Economics Working Paper Series

2022/001

Labor Share Decline and Productivity Slowdown: A Micro-Macro Analysis

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Labor Share Decline and Productivity Slowdown: A Micro-Macro Analysis *

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First Draft: June 2019

March 2022

Abstract

This paper uses firm-level data to empirically investigate the relative contribution of the declining relative price of investments, the increasing automation, and the rising price markups on the labor share decline and productivity slowdown witnessed in the last 20 years in the Spain manufacturing sector. The results point to automation and markups as important drivers of both phenomena, while the relative price of investments has the opposite sign, coherent with the evidence of capital-labor complementarity. A theoretical model characterized by firm heterogeneity, endogenous markups distribution, and financial market frictions, parsimoniously accounts for the empirical findings, and it is used to draw aggregate implications. Last, the model accounts for the observed changes in the distribution of firm markup and size and for the decline in business dynamism that occurred in the last decades.

JEL Classification: E22, E25, O16, O33, O40
Keywords: Labor share, TFP Losses, Firm dynamics, Capital Misallocation

*The authors particularly thank Francisco Buera for the feedback and suggestions given during Francesca's visiting at Washington University in Saint Louis. They also thank Francesco Furlanetto, Jakob Grazzini, Miguel Leon Ledesma, Virgiliu Midrigan, Morten Ravn, Gianluca Violante, the participants at the University of Kent Macro and Finance 2019, the CEF Conference 2021, the INFER annual Conference 2021, the CefES Conference 2019, the Dynare Conference 2019, the seminar participants at the University of Milan Bicocca, University of Siena and the University of Pavia.

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1 Introduction

The objective of this paper is to investigate the relative contribution of the declining relative price of investments, increasing automation, and rising firm markups to the labor share decline and productivity slowdown. As witnessed by the recent empirical literature, the labor income share has experienced a global downward trend in the last decades. In most countries, the fall accelerated in the nineties and reached its lowest level at the beginning of the last ten years, just in the aftermath of the great recession. A similar picture appears for the Spain economy.[1] The usual explanations for changes in labor shares include technological change, leading to the decline in the relative price of investments goods (Karabarbounis and Neiman (2014)) or increased in automation (Acemoglu and Restrepo (2017), Martinez (2021), Autor and Salomons (2018), Bergholt et al. (2021)), the emergence of superstar firms Autor et al. (2020)), the reduction in the bargaining power of labor (Blanchard and Giavazzi (2003), Piketty (2014),) and the increased firms' markups (Barkai (2020); De Loecker and Eeckhout (2018)). Kehrig and Vincent (2020) try to disentangle these explanations by studying empirically the labour share decline using micro-level data of the US manufacturing sector.

Though the literature that studies the determinants of labor share decline has grown widely, most of this literature focuses on one explanation at the time, lacking a comprehensive framework and not considering the effects of their interaction. Moreover, it rarely relates the dynamic of labor share to that of aggregate TFP, though there might be common explanations of the two long-run trends. For instance, part of the recent literature on increased markups, for example, Reinelt and Meier (2020) and Baqaee and Farhi (2020)), shows that larger and more dispersed markup had contributed to increasing the TFP losses. On the other hand, looking at the implication of technological change for TFP, Acemoglu and Restrepo (2019), find that an excessive substitution of labor with capital not only may create direct inefficiency but may cause productivity growth slowdown by wastefully using resources and displacing labor. An aspect that frequently emerges in the literature on this topic is the relevance of the analysis at the micro-level and, consequently, of micro-level data for the interpretation of macroeconomic facts. This is exactly the scope of this paper, and to this aim, its contribution is twofold. First, using ORBIS firm-level data the paper empirically evaluates and quantifies the role of automation, markup, and price of investments for the observed labor share dynamics in the Spain Manufacturing sector. Hence, using sectoral data, it investigates the significance of the same set of explanatory variables in affecting the TFP. Second, it rationalizes the empirical

[1] Section 2 of this paper reports and discusses the aggregate dynamics of the labor share in the Spain manufacturing sector together with the series of the relative price of investments, markup, and the stock of robots (used as a measure of automation).

