat{Z}^j(t) &= \gamma_Z^j\left(\frac{A^j}{Z^j}\right)^{\frac{\sigma_Z^j-1}{\sigma_Z^j}}\hat{A}^j(t)+\left(1-\gamma_Z^j\right)\left(\frac{B^j}{Z^j}\right)^{\frac{\sigma_Z^j-1}{\sigma_Z^j}}\hat{B}^j(t), \\ &= s_L^j\hat{A}^j(t)+\left(1-s_L^j\right)\hat{B}^j(t). \end{aligned} \tag{345}$$

Solving eq. (345) and the log-linearized version of the demand for factors of production (305) leads to the solutions for $\hat{A}^j(t)$ and $\hat{B}^j(t)$. By using the fact that factor-augmenting productivity has a symmetric and an asymmetric component across sectors, i.e., $X^j = X^j\left(X_S^j, X_D^j\right)$ (see eq. (333)), leads to the solutions for $\hat{A}_c^j(t)$ and $\hat{B}_c^j(t)$ described by (32a)-(32b) in Online Appendix J.10.

P Solving for Permanent Technology Shocks

In this section, we detail the steps to solve the model for permanent technology shocks which have a symmetric and an asymmetric component.

The percentage deviation of factor-augmenting efficiency $X_c^j = A_c^j, B_c^j$ relative to its long-run **new** value X_c^j ($c = S, D$, $j = H, N$) is described by:

$$\hat{X}_S^j(t) = e^{-\xi_{X,S}^j t}-\left(1-x_S^j\right)e^{-\chi_{X,S}^j t}, \tag{346a}$$

$$\hat{X}_D^j(t) = e^{-\xi_{X,D}^j t}-\left(1-x_D^j\right)e^{-\chi_{X,D}^j t}, \tag{346b}$$

where $\hat{X}_c^j(t) = \frac{X_c^j(t)-X_c^j}{X_c^j}$, x_c^j ($c = S, D$, $j = H, N$) parameterizes the impact response of factor-augmenting technological change; $\xi_X^j > 0$ and $\chi_X^j > 0$ are (positive) parameters which are set in order to reproduce the dynamic adjustment of factor-augmenting technological change.

Linearizing the dynamic equations of physical capital and its shadow price in the neighborhood of the steady-state, we get in a matrix form:

$$\begin{pmatrix}\dot{K}(t)\\ \dot{Q}(t)\end{pmatrix} = \begin{pmatrix}\Upsilon_K & \Upsilon_Q\\ \Sigma_K & \Sigma_Q\end{pmatrix}\begin{pmatrix}dK(t)\\ dQ(t)\end{pmatrix}+\begin{pmatrix}\sum_{c=S,D}\sum_{j=H}^N\Upsilon_{A_c^j}dA_c^j(t)+\sum_{c=S,D}\sum_{j=H}^N\Upsilon_{B_c^j}dB_c^j(t)\\ \sum_{c=S,D}\sum_{j=H}^N\Sigma_{A_c^j}dA_c^j(t)+\sum_{c=S,D}\sum_{j=H}^N\Sigma_{B_c^j}dB_c^j(t)\end{pmatrix}, \tag{347}$$

where the coefficients of the Jacobian matrix are partial derivatives evaluated at the steady-state, e.g., $\Upsilon_X = \frac{\partial \Upsilon}{\partial Y}$ with $Y = K, Q$, and the direct effects of an exogenous change in factor-augmenting productivity on K and Q are described by $\Upsilon_X = \frac{\partial \Upsilon}{\partial X}$ and $\Sigma_X = \frac{\partial \Sigma}{\partial X}$, also evaluated at the steady-state.

Now define the auxiliary vector $\hat{X}(t) = \begin{pmatrix} \hat{X}_1(t) \\ \hat{X}_2(t) \end{pmatrix}$ as follows:

$$\hat{X}(t) = \mathbf{V}^{-1}\hat{Y}(t) \tag{348}$$

Given this renaming, we can write the system as:

$$\dot{\hat{X}}(t) = \Lambda \hat{X}(t) + \mathbf{V}^{-1}\Sigma \hat{S}(t)$$

where $\Lambda = \begin{pmatrix} \nu_1 & 0 \\ 0 & \nu_2 \end{pmatrix}$, $\mathbf{V}^{-1}$ is the inverse of the matrix of eigenvectors; let us write out the product $\mathbf{V}^{-1}\Sigma$

$$\begin{pmatrix} u_{11} & u_{12} \\ & \\ u_{21} & u_{22} \end{pmatrix} \times \begin{pmatrix} \Upsilon_{A_S^H} & \Upsilon_{B_S^H} & \Upsilon_{A_S^N} & \Upsilon_{B_S^N} & \Upsilon_{A_D^H} & \Upsilon_{B_D^H} & \Upsilon_{A_D^N} & \Upsilon_{B_D^N} \\ \Sigma_{A_S^H} & \Sigma_{B_S^H} & \Sigma_{A_S^N} & \Sigma_{B_S^N} & \Sigma_{A_D^H} & \Sigma_{B_D^H} & \Sigma_{A_D^N} & \Sigma_{B_D^N} \end{pmatrix}.$$

The product leads to a matrix of the same size as the matrix of shocks, i.e., with two rows and eight columns with elements denoted by $s_{1k} = u_{11}\Upsilon_{X_c^j} + u_{12}\Sigma_{X_c^j}$ and $s_{2k} = u_{21}\Upsilon_{X_c^j} + u_{22}\Sigma_{X_c^j}$ (l indexes the row, k indexes the column).

The differential equation for $X_1(t)$ reads:

$$\dot{X}_1(t) = \nu_1 X_1(t) + \sum_{c=S,D}\sum_{j=H,N}\sum_{X=A,B} s_{1k}X_c^j \left[e^{-\xi_{X,c}^j t} - \left(1 - x_c^j\right) e^{-\chi_{X,c}^j t}\right], \tag{349a}$$

$$\dot{X}_2(t) = \nu_2 X_2(t) + \sum_{c=S,D}\sum_{j=H,N}\sum_{X=A,B} s_{1k}X_c^j \left[e^{-\xi_{X,c}^j t} - \left(1 - x_c^j\right) e^{-\chi_{X,c}^j t}\right]. \tag{349b}$$

Solving (349a)-(349b) for $X_1(t)$ and $X_2(t)$ leads to:

$$dX_1(t) = dX_1(0) + \sum_{c=S,D}\sum_{j=H,N}\sum_{X=A,B} \frac{s_{1k}X_c^j}{\nu_1 + \xi_{X,c}^j}\left[\left(e^{\nu_1 t} - e^{-\xi_{X,c}^j t}\right) - \left(1 - x_c^j\right)\left(\frac{\nu_1 + \xi_{X,c}^j}{\nu_1 + \chi_{X,c}^j}\right)\left(e^{\nu_1 t} - e^{-\chi_{X,c}^j t}\right)\right], \tag{350a}$$

$$dX_2(t) = dX_2(0) + \sum_{c=S,D}\sum_{j=H,N}\sum_{X=A,B} \frac{s_{1k}X_c^j}{\nu_1 + \xi_{X,c}^j}\left[\left(e^{\nu_2 t} - e^{-\xi_{X,c}^j t}\right) - \left(1 - x_c^j\right)\left(\frac{\nu_2 + \xi_{X,c}^j}{\nu_2 + \chi_{X,c}^j}\right)\left(e^{\nu_2 t} - e^{-\chi_{X,c}^j t}\right)\right]. \tag{350b}$$

As shall be useful to write the solutions in a compact form, we set

$$\Delta_1^{X_c^j} = -\frac{s_{1k}X_c^j}{\nu_1 + \xi_{X,c}^j}, \tag{351a}$$

$$\Delta_2^{X_c^j} = -\frac{s_{2k}X_c^j}{\nu_2 + \xi_{X,c}^j}. \tag{351b}$$

$$\Theta_1^{X_c^j} = \left(1 - x_c^j\right)\frac{\nu_1 + \xi_{X,c}^j}{\nu_1 + \chi_{X,c}^j}, \tag{351c}$$

$$\Theta_2^{X_c^j} = \left(1 - x_c^j\right)\frac{\nu_2 + \xi_{X,c}^j}{\nu_2 + \chi_{X,c}^j}, \tag{351d}$$

The solution for $X_1(t)$ and the 'stable' solution for $X_2(t)$, i.e., consistent with convergence toward the steady-state when t tends toward infinity, is thus given by:

$$dX_1(t) = X_{11}e^{\nu_1 t} + \sum_{c=S,D}\sum_{j=H,N}\sum_{X=A,B} \Delta_1^{X_c^j}\left[e^{-\xi_{X,c}^j t} - \left(1 - x_c^j\right)e^{-\chi_{X,c}^j t},\right], \tag{352a}$$

$$dX_2(t) = -\sum_{c=S,D}\sum_{j=H,N}\sum_{X=A,B} \Delta_2^{X_c^j}\left[e^{-\xi_{X,c}^j t} - \left(1 - x_c^j\right)e^{-\chi_{X,c}^j t},\right], \tag{352b}$$

where

$$X_{11} = dX_1(0) - \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \Delta_1^{X_c^j} \left(1 - \Theta_1^{X_c^j}\right). \tag{353}$$

Using the definition of $X_i(t)$ (with $i = 1, 2$) given by (348), we can recover the solutions for $K(t)$ and $Q(t)$:

$$K(t) - \tilde{K} = X_1(t) + X_2(t), \tag{354a}$$

$$Q(t) - \tilde{Q} = \omega_2^1 X_1(t) + \omega_2^2 X_2(t). \tag{354b}$$

Linearizing the current account equation around the steady-state:

$$\begin{aligned}
\dot{N}(t) &= r^\star dN(t) + \Xi_K dK(t) + \Xi_Q dQ(t) + \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \Xi_{X_c^j} dX_c^j(t), \\
&= \left(\Xi_K + \Xi_Q \omega_2^1\right) X_1(t) + \left(\Xi_K + \Xi_Q \omega_2^2\right) X_2(t) \\
&+ \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} X_c^j \left[e^{-\xi_{X,c}^j t} - \left(1 - x_c^j\right) e^{-\chi_{X,c}^j t}\right].
\end{aligned} \tag{355}$$

Setting $N_1 = \Xi_K + \Xi_Q \omega_2^1$, $N_2 = \Xi_K + \Xi_Q \omega_2^2$, inserting solutions for $K(t)$ and $Q(t)$ given by (354), solving yields the solution for traded bonds:

$$\begin{aligned}
dN(t) &= e^{r^\star t}\Bigg[(N_0 - N) - \frac{\omega_N^1}{\nu_1 - r^\star} + \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Xi_{X_c^j} X_c^j}{\xi_{X,c}^j + r^\star} \left(1 - \Theta^{X_c^j,\prime}\right) \\
&+ N_1 \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Delta_1^{X_c^j} X_c^j}{\xi_{X,c}^j + r^\star} \left(1 - \Theta_1^{X_c^j,\prime}\right) - N_2 \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Delta_1^{X_c^j} X_c^j}{\xi_{X,c}^j + r^\star} \left(1 - \Theta_2^{X_c^j,\prime}\right)\Bigg] \\
&+ \frac{\omega_N^1}{\nu_1 - r^\star} e^{\nu_1 t} - \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Xi_{X_c^j} X_c^j}{\xi_{X,c}^j + r^\star} \left[e^{-\xi_{X,c}^j t} - \Theta^{X_c^j,\prime} e^{-\chi_{X,c}^j t},\right] \\
&- N_1 \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Delta_1^{X_c^j} X_c^j}{\xi_{X,c}^j + r^\star} \left[e^{-\xi_{X,c}^j t} - \Theta_1^{X_c^j,\prime} e^{-\chi_{X,c}^j t},\right] \\
&+ N_2 \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Delta_2^{X_c^j} X_c^j}{\xi_{X,c}^j + r^\star} \left[e^{-\xi_{X,c}^j t} - \Theta_2^{X_c^j,\prime} e^{-\chi_{X,c}^j t},\right],
\end{aligned} \tag{356}$$

where $\omega_N^1 = N_1 X_{11}$ and we set

$$\Theta^{X_c^j,\prime} = \left(1 - x_c^j\right) \frac{\xi_{X,c}^j + r^\star}{\chi_{X,c}^j + r^\star}, \tag{357a}$$

$$\Theta_1^{X_c^j,\prime} = \Theta_1^{X_c^j} \frac{\xi_{X,c}^j + r^\star}{\chi_{X,c}^j + r^\star}, \tag{357b}$$

$$\Theta_2^{X_c^j,\prime} = \Theta_2^{X_c^j} \frac{\xi_{X,c}^j + r^\star}{\chi_{X,c}^j + r^\star}. \tag{357c}$$

Inserting the transversality condition into (356) leads to the 'stable' solution for the stock of foreign assets:

$$\begin{aligned}
dN(t) &= \frac{\omega_N^1}{\nu_1 - r^\star} e^{\nu_1 t} - \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Xi_{X_c^j} X_c^j}{\xi_{X,c}^j + r^\star} \left[e^{-\xi_{X,c}^j t} - \Theta^{X_c^j,\prime} e^{-\chi_{X,c}^j t},\right] \\
&- N_1 \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Delta_1^{X_c^j} X_c^j}{\xi_{X,c}^j + r^\star} \left[e^{-\xi_{X,c}^j t} - \Theta_1^{X_c^j,\prime} e^{-\chi_{X,c}^j t},\right] \\
&+ N_2 \sum_{c=S,D} \sum_{j=H,N} \sum_{X=A,B} \frac{\Delta_2^{X_c^j} X_c^j}{\xi_{X,c}^j + r^\star} \left[e^{-\xi_{X,c}^j t} - \Theta_2^{X_c^j,\prime} e^{-\chi_{X,c}^j t},\right],
\end{aligned} \tag{358}$$

which is consistent with the intertemporal solvency condition

$$\begin{aligned} dN &= -\frac{\omega_N^1}{\nu_1 - r^\star} + \sum_{c=S,D}\sum_{j=H,N}\sum_{X=A,B} \frac{\Xi_{X_c^j} X_c^j}{\xi_{X,c}^j + r^\star}\left(1 - \Theta^{X_c^j,\prime}\right) \\ &+ N_1 \sum_{c=S,D}\sum_{j=H,N}\sum_{X=A,B} \frac{\Delta_1^{X_c^j} X_c^j}{\xi_{X,c}^j + r^\star}\left(1 - \Theta_1^{X_c^j}\right) - N_2 \sum_{c=S,D}\sum_{j=H,N}\sum_{X=A,B} \frac{\Delta_2^{X_c^j} X_c^j}{\xi_{X,c}^j + r^\star}\left(1 - \Theta_2^{X_c^j}\right), \end{aligned} \tag{359}$$

where $dN = N - N_0$. Eq. (359) determines the change in the equilibrium value of the marginal utility of wealth which adjusts once for al once the permanent shock hits the economy so that the open economy remains solvent.

Q Semi-Small Open Economy Model with Sticky Prices

In this section, we extend our baseline model by introducing nominal price rigidities on non-traded goods. We allow for non-separable preferences and assume both imperfect mobility of labor and capital across sectors. Sectoral goods are produced by means of CES production functions. We do not repeat the main elements of the model, see section O, and emphasize the main changes caused by the assumption of sticky prices.

Building on Farhi and Werning [2016] and Kaplan, Moll, and Violante [2018], we propose a New Keynesian model with heterogeneous good producers. Like Farhi and Werning [2017] we consider a two-sector open economy with sticky prices in the non-traded sector. While Farhi and Werning [2017] abstract from capital accumulation, in the lines of Kaplan et al. [2018], we allow for capital accumulation and generate sticky prices by assuming quadratic adjustment costs. Time is continuous.

There are five agents: households, the government, intermediate good firms, retailers and final goods producers. While the terms of trade deteriorate significantly on impact and along the dynamics, non-traded goods prices adjustment only gradually. Therefor we assume that only non-traded goods are subject to sticky prices. To allow for sticky prices in the non-traded sector, we assume that there are imperfectly competitive intermediate good producers in the non-traded sector which produce differentiated goods which are sold at (flexible) prices M^N to retailers. Monopolistically competitive retailers purchase input goods from the input good firms, differentiate them and sell them to final good producers. Each retailer i chooses the sales price to maximize profits subject to price adjustment costs as in Rotemberg [1982], taking as given the demand curve and the price of input goods M^N. Adjustment costs are assumed to be quadratic in the rate of price change and to be proportional to value added in the non-traded sector:

$$\theta\left(\frac{\dot{P}_i^N}{P_i^N}\right) = \frac{\theta}{2}\left(\frac{\dot{P}_i^N}{P_i^N}\right)^2 P^N Y^N, \tag{360}$$

where $\frac{\dot{P}_i^N}{P_i^N}$ stands for the individual price inflation π_i^N; $\theta > 0$ determines the degree of price stickiness in the non-traded sector. Existence of quadratic costs generates profits in the retail sector, $\Pi_i^{N,R}$. While the government provides a subsidy τ^N to retailers so as to reduce the price over the marginal cost to one, the subsidy is financed by means of a lump-sump tax T^N which is transferred to the households lump sum. Finally, a competitive representative final goods producer aggregates a continuum of output produced by retailers.

The small open economy takes as given the world interest rate. Like Chodorow-Reich et al. [2023], we consider an open economy with a fixed exchange rate regime which has removed all capital controls so that the domestic interest rate collapses to the world interest rate. While this assumption avoids adding too much complexity because the Taylor rule collapses to $r = r^\star$, this ensures that the baseline model is obtained when we let the parameter of the price adjustment cost function be zero.

