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Productivity with endogenous FDI spillovers: A novel estimation approach

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ABSTRACT

The paper develops a new methodological framework for evaluating the role of FDI in the domestic economy. We firstly propose a measurement of Total Factor Productivity (TFP), which accounts for endogenous FDI knowledge spillovers. Our estimation allows knowledge spillovers to co-evolve with output and inputs selection, ensuring that the estimated production inputs are consistent whilst correctly identifying performance improvements. After deriving unbiased TFP measures at the firm level, we aggregate them at the industry level to search for reallocation effects driven by the FDI presence. Our methodology distinguishes between within-firm gains and industry reallocation effects from FDI. We apply our novel framework to a sample of 7699 manufacturing firms from six EU countries. The main findings are: (i) endogenous FDI spillovers correct for the omitted variable bias in the estimation of production inputs; (ii) inter-industry spillovers are important sources of TFP gains; (iii) the realization of gains from FDI knowledge spillovers are dependent on the absorptive capacity of the firm (iv) higher levels of FDI presence in the local economy can contribute to aggregate TFP increases as much as 33%. The paper offers the basis for considering new policy perspectives on FDI incentives and suggests new approaches for modeling the mechanisms through which domestic firms can experience productivity gains from their interaction with foreign counterparts in a globalized business environment.

1. Introduction

A highly contentious issue in production economics is the estimation and evolution of productivity. The literature documents substantial Total Factor Productivity (TFP) differentials even within narrowly defined industries (Decker et al., 2016; Hsieh and Klenow, 2009; Syverson, 2004), which always raises the question of what are the drivers behind these differentials. Potential candidates for explaining these disparities include mechanisms of globalization (e.g. changes in the trade regime, FDI activity), innovation (e.g. R&D) and alternations in the fiscal environment (Bournakis and Mallick, 2021). The interest in understanding the sources of productivity differences within and across countries (De Loecker and Goldberg, 2014) is related to the direct link between productivity improvements and welfare gains.[1] As firms increase their productivity, these improvements are translated into aggregate gains (industry and national) that enable a country to achieve higher standards of living. Despite the importance of the topic, some of the determinants of productivity are not appropriately elaborated in the firm's production process, which causes inaccurate and misleading inferences. One of the main contributions of the present paper is to object to the methodological approach currently employed in evaluating the impact of FDI on the performance of domestic firms.

So far, the effect of FDI-related spillovers on the productivity of domestic firms encompasses regressions of TFP on indices of foreign knowledge spillovers (Bournakis, 2021; Iršová and Havránek, 2013; Havránek and Iršová, 2011). This analytical framework provides reasonable point estimates for the economic importance of spillovers, but it does so in an ex-post fashion without treating spillovers as integral components of the production function (Javorcik, 2004; Lu et al., 2017; Newman et al., 2015). Assuming that FDI spillovers evolve independently from productivity, as the current literature does, is a serious limitation, which does not allow for external knowledge to interact endogenously with the selection of capital and labour in the production process. Hence, results that presume spillovers are exogenous to output

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[1] A google scholar search with keywords "globalization" and "productivity growth" returns almost 253,000 papers, which shows the substantial interest gathered in the topic from academics and policymakers.

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can mislead us about the true impact of FDI on domestic firms' performance.[2]

In theory, knowledge spillovers are expected to generate learning gains that boost the TFP of domestic firms.[3] TFP gains of this type are within-firm improvements. Additionally, FDI enhances reallocation effects at the aggregate level. Embracing foreign knowledge helps domestic firms become more productive, increasing market share and outperforming less productive rivals. FDI also fosters competition within the industry and, in conjunction with the gains from learning within firms, enhances sectoral productivity. Although *within-firm* productivity gains and industry *reallocation* gains represent significant welfare channels improvements, the regression analysis that has been used for evaluating FDI spillovers does not separate the two. This severe limitation defines the departure point of our paper that assumes endogenous evolution of FDI spillovers (*within-firm* effects). It then searches for aggregate gains that emerge from the reallocation dynamics within the industries (*reallocation* effects). Our methodology addresses two significant points; first, spillovers are allowed to co-evolve endogenously with firm productivity in the production function. We suggest an estimation procedure that accounts for the effect of external knowledge spillovers in the derivation of input estimates in the production function. Second, we search for market share reallocation effects driven by the FDI presence in the industry after domestic firms have improved productivity from the absorption of FDI knowledge spillovers. By distinguishing between *within-firm* and *across-firm* effects, our estimation approach moves the literature beyond the current state of simple regressions of domestic TFP on FDI to a more systematic evaluation of FDI in the domestic economy.

In the first part of the paper, we depart from the estimation methodology of De Loecker and Warzynski (2012) to endogenize FDI knowledge spillovers in the output process of the firm. Within this behavioral framework,[4] we estimate the parameters of the production function controlling for unobserved productivity using observables. Specifically, we use the demand function of intermediate input materials to proxy for unobserved productivity shocks *ala* Levinsohn and Petrin (2003).[5] A two-stage method is adopted. In the first stage, the demand of materials is used as a control function to obtain the expected output (De Loecker and Warzynski, 2012; Ackerberg et al., 2015). The second stage recovers estimates of all inputs and TFP. We examine alternative specifications of how FDI knowledge spillovers govern productivity in the second stage of the estimation procedure. In addition to spillovers, intangible capital is another important productivity shifter in the second stage. Biased estimate coefficients of the production function result from neglecting activities that are expected to be correlated with the use of inputs, thus productivity. Biased estimated coefficients of the production function are caused by neglecting firm activities that are expected to be correlated with the use of inputs, thus productivity. In this respect, coefficients of the non-dynamic inputs are upward biased (labor and intermediate materials), while the quasi-fixed input of capital is downward biased (Olley and Pakes, 1996). Therefore, our paper also serves as a guide to a modified law of motion model of productivity (De Loecker, 2013; De Loecker and Goldberg, 2014) that addresses the omitted variable bias caused by excluding productivity-enhancing factors correlated with the use of inputs.

In the second part of the paper, we aggregate firm TFP at the two-digit industry level to search for reallocation effects. We are investigating whether industries that attract higher levels of FDI achieve a higher level of TFP due to reallocation gains. The latter implies that the absorption of knowledge spillovers makes domestic firms obtain higher market shares, promoting industry TFP. This approach is unique in the literature to the best of our knowledge. It studies the effect of FDI at the sectoral level after aggregating micro-firm level TFP that already internalizes knowledge spillovers.

The paper's contributions are fourfold: (a) we separate the sources of gains from FDI. Prior literature mixes knowledge gains from the advanced know-how of MNEs with the reallocation dynamics emerging from the exposure of the domestic market to higher levels of competition. Instead, we distinguish between the two, which analyses more systematically the role of FDI in the domestic economy; (b) we endogenize FDI knowledge spillovers within a semi-parametric estimation of firm-level TFP, reducing the omitted variable bias, whilst ensuring that sources of productivity improvement are adequately identified; (c) we inform the law of motion of productivity with other factors of internal knowledge capital (i.e.intangibles) that also interact endogenously with FDI spillovers and inputs selection; (d) since we identify different sources of FDI gains, our findings provide the basis for a more tuned policy design, which can potentially target specific aspects of FDI to maximize the benefits for local firms.

We apply our methodological framework to a sample of 7699 manufacturing firms from six EU countries using the European Firms in the Global Economy (EFIGE) data set. Findings indicate that incorporating spillovers into the evolution of productivity leads to higher TFP estimates; however, not all spillovers positively impact domestic TFP. For domestic firms to increase productivity, they must form inter-industry partnerships with multinational organizations (MNEs). Productivity gains from knowledge spillovers depend on domestic firms' absorptive capacity. The analysis reveals that higher levels of FDI presence in the local economy can contribute to reallocation gains of as much as 33%. Aggregate (sectoral) productivity gains from reallocation dynamics appear to generate a one-off effect without strong time persistence. The paper is structured as follows: section 2 outlines the links between spillovers and productivity, section 3 describes the estimation methodology, section 4 describes the data and the results obtained from the estimation of the productivity parameter under different frameworks, section 5 shows TFP results with endogenous FDI spillovers, section 6 estimates the reallocation effects, section 6 conducts robustness analysis and section 7 concludes the paper.