findings using a theoretical model characterized by firm heterogeneity and dynamics, endogenous markup distribution, and financial market frictions. In detail, the first part of the paper provides empirical evidence on the relationship between markup, automation, and the relative price on investments on firms' labor share and sectoral TFP. The data set used merges firm-level data of Spain's manufacturing sector with sub-sectoral data on the relative price of investments, the stock of robots per worker, and, the TFP. Then, two batteries of regressions are run, one having as a dependent variable firm's labor share, and one having as a dependent variable sectoral TFP. For what concerns the estimates on the firm's labor share, the main results can be summarized as follows. Firms with a higher markup have simultaneously a lower labor share. Similarly, the installation of new robots has a negative effect on the labor share dynamics: firms operating in sectors where the installation of new robots is high register a relatively lower labor share. Finally, a negative change in the relative price of the investments generates a positive change in the labor share of firms. This last result is in favor of the hypothesis of a production function where capital and labor are complements inputs, which is also in accordance with micro evidence and in line with the estimates obtained using the micro-data sample considered in this paper.[2] The estimation of the input elasticity of substitution between capital and labor using our sample of firms, finds a value of about 0.817, confirming the hypothesis that labor and capital are rather complementary inputs and not substitutes. Therefore, according to the results found in this paper, the decline in the relative price of the investment observed over the last few decades would not have contributed to the observed dynamics of the labor share in the Spain economy, but rather would have attenuated its decline. Concerning the estimates on sectoral TFP, this paper finds that higher dispersion in the firms' markup distribution is associated with lower TFP in a specific sector. These results are in line with what was found recently by Baqaee and Farhi (2020) and Reinelt and Meier (2020) for the US economy. Furthermore, the relative price of investments has a significant and positive effect on TFP, while the opposite is true for automation, recalling the result in Acemoglu and Restrepo (2019). The second part of the paper is dedicated to the theoretical model. In particular, it develops a model with a well-structured supply side. The model is characterized by an intermediate goods production sector, and two final goods production sectors, the investment good and consumption good sector. These two sectors allow introducing an investment-specific technology change that drives the fall in the relative price of investment. Firms in both sectors are homogeneous and they operate in perfectly competitive markets. The characterization of the intermediate production sector is key in the model. Firms in this sector are heterogeneous in terms of productivity and

[2]The consensus in the literature is that capital and labor are complements rather than substitutes (e.g., Chirinko, 2008; León-Ledesma et al., 2010; de La Grandville, 2016; Knoblach et al., 2020).