Q.1 Households

All elements which characterize the behavior of households is detailed in section N.1. While households supply labor and capital services, they also choose the capital utilization rates. They are the owners of retailers and thus receive the profit $\Pi_i^{N,R}$ which will be detailed later:

$$
\begin{aligned}
\dot{N}(t) \quad & +P_C(t)C(t) + P_J(t)J(t) + \sum_{j=H,N} P^j(t)C^{K,j}(t)\nu^{K,j}(t)K(t) + \frac{\theta}{2}\left(\pi^N(t)\right)^2 P^N(t)Y^N(t) \\
= \quad & r^\star N(t) + W(t)L(t) + \int_0^1 \Pi_i^{N,R}(t)di + R^K(t)K(t) \sum_{j=H,N} \alpha_K^j(t)u^{K,j}(t) - T(t). \quad (361)
\end{aligned}
$$

Households maximize their lifetime utility where instantaneous utility is assumed to be non-separable in consumption and leisure (214)-(215) (i.e., we consider Shimer [2009] preferences) subject to the budget constraint (361). First-order conditions are described by the set of equations (220a)-(220f).

Q.2 Home-Produced Traded Good Firms: Flexible Terms of Trade

Firms in the traded sector faces two cost components: a capital rental rate $R^H(t)$ and a wage rate $W^H(t)$:

$$
\max_{\tilde{K}^H(t),L^H(t)} \Pi_I^H(t) = \max_{\tilde{K}^H(t),L^H(t)} \left\{P^H(t)Y^H(t) - W^H(t)L^H(t) - R^H(t)\tilde{K}^H(t)\right\}. \quad (362)
$$

The first order conditions of the firm problem in the traded sector are:

$$
P^H\left(1-\gamma^H\right)\left(B^H\right)^{\frac{\sigma^H-1}{\sigma^H}}\left(u^{K,H}K^H\right)^{-\frac{1}{\sigma^H}}\left(Y^H\right)^{\frac{1}{\sigma^H}} = R^H, \quad (363a)
$$

$$
P^H\gamma^H\left(A^H\right)^{\frac{\sigma^H-1}{\sigma^H}}\left(L^H\right)^{-\frac{1}{\sigma^H}}\left(Y^H\right)^{\frac{1}{\sigma^H}} \equiv W^H. \quad (363b)
$$

Q.3 Final and Intermediate Non-Traded Good Producers

We assume that within the non-traded sector, there are a large number of intermediate good producers which produce differentiated varieties and thus are imperfectly competitive.

Final Non-Traded Good Firms

The final non-traded output, Y^N, is produced in a competitive retail sector using a constant-returns-to-scale production function which aggregates a continuum measure one of sectoral goods:

$$
Y^N = \left[\int_0^1 \left(X_i^N\right)^{\frac{\omega-1}{\omega}} \mathrm{d}i\right]^{\frac{\omega}{\omega-1}}, \quad (364)
$$

where $\omega > 0$ represents the elasticity of substitution between any two different varieties and X_i^N stands for intermediate consumption of ith-variety (with $i \in (0,1)$). The final good producers behave competitively, and the households use the final good for both consumption and investment.

Denoting by P^N and P_i^N the price of the final good in the non-traded sector and the price of the ith variety of the intermediate good, respectively, the profit of the final good producer reads:

$$
\Pi_F^N = P^N\left[\int_0^1 \left(X_i^N\right)^{\frac{\omega-1}{\omega}} \mathrm{d}i\right]^{\frac{\omega}{\omega}} - \int_0^1 P_i^N X_i^N \mathrm{d}i. \quad (365)
$$

Total cost minimizing for a given level of final output gives the (intratemporal) demand function for each input:

$$
X_i^N = \left(\frac{P_i^N}{P^N}\right)^{-\omega} Y^N, \quad (366)
$$

and the price of the final output is given by:

$$
P^N = \left(\int_0^1 \left(P_i^N\right)^{1-\omega} \mathrm{d}i\right)^{\frac{1}{1-\omega}}, \quad (367)
$$

where P_i^N is the price of variety i in sector j and P^N is the price of the final good in sector $j = H, N$. According to eq. (366), the price-elasticity of output of the ith variety within the non-traded sector is:

$$-\frac{\partial X_i^N}{\partial P_i^N}\frac{P_i^N}{X_i^N} = \omega. \tag{368}$$

Intermediate Goods Firms

Each intermediate good producer faces two cost components: a capital rental cost equal to $R^N(t) = R^N(t)$, and a labor cost equal to the wage rate $W^N(t) = W^N(t)$,. Intermediate good producers choose capital services and labor by taking prices as given:

$$\max_{\tilde{K}^N(t),L^N(t)} \Pi_I^N(t) = \max_{\tilde{K}^N(t),L^N(t)} \left\{M^N(t)Y^N(t) - W^N(t)L^N(t) - R^N(t)\tilde{K}^N(t)\right\}, \tag{369}$$

where $\tilde{K}^N = u^{K,N}K^N$ and Y^N is given by eq. (364).

The first-order conditions of the firm problem are:

$$M^N\left(1-\gamma^N\right)\left(B^N\right)^{\frac{\sigma^N-1}{\sigma^N}}\left(u^{K,N}K^N\right)^{-\frac{1}{\sigma^N}}\left(Y^N\right)^{\frac{1}{\sigma^N}} \equiv R^N, \tag{370a}$$

$$M^N\gamma^N\left(A^N\right)^{\frac{\sigma^N-1}{\sigma^N}}\left(L^N\right)^{-\frac{1}{\sigma^N}}\left(Y^N\right)^{\frac{1}{\sigma^N}} \equiv W^N. \tag{370b}$$

Q.4 Retailers and Price Stickiness

We assume that the monopolistic competition occurs at the retail level. The retailers purchase input goods from intermediate good producers, differentiate them and sell them to final good producers. Each retailer chooses the sales price P_i^N to maximize profits subject to price adjustment costs as they differentiate and sell them to final good producers. Retailers experience quadratic costs in adjusting type-i good variety and thus are the source of sticky prices: the price P_i^N is therefore a state variable. Each retailer i in the non-traded sector charges a price P_i^N to maximize profits subject to price adjustment costs à la Rotemberg [1982], taking as given the demand curve for type-i good variety and the aggregate price index in the non-traded sector P^N. The adjustment costs are assumed to be quadratic in the rate of change of non-traded prices and are assumed to be proportional to value added in non-traded sector:

$$\theta\left(\frac{\dot{P}_i^N}{P_i^N}\right) = \frac{\theta}{2}\left(\frac{\dot{P}_i^N}{P_i^N}\right)^2 P^N Y^N, \tag{371}$$

where $\theta > 0$ the individual wage inflation is $\pi_i^N = \frac{\dot{P}_i^N}{P_i^N}$; θ determines the degree of price stickiness in the non-traded sector. We assume that retailers receive a proportional constant subsidy on type-i good variety, τ^N, setting the steady-state markup to one. This subsidy is financed by a lump sum tax on retailers T^N.

Each retailed maximizes the expected profit stream discounted at the real rate $r^N(s) = r^\star - \pi^N(s)$, i.e.,

$$\begin{aligned} &\max_{\dot{P}_i^N,P_i^N} \frac{\Pi_i^N(t)}{P^N(t)}, \\ \equiv\ &\max_{\dot{P}_i^N,P_i^N} \int_0^\infty e^{-\int_0^t r^N(s)ds}\left[\frac{P_i^N\left(1+\tau^N\right)-M^N}{P^N}X_i^N - \frac{\theta}{2}\left(\frac{\dot{P}_i^N}{P_i^N}\right)^2 Y^N\right], \end{aligned} \tag{372}$$

subject to $\dot{P}_i^N(t) = \pi_i^N(t)P_i^N(t)$. Note that in line with the current practice, we divide the profit by the price index. The control variable is $\dot{P}_i^N(t)$ and the state variable is $P_i^N(t)$. To solve the optimization problem, we set up the current-value Hamiltonian for the i-th retailers (R) in the non-traded sector (N):

$$\begin{aligned} \mathcal{H}_i^{R,N} &= \frac{P_i^N}{P^N}\left(1+\tau^N\right)\left(\frac{P_i^N}{P^N}\right)^{-\omega}Y^N - \frac{M^N}{P^N}\left(\frac{P_i^N}{P^N}\right)^{-\omega}Y^N - \frac{\theta}{2}\left(\frac{\dot{P}_i^N}{P_i^N}\right)^2 Y^N + \Lambda_i^N\dot{P}_i^N, \\ &= \left(\frac{P_i^N}{P^N}\right)^{1-\omega}\left(1+\tau^N\right)Y^N - \frac{M^N}{\left(P^N\right)^{1-\omega}}\left(P_i^N\right)^{-\omega}Y^N - \frac{\theta}{2}\left(\frac{\dot{P}_i^N}{P_i^N}\right)^2 Y^N + \Lambda_i^N\dot{P}_i^N, \end{aligned} \tag{373}$$

where we have inserted $X_i^N = \left(\frac{P_i^N}{P^N}\right)^{-\omega} Y^N$ (see eq. (366)). First-order conditions read:

$$\frac{\partial \mathcal{H}_i^{R,N}}{\partial \dot{P}_i^N} = 0, \qquad \theta \frac{\pi_i^N}{P_i^N} = \Lambda_i^N, \tag{374a}$$

$$\frac{\partial \mathcal{H}_i^{R,N}}{\partial P_i^N} = \left(r^\star - \pi^N\right) \Lambda_i^N - \dot{\Lambda}_i^N,$$

$$\frac{(1-\omega)\left(P_i^N\right)^{-\omega}}{\left(P^N\right)^{1-\omega}} \left(1+\tau^N\right) Y^N + \frac{M^N}{\left(P^N\right)^{1-\omega}} \omega \left(P_i^N\right)^{-\omega-1} Y^N + \theta \frac{\left(\dot{P}_i^N\right)^2}{\left(P_i^N\right)^3} Y^N$$
$$= \left(r^\star - \pi^N\right) \Lambda_i^N - \dot{\Lambda}_i^N,$$
$$\frac{(1-\omega)\left(1+\tau^N\right) Y^N}{P^N} + \frac{M^N \omega Y^N}{\left(P^N\right)^2} + \theta \frac{\left(\pi^N\right)^2}{P^N} Y^N$$
$$= \left(r^\star - \pi^N\right) \theta \frac{\pi^N}{P^N} Y^N - \theta \frac{\dot{\pi}^N}{P^N} Y^N - \theta \frac{\pi^N}{P^N} \dot{L}^j + \theta \frac{\pi^N}{P^N} \frac{\dot{W}^j}{P^N} Y^N,$$
$$\frac{(1-\omega)\left(1+\tau^N\right)}{\theta} + \frac{M^N}{\theta} \frac{\omega}{P^N} + \left(\pi^N\right)^2 = \left(r^\star - \pi^N\right) \pi^N - \dot{\pi}^N - \pi^N \frac{\dot{L}^j}{Y^N} + \left(\pi^N\right)^2,$$
$$\dot{\pi}^N + \frac{\omega}{\theta} \left[\frac{M^N}{P^N} - \left(\frac{\omega-1}{\omega}\right)\left(1+\tau^N\right)\right] = \pi^N \left[r^\star - \pi^N - \frac{\dot{L}^j}{Y^N}\right],$$
$$\dot{\pi}^N + \frac{\omega}{\theta} \left[\frac{M^N}{P^N} - 1\right] = \pi^N \left[r^\star - \pi^N - \frac{\dot{Y}^N}{Y^N}\right], \tag{374b}$$

where we assume a symmetric situation to get the second line of the second first-order condition, i.e., $P_i^N = P^N$, and we have inserted (374a) which has also been differentiated w.r.t. time:

$$\dot{\Lambda}_i^N = \theta \frac{\dot{\pi}^N}{P^N} Y^N + \theta \frac{\pi^N}{P^N} \dot{Y}^N - \theta \frac{\pi^N}{P^N} \frac{\dot{P}^N}{P^N} Y^N.$$

To get the last line, we assume that the government sets the revenue subsidy τ^N so that $\left(\frac{\omega-1}{\omega}\right)\left(1+\tau^N\right) = 1$, i.e.,

$$\tau^N = \frac{1}{\omega - 1} > 0. \tag{375}$$

This subsidy τ^N is financed by a lump sum tax on retailers T^N which is transferred to the households lump sum. We drop the subindex i because we consider a symmetric situation. The total profit of retailers, net of the lump sum tax, is:

$$\int_0^1 \Pi_i^{R,N} di = \Pi^N = \left(P^N - M^N\right) X_i^N - \frac{\theta}{2} \left(\frac{\dot{P}_i^N}{P_i^N}\right)^2 P^N Y^N. \tag{376}$$

where $X_i^N = X^N = Y^N$ in a symmetric steady-state.

Q.5 Solving the Model

Totally differentiating (363a)-(363b), (370a)-(370b) and inserting solutions for L^H and L^N given by eq. (245) and solutions for K^H and K^N given by eq. (247) into (363a)-(363b) allow us to solve the demand for labor and capital in the traded and the non-traded sector for sectoral wage rates and sectoral capital rental rates:

$$W^H, W^N, R^H, R^N \left(M^N, P^H, K, P^N, u^{K,H}, u^{K,N}, A^H, B^H, A^N, B^N, \bar{\lambda}\right). \tag{377}$$

Plugging the demand for capital (370a) in the non-traded sector into the decision about capital utilization rate (298b), and totally differentiating leads to:

$$\left[\frac{\xi_2^N}{\xi_1^N} + \frac{s_L^N}{\sigma^N}\right] \hat{u}^{K,N} + \frac{s_L^N}{\sigma^N}\left(\hat{K}^N - \hat{L}^N\right) = \left(\frac{\sigma^N - s_L^N}{\sigma^N}\right) \hat{B}^N + \left(\frac{s_L^N}{\sigma^N}\right) \hat{A}^N, \tag{378}$$

where we do not repeat the log-linearized versions of the optimal decisions for the capital utilization rates for the traded sector described by eq. (321). Inserting first solutions for L^j, K^j, and Y^j, and invoking the implicit functions theorem leads to:

$$u^{K,j}\left(M^N, P^H, K, P^N, A^H, B^H, A^N, B^N, \bar{\lambda}\right). \tag{379}$$

Plugging back solutions for capital and technology utilization rates into (377) yields:

$$L^j, K^j, Y^j, C^g\left(M^N, P^H, K, P^N, A^H, B^H, A^N, B^N, \bar{\lambda}\right), \tag{380}$$

Inserting appropriate solutions, the non-traded goods market clearing condition (326) can be rewritten as follows:

$$\begin{aligned} & Y^N\left(M^N, P^H, K, P^N, A^H, B^H, A^N, B^N, \bar{\lambda}\right) = C^N\left(\bar{\lambda}, P^N, P^H\right) + G^N + J^N\left(K, Q, P^N, P^H\right) \\ + \quad & C^{K,N}\left[u^{K,N}\left(M^N, P^H, K, P^N, A^H, B^H, A^N, B^N, \bar{\lambda}\right)\right] K^N + \frac{\theta}{2}\left(\pi^N(t)\right)^2 Y^N(t) \end{aligned} \tag{381}$$

Linearizing (381) leads to:

$$dY^N(t) = dC^N(t) + dJ^N(t) + K^N \xi_1^N du^{K,N}(t), \tag{382}$$

where we used the fact that $\pi^N = 0$ at the steady-state so that the term $\theta \pi^N Y^N d\pi^N(t)$ vanishes.

Inserting appropriate solutions, the traded goods market clearing condition (327) can be rewritten as follows:

$$\begin{aligned} & Y^H\left(M^N, P^H, K, P^N, A^H, B^H, A^N, B^N, \bar{\lambda}\right) = C^H\left(\bar{\lambda}, P^N, P^H\right) + G^H + J^H\left(K, Q, P^N, P^H\right) \\ + \quad & C^{K,H}\left[u^{K,H}\left(M^N, P^H, K, P^N, A^H, B^H, A^N, B^N, \bar{\lambda}\right)\right] K^H. \end{aligned} \tag{383}$$

Linearizing (383) leads to:

$$dY^H(t) = dC^H(t) + dJ^H(t) + dX^H(t) + K^H \xi_1^H du^{K,H}(t), \tag{384}$$

The market clearing conditions for the home-produced and non-traded goods, i.e., (381) and (383) allow us to solve for terms of trade and non-traded intermediate good prices:

$$P^H, M^N\left(K, P^N, A^H, B^H, A^N, B^N, \bar{\lambda}\right). \tag{385}$$

Inserting (385) into (379) and (380) leads to:

$$L^j, K^j, Y^j, C^g, u^{K,j}\left(K, P^N, A^H, B^H, A^N, B^N, \bar{\lambda}\right). \tag{386}$$

Dynamic System
The dynamic system comprises four dynamic equations:

$$\dot{K} = \frac{Y^N - C^N - G^N - C^{K,N}\left(u^{K,N}\right) K^N - \frac{\theta}{2}\left(\pi^N\right)^2 Y^N}{(1-\iota)\left[\frac{P^N}{P_J}\right]^{-\phi_J}} - \delta_K K - \frac{K}{2\kappa}\left[\frac{Q}{P_J} - 1\right]^2, \tag{387a}$$

$$\begin{aligned} \dot{Q} = \left(r^\star + \delta_K\right) Q - \Bigg\{ & \frac{1}{K}\left[R^H u^{K,H} K^H + R^N u^{K,N} K^N\right] \\ & -P^H C^{K,H} \nu^{K,H} - P^N C^{K,N} \nu^{K,N} + P_J \frac{\kappa}{2}\left(\frac{I}{K} - \delta_K\right)\left(\frac{I}{K} + \delta_K\right)\Bigg\}, \end{aligned} \tag{387b}$$

$$\dot{P}^N = \pi^N P^N, \tag{387c}$$

$$\dot{\pi}^N = \pi^N\left[r^\star - \pi^N - \frac{\dot{Y}^N}{Y^N}\right] - \frac{\omega}{\theta}\left[\frac{M^N}{P^N} - 1\right] \tag{387d}$$

where $Y^N, C^N, J^N, u^{K,H}, u^{K,N}, M^N \left(K, Q, P^N, A^H, B^H, A^N, B^N, G\right)$. The dynamic system can be rewritten in a compact form:

$$\dot{K} = \Upsilon\left(K, Q, P^N, A^H, B^H, A^N, B^N\right), \tag{388a}$$

$$\dot{Q} = \Sigma\left(K, Q, P^N, A^H, B^H, A^N, B^N\right), \tag{388b}$$

$$\dot{P}^N = \pi^N P^N, \tag{388c}$$

$$\dot{\pi}^N = \Pi\left(K, Q, P^N, A^H, B^H, A^N, B^N\right). \tag{388d}$$

Linearization and Solutions

Linearizing (388a)-(388d) in the neighborhood of the steady-state, we get in a matrix form:

$$\begin{pmatrix} \dot{K}(t) \\ \dot{Q}(t) \\ \dot{P}^N(t) \\ \dot{\pi}^N(t) \end{pmatrix} = \begin{pmatrix} \Upsilon_K & \Upsilon_Q & \Upsilon_{P^N} & 0 \\ \Sigma_K & \Sigma_Q & \Sigma_{P^N} & 0 \\ 0 & 0 & 0 & \pi^N \\ \Pi_K & \Pi_Q & \Pi_{P^N} & r^\star \end{pmatrix} \begin{pmatrix} dK(t) \\ dQ(t) \\ dP^N(t) \\ d\pi^N(t) \end{pmatrix} + \begin{pmatrix} \sum_{j=H}^N \Upsilon_{A^j} dA^j(t) + \sum_{j=H}^N \Upsilon_{B^j} dB^j(t) \\ \sum_{j=H}^N \Sigma_{A^j} dA^j(t) + \sum_{j=H}^N \Sigma_{B^j} dB^j(t) \\ 0 \\ \sum_{j=H}^N \Pi_{A^j} dA^j(t) + \sum_{j=H}^N \Pi_{B^j} dB^j(t) \end{pmatrix}, \tag{389}$$

where the coefficients of the Jacobian matrix are partial derivatives evaluated at the steady-state.