2. Spillovers and firm productivity

Measurement of productivity at the micro-level is primarily concerned with avoiding simultaneity bias resulting from unobserved productivity shocks and input selection. The econometrician may not be aware of contemporaneous productivity shocks known to the firm manager. In the presence of simultaneity bias, standard OLS produces estimates of the production input that are upward biased. The previous literature uses the demand of investment Olley and Pakes (1996) and materials Levinsohn and Petrin (2003) to approximate unobserved productivity shocks. These estimation techniques rely on two assumptions about the *nature* and the *timing* of inputs selection. Concerning *nature*, inputs are distinguished into dynamic and non-dynamic. Accordingly, the cost of a dynamic input affects the future profit of the firm (capital), while as regards *timing*, some inputs can be chosen within the same period (labour) and inputs that are determined in the year before (capital). On the basis of these assumptions, Olley and Pakes (1996) and Levinsohn and Petrin (2003) derive estimates of TFP using a two-stage procedure. The first stage generates expected output, a coefficient of labour (non-dynamic input) and an estimate of the usual statistical noise of the residuals. The second stage specifies a first-order exogenous

[2] Crespo and Fontoura (2007) provide an extensive conceptual discussion about the role of FDI in the domestic economy.

[3] Gains from FDI include the diffusion of advanced technologies and better management and organizational practices from MNEs, as well as the possibility of hiring personnel trained by MNEs (Meyer and Sinani, 2009).

[4] The firm solves a common cost minimization problem to obtain the optimal input demand and output elasticity of a variable input without adjustment costs.

[5] Using the demand for investment to control for unobserved productivity shocks, Olley and Pakes (1996) offers the first semi-parametric estimation of firm-level TFP.

Markov process of productivity and recovers an estimate of capital (dynamic input).[6] The framework we propose relaxes this restriction by assuming that productivity evolves endogenously with knowledge spillovers.

Two are the core questions regarding the implementation of our framework: how knowledge spillovers occur and subsequently how they govern firm productivity. In an increasingly globalized environment, on the one hand, firms are exposed to severe competition, while on the other hand, they learn from interaction with international counterparts. This internationalization process makes Multinational Enterprises (MNEs) and domestic firms develop partnerships mainly in inputs transactions. These are either industrial linkages of domestic firms with MNEs in upstream industries that sell inputs or linkages with MNEs in downstream industries that buy inputs from domestic firms. The contracts, which formalize these inter-industry transactions, do not constitute spillovers *per se*. However, the commodities that domestic firms purchase from MNEs embody the producer's know-how, while those commodities that MNEs order from domestic firms should satisfy the buyer's technological requirements. These vertical (inter-industry) linkages encompass tacit knowledge that contributes to the domestic firm's internal expertise, thus potentially increasing performance and efficiency.

Moreover, the presence of MNEs within the same industry exposes the domestic market to higher levels of competition. As a response to competition pressure oriented from MNEs, domestic firms reorganize operations and production to increase efficiency and better allocate the existing resources. Domestic firms replace older managers, readjust scale size, and (or) reorganize the production chain more cost-effectively. FDI, either in the form of inter-industry knowledge spillovers or intra-industry competition effects, creates an array of opportunities and challenges that can affect the productivity of domestic firms. It is not guaranteed that FDI will positively impact the host economy. The presence of MNEs in a domestic market is likely to crowd out domestic firms (i.e. market stealing effect), causing productivity losses. Most commonly, MNEs create agglomeration effects that stimulate the diffusion of knowledge in the local market (Aitken and Harrison, 1999; Orlando, 2004). Although the manager of the domestic firm observes these effects, they remain unobserved to the researcher. From a modeling point of view, if we fail to account for knowledge spillovers in the evolution of physical productivity, the estimated coefficients of the production function remain highly biased.

Bias emerges not only if we neglect spillovers but also in other forms of knowledge capital, such as intangible assets. To reduce the bias caused by omitted variables, we consider the increasing role of intangible assets in firm performance, which represent a firm's organizational capital.[7] Recent literature (Crass and Peters, 2014) has demonstrated that intangible capital as a measure of organizational practices influences innovation activities and has a positive impact on productivity (Bloom et al., 2010, 2012). Marrocu et al. (2012) show that some components of intangible assets tend to be as productive as tangible capital.[8] Firm management and organizational practices are complementary to spillovers in our context because they determine a firm's ability to assimilate external knowledge. The combination of the two determines absorptive capacity, an important driver of productivity (Escribano et al., 2009; Aldieri et al., 2018).

3. Estimation methodology

In our structural framework, production input coefficients correspond to cost input shares consistent with the existence of input adjustment costs. This assumption follows the formulation of Ackerberg et al. (2015), while it differs from Olley and Pakes (1996) and Levinsohn and Petrin (2003) that consider labour as a free input without cost adjustments. Within an EU context with strong employment protection legislation (EPL) in place, it becomes more realistic to assume that firm decisions about labour hiring maintain a more persistent impact on future profits. The two underlying assumptions of our structural framework are that producers are cost-minimizers, and technological change is Hicks-neutral. We specify a generic form of a log value-added production function as follows:

$$y_{ict} = f(l_{ict}, k_{ict}; \beta) + v_{ict}, \tag{1}$$

where l stands for labour, k stands for the capital stock and β are parameters of interest to be estimated. The usual notation applies with i and t to index firms and years, respectively. Although our panel includes a country index c, it is suppressed hereafter to improve readability. Residual v_{it} can be further decomposed into:

$$v_{it} = \omega_{it} + u_{it}, \tag{2}$$

where ω_{it} is an unobserved factor that affects a firm i's output (productivity), and u_{it} is the standard statistical noise that captures random errors. In industrial organization and trade literature, parameter ω_{it} is driven by exporting (De Loecker, 2013), changes in trade policy and within-firm efforts to reduce X-inefficiencies (De Loecker and Goldberg, 2014). In the present context, we shed light on spillovers and how they interact with characteristics within firms, such as intangible assets as the major sources of spillovers ω_{it}. In a reduced static form representation, ω_{it} is essentially a function:

$$\omega_{it} = h(spill_{jt}, X_{it}, spill_{jt} \times X_{it}), \tag{3}$$

where $spill_{jt}$ stands for industry-wise spillovers and X_{it} represents firm specific characteristics. For the purposes of the estimation framework, ω_{it} is assumed to follow a dynamic pattern (the law of motion) that captures the high degree of persistence in productivity.

The functional form of (1) is the translog that allows for greater flexibility between inputs. We also nest the baseline translog with a Cobb-Douglass production function for comparability (see results in Appendix B). To recover estimates for β that are preceding the derivation of TFP (ω_{it}), we first need to address the simultaneity bias between inputs choice and unobserved ω_{it}. Following Levinsohn and Petrin (2003) and Ackerberg et al. (2015), we rely on the use of materials as a proxy for unobserved productivity shocks. We specify the demand of materials as follows:

$$m_{it} = m(\omega_{it}, k_{it}), \tag{4}$$

with the inverse function of m to give us an expression of ω_{it} as follows: $\omega_{it} = \Omega(m_{it}, k_{it})$. If $(\partial m_{it}/\partial \omega_{it}) > 0$, then function $\Omega(.)$ is a good approximation of ω_{it} in the sense that a positive productivity shock means higher consumption of intermediate material inputs. Melitz and Levinsohn (2006) and Aw et al. (2011) have shown that as long as more productive firms charge only ordinarily higher mark-ups than non-productive firms, then the monotonicity condition of materials in ω_{it} holds with productivity shocks to reduce marginal costs raising the demand of materials and output at any given level of demand. While input estimates β and ω_{it} are recovered in the second stage, first stage is used to run:

[6] In the Olley and Pakes (1996) jargon, the dynamic inputs of capital and age are called state variables, while labour is called a free variable.

[7] Appendix A shows how the ratio of intangible to tangible assets evolves over the period for each country. Apart from Spain, the graphs depict an upward trend in the relative use of intangibles within the firm.

[8] Intangible assets include R&D expenditure, patents, copyrights, software, employee training, trademarks, and other similar items. More importantly, Efige has extracted these data from Amadeus-Bureau Van Dijk (BDV), which has previously harmonized expenses on intangible assets across countries following international accounting rules. Therefore, our variable of intangible assets has been capitalized, and it is fully comparable across countries.

$$y_{it} = \varphi(l_{it}, k_{it}, m_{it}) + u_{it}, \tag{5}$$

where we obtain predicted output $\hat{\varphi}$ and an estimate of the statistical noise $\hat{u}$ from the following translog specification augmented with the elements of the inverse materials function:

$$\varphi_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \Omega(m_{it}, k_{it}). \tag{6}$$

The control function $\Omega(m_{it}, k_{it})$ accounts for productivity in the production function estimation in the first stage.