they are subject to a borrowing constraint for capital. Moreover, they are engaged in monopolistic competition with non-CES demand, as in Kimball (1995), so that firms' markups are endogenous and heterogeneous. Further, the intermediate sector features Constant Elasticity of Substitution (CES) production technology with capital and labor being the two production inputs. The elasticity of substitution between these inputs is set less than one, as estimated in this paper using micro-data. This design makes the model economy suited to study the long-run effects of a change in the level of technology in the investment good production sector, a change in the degree of automation in the production function, and an increase in firms' market power. Importantly, the model economy is characterized by financial market frictions, such that entrepreneurs operating in the intermediate good market face borrowing constraint. This aspect is crucial to quantify the inefficiency that might be generated by the three structural changes considered in the analysis, to which extent they contribute to the misallocation of capital among heterogeneous firms or, in the case of markup, it may induce sub-optimal entrepreneurial decision and foster inefficient firms dynamics, leading, in both cases, to productivity slowdown. The model is, in fact, well equipped to disentangle and quantify TFP losses associated with the three structural shocks. Moreover, it is also suitable to do both macro and micro-level analysis and therefore to assess the effect of the structural shocks not only on aggregated variables but also on the distribution of firms markup, firm productivity, and size. The main results of the theoretical part can be summarized as follows. In the model economy, as in the data, the rise in automation and markup plays a similarly relevant role in the decline of the labor share, though as for the data the markup effect is stronger. Also, in accordance with the empirical results, a decline in the relative price of investment is followed by a small increase in the labor share. Further, the model well replicates the change in the markup distribution observed in the data (See Section 2 for details), the increase in small size firms, as well as the recent decline in business dynamism. Finally, at the aggregate level markup and automation shocks have very different consequences. While automation has a positive effect on output, investment, and consumption, the opposite is true for the increased markup. Further, though both the shocks generate substantial TFP losses, particularly the increased aggregate markups and its dispersion, the mechanism driving these losses is completely different. In fact, the model is characterized by two mechanisms through which the structural changes affect the TFP: (i) the intensive margin mechanism, that is the allocation of capital among entrepreneurs; (ii) the extensive margin mechanism, that is the distribution of firms and their dynamism. In the case of higher markup, the decline of the TFP is mainly due to the extensive margin mechanism, i.e. to the dynamics of the entrepreneurs. As the markups increase, higher profitability induces less productive entrepreneurs to enter the market, so that firms' productivity distribution moves to the left and total factor productivity lowers. At the same time, markup dispersion increases. On the other hand, the intensive margin mechanism operates by reducing capital misallocation and therefore contributing to improving the TFP. The latter result is explained by the wealth effect induced by the increased profits that in turn increase entrepreneurs' savings possibility, making them ultimately less financially constrained. Nonetheless, the effect coming from the extensive margin mechanism more than compensates for the effect coming from the intensive margin mechanism. As a result, the TFP losses generated by a permanent markup shock are substantially strong. In case of an automation shock, the extensive margin mechanism remains mute. Indeed, firms' distribution in the new steady state almost overlaps with the one of the initial steady state. The decline in TFP that originates from automation comes exclusively from intensive margin mechanisms, that from increased capital misallocation that follows the automation shock. The reason is the following. An automation shock increases the marginal productivity of capital, especially for those entrepreneurs with high ability. This, in turn, increases their desired demand for capital. However, due to financial constraints, they cannot increase their stock of capital up to the desired level. This in turn generates capital misallocation and TFP losses.

Related Literature This paper is related to the recent literature on labor share. Several works documented a decline in the share of GDP going to labor in many nations over recent decades e.g., Elsby et al. (2013); Karabarbounis and Neiman (2014) Piketty (2014). Dao et al. (2017) point to a decline in the labor share between 1991 and 2014 in 29 large countries that account for about two-thirds of world GDP in 2014. Although there is controversy over the degree to which the fall in the labor share of GDP is due to measurement issues (Bridgman (2018), Rognlie (2016), Gollin (2002); Koh et al. (2020), Smith et al. (2019)), there is a general consensus that the decline is real and significant. There is less consensus, however, on what are the causes of this dynamic. A consistent strand of literature associates the decline of the labor share of income to technical changes, in particular to a rise in the automation of tasks performed by labor. Martinez (2021), by using industry-level data for the US, provides evidence that automation was an important driving force for the change in the labor share between 1972 and 2010. Similarly, Acemoglu and Restrepo (2020) propose a model in which robots compete against human labor in the production of different tasks. They show that robots may reduce employment and wages. Differently, Karabarbounis and Neiman (2014) hypothesize that the cost of capital relative to labor has fallen, driven by rapid declines in quality-adjusted equipment prices, especially of information and communication technologies (ICT), which could lower the labor share if the capital-labor elasticity of substitution is greater than 1. Grazzini and Rossi (2020) links the change in the income labor share to the fall of the relative investment price. However, they propose a significantly different mechanism, dropping the hypothesis of substitutability between capital and labor in the production function, which is not supported by micro evidence. In the paper, the authors show that a shock to the relative price of investment goods leads to a decline in the labor share by favoring the entrance of new firms characterized by higher capital intensity of production and lower labor income share. Baqaee and Farhi (2020) find that the labor share of income has decreased because low labor-share firms have become larger, and not because the labor share has declined within firms. Likewise, Autor et al. (2020) suggests and empirically explores the hypothesis that the decline in the labor share was mainly driven by the rise of superstar firms, which charge higher markups and whose production is more capital intensive. Barkai (2020) shows that according to data, the decline in the labor share over the last 30 years was not offset by an increase in the capital share. Then, only an increase in markups can generate a simultaneous decline in the shares of both labor and capital. In the same line also De Loecker et al. (2020). Finally, a paper on the labor share which is closely related to this paper is the one of Bergholt et al. (2021). In their paper they use Structural VAR analysis to estimate the importance of four main explanations for the decline of the US labor income share, that is rising firm markups, falling bargaining power of workers, higher investment-specific technology growth, and more automated production processes. Their results suggest that automation has been the main driver of the US labor share, although rising markups have played an important role in the last 20 years. They also find evidence of capital-labor complementarity, questioning the importance of the relative price of investments as a driver of the labor share decline. This paper differentiates from Bergholt et al. (2021) by at least three aspects. First, it investigates the dynamics of both the labor share and its linkage with the dynamics of the TFP. Second, the empirical results are obtained using micro-level data combined with sectoral data of the Spain manufacturing sector. Third, it rationalizes the empirical results using a completely different theoretical model, that sheds new light on the importance of firm heterogeneity and capital misallocation in understanding both labor share decline and productivity slowdown. Last, the theoretical model considered in this paper well replicates the observed changes in firms' markups and size distributions and the decline in business dynamism.