We define auxiliary variables $\dot{X}(t) = \Lambda X(t) + V^{-1}\Sigma Z(t)$ where $Z(t)$ is the vector of technology shocks and Σ is a matrix which collects the effects of shocks on the dynamics, and Λ is the matrix of eigenvalues with $\nu_1, \nu_2 < 0$ and $\nu_3, \nu_4 > 0$ on its diagonal, and V is the matrix of eigenvectors. We define $V^{-1}\Sigma = S$ which is a matrix which has the same size as the matrix of shocks.

The solutions for capital, the shadow price of capital, non-traded prices and inflation of non-tradables read:

$$K(t) - K = \sum_{i=1}^{4} X_i(t), \tag{390a}$$

$$Q(t) - Q = \sum_{i=1}^{4} \omega_2^i X_i(t), \tag{390b}$$

$$P^N(t) - P^N = \sum_{i=1}^{4} \omega_3^i X_i(t), \tag{390c}$$

$$\pi^N(t) - \pi^N = \sum_{i=1}^{4} \omega_4^i X_i(t), \tag{390d}$$

where $\pi^N = 0$ at the steady-state.

Current Account and Intertemporal Solvency Condition

The current account reads:

$$\dot{N}(t) = r^\star N(t) + P^H(t) X^H(t) - M^F(t), \tag{391}$$

where $X^H = Y^H - C^H - G^H - J^H - C^{K,H} K^H$ stands for exports of home goods and we denote by M^F imports of foreign consumption and investment goods:

$$M^F = C^F + G^F + J^F. \tag{392}$$

Inserting appropriate solutions, the current account equation reads:

$$\dot{N}(t) = r^\star N(t) + \Xi\left(K(t), Q(t), P^N(t), X^j(t)\right), \qquad j = H, N, \tag{393}$$

where $X^j = A^j, B^j$. Let us denote by Ξ_K, Ξ_Q, Ξ_{P^N}, Ξ_{X^j} the partial derivatives evaluated at the steady-state of the dynamic equation for the current account w.r.t. K, Q, P^N, and X^j. Linearizing (393) in the neighborhood of the steady-state, inserting solutions for $K(t)$, $Q(t)$, $P^N(t)$, together with the law of motion of $X^j(t)$ and solving yields the general solution for the net foreign asset position:

$$dN(t) = \left[(N_0 - N) - \sum_{i=1}^{4} \Psi_i D_i - \Psi_2 D_2\right] e^{r^\star t} + \Psi_1 D_1 e^{\nu_1 t} + \Psi_2 D_2 e^{\nu_2 t}, \tag{394}$$

where N_0 is the initial stock of traded bonds and we set

$$E_i = \Xi_K + \Xi_Q \omega_2^i + \Xi_{P^N} \omega_3^i, \tag{395a}$$

$$\Psi_i = \frac{E_i}{\nu_i - r^\star}. \tag{395b}$$

Invoking the transversality condition, we eliminate explosive paths and set $D_3 = D_4 = 0$. It leads to the linearized version of the nations's intertemporal solvency condition

$$N_0 - N = \Psi_1 D_1 + \Psi_2 D_2. \tag{396}$$

Setting $t = 0$ into (390a) and (390c) leads to $K_0 - K = D_1 + D_2$ and $P_0^N - P^N = \omega_3^1 D_1 + \omega_3^2 D_2$ which can be written in a matrix form:

$$\begin{pmatrix} 1 & 1 \\ \omega_3^1 & \omega_3^2 \end{pmatrix} \begin{pmatrix} D_1 \\ D_2 \end{pmatrix} = \begin{pmatrix} K_0 - K \\ P_0^N - P^N \end{pmatrix}.$$

The solutions are:

$$D_1 = \frac{(K_0 - K)\,\omega_3^2 - \left(P_0^N - P^N\right)}{\omega_3^2 - \omega_3^1}, \tag{397a}$$

$$D_2 = \frac{\left(P_0^N - P^N\right) - (K_0 - K)\,\omega_3^1}{\omega_3^2 - \omega_3^1}. \tag{397b}$$

Inserting (397) into (396) leads to the linearized version of the net foreign asset position

$$N_0 - N = \Phi_K (K_0 - K) + \Phi_{PN} \left(P_0^N - P^N\right), \tag{398}$$

where

$$\Phi_K = \frac{E_1 \omega_3^2 (\nu_2 - r^\star) - E_2 \omega_3^1 (\nu_1 - r^\star)}{(\nu_1 - r^\star)(\nu_2 - r^\star)\left(\omega_3^2 - \omega_3^1\right)}, \tag{399a}$$

$$\Phi_{PN} = \frac{E_2 (\nu_1 - r^\star) - E_1 (\nu_2 - r^\star)}{(\nu_1 - r^\star)(\nu_2 - r^\star)\left(\omega_3^2 - \omega_3^1\right)}. \tag{399b}$$

Accumulation Equation of Non Human Wealth

Remembering that the stock of financial wealth $A(t)$ is equal to $N(t) + Q(t)K(t)$, differentiating w.r.t. time, i.e., $\dot{A}(t) = \dot{N}(t) + \dot{Q}(t)K(t) + Q(t)\dot{K}(t)$, plugging the dynamic equation for the marginal value of capital (220e), inserting the accumulation equations for physical capital (217) and foreign assets (361), yields the accumulation equation for the stock of financial wealth or the dynamic equation for private savings:

$$\begin{aligned}
\dot{A}(t) &= r^\star N(t) + W(t)L(t) + R^K(t)K(t) \sum_{j=H,N} \alpha_K^j(t) u^{K,j}(t) + Y^N(t)\left(P^N(t) - M^N(t)\right) - G(t) \\
&- \frac{\theta}{2}\left(\pi^N(t)\right)^2 P^N(t) Y^N(t) - P_C(t)C(t) + P_J(t)J(t) - \sum_{j=H,N} P^j(t) C^{K,j}(t) \nu^{K,j}(t) K(t) + Q(t)\left[I(t) - \delta_I\right. \\
&+ K(t)(r^\star + \delta_K) Q(t) - K(t)\left\{\sum_j \alpha_K^j(t) u^{K,j}(t) R^K(t) - \sum_j P^j(t) C^{K,j}(t) \nu^{K,j}(t) - P_J(t)\frac{\partial J(t)}{\partial K(t)}\right\}, \\
&= r^\star A(t) + \tilde{\Pi}^N(t) + W(t)L(t) - T(t) - P_C(t)C(t),
\end{aligned}$$

where $j = H, N$ and we used the fact that $\tilde{\Pi}^N(t) \equiv \int_0^1 \Pi_i^{N,R}(t) di = P^N Y^N - M^N Y^N - \frac{\theta}{2}\left(\pi^N\right)^2 P^N Y^N$ and we assume that the government levies lump-sum taxes, T, to finance purchases of foreign-produced, home-produced and non-traded goods, i.e., $T = G = \left(G^F + P^H(.)G^H + P^N(.)G^N\right)$.

Q.6 Solutions to Permanent Technology Shocks

When we solve the model with sticky prices, we consider an aggregate technology shock as we are not investigating the effects of a rising share of asymmetric technology shocks. We calibrate the shocks to $A^j(t)$ and $B^j(t)$ so that the adjustment in $Z^j(t)$ they generate is identical to its adjustment when consider we consider shocks to the symmetric and asymmetric components of $A^j_c(t)$ and $B^j_c(t)$. The percentage deviation of factor-augmenting efficiency $X^j = A^j, B^j$ relative to its long-run *new* value X^j $(j = H, N)$ is described by:

$$\hat{X}^j(t) = e^{-\xi^j_X t} - \left(1 - x^j\right) e^{-\chi^j_X t}, \quad j = H, N. \tag{401}$$

where $\hat{X}^j(t) = \frac{X^j(t) - X^j}{X^j}$ with X^j the new steady-state level, x^j $(j = H, N)$ parameterizes the impact response of factor-augmenting technological change; $\xi^j_X > 0$ and $\chi^j_X > 0$ are (positive) parameters which are set in order to reproduce the dynamic adjustment of factor-augmenting technological change.

We define auxiliary variables $\dot{X}(t) = \Lambda X(t) + V^{-1}\Sigma Z(t)$ where $Z(t)$ is the vector of technology shocks and Σ is a matrix which collects the effects of shocks on the dynamics, and Λ is the matrix of eigenvalues with $\nu_1, \nu_2 < 0$ and $\nu_3, \nu_4 > 0$ on its diagonal, and V is the matrix of eigenvectors. We define $V^{-1}\Sigma = S$ which is a matrix which has the same size as the matrix of shocks. More specifically, let us write out the elements of $V^{-1}\Sigma$:

$$\begin{pmatrix} u_{11} & u_{12} & u_{13} & u_{14} \\ u_{21} & u_{22} & u_{23} & u_{24} \\ u_{31} & u_{32} & u_{33} & u_{34} \\ u_{41} & u_{42} & u_{43} & u_{44} \end{pmatrix} \times \begin{pmatrix} \Upsilon_{A^H} & \Upsilon_{B^H} & \Upsilon_{A^N} & \Upsilon_{B^N} \\ \Sigma_{A^H} & \Sigma_{B^H} & \Sigma_{A^N} & \Sigma_{B^N} \\ P^N_{A^H} & P^N_{B^H} & P^N_{A^N} & P^N_{B^N} \\ \Pi_{A^H} & \Pi_{B^H} & \Pi_{A^N} & \Pi_{B^N} \end{pmatrix} = \begin{pmatrix} s_{11} & s_{12} & s_{13} & s_{14} \\ s_{21} & s_{22} & s_{23} & s_{24} \\ s_{31} & s_{32} & s_{33} & s_{34} \\ s_{41} & s_{42} & s_{43} & s_{44} \end{pmatrix}. \tag{402}$$

The product leads to a matrix of the same size as the matrix of shocks, i.e., with four rows and four columns with elements denoted by $s_{1k} = u_{11}\Upsilon_{X^j} + u_{12}\Sigma_{X^j} + u_{13}P^N_{X^j} + u_{14}\Pi_{X^j}$, $s_{2k} = u_{21}\Upsilon_{X^j} + u_{22}\Sigma_{X^j} + u_{23}P^N_{X^j} + u_{24}\Pi_{X^j}$, $s_{3k} = u_{31}\Upsilon_{X^j} + u_{32}\Sigma_{X^j} + u_{33}P^N_{X^j} + u_{34}\Pi_{X^j}$, $s_{4k} = u_{41}\Upsilon_{X^j} + u_{42}\Sigma_{X^j} + u_{43}P^N_{X^j} + u_{44}\Pi_{X^j}$ (l indexes the row, k indexes the column).

As shall be useful below to write the solutions in a compact form, we index eigenvalues with the subscript i (i.e., ν_i) and we denote

$$\Delta^{X^j}_i = -\frac{s_{ik}X^j}{\nu_i + \xi^j_X}, \tag{403a}$$

$$\Theta^{X^j}_i = \left(1 - x^j\right)\frac{\nu_{1i} + \xi^j_X}{\nu_i + \chi^j_X}, \tag{403b}$$

where $\Delta^{X^j}_i$ and $\Delta^{X^j}_i$ are terms which are functions of eigenvalue ν_i and shock parameters. Solving $\dot{X}_i(t) = \nu_i X_i(t) + \sum_{i=1}^4 s_{ik} dX_i(t)$, the solutions for $X_i(t)$ are:

$$X_1(t) = X_{11}e^{\nu_1 t} + \sum_{X^j} \Delta^{X^j}_1 \left[e^{-\xi^j_X t} - \left(1 - x^j\right) e^{-\chi^j_X t}\right], \tag{404a}$$

$$X_2(t) = X_{21}e^{\nu_2 t} + \sum_{X^j} \Delta^{X^j}_2 \left[e^{-\xi^j_X t} - \left(1 - x^j\right) e^{-\chi^j_X t}\right], \tag{404b}$$

$$X_3(t) = -\sum_{X^j} \Delta^{X^j}_3 \left[e^{-\xi^j_X t} - \left(1 - x^j\right) e^{-\chi^j_X t}\right], \tag{404c}$$

$$X_4(t) = -\sum_{X^j} \Delta^{X^j}_4 \left[e^{-\xi^j_X t} - \left(1 - x^j\right) e^{-\chi^j_X t}\right], \tag{404d}$$

where $X^j = A^j, B^j$ (with $j = H, N$) and

$$X_{11} = X_1(0) - \sum_{X^j} \Delta_1^{X^j} \left(1 - \Theta_1^{X^j}\right), \tag{405a}$$

$$X_{21} = X_2(0) - \sum_{X^j} \Delta_2^{X^j} \left(1 - \Theta_2^{X^j}\right), \tag{405b}$$

$$\Delta_1^{X^j} = -\frac{u_{1x} X^j}{\nu_1 + \xi_X^j}, \quad \Delta_2^{X^j} = -\frac{u_{2x} X^j}{\nu_2 + \xi_X^j}, \tag{405c}$$

$$\Delta_3^{X^j} = \frac{u_{3x} X^j}{\nu_3 + \xi_X^j}, \quad \Delta_4^{X^j} = \frac{u_{4x} X^j}{\nu_4 + \xi_X^j}, \tag{405d}$$

where $X^j = A^j, B^j$ with $j = H, N$ and $x = 1, 2, 3, 4$. Solutions for $X_1(0)$ and $X_2(0)$ are given by

$$X_1(0) = \frac{\omega_3^2 (K_0 - K) - (P_0^N - P^N) - X_3(0)\left(\omega_3^2 - \omega_3^3\right) - X_4(0)\left(\omega_3^2 - \omega_3^4\right)}{\omega_3^2 - \omega_3^1}, \tag{406a}$$

$$X_1(0) = \frac{(P_0^N - P^N) - \omega_3^1 (K_0 - K) + X_3(0)\left(\omega_3^1 - \omega_3^3\right) + X_4(0)\left(\omega_3^1 - \omega_3^4\right)}{\omega_3^2 - \omega_3^1}, \tag{406b}$$

where $K(0) = K_0$ and $P^N(0) = P_0^N$. Using the definition of $Y(t) = \mathbf{V}X(t)$, we obtain solutions for capital, the shadow price of capital, non-traded goods prices and inflation rate of non-tradables which are described by (390). Setting $t = 0$ into the solutions of state variables (390a) and (390c) leads to $K(0) - K = \sum_{i=1}^4 X_i(0)$ and $P^N(0) - P^N = \sum_{i=1}^4 \omega_3^i X_i(0)$. Solutions for $X_1(0)$ and $X_2(0)$ are:

$$X_1(0) = \frac{\omega_3^2 (K_0 - K) - (P_0^N - P^N) - X_3(0)\left(\omega_3^2 - \omega_3^3\right) - X_4(0)\left(\omega_3^2 - \omega_3^4\right)}{\omega_3^2 - \omega_3^1}, \tag{407a}$$

$$X_1(0) = \frac{(P_0^N - P^N) - \omega_3^1 (K_0 - K) + X_3(0)\left(\omega_3^1 - \omega_3^3\right) + X_4(0)\left(\omega_3^1 - \omega_3^4\right)}{\omega_3^2 - \omega_3^1}. \tag{407b}$$