Second stage specifies an endogenous productivity process that allows for last year's external foreign knowledge (spillovers) to interact with in-house intangible assets in governing ω_{it}. The first-order Markov process (AR1) is specified as:

$$\omega_{it} = h(\omega_{it-1}, \mathbf{z}_{it-1}) + \psi_{it}, \tag{7}$$

where ω_{it} is estimated by:

$$\hat{\omega}_{it}(\beta) = \hat{\varphi}_{it} - \beta_l l_{it} - \beta_k k_{it} - \beta_{ll} l_{it}^2 - \beta_{kk} k_{it}^2 - \beta_{lk} lk_{it}. \tag{8}$$

We collect in $\mathbf{z}_{it}$ all the additional drivers of ω_{it}: $\sum^{\kappa=3} spill_{jt-1}$ is the sum of the industrial knowledge spillovers with the summation to run over the three FDI spillover indices, $\kappa = [horizontal, backward, forward]$; int_{it-1} is a measure of firm i's specific organizational capital represented by intangible assets; $\sum^{\kappa=3} spill_{it-1} \times int_{it-1}$ is a term of a firm i's absorptive capacity.[9] As mentioned the interaction term $\sum^{\kappa=3} spill_{it-1} \times int_{it-1}$ measures the capability of the firm to assimilate external discoveries and capitalize on productivity from foreign knowledge. These capabilities depend on the organizational profile of the firm, and are referred to in the literature as "absorptive capacity" (Aldieri et al., 2018; Griffith et al., 2003; Blalock and Gertler, 2009). Term ψ_{it} represents an i.i.d shocks common across firms and years. Equation (7) regresses non-parametrically the predicted output φ_{it} from the first stage on past values of ω_{it}, spillovers, intangible assets and absorptive capacity. This formulation relaxes the standard assumption of exogenous ω_{it} offering a more realistic set-up within which knowledge spillovers feedback directly in firm i's productivity.

Equation (7) represents the second stage of our estimation algorithm and retrieves estimates for input parameters β and productivity ω_{it}. Various alternative techniques exist for estimating (7). Originally Olley and Pakes (1996) suggest a polynomial or a Kernel function. Rizov and Walsh (2009) use a fourth-order polynomial, which yields very similar results to the non-parametric Kernel function. In the present methodology, we apply GMM with cluster robust standard errors at the firm level following the original estimator used in De Loecker and Warzynski (2012). A crucial aspect of the GMM estimator is identifying the momentary conditions. We allow lagged labour and its squared term to be an instrument for current labour. The exogeneity condition for such assumption, $E\left[l_{it-1} \upsilon_{it}\right] = 0$ implies that only contemporaneous labour reacts to productivity shocks. Lagged labour values are valid instruments of current labour if there is no correlation between the two over time. The second instrument considered is the current value of the capital stock, the state variable, and its squared term. The momentary conditions are summarized below:

$$\begin{aligned} &E\left[l_{it-1}\psi_{it}\right] = 0, \\ &E\left[k_{it}\psi_{it}\right] = 0, \\ &E\left[k_{it}^2\psi_{it}\right] = 0, \\ &E\left[\left(k_{it} l_{it-1}^2\right)\psi_{it}\right] = 0, \\ &E\left[\left(k_{it}^2 l_{it-1}^2\right)\psi_{it}\right] = 0. \end{aligned} \tag{9}$$

Once, we have retrieved GMM estimates for input parameters $\beta = \{\beta_l, \beta_k, \beta_{ll}, \beta_{kk}, \beta_{lk}\}$, we can obtain ω_{it} by:

$$\omega_{it} = \hat{\varphi}_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_{ll} l_{it}^2 - \hat{\beta}_{kk} k_{it}^2 - \hat{\beta}_{lk} l_{it} k_{it}. \tag{10}$$

We calculate ω_{it} under different formulations of the law of motion (7) starting from a parsimonious specification without spillovers and then we augment gradually with additional determinants. The empirical results from these calculations are discussed in section 5.2. To verify specifically the impact of spillovers on ω_{it} (productivity), we show results separately from the parametric estimation of (7):

$$\omega_{it}(\beta_k, \beta_l) = \theta_1 \omega_{it-1}(\beta_k, \beta_l) + \mathbf{z}_{it-1}' \Theta_z + \psi_{it}. \tag{11}$$

Equation (11) is an integral part of the second stage in our estimation framework, which also derives the coefficients of capital and labour. We consider the same GMM momentary conditions described in (8) with vector Θ to include parameters to be estimated of the variables in $\mathbf{z}_{it-1}$. For simplicity, we show results in Table 3 only from the four variants of (11), which include interchangeably an aggregate index of spillovers, intangible assets and the interaction term of absorptive capacity.

4. Data and measurement issues

4.1. The Efige data set

Bruegel provides the Efige data, a Belgian non-profit international organization that gathered together a survey and balance sheet information from 7699 manufacturing firms (with 10 employees and above) from France, Germany, Hungary, Italy, Spain, UK over the period 2001–2014. Estimating the production function in two stages as per the specifications (1) to (8), we use value-added (y), defined as the operating revenue (OPRE) minus costs of materials (MATE); capital stock (k) measured by the book value of fixed assets (FIAS); labour (l) measured by the number of employees (EMPL) and wages measured by staff remuneration (STAF). We remove observations from the sample with missing and negative values for FIAS, OPRE, and MATE as they are undefinable for the log specifications (5), (7) and (9). We deflate nominal euro values of OPRE, MATE and FIAS using a 2-digit NACE industry production price index (2005 = 100) from Eurostat. Appendix C shows summary statistics of the deflated variables used to estimate the production function. Furthermore, the Efige dataset provides information about the ownership status of the firm and its export activities. Specifically, we define a firm as a foreign MNE if the first shareholder is of foreign nationality and owns at least 10% of the capital shares (IMF, 2009). We utilize the following items from the Efige survey regarding export status: (a) which percentage of your 2008 annual turnover did the export activities represent?, and (b) has the firm exported before 2008? Based on the two items, we define $export = 1$ if $foreign\ sales > 0$ in 2008 and firm i always exports before 2008; 0 otherwise.[10] This definition includes only firms that are established exporters with exports throughout the entire period of the sample. Appendix D shows the total

[9] The current data Efige availability imposes the use of intangible assets in an aggregate form instead of using separate components.

[10] Question coded D4 in the Efige questionnaire asks: *Which percentage of your 2008 annual turnover did the export activities represent*? and question coded D5 asks: *Before 2008, has the firm exported any of its products*? The available answers to these questions are: (i) always, (ii) sometimes, and (iii) never.

number of firms by country based on the status of internationalization. Further information about the areas covered in the Efige survey can be found in Altomonte and Aquilante (2012) and Altomonte et al. (2013).

4.2. Spillovers

FDI is expected to generate spillovers through strengthening competition in the domestic market, unintended transfer of sophisticated technology from MNEs, dissemination of advanced organizational and managerial practices, and the establishment of better distributional networks. We identify three channels through which domestic firms can benefit from these spillovers: (a) intra-industry spillovers (*horizontal*) from MNEs in the same industry, (b) inter-industry spillovers (*forward*) through the purchase of inputs from MNEs in upstream industries, and (c) inter-industry spillovers (*backward*) through the sale of inputs to MNEs in downstream industries. The effect from intra-industry linkages (horizontal spillovers) is not favorable by default as it is possible to capture both gains from higher competition but also crowing out effects on domestic firms within the same 3-digit level industry:

$$Horizontal_{jct} = \frac{\Sigma_{F\epsilon j} S_{Fjct}}{\Sigma_{i\epsilon j} S_{ijct}}, \tag{12}$$

where S is the sales revenue of MNEs (F) to total sales in industry j (3-digit NACE. Rev2) at year t (country index c is again suppressed for readability).