The paper also relates to the literature on capital misallocation and productivity slowdown, particularly the paper by Gopinath et al. (2017). The latter uses data for Spain manufacturing firms to document a significant increase in capital misallocation (proxied by the increase in the dispersion of the return to capital across firms) and a significant increase in productivity losses over time. This paper uses the same database used by Gopinath et al. (2017), though it considers a longer sample which is also integrated by sub-sectoral data on automation and the relative price of investment. Using these data it first investigates the empirical relationship between change in labor share, automation, the relative price of investments, and markups. Then, it proposes a coherent theoretical model based on firm heterogeneity and endogenous

markups distribution able to rationalize the empirical results on the labor share decline and TFP losses found in the empirical section. Furthermore, differently from what was done in the previous literature, this paper proposes a new framework that can quantify the relative contribution of increasing automation, increasing markup, and the declining relative price of investments, and validates these three candidates along multiple dimensions: the dynamics of the labor share, the distribution of firms' markups and firms' size, the long-run productivity losses and declining business dynamism. Thus, overall this paper contributes to the literature by proposing a coherent theory that can be used to understand the links between several of the observed long-run trends mentioned above.
The rest of the paper is organized as follows. Section 2 present the empirical analysis on the labor share and TFP decline, trying to disentangle the contribution of automation from that of the relative price of investment and markups. Section 3 presents the theoretical model and the results on the long-run analysis of the three structural shocks. Section 4 concludes. Technical details are left in the Appendix.

2 Empirical Evidence and Data Description

The database used in this section is composed of two main classes of data: firm-level data and sectoral level data of the Spain manufacturing sector. Sectoral data are the number of robots, the relative price of investments, and TFP. For the stock of robots, the source used is the annual World Robotics Report provided by the International Federation of Robotics (IRF) from the early nineties to 2019. The World Robotics Report contains data on robot stock and installations by type, country, industry, and application. It relies on primary and secondary data. The primary source is data that industrial robot suppliers worldwide report to the IFR Statistical Department directly. On the other hand, several national robot associations collect data on their national robot markets and provide their results as secondary data to the IFR. This data is used to validate the IFR primary data, thus ensuring data quality and to fill in the missing information of companies not reporting to the IFR directly. The variables used from this database are Total Number of Operational Robot Stock by year (Rob. Stock.) which measures the number of robots currently deployed and, Total number of Robot installations (Rob. Inv.). For both variables, data of Spain's manufacturing sub-sectors are considered. The 4-digit NACE sectors cover from C1000 to C3100, available collected in a total of 37 categories. To compute the relative price of investments the source used is instead the EU-KLEMS database. EU-KLEMS database provides harmonized sectoral data on output, inputs, productivity, TFP, labor share, and prices at the industry level for a broad set of countries around the world. The latest release of this database was out in 2019, and for Spain, it provides data for the period 1995-2016. The data are consistent with official statistics as available from Eurostat at the corresponding industry and country levels. The relative price of Investment is obtained by dividing the series of Gross Fixed Capital Formation (GFCF) Price Index for all assets by the series of Consumer Price Index.[3] The 4-digit NACE sectors cover from C1000 to C3300, available collected in a total of 10 categories.