Linearizing the current account equation, inserting solutions and solving leads to:

$$\begin{aligned} dN(t) \; = \; & \frac{\omega_B^1}{\nu_1 - r^\star} e^{\nu_1 t} + \frac{\omega_B^2}{\nu_2 - r^\star} e^{\nu_2 t} - \sum_{X^j} \frac{\Xi_{X^j} X^j}{\xi_{X^j} + r^\star} \left(e^{-\xi_{X^j} t} - \Theta^{X^j,\prime} e^{-\chi_{X^j} t}\right) \\ - \; & E_1 \sum_{X^j} \frac{\Delta_1^{X^j}}{\xi_{X^j} + r^\star} \left(e^{-\xi_{X^j} t} - \Theta_1^{X^j,\prime} e^{-\chi_{X^j} t}\right) - E_2 \sum_{X^j} \frac{\Delta_2^{X^j}}{\xi_{X^j} + r^\star} \left(e^{-\xi_{X^j} t} - \Theta_2^{X^j,\prime} e^{-\chi_{X^j} t}\right), \\ + \; & E_3 \sum_{X^j} \frac{\Delta_3^{X^j}}{\xi_{X^j} + r^\star} \left(e^{-\xi_{X^j} t} - \Theta_3^{X^j,\prime} e^{-\chi_{X^j} t}\right) + E_4 \sum_{X^j} \frac{\Delta_4^{X^j}}{\xi_{X^j} + r^\star} \left(e^{-\xi_{X^j} t} - \Theta_4^{X^j,\prime} e^{-\chi_{X^j} t}\right) \end{aligned} \tag{408}$$

where $\omega_B^1 = E_1 X_{11}$, $\omega_B^2 = E_2 X_{21}$ and indexing eigenvalues with $i = 1, 2, 3, 4$, we set

$$X_{11} = dX_1(0) - \sum_{j=H,N} \sum_{X^j = A^j, B^j} \Delta_1^{X^j} \left(1 - \Theta_1^{X^j}\right), \tag{409a}$$

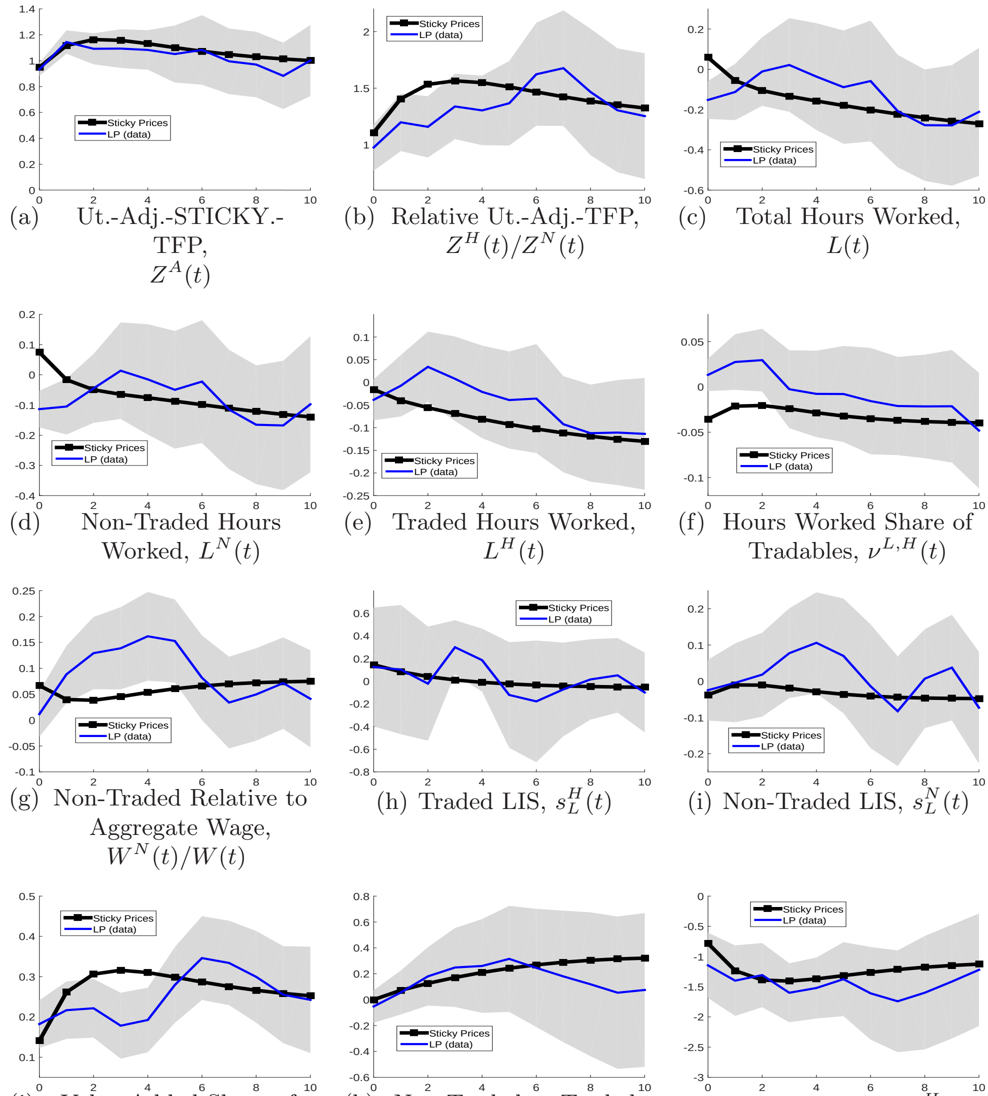
$$X_{21} = dX_2(0) - \sum_{j=H,N} \sum_{X^j = A^j, B^j} \Delta_2^{X^j} \left(1 - \Theta_2^{X^j}\right), \tag{409b}$$

$$\Theta_i^{X^j,\prime} = \Theta_i^{X^j} \frac{\xi_X^j + r^\star}{\chi_X^j + r^\star}, \tag{409c}$$

$$\Theta^{X^j,\prime} = \left(1 - x^j\right) \frac{\xi_X^j + r^\star}{\chi_X^j + r^\star}. \tag{409d}$$

where $X^j = A^j, B^j$ and $j = H, N$. To get the convergent solution (408), we have imposed the transversality condition which in turn requires that the intertemporal solvency condition holds:

$$(N - N_0) = \frac{\omega_B^1}{r^\star - \nu_1} + \frac{\omega_B^2}{r^\star - \nu_2} + \sum_{X^j} \frac{\omega_B^{X^j}}{r^\star + \xi_{X^j}}, \tag{410}$$



(a) Ut.-Adj.-STICKY.-TFP, $Z^A(t)$
(b) Relative Ut.-Adj.-TFP, $Z^H(t)/Z^N(t)$
(c) Total Hours Worked, $L(t)$
(d) Non-Traded Hours Worked, $L^N(t)$
(e) Traded Hours Worked, $L^H(t)$
(f) Hours Worked Share of Tradables, $\nu^{L,H}(t)$
(g) Non-Traded Relative to Aggregate Wage, $W^N(t)/W(t)$
(h) Traded LIS, $s_L^H(t)$
(i) Non-Traded LIS, $s_L^N(t)$
(j) Value Added Share of Tradables, $\nu^{Y,H}(t)$
(k) Non-Traded to Traded Prices, $P(t)$
(l) Terms of Trade, $P^H(t)$

Figure 44: Theoretical vs. Empirical Responses Following a Technology Shock. Notes: 'LP (data)' refers to the solid blue line which displays point estimate from local projections with shaded areas indicating 90% confidence bounds; 'Sticky Prices' refers to the thick solid black line with squares which displays model predictions in the non-traded goods sticky price extension of the baseline model. We consider a permanent technology improvement normalized to one percent in the long-run, see Fig. 44(a).

where we set

$$\begin{aligned} \omega_B^{X^j} &= \Xi_{X^j} X^j \left(1 - \Theta^{X^j,\prime}\right) + E_1 \Delta_1^{X^j} \left(1 - \Theta_1^{X^j,\prime}\right) + E_2 \Delta_2^{X^j} \left(1 - \Theta_2^{X^j,\prime}\right) \\ &- E_3 \Delta_3^{X^j} \left(1 - \Theta_3^{X^j,\prime}\right) - E_4 \Delta_4^{X^j} \left(1 - \Theta_4^{X^j,\prime}\right). \end{aligned} \tag{411}$$

Q.7 Numerical Results

In this subsection, we explore quantitatively the dynamic effects of a permanent technology improvement normalized to 1% in the long-run. We consider the same model as in the main text except that we assume that non-traded goods prices are sticky and thus adjust only gradually. The calibration is identical to that in the main text. We have to calibrate two new parameters. Following Kaplan et al. [2018] we choose a value of 10 for the elasticity of substitution ω between intermediate goods for final goods producers, implying a steady-state markup of 11%. We set θ in the price adjustment cost function to 100, so that the slope of the Phillips curve is $\frac{\omega}{\theta} = 0.1$.

Fig. 44 contrasts dynamic responses estimated empirically which are displayed by solid blue lines with model's predictions which are shown in solid black lines with squares. As in the main text, we consider the same dynamic adjustment of utilization-adjusted-TFP associated with a productivity differential between tradables and non-tradables as shown in Fig. 44(a) and Fig. 44(b). For the purpose of comparison, we consider the same macroeconomic variables as in Fig. 5 in the main text except that we replace the relative price of non-tradable (i.e., $P^N(t)/P^H(t)$) with the price of non-traded goods $P^N(t)$. In a one-sector closed economy model as in Gali [1999], assuming that money supply is fixed, a technology shock unambiguously lowers hours. A model with flexible prices can account for the decline in hours once we assume that the economy has access to world capital markers and trades with the rest of the world. Intuitively, when the country is open to international trade and world capital markets, households can work less as they can import goods from abroad to meet a higher demand for traded goods. As long as mobility costs are not prohibitive, labor shifts away from the traded sector and toward the non-traded sector to meet the higher demand for non-traded goods. However, since technology improvements are concentrated within traded industries, the higher marginal cost leads non-traded firms to set higher prices which mitigate the rise in the demand for non-traded goods. In the model with flexible prices, non-traded hours decline disproportionately compared with traded hours. By contrast, when non-traded good prices are sticky, see Fig. 44(k), hours increase in the non-traded sector, as displayed by Fig. 44(d). Intuitively, in a model with flexible prices, higher demand for non-tradables gives rise to an appreciation in non-traded goods prices which eliminates the excess demand in the non-traded sector. Conversely, when non-traded goods prices are sticky, the excess demand which arises in the non-traded sector must give rise to an increase in non-traded hours worked as prices cannot adjust to eliminate the excess demand. Because non-traded hours significantly increase and the non-traded sector accounts for two-third of labor, total hours worked increase as displayed by the black line in Fig. 44(c)

R Skilled vs. Unskilled Labor: Evidence

So far, we have considered that workers' skills were homogenous across sectors. One key question is whether the decline in total hours worked is uniformly distributed across workers' skills and if not, how does the skill composition effect drive the time-increasing response of hours. The evidence we document below reveals that the decline in total hours worked in the short-run caused by a technology improvement is concentrated among skilled workers.

R.1 Skill Composition Effects: The Framework

R.1.1 Households

The representative household supplies both skilled and unskilled labor. We denote hours worked for skilled and unskilled labor by $S(t)$ and $U(t)$. In exchange for offering skilled and unskilled labor services, the worker receives a wage rate of $W^S(t)$ and $W^U(t)$, respectively. Total labor income is:

$$W(t)L(t) = W^S(t)S(t) + W^U(t)U(t). \tag{412}$$

We thus assume that the disutility from aggregate labor supply is split into the disutility from the supply of skilled labor and the supply of unskilled labor:

$$\zeta \frac{\sigma_L}{1+\sigma_L} L^{\frac{1+\sigma_L}{\sigma_L}} = \left[\zeta_S \frac{\sigma_L}{1+\sigma_L} (S)^{\frac{\sigma_L+1}{\sigma_L}} + \zeta_U \frac{\sigma_L}{1+\sigma_L} (U)^{\frac{\sigma_L+1}{\sigma_L}}\right], \tag{413}$$

where $0 < \zeta_s < 1$ ($s = S, U$) is the weight of skilled (unskilled) labor supply to the labor index $L(.)$ and σ_L is the Frisch elasticity of labor supply. The aggregage wage index is:

$$W(t) = \left[\zeta_S \left(W^S(t)\right)^{\sigma_L+1} + \zeta_U \left(W^U(t)\right)^{\sigma_L+1}\right]^{\frac{1}{\sigma_L+1}}. \tag{414}$$

The supply of skilled and unskilled hours worked is described by:

$$S(t) = \zeta_S \left(\frac{W^S(t)}{W(t)}\right)^{\sigma_L} L(t), \tag{415a}$$

$$U(t) = \zeta_U \left(\frac{W^U(t)}{W(t)}\right)^{\sigma_L} L(t). \tag{415b}$$

Log-linearizing (414) leads to:

$$\hat{W}(t) = \alpha_S \hat{W}^S(t) + (1-\alpha_S)\,\hat{W}^U(t), \tag{416}$$

where α_S and α_U stands for the skilled and unskilled share of labor income, respectively:

$$\alpha_S = \frac{W^S S(t)}{W(t)L(t)} = \zeta_S \left(\frac{W^S(t)}{W(t)}\right)^{\sigma_L+1}, \tag{417a}$$

$$\alpha_U = \frac{W^U U(t)}{W(t)L(t)} = \zeta_U \left(\frac{W^U(t)}{W(t)}\right)^{\sigma_L+1}. \tag{417b}$$

We made use of (415a) and (415b) to get (417a)-(417b).

Following Horvath [2000], we assume that hours worked in the traded and the non-traded sectors are aggregated by means of a CES function:

$$S(t) = \left[\vartheta_S^{-1/\epsilon_S}\left(S^H\right)^{\frac{\epsilon_S+1}{\epsilon_S}} + (1-\vartheta_S)^{-1/\epsilon_S}\left(S^N\right)^{\frac{\epsilon_S+1}{\epsilon_S}}\right]^{\frac{\epsilon_S}{\epsilon_S+1}}, \tag{418a}$$

$$U(t) = \left[\vartheta_U^{-1/\epsilon_U}\left(U^H\right)^{\frac{\epsilon_U+1}{\epsilon_U}} + (1-\vartheta_U)^{-1/\epsilon_U}\left(U^N\right)^{\frac{\epsilon_U+1}{\epsilon_U}}\right]^{\frac{\epsilon_U}{\epsilon_U+1}}, \tag{418b}$$

where $0 < \vartheta_S < 1$ (ϑ_U) is the weight of skilled (unskilled) labor supply to the traded sector in the skilled (unskilled) labor index $S(.)$ ($U(.)$) and ϵ_S (ϵ_U) measures the ease with which skilled (unskilled) hours worked can be substituted for each other and thereby captures the degree of skilled (unskilled) labor mobility across sectors.

The aggregate wage index $W(.)$ associated with the above defined labor index for skilled (418a) and unskilled (418b) labor supply is:

$$W^S(t) = \left[\vartheta_S\left(W^{S,H}(t)\right)^{\epsilon_S+1} + (1-\vartheta_S)\left(W^{S,N}(t)\right)^{\epsilon_S+1}\right]^{\frac{1}{\epsilon_S+1}}, \tag{419a}$$

$$W^U(t) = \left[\vartheta_U\left(W^{U,H}(t)\right)^{\epsilon_U+1} + (1-\vartheta_U)\left(W^{U,N}(t)\right)^{\epsilon_U+1}\right]^{\frac{1}{\epsilon_U+1}}, \tag{419b}$$

where $W^{S,H}(t)$ ($W^{U,H}(t)$) and $W^{S,N}(t)$ ($W^{U,N}(t)$) are wages paid in the traded and the non-traded sectors for skilled (unskilled) labor.

Given the aggregate wage index for skilled labor (419a) and unskilled labor (419b), we can derive the allocation of labor supply to the traded and the non-traded sector for each type of skill:

$$S^H(t) = \vartheta_S\left(\frac{W^{S,H}(t)}{W^S(t)}\right)^{\epsilon_S} S(t), \qquad S^N(t) = (1-\vartheta_S)\left(\frac{W^{S,N}(t)}{W^S(t)}\right)^{\epsilon_S} S(t). \tag{420a}$$

$$U^H(t) = \vartheta_U\left(\frac{W^{U,H}(t)}{W^U(t)}\right)^{\epsilon_U} U(t), \qquad S^N(t) = (1-\vartheta_U)\left(\frac{W^{U,N}(t)}{W^U(t)}\right)^{\epsilon_U} U(t). \tag{420b}$$

Aggregating labor compensation across sectors and skills leads to:

$$W^{S,H}S^H + W^{S,N}S^N = W^S S, \tag{421a}$$

$$W^{U,H}U^H + W^{U,N}U^N = W^U U, \tag{421b}$$

where W is the aggregate wage and L is aggregate labor supply.

As will be useful later, log-linearizing the wage index in the neighborhood of the initial steady-state leads to:

$$\hat{W}^S(t) = \alpha_S^H \hat{W}^{S,H}(t) + \left(1-\alpha_S^H\right)\hat{W}^{S,N}(t), \tag{422a}$$

$$\hat{W}^U(t) = \alpha_U^H \hat{W}^{U,H}(t) + \left(1-\alpha_U^H\right)\hat{W}^{U,N}(t), \tag{422b}$$

where $\alpha_S^H = \frac{W^{S,H}S^H}{W^S S}$ and $\alpha_U^H = \frac{W^{U,H}U^H}{W^U U}$ tradable content of aggregate labor compensation:

$$\alpha_S^H = \vartheta_S\left(\frac{W^{S,H}}{W^S}\right)^{1+\epsilon_S}, \qquad 1-\alpha_S^H = (1-\vartheta_S)\left(\frac{W^{S,N}}{W^S}\right)^{1+\epsilon_S}, \tag{423a}$$

$$\alpha_U^H = \vartheta_U\left(\frac{W^{U,H}}{W^U}\right)^{1+\epsilon_U}, \qquad 1-\alpha_U^H = (1-\vartheta_U)\left(\frac{W^{U,N}}{W^U}\right)^{1+\epsilon_U}. \tag{423b}$$

R.1.2 Firms

Each sector consists of a large number of identical firms which use labor, L^j, and physical capital (inclusive of capital utilization), $\tilde{K}^j$, according to a technology described by a CES production function:

$$Y^j(t) = \left[\gamma^j \left(A^j(t)L^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right)\left(B^j(t)\tilde{K}^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}, \tag{424}$$

where $0 < \gamma^j < 1$ is the weight of labor in the production technology, σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$, and $A^j(t)$ and $B^j(t)$ are labor- and capital-augmenting efficiency.