Forward and backward spillovers represent vertical connections between MNEs and domestic firms. Forward spillovers are derived from MNEs inputs suppliers with:

$$Forward_{jct} = \Sigma_{j \neq h}^{J-1} \gamma_{jh} Horizontal_{hct}, \tag{13}$$

where γ_{jh} is the coefficient of the Leontief input-output inverse matrix (OECD, 2012b) that represents the amount of intermediate output purchased from upstream industry h in order to produce one unit of output in the downstream industry j at year t.[11] *Horizontal* measures horizontal spillovers in the upstream industry h. Analogously, backward spillovers are derived from MNEs input buyers:

$$Backward_{jct} = \Sigma_{j \neq w}^{J-1} \gamma_{jw} Horizontal_{wct}, \tag{14}$$

where γ_{jw} is now the coefficient that represents the amount of intermediate output purchased from upstream industry j in order to produce one unit of output in downstream industry w. Coefficients γ_{jh} and γ_{jw} are time invariant parameters that captures transactions at the 2-digit industry level (OECD, 2012a). In our empirical implementation, we use summation of the three indices:

$$spill_{jt} = Horizontal_{jt} + Forward_{jt} + Backward_{jt}. \tag{15}$$

We also separate between horizontal and vertical. The latter is the sum of forward and backward spillovers. By disentangling the two, we check whether horizontal spillovers induce adverse effects through "market stealing" that prevents domestic firms from exploiting economies of scale. Not achieving a certain size threshold can be detrimental and potentially a source of slack for the performance of domestic firms. Nonetheless, vertical spillovers are expected to only positively affect productivity as they are derived from economic transactions in the form of purchase and sale of inputs between technologically superior MNEs and laggard domestic firms.

5. Empirical results

After considering various formulations of vector z_{it} and different assumptions about the evolution of ω_{it} in equation (7), we estimate nine specifications. We start with a benchmark specification **S1** of a value-added translog production function that allows for a first-order Markov-process of ω_{it+1} without controlling for any source of spillovers in the second stage. **S1** is identical to the estimation framework suggested by De Loecker and Warzynski (2012). **S2** derives ω_{it+1} from a translog production function that assumes industry homogeneity in the production input parameters and also allows for $\sum^{\kappa=3} spill_{jt}$ to enter the evolution of ω_{it+1} in the second stage. **S3**: **S2** with industry heterogeneity in the production input parameters. **S4**: **S2** with only $vertical_{jt}$ to be included in the Markov process in the evolution of ω_{it+1} in the second stage. **S5**: **S2** with only $horizontal_{jt}$ to be included in the evolution of ω_{it+1}. **S6**: **S2** plus investment in intangibles (int_{it}) and absorptive capacity ($int_{it} \times \sum^{\kappa=3} spill_{jt}$) entering z_{it} in the Markov-process in (7). **S7**:**S2** but with a second order Markov-process in the evolution of ω_{it+1} in the second stage. **S8** is a third order translog production function in inputs with $\sum^{\kappa=3} spill_{jt}$ entering z_{it} in the evolution of ω_{it+1}. To capture the notion that exporters produce under a different technology (López, 2009; Farinas and Martín-Marcos, 2007), we run **S9**, a value-added translog production function with an export dummy as an additional input and $\sum^{\kappa=3} spill_{jt}$ in the evolution of ω_{it+1}. Appendix B shows estimates of a Cobb-Douglass value-added production function with industry heterogeneity and two variant specifications for the evolution of ω_{it} in the second stage; one without spillovers and one with an aggregate index of spillovers, $\sum^{\kappa=3} spills_{jt}$. Finally, Appendix B shows also results from a translog production function with a dummy for domestic multinationals as an additional input. Table 2 summarizes the description of each specification and shows the sample means of TFP. We provide a further discussion of these results in the next section.

5.1. Estimates of the production function

The main objective of the estimation technique is to include productivity factors that are potentially correlated with the selection of inputs. We mitigate the omitted variable bias from assuming an exogenous evolution of productivity by augmenting (7) with spillovers and intangible assets (organizational capital). Our approach ensures that the estimated production inputs are consistent while performance improvements of the firm are appropriately identified. Without considering, for example, knowledge spillovers in the law of motion, equation (7), some variation in output can be mistakenly attributed to inputs, while the true source of improvement is learning from FDI spillovers. We consider S3 and S6 to be our baseline specifications as they control for the core elements of the analysis; these are spillovers, organizational capital, and absorptive capacity. Excluding these factors, from the evolution of ω_{it} causes potentially biased input coefficients. Table 2 presents the coefficient estimates of the translog production function for five specifications, including S1 for comparability despite not accounting for spillovers.

Comparing input coefficients between S1 and S3 in Table 2, there are considerable differences concerning the labour input. S3 with spillovers in the process of ω_{it} generates a labour coefficient smaller by 8.5% (0.87) relative to S1 (0.95). As we include additional productivity enhancers in S4 and S6, the labour coefficient decreases further. The labour coefficient reaches the value of 0.61 in S6 when the term of absorptive capacity is present in the process of ω_{it}. As expected the coefficient of capital increases to 0.37 after the inclusion of spillovers and absorptive capacity in the law of motion in S6. Nonetheless, the downward bias in the capital coefficient from neglecting spillovers is some-

[11] Assume that total output in the economy is described by the following expression: $\mathbf{y} = \widetilde{\Gamma}\mathbf{x}$, where $\widetilde{\Gamma}\mathbf{x}$ is the demand for intermediate products that should be consumed for the production of the final output. The solution of this linear programming problem in an economy with J sectors can be written as: $y = (I_J - \widetilde{\Gamma})^{-1}$, with I_J to be the $J \times J$ identity matrix and $(I_J - \widetilde{\Gamma})^{-1}$ to be the Leontief inverse matrix. Each element of this matrix is a non-negative number smaller or equal than one.

Table 1
Estimated TFP (ω) under different frameworks.

Spec	Description	Mean
S1	Translog with endogenous ω_{it+1} in the 2nd stage without spillovers	3.11
S2	Translog with industry homogeneity and $\sum^{\kappa=3} spill_{jt}$ in the evolution of ω_{it+1}	4.25
S3	Translog with industry heterogeneity and $\sum^{\kappa=3} spill_{jt}$ in the evolution of ω_{it+1}	3.50
S4	S3 with only $vertical_{jt}$ in the evolution of ω_{it+1}	3.82
S5	S3 with only $horizontal_{jt}$ in the evolution of ω_{it+1}	3.36
S6	S3 $+ (int_{it}) + (int_{it} \times \sum^{\kappa=3} spill_{jt})$ in the evolution of ω_{it+1}	4.31
S7	Translog with 2nd order Markov precess in ω_{it+1} that allows for $\sum^{\kappa=3} spill_{jt}$	5.74
S8	Third order Translog in inputs that allows for $\sum^{\kappa=3} spill_{jt}$ in ω_{it+1}	1.64
S9	Translog with an export dummy as production input and $\sum^{\kappa=3} spill_{jt}$ in the evolution of ω_{it+1}	4.06

Table 2
Production function estimates.

	S1	S3	S4	S6	S7
β_l	**0.95**	**0.87**	**0.81**	**0.61**	**0.87**
	(0.14)	(0.09)	(0.15)	(0.22)	(0.24)
β_k	**0.32**	**0.37**	**0.34**	**0.37**	**0.35**
	(0.06)	(0.05)	(0.08)	(0.12)	(0.06)
β_{ll}	0.07	0.07	**0.10**	**0.13**	0.07
	(0.15)	(0.12)	(0.02)	(0.07)	(0.05)
β_{kk}	0.02	**0.02**	0.02	−0.01	**0.03**
	(0.04)	(0.01)	(0.2)	(0.15)	(0.01)
β_{kl}	**−0.11**	−0.11	−0.12	−0.03	**−0.10**
	(0.05)	(0.05)	(0.39)	(0.08)	(0.03)

Notes: Cluster robust standard errors at the firm level are shown in parentheses.Coefficients in bold indicate significance at 5% and above. Refer to Table 1 for a full description of each specification (S).

how more negligible. Overall, Table 2 indicates that the augmentation of ω_{it} in S6 with spillovers tends to decrease the overestimation of labour relative to S1, which assumes productivity to evolve independently from FDI spillovers. To a lesser extent, S6 also corrects for underestimating the elasticity of capital. The upward bias in the coefficient of labour is 55% (i.e. the percentage difference in the $\widehat{\beta}_l$ between S1 and S6), and it is mainly caused by assuming that FDI spillovers are exogenous. Intuitively, this finding implies that significant learning externalities have been attributed to labor, but are primarily the result of MNEs'presence in the domestic market, the internal organization capital of the firm, and the interdependence between both.