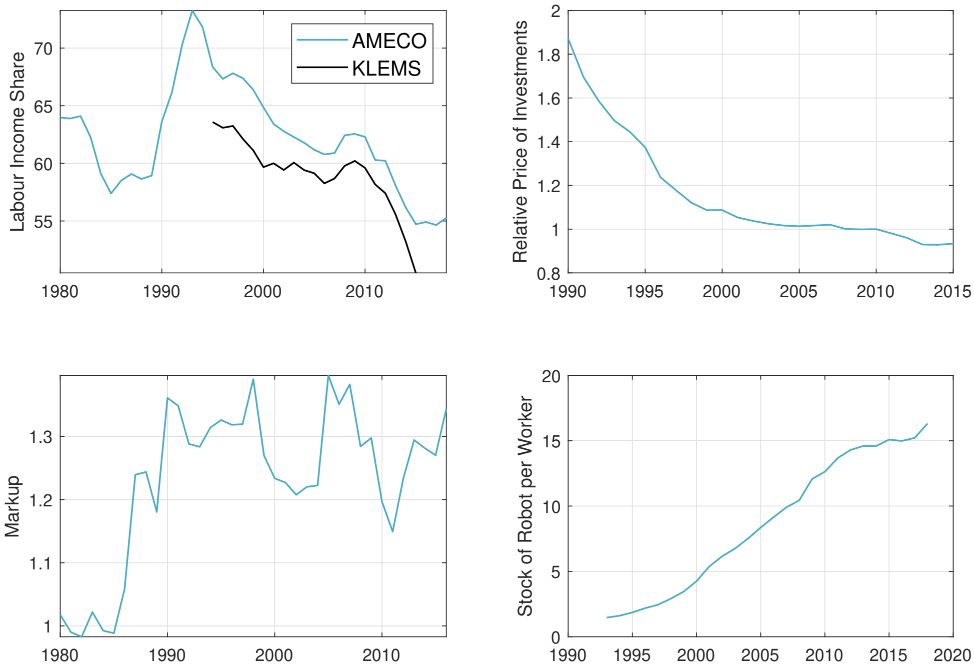

Figure 1: **Left Upper panel**: labor income share, Spain Manufacturing sector (Data: AMECO - blu line; KLEMS - black line) **Right Upper Panel**: Relative Price of Investment, Spain Manufacturing sector. Ratio between the price index for private fixed investment and price index for personal consumption expenditures. (Data: KLEMS). **Left Lower panel**: Markup in Spain Manufacturing sector (Data: De Loecker et al. (2020)). **Right Lower panel**:Stock of Robot per Worker Spain Manufacturing sector. Ratio between the Stock of Robots (Data: IFR) and Total Employment (Data: AMECO)

Figure 1 shows a first inspection of the dynamics of the labor share and its explanations is done using aggregate data of the labor share in the manufacturing sectors, together with the corresponding data for markups, robots, and the relative price of investments. The top left panel of Figure 1, shows the pattern of the labor in-

[3]the GFCF Index is obtained by computing the Deflator, which is dividing the GFCF at the current price by the GFCF in volume.