We assume that efficient labor is a CES aggregator of skilled and unskilled labor:

$$A^jL^j(t) = \left[\gamma_L^j \left(A_S^j(t)S^j(t)\right)^{\frac{\sigma_L^j-1}{\sigma_L^j}} + \left(1-\gamma_L^j\right)\left(A_U^j(t)U^j(t)\right)^{\frac{\sigma_L^j-1}{\sigma_L^j}}\right]^{\frac{\sigma_L^j}{\sigma_L^j-1}}, \tag{425}$$

where $0 < \gamma_L^j < 1$ is the weight of skilled labor in the efficient labor index, σ_L^j is the elasticity of substitution between skilled and unskilled labor in sector $j = H, N$, and $A_S^j(t)$ and $A_U^j(t)$ are skilled labor- and unskilled labor-augmenting efficiency.

Because we assume that goods and factor products are perfectly competitive and since CES production functions display constant returns to scale, one can define the labor content of value added in sector $j = H, N$ or the labor income share:

$$\frac{\partial Y^j}{\partial L^j}\frac{L^j}{Y^j} = \frac{W^jL^j}{P^jY^j} \equiv s_{SL}^j, \tag{426}$$

and the skilled (unskilled) content of labor in sector $j = H, N$ denoted by s_S^j (s_U^j) or the skilled (unskilled) labor income share:

$$\frac{\partial L^j}{\partial S^j}\frac{S^j}{L^j} = \frac{W^{S,j}S^j}{W^jL^j} \equiv s_S^j, \tag{427a}$$

$$\frac{\partial L^j}{\partial U^j}\frac{S^j}{L^j} = \frac{W^{U,j}U^j}{W^jL^j} \equiv s_U^j = 1 - s_S^j. \tag{427b}$$

Aggregating labor compensation across skills leads to:

$$W^{S,H}S^H + W^{U,H}U^H = W^HL^H, \tag{428a}$$

$$W^{S,N}S^N + W^{U,N}U^N = W^NL^N. \tag{428b}$$

Aggregating labor compensation across sectors leads to:

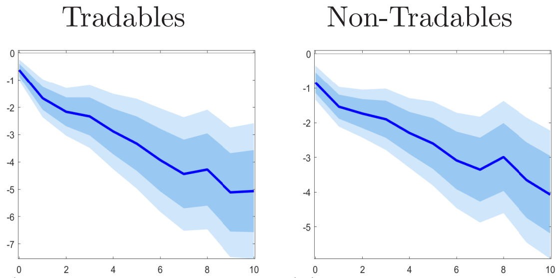
$$W(t)L(t) = W^H(t)L^H(t) + W^N(t)L^N(t), \tag{429}$$

where W is the aggregate wage and L is aggregate labor supply.

R.2 Skill-Biased Technological Change and Sectoral Labor Income

As shall be useful later, we draw on Caselli and Coleman [2006] and Caselli [2016] to construct time series for SBTC. Denoting the elasticity of substitution between skilled and unskilled labor in sector j by σ_L^j, skilled-labor- and unskilled-labor-augmenting efficiency by $A_t^{S,j}$ and $A_t^{U,j}$, respectively, and the skilled labor income share by $s_{S,it}^j = \frac{W_{it}^{S,j}S_{it}^j}{W_{it}^jL_{it}^j}$, our measure of capital-utilization-adjusted-FBTC, denoted by SBTC_t^j, reads:

$$\text{SBTC}_{it}^j = \left(\frac{A_{it}^{S,j}/\bar{A}_i^{S,j}}{A_{it}^{U,j}/\bar{A}_i^{U,j}}\right)^{\frac{\sigma_L^j-1}{\sigma_L^j}} = \left(\frac{S_{S,it}^j}{\bar{S}_{S,i}^j}\right)\left(\frac{S_{it}^j/\bar{S}_i^j}{U_{it}^j/\bar{U}_i^j}\right)^{-\left(\frac{\sigma_L^j-1}{\sigma_L^j}\right)}, \tag{430}$$



(a) Skill-Biased Technological Change in the Traded Sector (b) Skill-Biased Technological Change in the Non-Traded Sector

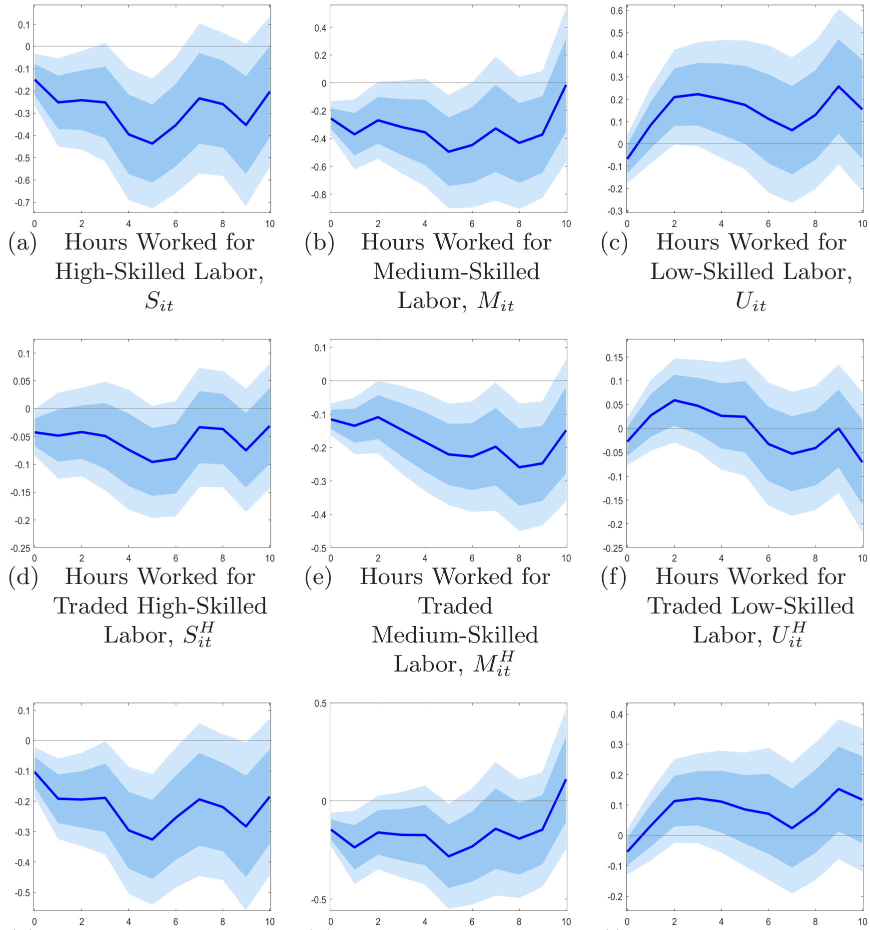
Figure 45: Technology Shock and Skill-Biased Technological Change Notes: The solid blue line shows the response of skill-biased technological change to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. To estimate the dynamic responses to a technology shock, we adopt a two-step method. In the first step, we estimate a VAR model that includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage and the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the second step, we estimate the effects by using Jordà's [2005] single-equation method. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in total hours worked units (sectoral hours worked). Sample: 11 OECD countries, 1970-2017, annual data.

where a bar refers to averaged values of the corresponding variable over 1970-2017. To construct time series for SBTC_{it}^{j}, we plug time series for the ratio of the skilled to unskilled labor income share, $S_{S,t}^{j} = s_{S,t}^{j}/\left(1 - s_{S,t}^{j}\right)$, the ratio of skilled to unskilled hours worked, $\frac{S^j(t)}{U^j(t)}$. We also plug values for σ_L^j we have estimated for each country of the sample (11 OECD countries, 1970-2017). We find values for σ_L^j larger than one for the whole sample (and most of countries/sectors) thus corroborating the gross substitutability between skilled and unskilled workers documented by Havranek et al. [2024]. When SBTC_{it}^{j} increases, technological change is biased toward skilled labor while a fall indicates that technological change is biased toward unskilled labor. Since $s_{S,t}^{j}$ and S^j/L^j falls in both sectors, we expect a decline in SBTC_{it}^{j}. This hypothesis is corroborated by our evidence shown in Fig. 45. Both panels plot the dynamic response of SBTC in the traded and the non-traded sector after a technology shock. For both sectors, our measure (430) of SBTC declines. Since $\sigma_L^j > 1$ (with $j = H, N$), it means that unskilled-labor-augmenting increases relative to skilled-labor-augmenting productivity. Intuitively, as unskilled-labor-augmenting productivity increases more rapidly than skilled-labor-augmenting productivity, because skilled and unskilled labor are gross substitutes in production, firms find it more profitable to increase the demand for unskilled labor, which makes production more intensive in unskilled hours and less intensive in skilled labor.

R.3 Data Construction and Source

To disentangle the labor effects of a technology improvement across workers' skills, we use time series from EU KLEMS [2008] which are available for eleven OECD countries, see below. The maximum time period of time is 1970-2017 and the minimum time period is 2008-2017. As shown in subsection R.4, the responses of high- and medium-skilled labor are very similar and quite distinct from those obtained for low-skilled workers. Thus, for the purpose of clarity, we consider two types of workers: those who are skilled by aggregating high- and medium-skilled labor and those who are unskilled. Skilled hours worked are denoted by S_{it} and unskilled hours worked are denoted by U_{it}.

Source. Time series about high- (denoted by the superscript S), medium- (denoted by the superscript M), and low-skilled labor (denoted by the superscript U) are taken from EU KLEMS Database, Timmer et al. [2008]. Data are available for eleven OECD countries. The baseline period is running from 1970 to 2017 but is different and shorter for several countries as indicated in braces for the corresponding countries: Austria (1980-2017), Belgium (1980-2017), Canada (1970-2005), Denmark (1980-2017), Finland (1970-2017), Italy (1970-2017), Japan (1973-2017), the Netherlands (1979-2017), Spain (1980-2017), the United Kingdom (1970-2017), and the United States (1970-2005). We calculate the share of labor compensation in industry j for skilled labor as the ratio of the sum of



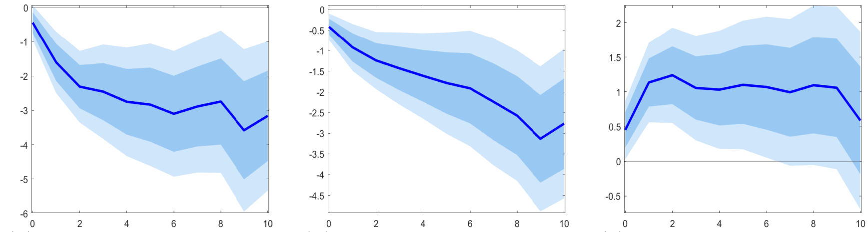
(a) Hours Worked for High-Skilled Labor, S_{it}
(b) Hours Worked for Medium-Skilled Labor, M_{it}
(c) Hours Worked for Low-Skilled Labor, U_{it}
(d) Hours Worked for Traded High-Skilled Labor, S_{it}^H
(e) Hours Worked for Traded Medium-Skilled Labor, M_{it}^H
(f) Hours Worked for Traded Low-Skilled Labor, U_{it}^H
(g) Hours Worked for Non-Traded High-Skilled Labor, S_{it}^N
(h) Hours Worked for Non-Traded Medium-Skilled Labor, M_{it}^N
(i) Hours Worked for Non-Traded Low-Skilled Labor, U_{it}^N

Figure 46: Effects of a Technology Shock across Workers' Skills Notes: The solid blue line shows the response of labor hours across workers' skills to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. To estimate the dynamic responses to a technology shock, we adopt a two-step method. In the first step, we estimate a VAR model that includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage and the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the second step, we estimate the effects by using Jordà's [2005] single-equation method. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in total hours worked units (sectoral hours worked). Sample: 11 OECD countries, 1970-2017, annual data.

labor compensation of high- and medium-skilled labor to total labor compensation in sector j, i.e., $s_S^j = \frac{W^{S,j}S^j + W^{M,j}M^j}{W^jL^j}$. To calculate the intensity of industry j in skilled labor, we multiply the share of labor compensation is skilled labor by the labor income share, i.e., $s_S^j \times s_L^j$, to ensure a consistency with the measure of capital intensity which is expressed as a percentage of value added.

R.4 Evidence about the Labor Market Effects of a Technology Shock across Workers' Skills

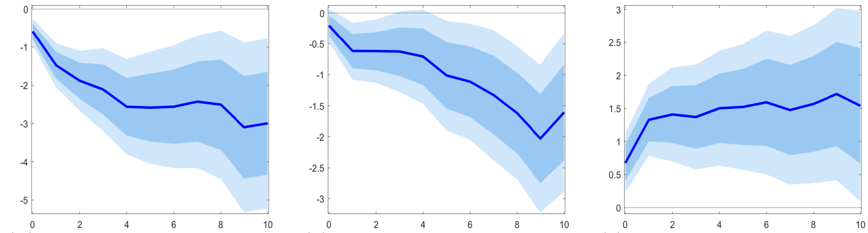
In the data, there are three types of labor, say high-, medium-, and low-skilled. As it stands out from the evidence we document in Fig. 46 and Fig. 47 which shows the dynamic effects of a 1% permanent increase in utilization-adjusted-aggregate-TFP, the responses of both high- and medium-skilled labor are quite distinct from the responses of low-skilled labor. More specifically, the evidence reveals that both high- and medium-skilled labor decline significantly at both an aggregate and sectoral level while the fall in hours of low-skilled workers is never statistically significant at any horizon. Importantly, as can be seen in Fig. 47, the labor income shares of both high- and medium-skilled labor, i.e., $s_S^j = \frac{W^{S,j}S^j}{W^jL^j}$ and $s_M^j = \frac{W^{M,j}M^j}{W^jL^j}$, decline dramatically while the labor income share of low-skilled labor, i.e., $s_U^j = \frac{W^{U,j}U^j}{W^jL^j}$, increases.



(a) High-Skilled Labor Income Share of Tradables, $s^H_{S,it}$

(b) Medium-Skilled Labor Income Share of Tradables, $s^H_{M,it}$

(c) Low-Skilled Labor Income Share of Tradables, $s^H_{U,it}$



(d) High-Skilled Labor Income Share of Non-Tradables, $s^N_{S,it}$

(e) Medium-Skilled Labor Income Share of Non-Tradables, $s^N_{M,it}$

(f) Low-Skilled Labor Income Share of Non-Tradables, $s^N_{U,it}$

Figure 47: Effects of a Technology Shock on Labor Income Shares across Workers' Skills

Notes: The solid blue line shows the response of labor hours across workers' skills to an exogenous increase in utilization-adjusted aggregate TFP by 1% in the long-run. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. To estimate the dynamic responses to a technology shock, we adopt a two-step method. In the first step, we estimate a VAR model that includes utilization-adjusted aggregate TFP, real GDP, total hours worked, the real consumption wage and the technology shock is identified by imposing long-run restrictions, i.e., technology shocks are driven by the permanent increase in utilization-adjusted aggregate TFP. In the second step, we estimate the effects by using Jordà's [2005] single-equation method. Horizontal axes indicate years. Vertical axes measure percentage deviation from trend in labor compensation units. Sample: 11 OECD countries, 1970-2017, annual data.

S Semi-Small Open Economy with Skilled and Unskilled Labor

This Appendix puts forward an open economy model with tradables and non-tradables, imperfect mobility of labor and capital across sectors, capital adjustment costs, endogenous terms of trade where we make the distinction between skilled and unskilled labor and allow for skill-biased technological change in addition to factor-biased technological change.

S.1 Households

At each instant of time, the representative household consumes traded and non-traded goods denoted by C^T and C^N, respectively, which are aggregated by means of a CES function:

$$C = \left[\varphi^{\frac{1}{\phi}}\left(C^T\right)^{\frac{\phi-1}{\phi}} + (1-\varphi)^{\frac{1}{\phi}}\left(C^N\right)^{\frac{\phi-1}{\phi}}\right]^{\frac{\phi}{\phi-1}}, \tag{431}$$

where $0 < \varphi < 1$ is the weight of the traded good in the overall consumption bundle and ϕ corresponds to the elasticity of substitution between traded goods and non-traded goods. The index C^T is defined as a CES aggregator of home-produced traded goods, C^H, and foreign-produced traded goods, C^F:

$$C^T = \left[\left(\varphi^H\right)^{\frac{1}{\rho}}\left(C^H\right)^{\frac{\rho-1}{\rho}} + (1-\varphi_H)^{\frac{1}{\rho}}\left(C^F\right)^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}}, \tag{432}$$

where $0 < \varphi_H < 1$ is the weight of the home-produced traded good in the overall traded consumption bundle and ρ corresponds to the elasticity of substitution between home-produced traded goods goods and foreign-produced traded goods.

The investment good is produced using inputs of the traded good and the non-traded good according to a constant-returns-to-scale function which is assumed to take a CES form:

$$J^K = \left[\iota^{\frac{1}{\phi_J}}\left(J^T\right)^{\frac{\phi_J-1}{\phi_J}} + (1-\iota)^{\frac{1}{\phi_J}}\left(J^N\right)^{\frac{\phi_J-1}{\phi_J}}\right]^{\frac{\phi_J}{\phi_J-1}}, \tag{433}$$

where ι is the weight of the investment traded input ($0 < \iota < 1$) and ϕ_J corresponds to the elasticity of substitution in investment between traded and non-traded inputs. The index J^T is defined as a CES aggregator of home-produced traded inputs, J^H, and foreign-produced traded inputs, J^F:

$$J^T = \left[(\iota_H)^{\frac{1}{\rho_J}} \left(J^H\right)^{\frac{\rho_J - 1}{\rho_J}} + (1 - \iota_H)^{\frac{1}{\rho_J}} \left(J^F\right)^{\frac{\rho_J - 1}{\rho_J}} \right]^{\frac{\rho_J}{\rho_J - 1}}, \tag{434}$$

where $0 < \iota_H < 1$ is the weight of the home-produced traded in input in the overall traded investment bundle and ρ_J corresponds to the elasticity of substitution between home- and

We allow for imperfect mobility of capital across sectors by assuming that the capital stock in the traded and the non-traded sectors are aggregated by means of a CES function:

$$K = \left[\vartheta_K^{-1/\epsilon_K} \left(K^H\right)^{\frac{\epsilon_K + 1}{\epsilon_K}} + (1 - \vartheta_K)^{-1/\epsilon_K} \left(K^N\right)^{\frac{\epsilon_K + 1}{\epsilon_K}} \right]^{\frac{\epsilon_K}{\epsilon_K + 1}}, \tag{435}$$

where $0 < \vartheta_K < 1$ is the weight of capital supply to the traded sector in the aggregate capital index $K(.)$ and ϵ_K measures the ease with which tangible assets can be substituted for each other and thereby captures the degree of capital mobility across sectors.