5.2. TFP measures under different estimation frameworks

Turning to the TFP results from different specifications as outlined in Table 1, the first remark is the existence of substantial industry heterogeneity as shown by the differences in the values of ω between S2 and S3. When comparing S1 and S3, a higher value of ω_{it} emerges in S3, which reinforces our view that productivity evolves endogenously. Separating the aggregate spillovers index into vertical and horizontal components reveals significant differences in ω_{it}. S4 includes only vertical spillovers with a sample average value of TFP, 3.82, 13% higher in comparison to S5 which includes only horizontal spillovers.

S3 generates a higher value of ω_{it} than S5 suggesting that FDI-related spillovers can be counter-productive as they can induce “market stealing” effects that undermine the capacity of domestic firms to benefit from economies of scale within the same narrowly defined industry. S4 highlights that vertical spillovers (inter-industry linkages) are the main source of productivity gains from FDI. Partnerships between domestic firms and MNEs, whether through the supply of inputs or the purchase of inputs, are among the most important channels of knowledge exchange.

Absorptive capacity (S6) $int_{it} \times spil_{jt}$, has a positive impact on productivity and increases the average value of ω_{it} to 4.31. Following the previous discussion, the in-house organizational efforts of the firm to improve innovation capabilities generate substantial productivity gains that can be as close as to 19% relative to specification S3. A second-order process in the evolution of ω_{it} (S7) produces the highest value of ω_{it} among all the alternative frameworks in Table 1. This is due to the high degree of persistence in the evolution of productivity, which further signifies the importance of knowledge accumulation partly driven by knowledge spillovers. A third-order translog in inputs with the augmentation of spillovers in the second stage (S8) produces the lowest value of ω in Table 2. The third-order translog reduces noise in the data and misspecification issues that can be otherwise captured by the composite error (i.e. $v_{it} = \omega_{it} + u_{it}$) in (2).

Based on the well-known fact that more productive companies self-select foreign markets, exporters are allowed to operate under a different technology in S9.[12] Controlling for domestic exporters provides on average a 14% higher value of ω_{it} relative to the baseline S3. S9 emphasizes the role of export status in productivity of domestic firms while explaining the importance of accounting for sources of firm heterogeneity in calculating productivity.

5.3. Measuring the effects of FDI knowledge spillovers on TFP

Table 3 shows two stages GMM results from the parameterized law of motion, equation (10). By identifying the specific effects of spillovers on productivity ω_{it}, we are able to compare the results obtained from the present approach with those derived from the standard regression framework (Havránek and Iršová, 2011; Iršová and Havránek, 2013).

Our novel estimation framework indicates that knowledge spillovers in vertical linkages (inter-industry spillovers) are the most critical productivity drivers, whereas horizontal effects from FDI tend to shrink productivity. Compared with a regression framework that measured vertical spillover effects using the same data set Bournakis (2021), the productivity gains from vertical spillovers are much smaller in economic terms. The present values are also smaller than the findings gathered in a meta-analysis study of vertical spillovers (Havránek and Iršová, 2011) that corrects for publication bias (the corresponding $\widehat{\theta}_{vertical}$ was revealed in the region of 0.25). Meta-analysis estimates that do not correct for publication bias are even higher.

5.4. An overview of the TFP estimates with endogenous FDI spillovers

The main message from the findings of the first part of the paper is that positive vertical spillover effects do exist, albeit their economic size is not as large as reported in the previous literature. More likely, this is due to the endogeneity bias that underlies the estimates, which assume that FDI spillovers evolve exogenously from the firm's productivity. Intuitively, TFP gains for domestic firms arise from MNEs in downstream and upstream industries rather than from agglomeration effects within the same industry (Lu et al., 2017). Accordingly, when MNEs are customers of domestic firms (backward linkages), the latter provide inputs tailored to the foreign investor's technical and quality requirements. In contrast, when domestic firms purchase inputs from MNEs (forward linkages), these inputs are infused with advanced tacit knowledge that enhances the technical expertise of the buyer.

Regarding horizontal spillovers (intra-industry linkages), MNEs tend to increase competition and “steal” market shares from local firms,

[12] See Temouri et al. (2013) and Schank et al. (2010) and the references thereafter for some relatively recent evidence on the export self-selection hypothesis.

Table 3
Estimates of the productivity process, Equation (11).

	S1	S3	S4	S6
θ_1	**0.99**	**0.99**	**0.99**	**0.99**
	(0.01)	(0.05)	(0.03)	(0.01)
θ_{spill}		**0.018**		**0.07**
		(0.009)		(0.019)
$\theta_{vertical}$			**0.14**	
			(0.07)	
θ_{inta}				**0.026**
				(0.003)
$\theta_{abs \times spill}$				**1.29**
				(0.67)
obs	62,946	62,946	62,946	62,583

which inevitably causes efficiency and productivity losses. The latter argument explains why ω under S5 has a lower value relative to S3 and S4. Negative or insignificant horizontal spillovers are frequently documented in the literature (Gorodnichenko et al., 2014). Organizational capital also contributes to productivity since it serves the dual purpose of stimulating TFP and indirectly improving the firm's capacity for facilitating foreign knowledge. The autonomous role of organizational capital in enhancing TFP in S6 is significant but economically smaller relative to vertical spillovers. In any case, TFP gains from FDI spillovers remain conditional to the firm's absorptive capacity. In conclusion, our analysis confirms that domestic firms in transition (Damijan et al., 2013) as well as in technologically frontier economies (i.e. the group of EU countries in the current sample) are urged to invest in their technological capabilities before benefiting from the MNEs' advanced knowledge.

6. FDI and aggregate productivity: revisiting the puzzle

After allowing for endogenous spillovers in the evolution of productivity, we are well suited to provide a more systematic assessment of the reallocation effects of FDI, which is the second significant contribution of the paper. This section estimates whether FDI presence measured as the share of FDI inflows over total industry output (at the two-digit level) is associated with higher on average productivity of purely domestic firms.[13] The objective of this empirical investigation is to identify whether a higher industry exposure to FDI initiates a reallocation mechanism among domestic firms. The internal gains in productivity from FDI knowledge spillovers documented in the previous section make domestic firms more productive and enable them to gain market share over their less effective competitors. The reallocation of market segments to more productive firms results in less productive firms losing gradually market share and eventually exiting the market, which increases aggregate (sectoral) productivity. Since the methodology presented in section 3 accounts endogenously for FDI knowledge spillovers within companies, any residual positive effect observed from FDI at the industry level is attributable to a reallocation mechanism that rewards domestic firms with a higher TFP with higher production shares in their industries. In other words, the regression framework that is used by the previous literature (Aitken and Harrison, 1999; Blomström and Sjöholm, 1999; Wooster and Diebel, 2010) in evaluating the role of FDI on the local economy mixes within-firm gains from knowledge spillovers with industry reallocation effects. This section separates the two and acknowledges the different sources of FDI gains.

We view this part of the paper as feeding into the traditional FDI literature (De Mello, 1999; Li and Liu, 2005) that investigates the size of inter-industry effects from FDI due to reallocation dynamics that promote aggregate industry productivity. For the identification of reallocation effects, we specify the following regression:

$$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it} = \delta_0 + \delta_1 \frac{FDI_{jt}}{Y_{jt}} + \pi'_{jt}\delta_\pi + (\lambda_j \times \eta_t) + (\varphi_c \times \eta_t) + \nu_{jt}, \tag{16}$$

where $\widetilde{\omega}_{it}$ is the weighted TFP adjusted for firm i's share to total output in industry j (2-digit NACE classification), $\frac{FDI}{Y}$ is the share of FDI inflows to total industry output in industry j, π is a vector of other industry-specific characteristics that drive productivity and δ are parameters to be estimated. Additionally, a variant specification (16) is formulated with additional lags (up to two) to account for delays in implementing reallocation effects:

$$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it} = \delta_0 + \sum_{s=0}^{2}\delta_{1t-s}\frac{FDI_{jt-s}}{Y_{jt-s}} + \pi'_{jt}\delta_\pi + (\lambda_j \times \eta_t) + (\varphi_c \times \eta_t) + \nu_{jt}. \tag{17}$$

Specifications (15) and (16) are augmented with industry λ_j, year η_t and country φ_c fixed effects. More preferably, we use the interaction of industry-year and country-year fixed effects to control for unobserved time-variant industry and time-invariant country factors that matter for TFP movements at the industry level. We are not more explicit for the nature of these idiosyncrasies in the present analysis as the main focus of this application is on the estimated parameter of δ_1 that captures the existence of reallocation effects due to higher FDI shares in the industry. The novelty of these specifications is that the dependent variable is the weighted industry average of firm-specific TFPs as these are derived from a production function that accounts for endogenous FDI knowledge spillovers.