Table 1: Share of Total Manufacturing Economic Activity By Size Class in Spain (2012)

		Firms	Empl.	Salaries	A.V.
EuroStat	0-19 employees	0.96	0.27	0.20	0.18
	20-49 employees	0.06	0.17	0.15	0.14
	50+ employees	0.03	0.56	0.66	0.67
ORBIS	0-19 employees	0.78	0.18	0.14	0.11
	20-49 employees	0.14	0.16	0.13	0.12
	50+ employees	0.08	0.66	0.73	0.77

come share coming from two different data sources, AMECO and KLEMS. The labor share measured using AMECO data (starting in 1980) is in terms of adjusted wage share, while the labor share measured by KLEMS data (starting in 1995) is the ratio between total compensation per employee and value-added [4]. The top right panel and the two bottom panels show the patterns of three explanations of the labor income share, respectively: the relative price of investments (KLEMS), aggregate firm' markup (De Loecker et al. (2020)), and the stock of robots per workers (IFR). As it is clear from the figure, the labor income share in Spain's manufacturing sector experienced a steady decline only from the early nineties, while the relative price of investments shows a negative and constant trend already in the eighties. As shown in the Figure and also reported by De Loecker et al. (2020) the markups have increased by 0.33 percent points between 1980 and 2016, passing from 1.01 to 1.34 in Spain's manufacturing sector, though being much more volatile than the other series. The stock of robots per worker has instead increased steadily from the early nineties, showing an almost constant upward trend.[5]

Though aggregate data are often a first useful inspection, they do not report information about how the variable is distributed across firms. For example, the recent literature has shown the importance of change in markups and their dispersion as a possible source of TFP losses. For example, Baqaee and Farhi (2020) using US data show that eliminating the effects of increased and largely more dispersed markup would raise aggregate TFP by about 15 percentage points. A similar result has been found by Reinelt and Meier (2020). This underlines the importance of micro-level data for the interpretation of macroeconomic facts. Following this literature, a firm-level database is also constructed.

[4]Notice that while the two series differ quantitatively, their dynamics is almost identical.

[5]Notice that data on robots are available only from 1993, while those on the relative price of investments only from 1990.

The firm-level data come from the ORBIS database for the Spain manufacturing sector for the period 2001-2018.[6] The firm-level variables used in the analysis are Value-added, Employment, Wage bill, Sales, Fixed Assets (differentiated by tangible and intangible assets). Following Gopinath et al. (2017) these data are partially downloaded from the online ORBIS website (data for the period 2009-2018) and partially from ORBIS Hard Disk containing historical data (data for the period(2001-2008). ORBIS provides administrative data for many countries worldwide, but one of the Spain economies is one of the more representatives of the universe of firms. The data set has financial accounting information from detailed harmonized balance sheets of firms. The analysis focuses on the Spanish manufacturing sector. In Spain, the manufacturing sector accounts for roughly 20 to 30 percent of aggregate employment and value-added. The ORBIS database for the Spain economy allows us to differentiate industries in the manufacturing sector according to their four-digit NACE Rev. 2 industry classification. The cleaned database contains information for 67,734 firms, over the period from 2001 to 2018. The representatives of the sample is checked comparing moments obtained from the data sample to the ones from Eurostat, which contains information on the universe of firms. Table 1 presents the share of economic activity by firms belonging in three size categories in Spain, the manufacturing sector in the year 2012. Each column presents a different measure of economic activity, namely the number of firms, employment, salaries, and value-added. The first three rows report statistics from Eurostat and the next three from the ORBIS data-set. For example, in ORBIS data-set, firms with 1-19 employees account for 78 percent of the total number of firms, firms with 20-249 employees account for 14 percent of the number of firms, and firms with 50 or more employees account for 0.08 percent. The corresponding numbers provided by Eurostat are 96, 0.06, and 0.03 percent. As it is usual for an ORBIS-based data-set, the sample is mainly composed of large and medium-sized firms that account for a small fraction of the universe of firms in Europe. However, table 1 illustrates that the sample is broadly representative in terms of contributions of small and medium-sized firms to manufacturing employment, wage bill, and value-added.

Figure 2 presents the unweighted firm markup distribution (left panel) and the firm sales distribution (right panel) resulting from the data, in the Spanish manufacturing sector for the years 2001-2003-2018. From the plots, it emerges that between 2001 and 2018 there has been a rightward shift in the distribution together with an increase in the variance. Most importantly, a fattening of the upper tail is observed. Notably, even in 2018, most firms have a relatively low markup. But in contrast, substantially

[6] At the time when the investigation started, 2019 was the latest year for which firm data were available in ORBIS, but there were too few observations for 2019. The sample is built using data for the period 2001-2018. The year 2001 was the first available on the Hard Disk.