The aggregate capital rental index $R^K(.)$ associated with the above defined capital index (435) is:

$$R^K(t) = \left[\vartheta_K \left(R^H(t)\right)^{\epsilon_K + 1} + (1 - \vartheta_K) \left(R^N(t)\right)^{\epsilon_K + 1} \right]^{\frac{1}{\epsilon_K + 1}}, \tag{436}$$

where $R^H(t)$ and $R^N(t)$ are capital rental rates paid in the traded and the non-traded sectors.

The representative agent is endowed with one unit of time, supplies a fraction $L(t)$ as labor, and consumes the remainder $1 - L(t)$ as leisure. At any instant of time, households derive utility from their consumption and experience disutility from working. The representative household maximizes the following objective function:

$$\mathcal{U} = \int_0^\infty \Lambda \left(C(t), L(t)\right) e^{-\beta t} \mathrm{d}t, \tag{437}$$

where $\beta > 0$ is the discount rate. We allow for non-separability in consumption and leisure in preferences. The household's period utility function is increasing in his/her consumption C and decreasing in his/her labor supply L, with functional form (see Shimer [2009]):

$$\Lambda \left(C, L\right) \equiv \frac{C^{1-\sigma} V(L)^\sigma - 1}{1 - \sigma}, \quad \text{if} \quad \sigma \neq 1, \quad V(L) \equiv \left(1 + (\sigma - 1) \zeta \frac{\sigma_L}{1 + \sigma_L} L^{\frac{1+\sigma_L}{\sigma_L}}\right) \tag{438}$$

and

$$U \left(C, L\right) \equiv \log C - \zeta \frac{\sigma_L}{1 + \sigma_L} L^{\frac{1+\sigma_L}{\sigma_L}}, \quad \text{if} \quad \sigma = 1. \tag{439}$$

These preferences are characterized by two crucial parameters: σ_L is the Frisch elasticity of labor supply, and $\sigma > 0$ determines the substitutability between consumption and leisure.

Each household supplies skilled and unskilled labor denoted by $S(t)$ and $U(t)$, respectively. We keep the labor-supply side of our model simple and do not model flows between occupations in order to focus on the role of skills in driving both the labor reallocation and wage effects of technology shocks. We thus assume that the disutility from aggregate labor supply is split into the disutility from the supply of skilled labor and the supply of unskilled labor:

$$\zeta \frac{\sigma_L}{1 + \sigma_L} L^{\frac{1+\sigma_L}{\sigma_L}} = \left[\zeta_S \frac{\sigma_L}{1 + \sigma_L} (S)^{\frac{\sigma_L + 1}{\sigma_L}} + \zeta_U \frac{\sigma_L}{1 + \sigma_L} (U)^{\frac{\sigma_L + 1}{\sigma_L}} \right], \tag{440}$$

where $0 < \zeta_s < 1$ ($s = S, U$) is the weight of skilled (unskilled) labor supply to the labor index $L(.)$.

As shall be useful below, we write down the partial derivatives of (439):

$$\Lambda_C = C^{-\sigma} V(L)^{\sigma}, \tag{441a}$$

$$\Lambda_{CC} = -\sigma \frac{\Lambda_C}{C}, \tag{441b}$$

$$\Lambda_S = \frac{C^{1-\sigma} \sigma V_S V^{\sigma-1}}{1-\sigma}, \tag{441c}$$

$$\Lambda_{SS} = \Lambda_S \left[\frac{V_{SS}}{V_S} + (\sigma - 1) \frac{V_S}{V} \right], \tag{441d}$$

$$\Lambda_U = \frac{C^{1-\sigma} \sigma V_U V^{\sigma-1}}{1-\sigma}, \tag{441e}$$

$$\Lambda_{UU} = \Lambda_U \left[\frac{V_{UU}}{V_U} + (\sigma - 1) \frac{V_U}{V} \right], \tag{441f}$$

$$\Lambda_{CS} = \sigma C^{-\sigma} V_S V^{\sigma-1}, \tag{441g}$$

$$\Lambda_{CU} = \sigma C^{-\sigma} V_U V^{\sigma-1}, \tag{441h}$$

$$\Lambda_{SU} = \Lambda_S \left(\sigma - 1\right) \frac{V_U}{V}, \tag{441i}$$

where $\Lambda_C = \frac{\partial \Lambda}{\partial C}$. According to eq. (441g) and (441h), the marginal utility of consumption is increasing in labor supply as long as $\sigma > 1$, i.e., if consumption and leisure are gross substitutes. To get (441i), we have used the fact that $V_{SU} = 0$ which comes from our assumption that skills are immobile across occupations although they are mobile (to a certain extent) across sectors. To see it formally, we write out the partial derivatives of the disutility from labor supply:

$$V_S = (\sigma - 1) \zeta_S \left(S\right)^{\frac{1}{\sigma_L}}, \tag{442a}$$

$$V_{SS} = (\sigma - 1) \frac{\zeta_S}{\sigma_L} \left(S\right)^{\frac{1}{\sigma_L}-1}, \tag{442b}$$

$$V_{SU} = 0, \tag{442c}$$

$$V_U = (\sigma - 1) \zeta_U \left(U\right)^{\frac{1}{\sigma_L}}, \tag{442d}$$

$$V_{UU} = (\sigma - 1) \frac{\zeta_U}{\sigma_L} \left(U\right)^{\frac{1}{\sigma_L}-1}. \tag{442e}$$

Following Horvath [2000], we assume that hours worked in the traded and the non-traded sectors are aggregated by means of a CES function:

$$S(t) = \left[\vartheta_S^{-1/\epsilon_S} \left(S^H(t)\right)^{\frac{\epsilon_S+1}{\epsilon_S}} + (1-\vartheta_S)^{-1/\epsilon_S} \left(S^N(t)\right)^{\frac{\epsilon_S+1}{\epsilon_S}} \right]^{\frac{\epsilon_S}{\epsilon_S+1}}, \tag{443a}$$

$$U(t) = \left[\vartheta_U^{-1/\epsilon_U} \left(U^H(t)\right)^{\frac{\epsilon_U+1}{\epsilon_U}} + (1-\vartheta_U)^{-1/\epsilon_U} \left(U^N(t)\right)^{\frac{\epsilon_U+1}{\epsilon_U}} \right]^{\frac{\epsilon_U}{\epsilon_U+1}}, \tag{443b}$$

where $0 < \vartheta_S < 1$ (ϑ_U) is the weight of skilled (unskilled) labor supply to the traded sector in the skilled (unskilled) labor index $S(.)$ ($U(.)$) and ϵ_S (ϵ_U) measures the ease with which skilled (unskilled) hours worked can be substituted for each other and thereby captures the degree of skilled (unskilled) labor mobility across sectors.

The aggregate wage index $W(.)$ associated with the above defined labor index for skilled (443a) and unskilled (443b) labor supply is:

$$W^S(t) = \left[\vartheta_S \left(W^{S,H}(t)\right)^{\epsilon_S+1} + (1-\vartheta_S) \left(W^{S,N}(t)\right)^{\epsilon_S+1} \right]^{\frac{1}{\epsilon_S+1}}, \tag{444a}$$

$$W^U(t) = \left[\vartheta_U \left(W^{U,H}(t)\right)^{\epsilon_U+1} + (1-\vartheta_U) \left(W^{U,N}(t)\right)^{\epsilon_U+1} \right]^{\frac{1}{\epsilon_U+1}}, \tag{444b}$$

where $W^{S,H}(t)$ ($W^{U,H}(t)$) and $W^{S,N}(t)$ ($W^{U,N}(t)$) are wages paid in the traded and the non-traded sectors for skilled (unskilled) labor.

We assume that the households own the physical capital stock and choose the level of capital utilization $u^{K,j}(t)$. Households lease capital services (the product of utilization and physical capital) to firms in sector j at rental rate $R^j(t)$. Thus capital income received by households reads $\sum_j R^j(t)u^{K,j}(t)K^j(t)$. Households supply labor services to firms in sector j at a wage rate $W^j(t)$. Thus labor income received by households reads $\sum_j W^j(t)L^j(t)$. In addition, households accumulate internationally traded bonds, $N(t)$, that yield net interest rate earnings of $r^\star N(t)$. Denoting lump-sum taxes by $T(t)$, households' flow budget constraint states that real disposable income can be saved by accumulating traded bonds, consumed, $P_C(t)C(t)$, invested in tangible assets, $P_J(t)J^K(t)$, and covers the capital utilization cost:

$$\begin{aligned}\dot{N}(t) &= r^\star N(t) + \left[\alpha_K(t)u^{K,H}(t) + (1-\alpha_K(t))\,u^{K,N}(t)\right] R^K(t)K(t) + W^S(t)S(t) \\ &+ W^U(t)U(t) - T(t) - P_C(t)C(t) - P_J(t)J^K(t) - \sum_j P^j(t)C^{K,j}(t)\nu^{K,j}K(t),\end{aligned} \tag{445}$$

where we denote the capital return share of tradables by $\alpha_K = \frac{R^H K^H}{R^K K}$ and the share of sectoral capital in the aggregate capital stock by $\nu^{K,j}(t) = K^j(t)/K(t)$.

The role of the capital utilization rate is to mitigate the effect of a rise in the capital cost. We let the function $C^{K,j}(t)$ denote the adjustment costs associated with the choice of capital and technology utilization rates which are increasing and convex functions of utilization rates $u^{K,j}(t)$:

$$C^{K,j}(t) = \xi_1^j\left(u^{K,j}(t) - 1\right) + \frac{\xi_2^j}{2}\left(u^{K,j}(t) - 1\right)^2, \tag{446}$$

where $\xi_2^j > 0$ is a free parameter; as $\xi_2^j \to \infty$, utilization is fixed at unity; ξ_1^j must be restricted so that the optimality conditions are consistent with the normalization of steady state utilization of 1.

The accumulation of tangible assets is governed by the following law of motions:

$$\dot{K}(t) = I^K(t) - \delta_K K(t), \tag{447}$$

where I^K is investment and $0 \leq \delta_K < 1$ is a fixed depreciation rate. We assume that capital accumulation is subject to increasing and convex cost of net investment:

$$J^K(t) = I^K(t) + \Psi\left(I^K(t), K(t)\right)K(t), \tag{448}$$

where $\Psi(.)$ is increasing (i.e., $\Psi'(.) > 0$), convex (i.e., $\Psi''(.) > 0$), is equal to zero at δ_K (i.e., $\Psi(\delta_K) = 0$), and has first partial derivative equal to zero as well at δ_K (i.e., $\Psi'(\delta_K) = 0$). We suppose the following functional form for the adjustment cost function:

$$\Psi^K\left(I^K(t), K(t)\right) = \frac{\kappa}{2}\left(\frac{I^K(t)}{K(t)} - \delta_K\right)^2. \tag{449}$$

Using (442), partial derivatives of total investment expenditure are:

$$\frac{\partial J^K(t)}{\partial I^K(t)} = 1 + \kappa\left(\frac{I^K(t)}{K(t)} - \delta_K\right), \tag{450a}$$

$$\frac{\partial J^K(t)}{\partial K(t)} = -\frac{\kappa}{2}\left(\frac{I^K(t)}{K(t)} - \delta_K\right)\left(\frac{I^K(t)}{K(t)} + \delta_K\right). \tag{450b}$$

To solve the representative household's optimization problem, we set up the current-value Hamiltonian:

$$\mathcal{H}^H(t) = \Lambda\left(C(t), S(t), U(t)\right) + \lambda(t)\dot{B}(t) + Q_K'\dot{K}(t), \tag{451}$$

where we denote the co-state variables associated with the flow budget constraint (445), investment in tangible assets (447) by λ, Q_K', respectively, The representative household chooses $C(t)$, $L(t)$, $J^K(t)$, $u^{K,j}t)$, which are control variables, $B(t)$, $K(t)$, which are state variables. Denoting $Q_K(t) = Q'_K(t)/\lambda(t)$, the first-order conditions characterizing the representative household's optimal plans are:

$$\Lambda_C(t) = P_C(t)\lambda(t), \tag{452a}$$

$$-\Lambda_S(t) = \lambda(t)W^S(t), \tag{452b}$$

$$-\Lambda_U(t) = \lambda(t)W^U(t), \tag{452c}$$

$$Q_K(t) = P_J(t)\left[1 + \kappa\left(\frac{I^K(t)}{K(t)} - \delta_K\right)\right], \tag{452d}$$

$$R^H(t) = P^H(t)\left[\xi_1^H + \xi_2^H\left(u^{K,H}(t) - 1\right)\right], \tag{452e}$$

$$R^N(t) = P^N(t)\left[\xi_1^N + \xi_2^N\left(u^{K,N}(t) - 1\right)\right], \tag{452f}$$

$$\dot{\lambda}(t) = \lambda\left(\beta - r^\star\right), \tag{452g}$$

$$\dot{Q}_K(t) = \left(r^\star + \delta_K\right)Q_K(t) - \Bigg\{\left[\alpha_K(t)u^{K,H}(t) + \left(1 - \alpha_K(t)\right)u^{K,N}(t)\right]R^K(t)$$

$$-P^H(t)C^{K,H}(t)\alpha_K(t) - P^N(t)C^{K,N}(t)\left(1 - \alpha_K(t)\right) - P_J(t)\frac{\partial J^K(t)}{\partial K(t)}\Bigg\}, \tag{452h}$$

and the transversality conditions $\lim_{t\to\infty}\bar{\lambda}B(t)e^{-\beta t} = 0$, $\lim_{t\to\infty}Q_K(t)K(t)e^{-\beta t} = 0$. We used the fact that $\dot{Q}_K(t) = \frac{\dot{Q}'_K(t)}{\lambda(t)} - \frac{\dot{\lambda}(t)}{\lambda(t)}\frac{Q'_K(t)}{\lambda(t)}$.

Given the above consumption indices, we can derive appropriate price indices. With respect to the general consumption index, we obtain the consumption-based price index P_C:

$$P_C = \left[\varphi\left(P^T\right)^{1-\phi} + (1-\varphi)\left(P^N\right)^{1-\phi}\right]^{\frac{1}{1-\phi}}, \tag{453}$$

where the price index for traded goods is:

$$P^T = \left[\varphi_H\left(P^H\right)^{1-\rho} + (1-\varphi_H)\right]^{\frac{1}{1-\rho}}. \tag{454}$$

Given the consumption-based price index (453), the representative household has the following demand of traded and non-traded goods:

$$C^T = \varphi\left(\frac{P^T}{P_C}\right)^{-\phi}C, \tag{455a}$$

$$C^N = (1-\varphi)\left(\frac{P^N}{P_C}\right)^{-\phi}C. \tag{455b}$$

Given the price indices (453) and (454), the representative household has the following demand of home-produced traded goods and foreign-produced traded goods:

$$C^H = \varphi\left(\frac{P^T}{P_C}\right)^{-\phi}\varphi_H\left(\frac{P^H}{P^T}\right)^{-\rho}C, \tag{456a}$$

$$C^F = \varphi\left(\frac{P^T}{P_C}\right)^{-\phi}(1-\varphi_H)\left(\frac{1}{P_T}\right)^{-\rho}C. \tag{456b}$$

As will be useful later, the percentage change in the consumption price index is a weighted average of percentage changes in the price of traded and non-traded goods in terms of foreign goods:

$$\hat{P}_C = \alpha_C\hat{P}^T + (1-\alpha_C)\hat{P}^N, \tag{457a}$$

$$\hat{P}^T = \alpha_H\hat{P}^H, \tag{457b}$$

where α_C is the tradable content of overall consumption expenditure and α^H is the home-produced goods content of consumption expenditure on traded goods:

$$\alpha_C = \varphi \left(\frac{P^T}{P_C}\right)^{1-\phi}, \tag{458a}$$

$$1 - \alpha_C = (1-\varphi)\left(\frac{P^N}{P_C}\right)^{1-\phi}, \tag{458b}$$

$$\alpha^H = \varphi_H \left(\frac{P^H}{P^T}\right)^{1-\rho}, \tag{458c}$$

$$1 - \alpha^H = (1-\varphi_H)\left(\frac{1}{P^T}\right)^{1-\rho}. \tag{458d}$$

Given the CES aggregator functions above, we can derive the appropriate price indices for investment. With respect to the general investment index, we obtain the investment-based price index P_J:

$$P_J = \left[\iota \left(P_J^T\right)^{1-\phi_J} + (1-\iota)\left(P^N\right)^{1-\phi_J}\right]^{\frac{1}{1-\phi_J}}, \tag{459}$$

where the price index for traded goods is:

$$P_J^T = \left[\iota^H \left(P^H\right)^{1-\rho_J} + \left(1-\iota^H\right)\right]^{\frac{1}{1-\rho_J}}. \tag{460}$$