Table 4 presents results from (16) considering as dependent variable the value of ω_{it} obtained from frameworks S1, S2, and S3. Note, S1 does not control for spillovers, S2 assumes industry homogeneity, and S3 assumes industry heterogeneity in the derivation of ω_{it}. We apply three econometric estimators for each of these specifications: a pooled OLS (POLS) without controlling for cross-sectional heterogeneity, a Least Squared Dummy Variable (LSDV), and an OLS with industry-year and country-year interaction fixed effects. The industry-specific characteristic in (16) and (17) is the degree of concentration in the industry (Herfindahl-Hirschman index) that measures the type of conduct in the market. Two competing scenarios are possible regarding the effect of market concentration on aggregate productivity. As Nickell (1996) highlights, the exercise of monopolistic power indicates a source of slack, which is detrimental to incentives and effort. As a result, high concentration rates signify misallocation of resources and lower levels of productive efficiency. There is sufficient empirical evidence to support the proposition that increases in the degree of competition enhance aggregate productivity (see among others Holmes and Schmitz Jr., 2010; Aghion et al., 2008). On the other hand, high levels of concentration might be an ex-post symptom of a market reallocation process that shifts shares towards the productivity leaders of the industry. In support of this view, Baqaee and Farhi (2020) finds that aggregate productivity depicts the performance of firms within the top quantile of the distribution rather than within-firm improvements across the entire spectrum. Since we have already considered within-firm productivity improvements (that is, spillovers from FDI and organizational capital), the degree of concentration is likely to correlate with the ability of firms to achieve significant scale economies making new entrants unable to compete on cost efficiency (Tsekouras and Daskalopoulou, 2006). Although an in-depth analysis of the productivity concentration relationship is beyond the scope of the present paper, the econometric estimates in the following tables scrutinize empirically the two competing scenarios providing up-to-date evidence regarding this debate.

The coefficients of δ_1 in Table 4 are statistically insignificant in the first three columns. No reallocation effects are found when aggregate TFP is derived from a specification that does not allow for knowledge

[13] Appendix G shows average values of FDI share, concentration, and leverage for the sample of the 2-digit NACE industries.

Table 4
Industry reallocation effects from FDI:Baseline specifications.

	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$
	S1			S2			S3		
	S1.1	S1.2	S1.3	S2.1	S2.2	S2.3	S3.1	S3.2	S3.3
	POLS	LSDV	OLS	POLS	LSDV	OLS	POLS	LSDV	OLS
δ_0	−0.135	0.104	3.017	−0.171***	−0.195	−0.291	−0.016	−0.084	−0.071
	(0.21)	(0.77)	(3.02)	(0.05)	(0.12)	(0.25)	(0.04)	(0.09)	(0.34)
δ_1	−0.011	−0.021	−0.017	0.018***	0.018***	0.014***	0.006*	0.006	0.007*
	(0.02)	(0.02)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\delta_{Concentration}$	0.022	0.018	0.006	0.018***	0.016***	0.012***	0.006**	0.005	0.003
	(0.03)	(0.03)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
δ_{Lev}			−0.054			0.005			0.001
			(0.06)			(0.00)			(0.01)
δ_{Lev2}			0.002			−0.000			0.000
			(0.00)			(0.00)			(0.00)
Industry FE	No	Yes		No	Yes		No	Yes	
Country FE	No	Yes		No	Yes		No	Yes	
Year FE	No	Yes		No	Yes		No	Yes	
Industry × *Year*	No	No	Yes	No	No	Yes	No	No	Yes
Country × *Year*	No	No	Yes	No	No	Yes	No	No	Yes
N	1189	1189	1141	1172	1172	1132	1142	1142	1096
adj. R-sq	0.02	0.11	−0.05	0.66	0.79	0.77	0.14	0.30	0.28
Log lik.	−3249	−3168	−2790	−902	−593	−365	−1025	−888	−569
Clusters	102	102	102	100	100	100	98	98	98

Notes: Cluster robust standard errors at the country and industry level are shown in parentheses. S1 specifications derive ω_{it} without allowing for spillovers in the law of motion. S2 specifications derive ω_{it} assuming industry homogeneity in the estimation of the production function. S3 specifications derive ω_{it} under industry heterogeneity and spillovers in the law of motion.

spillovers at the firm level. S2 and S3 indicate reallocation effects that tend to be larger when the estimation framework of ω_{it} controls for industry heterogeneity. Regarding $\delta_{Concentration}$, the current data set shows that the level of concentration in the industry does not always affect productivity but when it does (in all models of S2 and S3.1) the degree of concentration points to the existence of scale economies and efficiency gains that improve productivity, rather than a source of slack. Models S1.3, S2.3, and S3.3 include the linear and quadratic leverage term to account for a non-linear relationship between the industry's exposure to external financial dependence and investment in productivity-enhancing activities. We have not found such a non-linear effect (i.e. $\widehat{\delta}_{Lev} = \widehat{\delta}_{Lev2} = 0$) in any of the specifications shown in Table 4. Turning to the economic importance of the estimated coefficients, δ_1 ranges from 0.006 to 0.018, which suggests that a 10% increase in the share of FDI inflows of industry *j* raises- *ceteris paribus*- the aggregate productivity of the domestic firms in the industry by 6.1–18%. [14]

Table 5 replicates results from (16) using in $\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$ the value of ω_{it} obtained from the remaining estimation frameworks, S4–S8, of Table 1. We only consider the LSDV estimator with the interactions of industry-year and country-year FEs. Three out of the five specifications provide a statistically significant coefficient for δ_1 with the economic size of this parameter to be slightly higher than the values shown in Table 4. More precisely, the three specifications that generate significant effects for δ_1 are those that allow for vertical spillovers (S4), horizontal spillovers (S5), and absorptive capacity (S6) in the law of motion of productivity ω_{it}. Considering our baseline estimation framework for calculating ω_{it}, S6, the value of coefficient δ_1 suggests that a 10% increase in the share of FDI inflows increases industry TFP up to 15%. Table 5 shows that the elasticity of aggregate productivity from FDI driven reallocation effects is even higher under alternative estimation frameworks of ω_{it}, while the degree of concentration in the industry also impacts productivity (in four out of the five specifications), positively enhancing the scenario that low competition is more likely an ex-post feature of a reallocation process that made productive firms dominate the market.

[14] Given that ω_{it} is expressed in logs, the elasticity is derived as *exp* (0.006 × 10) = 1.061. Accordingly, a 10% increase in FDI share leads to a 6.1% higher TFP.

Table 5
Industry reallocation effects from FDI: Results under additional specifications for the derivation of firm TFP.

	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$
	S4	S5	S6	S7	S8
δ_0	−0.687	−0.143	−0.265*	0.054	0.026
	(0.57)	(0.13)	(0.15)	(0.17)	(0.05)
δ_1	0.024**	0.024***	0.015***	0.006	−0.004
	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
$\delta_{Concentration}$	0.025***	0.011	0.017***	0.017**	−0.000
	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
Industry × *Year* FE	Yes	Yes	Yes	Yes	Yes
Country × *Year* FE	Yes	Yes	Yes	Yes	Yes
N	1126	1140	1178	1126	1110
adj. R-sq	0.52	0.61	0.79	0.71	0.48
Log lik.	−1890	−1635	−569	−1484	−932
Clusters	96	98	101	96	93

Notes: Cluster robust standard errors at the country and industry level are shown in parentheses. S4 derives ω_{it} allowing for vertical spillovers in the law of motion. S5 derives ω_{it} allowing for horizontal spillovers in the law of motion. S6 derives ω_{it} allowing for absorptive capacity in the law of motion. S7 derives ω_{it} allowing for a 2nd order Markov process and spillovers in the law of motion. S8 derives ω_{it} from a 3rd order translog production function allowing for aggregate spillovers in the law of motion. All specifications assume industry heterogeneity in the estimation of the production function.

7. Robustness analysis

As a further test of robustness for identifying within-industry reallocation effects, Table 6 shows results from specification (16) using up to two lags ($s = 2$) of the FDI share $\frac{FDI_{jt-s}}{Y_{jt-s}}$ variable. The reason for using

Table 6
Industry reallocation effects from FDI with higher order lags.