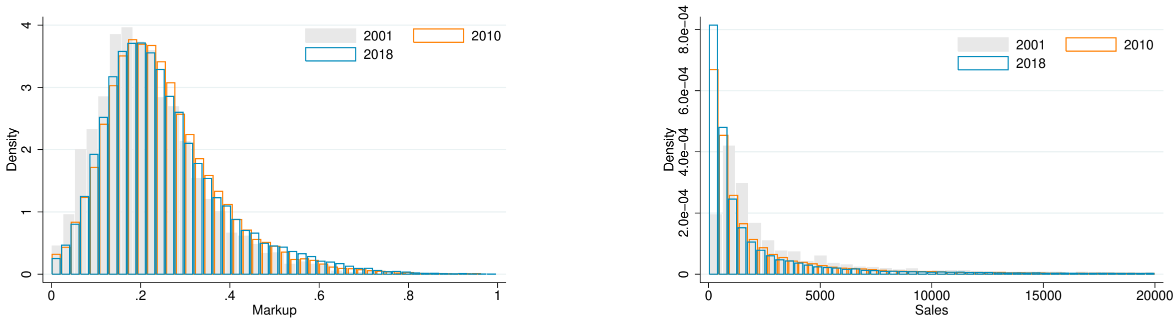

Figure 2: Firms' net markup distribution (left panel). Firms' sales distribution (right panel)

more firms in 2018 have relatively high markups. Moving to the size distribution (presented here in terms of sales, but a similar picture would emerge using value-added), it can be observed observe that in 2018 the fraction of small firms increased substantially compared to 2001. Remarkably, as it will be clear in the paper, the markup shock in the model well replicates the dynamics of the markup distributions observed in the data, as well as the increase in the number of small firms and the decline observed in business dynamism recently observed in the Spain economy.

2.1 Regression Estimates: Labor Share

This section investigates the empirical relationship between firm's labor share, firm's markup, robotization, and the relative price of investment.
For each year t, the index j defines the sector in which the firms operates, while the index i defines the firm, so that firm's i labor share in sector j is ls_{ijt} and computed as its wage bill w_{ijt} over firm's value added va_{ijt} :

$$ls_{ijt} = \frac{w_{ijt}}{va_{ijt}}$$

Firm's markup is computed following Anderson et al. (2018), that is defining it as the net profit margin:

$$markup_{ijt} = \frac{sales_{ijt} - w_{ijt} - material_{ijt}}{sales_{ijt}}$$

where $sale_{ist}$ is the income received by the firm from its sales of goods or the provision of services, and $material_{ist}$ is the total cost of raw materials or parts that

Table 2: Regression Estimate, Dependent variable Labor Share, standard error in parenthesis, $***p < 0.01, **p < 0.05, *p < 0.1$

	(1)	(2)	(3)
$markup$	-0.731***	-0.728***	-0.728***
	(0.003)	(0.003)	(0.003)
PI	-0.378***		-0.267***
	(0.026)		(0.029)
$log\,(Robot)$		-0.001***	-0.002***
		(0.000)	(0.000)
Controls	YES	YES	YES
Year Dummies	YES	YES	YES
Fixed Effects	YES	YES	YES
Number of obs.	276,955	276,955	276,955
Number of firms	67,734	67,734	67,734

go into producing products. All observations with labor share larger than one and observations with negative markup are dropped.
Differently from markup and labor share, the relative price of investments PI_t and the number of robots yearly installed $Robot_t$ (which is the used proxy for automation) are sectoral variables. Considering the time length of the data set and the limited number of sectors, in order to avoid any correlation issue, the result estimates are presented also in two separate regressions. Eq.1 with markup and relative price of investments only (plus controls c_{it}), and Eq.2 with markup and robot (plus controls c_{it}). Then, in both specifications, a panel regression with fixed effects is estimated of the form:

$$ls_{ijt} = \alpha + \ \gamma_1 markup_{ijt} \ + \gamma_2 PIjt + \gamma_3 c_{jt} + u_{ijt} \tag{1}$$

and

$$ls_{ijt} = \alpha + \ \beta_1 markup_{ijt} \ + \beta_2 log\,(Robot_{jt}) + \beta_3 c_{jt} + u_{ijt} \tag{2}$$