Given the physical investment-based price index (459), we can derive the demand for inputs of the traded good and the non-traded good:

$$J^T = \iota \left(\frac{P_J^T}{P_J}\right)^{-\phi_J} J, \tag{461a}$$

$$J^N = (1-\iota)\left(\frac{P^N}{P_J}\right)^{-\phi_J} J. \tag{461b}$$

Given the price indices (459) and (460), we can derive the demand for inputs of home-produced traded goods and foreign-produced traded goods:

$$J^H = \iota \left(\frac{P_J^T}{P_J}\right)^{-\phi_J} \iota^H \left(\frac{P^H}{P_J^T}\right)^{-\rho_J} J, \tag{462a}$$

$$J^F = \iota \left(\frac{P_J^T}{P_J}\right)^{-\phi_J} \left(1-\iota^H\right)\left(\frac{1}{P_J^T}\right)^{-\rho_J} J. \tag{462b}$$

As will be useful later, the percentage change in the investment price index is a weighted average of percentage changes in the price of traded and non-traded inputs in terms of foreign inputs:

$$\hat{P}_J = \alpha_J \hat{P}_J^T + (1-\alpha_J)\hat{P}^N, \tag{463a}$$

$$\hat{P}_J^T = \alpha_J^H \hat{P}^H, \tag{463b}$$

where α_J is the tradable content of overall investment expenditure and α_J^H is the home-produced goods content of investment expenditure on traded goods:

$$\alpha_J = \iota \left(\frac{P_J^T}{P_J}\right)^{1-\phi_J}, \tag{464a}$$

$$1 - \alpha_J = (1-\iota)\left(\frac{P^N}{P_J}\right)^{1-\phi_J}, \tag{464b}$$

$$\alpha_J^H = \iota^H \left(\frac{P^H}{P_J^T}\right)^{1-\rho_J}, \tag{464c}$$

$$1 - \alpha_J^H = \left(1-\iota^H\right)\left(\frac{1}{P_J^T}\right)^{1-\rho_J}. \tag{464d}$$

Given the aggregate wage index for skilled labor (444a) and unskilled labor (444b), we can derive the allocation of labor supply to the traded and the non-traded sector for each type of skill:

$$S^H(t) = \vartheta_S \left(\frac{W^{S,H}(t)}{W^S(t)}\right)^{\epsilon_S} S(t), \qquad S^N(t) = (1-\vartheta_S)\left(\frac{W^{S,N}(t)}{W^S(t)}\right)^{\epsilon_S} S(t). \tag{465a}$$

$$U^H(t) = \vartheta_U \left(\frac{W^{U,H}(t)}{W^U(t)}\right)^{\epsilon_U} U(t), \qquad S^N(t) = (1-\vartheta_U)\left(\frac{W^{U,N}(t)}{W^U(t)}\right)^{\epsilon_U} U(t). \tag{465b}$$

Aggregating labor compensation across sectors and skills leads to:

$$W^{S,H}S^H + W^{S,N}S^N = W^S S, \tag{466a}$$

$$W^{U,H}U^H + W^{U,N}U^N = W^U U, \tag{466b}$$

$$W^S S + W^U U = WL, \tag{466c}$$

where W is the aggregate wage and L is aggregate labor supply.

As will be useful later, log-linearizing the wage index in the neighborhood of the initial steady-state leads to:

$$\hat{W}^S(t) = \alpha_S^H \hat{W}^{S,H}(t) + \left(1-\alpha_S^H\right)\hat{W}^{S,N}(t), \tag{467a}$$

$$\hat{W}^U(t) = \alpha_U^H \hat{W}^{U,H}(t) + \left(1-\alpha_U^H\right)\hat{W}^{U,N}(t), \tag{467b}$$

where $\alpha_S^H = \frac{W^{S,H}S^H}{W^S S}$ and $\alpha_U^H = \frac{W^{U,H}U^H}{W^U U}$ tradable content of aggregate labor compensation:

$$\alpha_S^H = \vartheta_S \left(\frac{W^{S,H}}{W^S}\right)^{1+\epsilon_S}, \qquad 1-\alpha_S^H = (1-\vartheta_S)\left(\frac{W^{S,N}}{W^S}\right)^{1+\epsilon_S}, \tag{468a}$$

$$\alpha_U^H = \vartheta_U \left(\frac{W^{U,H}}{W^U}\right)^{1+\epsilon_U}, \qquad 1-\alpha_U^H = (1-\vartheta_U)\left(\frac{W^{U,N}}{W^U}\right)^{1+\epsilon_U}, \tag{468b}$$

Given the aggregate capital rental index, we can derive the allocation of aggregate capital supply to the traded and the non-traded sector:

$$K^H = \vartheta_K \left(\frac{R^H}{R^K}\right)^{\epsilon_K} K, \qquad K^N = (1-\vartheta_K)\left(\frac{R^N}{R^K}\right)^{\epsilon_K} K, \tag{469}$$

where the elasticity of capital supply across sectors ϵ captures the degree of capital mobility. As will be useful later, log-linearizing the capital rental index in the neighborhood of the initial steady-state leads to:

$$\hat{R}^K(t) = \alpha_K \hat{R}^H(t) + (1-\alpha_K)\hat{R}^N(t), \tag{470}$$

where $\alpha_K = \frac{R^H K^H}{R^K K}$ is the tradable content of aggregate capital return which reads as follows:

$$\alpha_K = \vartheta_K \left(\frac{R^H}{R^K}\right)^{1+\epsilon_K}, \qquad 1-\alpha_K = (1-\vartheta_K)\left(\frac{R^N}{R^K}\right)^{1+\epsilon_K}. \tag{471}$$

S.2 Firms

Each sector consists of a large number of identical firms which use labor, L^j, and physical capital (inclusive of capital utilization), $\tilde{K}^j$, according to a technology described by a CES production function:

$$Y^j(t) = \left[\gamma^j \left(A^j(t)L^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}} + \left(1-\gamma^j\right)\left(B^j(t)\tilde{K}^j(t)\right)^{\frac{\sigma^j-1}{\sigma^j}}\right]^{\frac{\sigma^j}{\sigma^j-1}}, \tag{472}$$

where $0 < \gamma^j < 1$ is the weight of labor in the production technology, σ^j is the elasticity of substitution between capital and labor in sector $j = H, N$, and $A^j(t)$ and $B^j(t)$ are labor- and capital-augmenting efficiency.

We assume that efficient labor is a CES aggregator of skilled and unskilled labor:

$$A^j L^j(t) = \left[\gamma_L^j \left(A_S^j(t) S^j(t)\right)^{\frac{\sigma_L^j - 1}{\sigma_L^j}} + \left(1 - \gamma_L^j\right) \left(A_U^j(t) U^j(t)\right)^{\frac{\sigma_L^j - 1}{\sigma_L^j}}\right]^{\frac{\sigma_L^j}{\sigma_L^j - 1}}, \tag{473}$$

where $0 < \gamma_L^j < 1$ is the weight of skilled labor in the efficient labor index, σ_L^j is the elasticity of substitution between skilled and unskilled labor in sector $j = H, N$, and $A_S^j(t)$ and $A_U^j(t)$ are skilled labor- and unskilled labor-augmenting efficiency. While capital-augmenting productivity has a symmetric and an asymmetric component across sectors, see eq. (7), both skilled- and and unskilled-labor augmenting productivity are made up of a symmetric component across sectors denoted by the subscript S and an asymmetric component denoted by the subscript D:

$$A^{S,j}(t) = \left(A_S^{S,j}(t)\right)^{\eta} \left(A_D^{S,j}(t)\right)^{1-\eta}, \qquad A^{U,j}(t) = \left(A_S^{U,j}(t)\right)^{\eta} \left(A_D^{U,j}(t)\right)^{1-\eta}, \tag{474}$$

where η is assumed to be symmetric across sectors.

Both sectors are assumed to be perfectly competitive and thus choose capital and labor by taking prices as given:

$$\max_{S^j, U^j, \tilde{K}^j} \Pi^j = \max_{S^j, U^j, \tilde{K}^j} \left\{ P^j Y^j - W^{S,j} S^j - W^{U,j} U^j - R^j \tilde{K}^j \right\}. \tag{475}$$

Since skilled, unskilled and capital cannnot move freely between the two sectors, the value of marginal revenue products in the traded and non-traded sectors do not equalize while costly labor and capital mobility implies a wage and a capital rental rate differential across sectors. The demand for skilled and unskilled labor together with the demand for capital by traded firms are described by:

$$P^H \frac{\partial Y^H}{\partial L^H} \frac{\partial L^H}{\partial S^H} = \gamma^H \left(A^H\right)^{\frac{\sigma^H - 1}{\sigma^H}} \left(L^H\right)^{-\frac{1}{\sigma^H}} \left(Y^H\right)^{\frac{1}{\sigma^H}} \gamma_S^H \left(\frac{A_S^H}{A^H}\right)^{\frac{\sigma_L^H - 1}{\sigma_L^H}} \left(S^H\right)^{-\frac{1}{\sigma_L^H}} \left(L^H\right)^{\frac{1}{\sigma_L^H}} = W^{S,H}, \tag{476a}$$

$$P^H \frac{\partial Y^H}{\partial L^H} \frac{\partial L^H}{\partial U^H} = \gamma^H \left(A^H\right)^{\frac{\sigma^H - 1}{\sigma^H}} \left(L^H\right)^{-\frac{1}{\sigma^H}} \left(Y^H\right)^{\frac{1}{\sigma^H}} \left(1 - \gamma_S^H\right) \left(\frac{A_U^H}{A^H}\right)^{\frac{\sigma_L^H - 1}{\sigma_L^H}} \left(U^H\right)^{-\frac{1}{\sigma_L^H}} \left(L^H\right)^{\frac{1}{\sigma_L^H}} = W^{U,H}, \tag{476b}$$

$$P^H \frac{\partial Y^H}{\partial \tilde{K}^H} = P^H \left(1 - \gamma^H\right) \left(B^H\right)^{\frac{\sigma^H - 1}{\sigma^H}} \left(\tilde{K}^H\right)^{-\frac{1}{\sigma^H}} \left(Y^H\right)^{\frac{1}{\sigma^H}} = R^H. \tag{476c}$$

The demand for skilled and unskilled labor together with the demand for capital by traded firms are described by:

$$P^N \frac{\partial Y^N}{\partial L^N} \frac{\partial L^N}{\partial S^N} = \gamma^N \left(A^N\right)^{\frac{\sigma^N - 1}{\sigma^N}} \left(L^N\right)^{-\frac{1}{\sigma^N}} \left(Y^N\right)^{\frac{1}{\sigma^N}} \gamma_S^N \left(\frac{A_S^N}{A^N}\right)^{\frac{\sigma_L^N - 1}{\sigma_L^N}} \left(S^N\right)^{-\frac{1}{\sigma_L^N}} \left(L^N\right)^{\frac{1}{\sigma_L^N}} = W^{S,N}, \tag{477a}$$

$$P^N \frac{\partial Y^N}{\partial L^N} \frac{\partial L^N}{\partial U^N} = \gamma^N \left(A^N\right)^{\frac{\sigma^N - 1}{\sigma^N}} \left(L^N\right)^{-\frac{1}{\sigma^N}} \left(Y^N\right)^{\frac{1}{\sigma^N}} \left(1 - \gamma_S^N\right) \left(\frac{A_U^N}{A^N}\right)^{\frac{\sigma_L^N - 1}{\sigma_L^N}} \left(U^N\right)^{-\frac{1}{\sigma_L^N}} \left(L^N\right)^{\frac{1}{\sigma_L^N}} = W^{U,N}, \tag{477b}$$

$$P^N \frac{\partial Y^N}{\partial \tilde{K}^N} = P^N \left(1 - \gamma^N\right) \left(B^N\right)^{\frac{\sigma^N - 1}{\sigma^N}} \left(\tilde{K}^N\right)^{-\frac{1}{\sigma^N}} \left(Y^N\right)^{\frac{1}{\sigma^N}} = R^N. \tag{477c}$$

Pre-multiplying the equality between the marginal revenue product of skilled labor by S^j/L^j, i.e., $P^j \frac{\partial Y^j}{\partial L^j} \frac{\partial L^j}{\partial S^j} \frac{S^j}{L^j} = \frac{W^{S,j} S^j}{L^j}$ and using the fact that $P^j \frac{\partial Y^j}{\partial L^j} = W^j$, leads to the equality between the elasticity of labor w.r.t. skilled labor and the skilled labor income share denoted by s_S^j. Applying the same logic to unskilled labor leads to:

$$\frac{\partial L^j}{\partial S^j}\frac{S^j}{L^j} = \frac{W^{S,j}S^j}{W^jL^j} \equiv s_S^j, \tag{478a}$$

$$\frac{\partial L^j}{\partial U^j}\frac{S^j}{L^j} = \frac{W^{U,j}U^j}{W^jL^j} \equiv s_U^j = 1 - s_S^j. \tag{478b}$$

Dividing the skilled labor income share by the unskilled labor income share and using (476a)-(476b) leads to a relationship between the skilled labor income share s_S^j and skilled-biased technological change:

$$\frac{s_S^j}{1-s_S^j} = \frac{\gamma_S^j}{1-\gamma_S^j}\left(\frac{A_S^j}{A_U^j}\right)^{\frac{\sigma_L^j-1}{\sigma_L^j}}\left(\frac{S^j}{U^j}\right)^{\frac{\sigma_L^j-1}{\sigma_L^j}} \tag{479}$$

We can recover the dynamics $\frac{A_S^j}{A_U^j}$ by using the dynamic responses of s_S^j and $\frac{S^j}{U^j}$.

S.3 Skill-Biased Technological Change (SBTC)

Costly labor and capital mobility implies a labor and capital cost differential across sectors:

$$\frac{\left(1-s_L^j(t)\right)P^j(t)Y^j(t)}{\tilde{K}^j(t)} = R^j(t), \tag{480a}$$

$$\frac{s_L^j(t)s_S^j(t)P^j(t)Y^j(t)}{S^j(t)} = W^{S,j}(t), \tag{480b}$$

$$\frac{s_L^j(t)\left(1-s_S^j(t)\right)P^j(t)Y^j(t)}{U^j(t)} = W^{U,j}(t), \tag{480c}$$

where $s_S^j(t)$ is the share of skilled labor in labor compensation in sector $j = H, N$, i.e.,

$$s_S^j(t) = \frac{W^{S,j}(t)S^j(t)}{W^j(t)L^j(t)} = \gamma_S^j\left(\frac{A^{S,j}(t)S^j(t)}{A^j(t)L^j(t)}\right)^{\frac{\sigma_L^j-1}{\sigma_L^j}}. \tag{481}$$

Dividing the demand for skilled labor by the demand for unskilled labor, inserting (481), and denoting the ratio of skilled to unskilled labor income share by $S_S^j(t) \equiv \frac{s_S^j(t)}{1-s_S^j(t)}$, leads to:

$$S_S^j(t) \equiv \frac{s_S^j(t)}{1-s_S^j(t)} = \frac{\gamma_S^j}{1-\gamma_S^j}\left(\text{SBTC}^j\right)^{-1}\left(\frac{S^j(t)}{U^j(t)}\right)^{-\frac{1-\sigma_L^j}{\sigma_L^j}}, \tag{482}$$

where $\text{SBTC}^j(t) = \left(\frac{A^{S,j}(t)}{A^{U,j}(t)}\right)^{\frac{1-\sigma_L^j}{\sigma_L^j}}$ is skill-biased technological change (SBTC henceforth). We assume imperfect substitution between skill types and one important question is whether skilled and unskilled labor are substitutes or complements. If $\sigma_L^j > 1$, an increase in unskilled- relative to skilled-labor-augmenting productivity increases the demand for unskilled labor.

Rearranging eq. (482) leads to the measure of SBTC within sector $j = H, N$:

$$\text{SBTC}^j(t) = \left(\frac{A_U^j}{A_S^j}\right)^{\frac{1-\sigma_L^j}{\sigma_L^j}} = \frac{1-\gamma_L^j}{\gamma_L^j}S_S^j(t)\left(\frac{S^j(t)}{U^j(t)}\right)^{\left(\frac{1-\sigma_L^j}{\sigma_L^j}\right)}, \tag{483}$$

$S_S^j = \frac{s_S^j}{1-s_S^j}$ with $s_S^j = \frac{W^{S,j}S^j}{W^jL^j}$. To construct time series for SBTC_{it}^j, we plug time series for the ratio of the skilled to unskilled labor income share, $S_S^j(t) = s_S^j(t)/\left(1-s_S^j(t)\right)$, and the ratio of skilled to unskilled hours worked, $\frac{S^j(t)}{U^j(t)}$. We also plug values for σ_L^j we have estimated for each country of the sample (11 OECD countries, 1970-2017), see section J.7.

S.4 Technology Frontier

While we keep assuming that firms within each sector $j = H, N$ decide about the split of capital-utilization-adjusted-TFP $Z^j(t)$ between labor- and capital-augmenting efficiency, we assume that firms choose a mix of skilled- and unskilled-labor-augmenting productivity $A^{S,j}(t)$ and $A^{U,j}(t)$ along a technology frontier (which is assumed to take a CES form):

$$\left[\gamma_Z^{S,j}\left(A^{S,j}(t)\right)^{\frac{\sigma_{L,Z}^{j}-1}{\sigma_Z^{L,j}}} + \left(1-\gamma_Z^{S,j}\right)\left(A^{U,j}(t)\right)^{\frac{\sigma_Z^{L,j}-1}{\sigma_Z^{L,j}}}\right]^{\frac{\sigma_Z^j}{\sigma_Z^{L,j}-1}} \leq A^j(t). \tag{484}$$

where $A^j(t) > 0$ is the height of the technology frontier, $0 < \gamma_Z^{S,j} < 1$ is the weight of skilled labor efficiency in labor-augmenting efficiency and $\sigma_Z^{L,j} > 0$ corresponds to the elasticity of substitution between skilled labor- and unskilled labor-augmenting productivity. The unit cost minimization requires that

$$s_S^j = \gamma_Z^{S,j}\left(\frac{A^{S,j}(t)}{A^j(t)}\right)^{\frac{\sigma_Z^{L,j}-1}{\sigma_Z^{L,j}}}. \tag{485}$$

Inserting this equality into the log-linearized version of the technology frontier shows that labor-augmenting technological change is driven by variations in skilled labor- and unskilled-labor-augmenting technological change (weighted by their contribution to the decline in the unit cost for labor in sector j):

$$\hat{A}^j(t) = s_S^j \hat{A}^{S,j}(t) + \left(1 - s_S^j\right)\hat{A}^{U,j}(t). \tag{486}$$

S.5 Calibration

The calibration procedure is identical to that described in section 4.1 except that we have to choose values for both production and preference parameters related to workers' skills. Because data for skilled and unskilled labor at a sectoral level are available for eleven countries only over a long enough time length, we calibrate the model to the data by estimating parameters such as ϵ and ϕ and computing ratios for this group of countries only.