	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$	$\frac{1}{N}\sum_{i\epsilon j}\widetilde{\omega}_{it}$
	S4	S5	S6	S7	S8
δ_0	−0.229	−0.094	−0.080	−0.082	−0.008
	(0.17)	(0.09)	(0.05)	(0.11)	(0.04)
$\delta_1(t)$	0.000	0.019*	0.011***	−0.003	−0.008
	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)
$\delta_1(t-1)$	−0.012	−0.016	0.001	−0.015	−0.008
	(0.02)	(0.01)	(0.00)	(0.02)	(0.01)
$\delta_1(t-2)$	0.033**	0.012	0.006	0.019**	0.011*
	(0.02)	(0.01)	(0.00)	(0.01)	(0.01)
$\delta_{Concentration}$	0.017**	0.008	0.011***	0.015**	−0.000
	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)
Industry × *Year* FE	Yes	Yes	Yes	Yes	Yes
Country × *Year* FE	Yes	Yes	Yes	Yes	Yes
N	927	935	966	923	912
adj. R-sq	0.5829	0.7001	0.7970	0.7546	0.5757
Log lik.	−1284	−962	−164	−1121	−637
Clusters	94	96	100	93	93

Notes: Cluster robust standard errors at the country and industry level are shown in parentheses. S4 derives ω_{it} allowing for vertical spillovers in the law of motion. S5 derives ω_{it} allowing for horizontal spillovers in the law of motion. S6 derives ω_{it} allowing for absorptive capacity in the law of motion. S7 derives ω_{it} allowing for a 2nd order Markov process and spillovers in the law of motion. S8 derives ω_{it} from a 3rd order translog production function allowing for aggregate spillovers in the law of motion. All specifications assume industry heterogeneity in the estimation of the production function.

higher-order lags lay within the hypothesis that productivity gains from reallocation take some time before being realized in full (Monastiriotis and Alegria, 2011). The time-hysteresis hypothesis implies that as new MNEs enter the domestic market, they gain share over domestic firms, thus causing some market stealing effects and a decline in productivity in the short run for domestic firms. In the long run, however, the group of domestic firms capitalizes on knowledge from the presence of MNEs rebounds by gaining market shares over their less competitive counterparts, which eventually generates substantial productivity gains for the aggregate sector. The introduction of higher-order lags of the FDI variable in Table 6 is expected to capture this time hysteresis.

The use of higher-order lags in FDI in Table 6 now provides statistically significant coefficients for t-2 in S7 and S8. At the same time, previously, the estimates of δ_1 for the same specifications were insignificant in Table 5. In S5 and S6, the reallocation effect of FDI takes place relatively quicker, with only the coefficient of δ_{1t} to be significant. For S4, the estimated coefficient in period *t* turns insignificant, while gains from reallocation become evident in period *t*-2. The main message of the estimation results from equation (17) supports the hysteresis hypothesis as positive FDI effects in aggregate (sectoral) productivity are not always instant. Rather, they occur with time delay; nonetheless, with only one of three coefficients in (17) being statistically significant in each specification, reallocation gains from FDI result in only a one-off boost without significant time persistence.

Overall, sections 6 and 7 highlight the statistical and economic importance of FDI for the aggregate productivity of domestic firms. The highest size of this effect is 0.033 for S4, which signifies productivity gains at the order of 33% after a 10% increase in the FDI share. This particular effect takes place more likely with a two years lag.[15] As our analytical framework treats FDI more systematically by distinguishing between within-firm knowledge and across-firm reallocation effects, we view the present results as a very encouraging piece of evidence for the positive role of FDI in the domestic economy.

8. Conclusions

8.1. Concluding remarks and policy implications

To the best of our knowledge, our paper is the first endeavor that endogenizes the effect of FDI spillovers in the TFP measurement of domestic firms. In light of this novelty, we revisit the debate on the role of FDI in boosting the productivity of the FDI recipient economies under a new lens. Our framework decomposes the potential FDI effects into within-firm knowledge spillovers and across-firms industry reallocation effects. In the former, spillovers are assumed to evolve endogenously in the production decisions of domestic firms. At the same time, in the latter, we relate the tendency of more productive firms to capitalize on learning gains and increase market shares. Using an array of different specifications, we explore various industrial linkages through which MNEs affect the performance of their domestic counterparts. The main advantage of endogenizing FDI spillovers is that it corrects for omitted variable bias in the evolution of productivity by accounting specifically for factors that were previously considered to be pure statistical noise leading to spurious estimates of the production inputs. Allowing for endogenous FDI spillovers, TFP estimates are higher, which implies that misleading and inaccurate estimations drive previous results on FDI spillovers. Gains from reallocation are also crucial as increases in FDI inflows by 10% can cause proportionally or even higher increases in aggregate productivity. When firms increase their productivity from FDI spillovers, they trigger a market reallocation mechanism that leads to a higher level of productivity in the aggregate industry. The combination of these effects not distinguishable in the previous literature points to multiple benefits from FDI, which is pretty encouraging for the welfare of the host economy.

Although the role of global value chains in improving productive efficiency is well attributed in the literature, what remains less acknowledged is their role as a conduit of knowledge and technology transfer. In this respect, the approach introduced in our paper provides a better methodological device. It should be regarded as the most appropriate modeling set-up for future research that examines how business interactions in a globalized environment affect the firm's performance.

The main policy lessons from our analysis can be summarized as follows: first, as inter-industry rather than intra-industry linkages are the primary sources of knowledge spillovers, the policy focus should be gathered on the origins of learning from partnerships between MNEs and domestic firms, whether through the sale or purchase of inputs. In this regard, economic policy initiatives should not be restricted to attracting foreign firms, since agglomeration gains from foreign firms (intra-industry) are either insignificant or negative, but rather incentives that encourage MNEs to partner with domestic firms and become embedded in the local economy. The second policy-related message that our work conveys is the substantial firm heterogeneity in how individual firms capitalize on productivity gains from foreign knowledge. This heterogeneity is partly based on the amount of organizational capital within a firm, determining how much the firm can absorb. Knowledge spillovers from FDI are dependent on the firm's internal capability to facilitate external knowledge. Consequently, encouraging firms to upgrade their technological expertise should remain a high priority on the policymakers' agenda.

8.2. Research limitations and future research

The present study develops some new methodological paths in modeling spillovers, but we are far from arguing that the current formulation includes all the possible sources of knowledge spillovers. We only

[15] The methodological derivation of our results differs from the standard approaches used in the FDI industry level literature, nonetheless, even a crude comparison with the previous findings will be useful. Present estimates are higher than productivity gains found in Haskel et al. (2007) for UK domestic firms that do not exceed 0.5%, while contradict the negative FDI effects found in Liu and Wang (2003), Aitken and Harrison (1999), Konings (2001) and Kugler (2006).

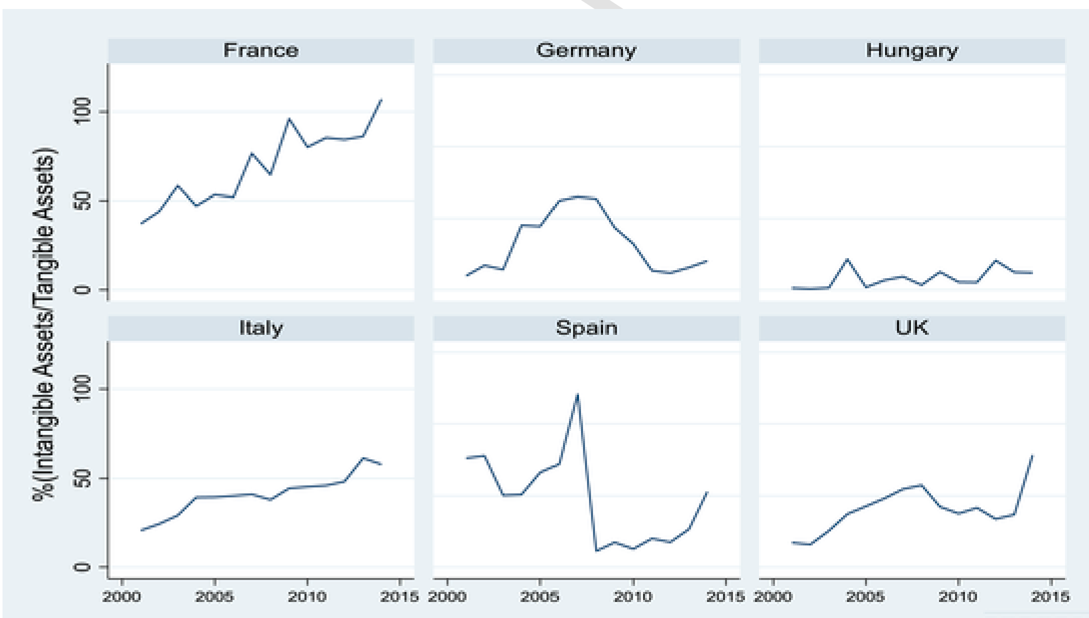
consider spillovers derived from MNEs, but our work can be extended to include in the law of motion of productivity factors such as trade from outsourcing materials and services. Trade in materials and services embody tacit knowledge that reflects the R&D effort of the trading partners. Therefore, trade can also serve as a conduit for the international transmission of knowledge. Similarly, domestic inter-industry input transactions can also facilitate R&D spillovers, as has been previously shown by (Bournakis et al., 2018; Giovannetti and Piga, 2017). There is also a regional and geographical element in the presence of spillovers. This is to say that productivity in a firm might be affected by the performance of its peers that are located within a close geographical distance (Iyoha, 2021). These aspects should be addressed in future research, given the availability of suitable data.