Production parameters. Since we choose the initial steady-state in a model with Cobb-Douglas production functions as the normalization point, we set both σ^j and σ_L^j to one. Building on pour estimates, the labor income share for the traded and non-traded sectors are set to $s_L^H = 0.636$ and $s_L^N = 0.682$ and and for the skilled labor income share to $s_S^H = 0.636$ and $s_S^N = 0.699$.

Preference parameters. We keep assuming $\sigma = 2$ and $\sigma_L = 3$ and choose a value for ζ_S so as to target a ratio of skilled to unskilled labor of $S/L = 56\%$. To pin down the degree of labor mobility of skilled (unskilled) labor across sectors, i.e., ϵ_S (ϵ_U), we run the regression in panel format on annual data of the percentage change in the skilled (unskilled) hours worked share of sector j on the percentage change in the relative share of value added paid to skilled ((unskilled) workers in sector j. In accordance with the evidence documented by Kambourov and Manovskii [2009] which reveals that industry (and occupational) mobility declines with education, our empirical findings reveal that the elasticity of labor supply across sectors is twice larger for unskilled than skilled workers. More specifically, we set $\epsilon_S = 0.63$ and $\epsilon_U = 1.13$, in line with our panel data estimates, see section J.4. We choose values for ϑ_S and ϑ_U so as to target a weight of skilled and unskilled labor supply of $S^N/S = 69\%$ and $U^N/U = 59\%$, respectively. Note that for the eleven countries of our sample, we set $\epsilon_K = 0.18$ and choose ϑ_K so as to target $K^H/K = 38\%$.

We estimate a value for the elasticity of substitution ϕ between traded and non-traded goods of 0.19 and choose a value for φ so as to target a non-tradable of consumption expenditure $1-\alpha_C = 58\%$. Keeping assuming $\phi_J = 1$, we choose $1-\alpha_J = 68\%$. We choose φ^H and ι^H so as to target $\alpha^H = 66\%$ and $\alpha_J^H = 43\%$. Using the fact that $\omega_J = 23\%$,

$\omega_C = 57\%$ and $\omega_G = 20\%$, the demand components for home-produced traded goods gives a value added share of tradables $P^H Y^H/Y$ of 35% in line with our estimates.

CES economy. In line with our panel data estimates, we choose for the elasticity of substitution between capital and labor $\sigma^H = 0.86$ and $\sigma^N = 0.83$ and for the elasticity of substitution between skilled and unskilled labor $\sigma_L^H = 0.77$ and $\sigma_L^N = 0.69$.

Factor-augmenting efficiency. We assume that factor-augmenting productivity is made up of a symmetric component across sectors denoted by the subscript S and an asymmetric component denoted by the subscript D. To recover the dynamics of $B^j(t)$ and $A^j(t)$, and the dynamics of $A^{S,j}(t)$ and $A^{U,j}(t)$, we proceed as in section J.10. Because the equations are identical for $B^j(t)$ and $A^j(t)$ (see eq. (32a)-(32b)), we focus on labor-augmenting efficiency across workers' skills. Log-linearizing the demand for skilled labor relative to the demand for unskilled labor (479), this equation together with the log-linearized versions of the technology frontier (486) can be solved for deviations of $A_c^{S,j}(t)$ and $A_c^{U,j}(t)$ relative to their initial steady-state values:

$$\hat{A}_c^{S,j}(t) = \hat{A}_c^j(t) - \left(1 - s_S^j\right)\left[\left(\frac{\sigma_L^j}{1-\sigma_L^j}\right)\hat{S}_{S,c}^j(t) - \left(\hat{S}_c^j(t) - \hat{U}_c^j(t)\right)\right], \quad c = S, D \tag{487a}$$

$$\hat{A}_c^{U,j}(t) = \hat{A}_c^j(t) + s_S^j\left[\left(\frac{\sigma_L^j}{1-\sigma_L^j}\right)\hat{S}_{S,c}^j(t) - \left(\hat{S}_c^j(t) - \hat{U}_c^j(t)\right)\right], \quad c = S, D. \tag{487b}$$

Plugging estimated values for σ_L^j and empirically estimated responses for $s_{S,c}^j(t)$, $S_c^j(t)/U_c^j(t)$, following a symmetric (asymmetric) technology shock across sectors into above equations enables us to recover the dynamics for $A_S^{S,j}(t)$ ($A_D^{S,j}(t)$) and $A_S^{U,j}(t)$ ($A_D^{U,j}(t)$ consistent with the demand for factors of production (167) and the technology frontier (486).

Share of symmetric technology shocks across sectors. By using the fact that technology improvements are a weighted average of symmetric and asymmetric technology shocks, we find that a value of $\eta = 80\%$ minimizes the discrepancy between the empirical response of $Z^A(t)$ following a permanent technology improvement and its response computed from $\hat{Z}^A(t) = \eta\hat{Z}_S^A(t) + (1-\eta)\,\hat{Z}_D^A(t)$. Note that the capital utilization rates are found to quite muted after a technology improvement for the eleven countries of our sample, and thus we let $\xi_{2,S}^j$, $\xi_{2,D}^j$ tend toward infinity.

S.6 Taking the Model to the Data

In this subsection, we analyze the effects of a permanent technology improvement by differentiating between skilled and unskilled labor. Our objective is twofold. First, we assess the ability of our model to account for the labor composition effects across workers' skills of a permanent technology improvement. Second, we investigate whether the model can generate the rise in impact responses of skilled and unskilled hours worked on rolling subperiods.

Framework. The framework we have in mind which is detailed in section S is a model where a representative household supplies both skilled and unskilled labor. We assume that skilled and unskilled hours worked are imperfect substitutes, thus giving rise to a costly transition from unskilled to skilled labor. Both skilled and unskilled workers experience costs of switching sectors. As described by eq. (6), we assume that sectoral goods are produced with labor and capital by means of a CES production function. We relax the assumption that labor is homogenous and suppose that efficient labor is a CES aggregator of skilled and unskilled labor. In addition to assuming that firms within each sector $j = H, N$ decide about the split of capital-utilization-adjusted-TFP $Z^j(t)$ between labor- and capital-augmenting efficiency, we also assume that firms choose a mix of skilled- and unskilled-labor-augmenting productivity $A^{S,j}(t)$ and $A^{U,j}(t)$ along a technology frontier whose height is measured by labor efficiency $A^j(t)$.

Labor composition effects across workers' skills. In Fig. 48, we contrast the dynamic effects of a 1% permanent technology improvement we estimate empirically (shown in the solid blue line) with the responses we compute numerically in the baseline model (shown in black line with squares). For comparison purposes, we show the predictions of the same model where we shut down skill- and factor-biased technological change in the dashed red lines.

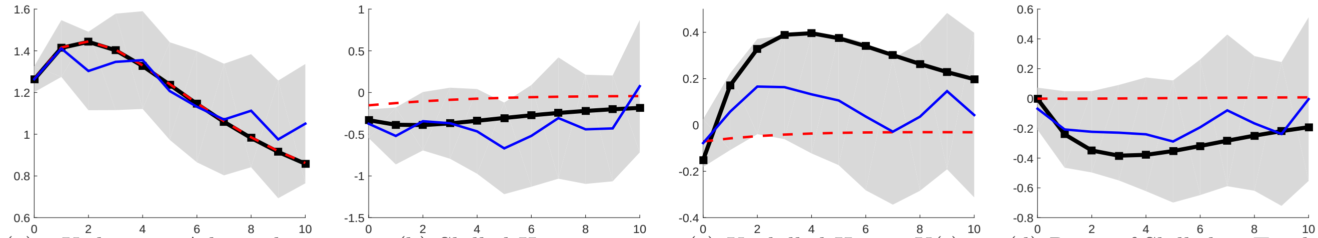
A permanent increase in utilization-adjusted-aggregate-TFP shown in Fig. 48(a) leads both skilled and unskilled workers to work less although the decline in hours is mostly concentrated on skilled labor. Quantitatively, hours worked of skilled workers decline by -0.33 percentage point of total hours worked while hours worked of unskilled workers decline by -0.15 percentage point of total hours worked, see Fig. 48(b) and Fig. 48(c). Therefore, total hours worked is reduced by -0.48% on impact which is very close to what we estimate empirically, i.e., -0.45%. Such a dramatic decline comes from the dominance of symmetric technology shocks which account for 80% of technology improvements. As mentioned in the main text, when technological change is uniformly distributed across sectors, higher productivity puts downward pressure on sectoral prices which curbs the increase in sectoral wages. In addition, symmetric technology shocks are strongly biased toward capital, especially in the traded sector.

As displayed by Fig. 48(b), the restricted model tends to understate the fall in skilled labor. In contrast, a model with FBTC and SBTC reproduces well the adjustment in skilled labor. Importantly, the decline in skilled labor (by -0.33 ppt of total hours in the model) contributes 69% to the fall in total hours worked. Inspection of Fig. 48(e) and Fig. 48(f) reveals that the baseline model reproduces well the dynamic responses of traded and non-traded hours of skilled labor. On impact, traded hours worked of skilled workers decline by -0.11 percentage point of total hours worked while non-traded hours worked of skilled workers fall twice as much, i.e., by -0.22 percentage point. The decline in non-traded skilled accounts for two-third of the fall in skilled labor and almost half of the reduction of total hours worked on impact.

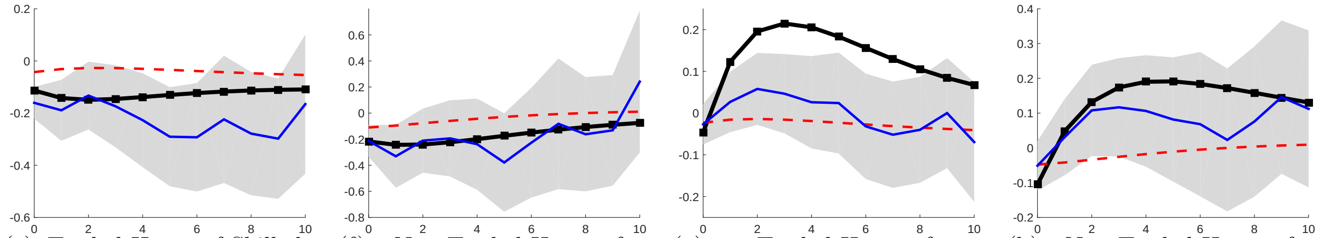
Skilled and unskilled labor are not impacted uniformly by a technology improvement. More specifically, as displayed by Fig. 48(d), a permanent technology improvement significantly lowers the ratio of skilled hours to total hours worked over time. The gradual decline in the skilled labor income share is driven by the decrease in the skilled labor income shares in both the traded and the non-traded sector which reveal that the demand for labor is tilted toward unskilled workers in both sectors. Intuitively, the combined effect of the rise in the unskilled workers efficiency and the gross substitutability between skilled and unskilled labor leads to an increase in the demand for unskilled labor and therefore causes a decrease in the skilled labor intensity of production of both sectors. As shown in the dashed red line in Fig. 48(d), a model abstracting from SBTC predicts a flat ratio of skilled labor to total labor in contrast to our evidence.

A shown in Fig. 48(l), labor shifts away from traded industries and toward non-traded industries but only gradually. While households shifts both skilled and unskilled hours toward the non-traded sector, both the ratio of skilled hours of tradables and non-tradables to total hours worked, see Fig. 48(i)-48(j), decline in line with the evidence because both traded and non-traded firms use more intensively unskilled labor following a permanent technology improvement. By contrast, as shown in Fig. 48(k), the share of unskilled hours of non-tradables in total hours worked increases significantly over time both because labor shifts toward the non-traded sector but also because there is a dramatic increase in labor demand for unskilled labor whose productivity increases.

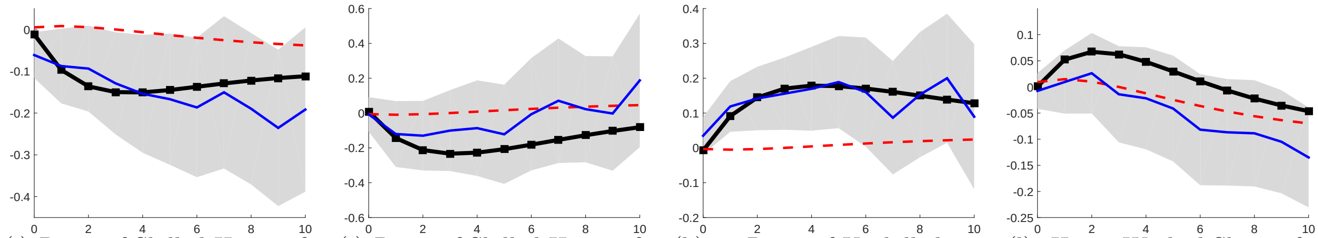
Time-increasing impact response of hours worked across workers' skills. As in section 4.4, we assess the ability of the model to account for the time-increasing response of hours worked by letting the share of asymmetric technology shocks increase over time. For the eleven countries of our sample, the share of asymmetric technology shocks increases from 19% to 39% in line with our empirical estimates for the sample of eleven OECD countries. As displayed by Fig. 49(a), the model reproduces well the shrinking contractionary effect of a permanent technology improvement on total hours worked. Fig. 49(b) and Fig. 49(c) reveal that both skilled labor and unskilled labor experience a time-increasing impact response to an aggregate technology shock and our model predictions shown in the black lines can account for these time-varying effects. The decline in total hours worked shrinks by 0.2 percentage point of total hours worked, i.e., the fall in labor shrinks from -0.49% to -0.29%. We find that half of the vanishing decline in total hours worked is driven by the



(a) Utilization-Adjusted-Aggregate-TFP, $Z^A(t)$ (b) Skilled Hours (c) Unskilled Hours, $U(t)$ (d) Ratio of Skilled to Total Hours worked, $S(t)/L(t)$

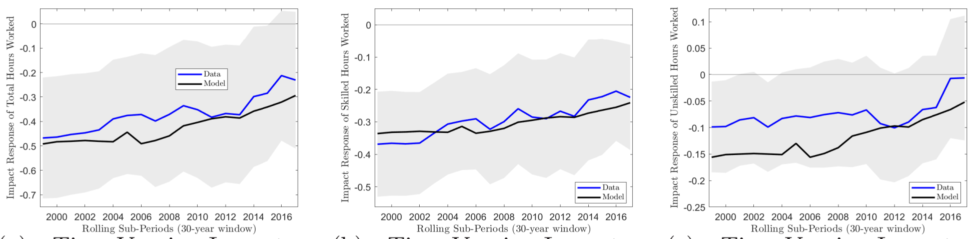


(e) Traded Hours of Skilled Workers $S^H(t)$ (f) Non-Traded Hours of Skilled Workers $S^N(t)$ (g) Traded Hours of Unskilled Workers $U^H(t)$ (h) Non-Traded Hours of Unskilled Workers $U^N(t)$



(i) Ratio of Skilled Hours of Tradables to Total Hours Worked $S^H(t)/L(t)$ (j) Ratio of Skilled Hours of Non-Tradables to Total Hours Worked $S^N(t)/L(t)$ (k) Ratio of Unskilled Hours of Non-Tradables to Total Hours Worked $U^N(t)/L(t)$ (l) Hours Worked Share of Tradables, $L^N(t)/L(t)$

Figure 48: Theoretical vs. Empirical Responses Following a Technology Shock: Labor Composition Effects across Workers' Skills. Notes: The solid blue line which displays point estimate from local projections with shaded areas indicating 90% confidence bounds; the thick solid black line with squares displays model predictions in the baseline scenario with FBTC and SBTC, while the dashed red line shows predictions of a model with Cobb-Douglas production functions (which amount to shutting down FBTC and SBTC).



(a) Time-Varying Impact Effect of Technology on Total Hours Worked (b) Time-Varying Impact Effect of Technology on Hours Worked of Skilled Labor (c) Time-Varying Impact Effect of Technology on Hours Worked of Unskilled Labor

Figure 49: Time-Varying Impact Effects of a Technology Shock. Notes: Fig. 49(a)-49(c) show the impact responses on total hours worked together with its skilled vs. unskilled components to a 1% permanent increase in utilization-adjusted aggregate TFP. The solid blue line shows the impact response we estimate empirically on rolling sub-periods by using Jordà's [2005] single-equation method. Shaded areas indicate the 90 percent confidence bounds based on Newey-West standard errors. The solid black line shows the impact response we compute numerically by calibrating the contribution of symmetric technology shocks to variations in utilization-adjusted-aggregate-TFP to what we estimate empirically. Note that we have normalized the rise in utilization-adjusted aggregate TFP to 1% at time $t = 0$ as we focus on impact effect. The horizontal axis shows the end year of the period of the sub-sample and the vertical line displays the of the impact effect of technology expressed n ppt of total hours worked. Sample: 11 OECD countries, 1970-2017

reduction in the decline in skilled hours worked from -0.34 ppt to -0.24 ppt of total hours worked and the rest is driven by the vanishing decline in unskilled hours. While the last thirty years, the decline in hours worked by skilled workers is still significant, the slight decline in hours of unskilled labor turns out to be insignificant.

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