Another issue that merits further investigation following our novel methodological framework in this paper is the relationship between concentration and productivity. The current findings contradict the stylized fact that highly concentrated industries suffer from slack and low incentives, which cause productivity degradation. However, our approach already incorporates the firm's internal efforts to improve productivity through foreign learning, which allows the more productive rivals of the industry to become price-competitive and naturally acquire a higher market share. After this reallocation process, the market equilibrium established does not necessarily imply a negative nexus of concentration -productivity. This proposition requires further empirical scrutiny, and it is also another path for future research.

From a more technical perspective, our approach ensures that the estimated production inputs are consistent while performance improvements of the firm are properly identified. An unavoidable limitation is that we perform this, at least, for the most part, using parametric methods. It would be interesting to examine, in future research, which components of our estimation procedure can be robustified further by using non-parametric or, at least, more flexible techniques.

Appendices.

Appendix A. The Evolution of Intangibles 2001–2014



Appendix B. Further Specifications in the derivation of ω_{it}

Spec	Description	mean
S1	CD without spillovers in ω_{it}	4.30
S2	CD with spillovers in ω_{it}	4.29
S3	Translog with spillovers in ω_{it} and domestic MNE as a production input	4.10

Appendix C. Summary Statistics, EFIGE Dataset, 6 European Countries, 2001–14

stats	OPRE	MATE	STAF	FIAS	EMPL
N	79,259	79,259	79,259	79,259	79,259
mean	13,791	7740	2394	5044	62
sd	131,036	100,429	19,317	67,085	322
min	0	0	0	0	10
p1	288	19	96	13	4
p25	1500	492	418	238	14

stats	OPRE	MATE	STAF	FIAS	EMPL
p50	3023	1266	705	665	23
p75	7004	3415	1389	1916	42
p90	18,369	10,062	3256	5365	92
p99	148,520	87,140	24,893	55,183	623
max	11,900,000	11,000,000	1,881,892	6,342,371	19,586

Notes: Values are expressed in Euros 2005 constant prices.

Appendix D. Number of Exporters, MNEs and Domestic Firms

country	Established Exporters	Sporadic Exporters	Foreign Firms
France	352	1173	532
Germany	75	217	178
Hungary	37	109	149
Italy	952	1966	300
Spain	541	2102	300
UK	59	114	291
Total	2016	5681	1750

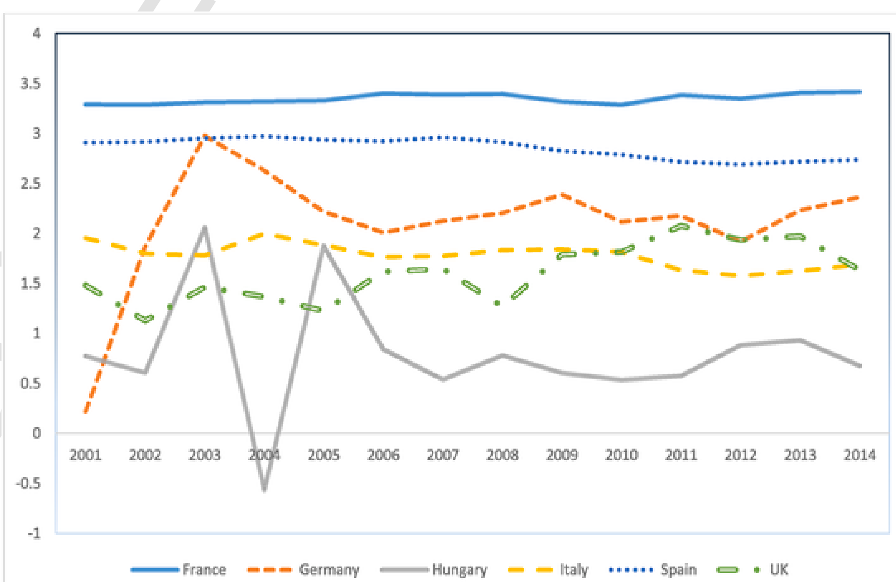
Notes: Sporadic exporters are domestic firms that export only in 2008, established exporters are domestic firms that export all years during the period 2001–2014. Foreign firms have at least one shareholder of foreign origin that holds at least 10% of capital shares.

Appendix E. TFP (2001–2014) of 7699 EU Firms Under Different Structural Specifications

country	S1	S2	S3	S4	S5	S6	S7	S8	S9
FRA	3.494	4.534	3.342	3.787	3.603	4.553	4.856	0.874	4.373
GER	3.082	4.832	2.159	4.614	2.660	4.331	4.683	0.575	3.392
HUN	0.787	3.289	0.688	2.942	2.196	3.142	1.898	0.180	2.352
ITA	3.641	4.435	1.767	3.882	3.680	4.550	6.887	3.914	4.443
SPA	2.567	3.920	2.861	3.787	2.918	4.022	5.333	0.080	3.498
UK	2.992	3.986	1.644	3.465	4.571	3.734	6.608	2.622	5.748

Appendix E presents mean values of ω by country. As expected, substantial differences in ω arise in the cross-sectional dimension of our panel. The ranking of countries based on productivity does not maintain the same pattern across specifications. Under **S3** France, Spain, and Germany have the leadership (Appendix E), whilst under **S4** the ability of German firms to gain from vertical spillovers plays an important role in the evolution of productivity. When it comes to the importance of horizontal spillovers (S5) UK firms benefit the most from the competition pressure induced by MNEs. The same pattern holds when we allow for the export status of the firm.

Appendix F. TFP of Domestic Firms. Estimated from S4



Appendix G. Industry Characteristics in (%)

nace2d	Description	FDI Share	Concentration	Leverage
10	Food products	3.01	22.95	64.40
11	Beverages	19.31	33.38	51.07
12	Tobacco	83.15	76.16	49.61
13	Textiles	6.97	15.56	55.71
14	Wearing Apparel	14.79	30.81	57.94
15	Leather and related products	10.41	8.54	56.83
16	Wood products	12.16	21.77	59.49
17	Paper	14.26	28.75	57.31
18	Printing	23.37	17.58	59.86
19	Coke	48.35	68.41	54.06
20	Chemicals	12.48	17.86	54.30
21	Pharmaceuticals	13.81	43.77	46.87
22	Rubber	7.17	15.02	57.51
23	Other non-metallic	7.65	21.24	50.43
24	Basic Metals	9.46	28.90	63.07
25	Fabricated Metals	13.61	20.93	57.39
26	Electronics	10.69	25.61	52.94
27	Electrical Equipment	23.18	23.94	55.81
28	Machinery	4.17	18.59	57.42
29	Motor Vehicles	9.71	27.44	59.69
30	Transport	32.43	43.57	64.53
31	Furniture	9.48	22.76	59.21
32	Other manufacturing	18.73	29.80	51.94
33	Repair and installation	12.14	39.03	50.99
Mean		13.88	26.36	56.56

Notes: FDI share is the ratio of FDI Inflows to Industry Output. Concentration is Herfindahl-Hirschman Index. Leverage is the sum of current and non-current liabilities over total assets.

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