Finally, as further evidence, the regressions containing both the relative price of investments and the number of robots variables are also considered.

$$ls_{ijt} = \alpha + \delta_1 markup_{ijt} \ + \delta_2 PI_{jt} + \delta_3 log\,(Robot_{jt}) + \delta_4 c_{jt} + u_{ijt} \tag{3}$$

Controls variables are firm size, computed in terms of relative sales-weight, sectoral GDP, and a year dummy variable. Precisely, firm size is computed as firm i's share

Table 3: Dependent variable Labor Share, standard error in parenthesis, $***p < 0.01, **p < 0.05, *p < 0.1$

	(1)	(2)	(3)
$markup2$	-0.023***	-0.021***	-0.021***
	(0.003)	(0.003)	(0.003)
PI	-0.394***		-0.280***
	(0.029)		(0.033)
$log\,(Robot)$		-0.002***	-0.002***
		(0.000)	(0.000)
Controls	YES	YES	YES
Year Dummies	YES	YES	YES
Fixed Effects	YES	YES	YES
Number of obs.	276,955	276,955	276,955
Number of firms	67,734	67,734	67,734

of sales in the industry. Then, for each industry:

$$size_{ijt} = \frac{sales_{ijt}}{\sum_i sales_{ijt}}$$

The results of the regressions are reported in Table 2.

The first column of Table 2 reports the estimated coefficients of Eq.1. In the second column, the estimates for Eq. 2 and, in the third column, the estimates for Eq.3. Across all specifications, the estimated coefficient for markups remains negative and highly significant. Also, the magnitude is almost unchanged across the three specifications. The relative price of investment reports a negative and significant coefficient, meaning that in sectors where the relative price of the investment is larger, the firm's labor share is smaller. This is in favor of the hypothesis of a production function where capital and labor are complements rather than substitutes, and then their elasticity of substitution is smaller than 1. Therefore, the decline in the relative price of the investment which has been observed over the last few decades would not have contributed to the observed dynamics of the labor share, but rather would have attenuated its decline.

The installation of new robots also has a negative effect on the labor share. Firms in sectors where the number of new robots installed is larger register a lower labor share. The last column of Table 2 shows that having both the relative price of investment and the number of robots in the estimation model does not affect the sign or the significance of any of the variables.

To further investigate the results, the same set of regressions using an alternative measure of markup is considered, this is to make sure that the estimate is not driven

Table 4: Dependent variable Labor Share, standard error in parenthesis, $***p < 0.01, **p < 0.05, *p < 0.1$

	(1)	(2)
$markup$	-0.731***	-0.730***
	(0.003)	(0.003)
PI		-0.229***
		(0.029)
$log\,(RobotS)$	-0.005***	-0.004***
	(0.001)	(0.001)
Controls	YES	YES
Year Dummies	YES	YES
Fixed Effects	YES	YES
Number of obs.	276,955	276,955
Number of firms	67,734	67,734

by the fact that markup is computed using the data on the wage bill, which is also used to compute labor share. In Table 3 column 1, 2 and 3 report the estimation coefficients of the same regression Eq.1, Eq.2 and Eq.3 respectively, the only difference being that here markup computed as follow, by subtracting only material costs to sales in the denominator:

$$markup2_{ijt} = \frac{sales_{ijt} - material_{ijt}}{sales_{ijt}}$$

Unsurprisingly, the coefficient of markup is here considerably lower than in the previous set of estimates. Nevertheless, it stays significant and negative across all three specifications. As regards the relative price of investment and the number of robots, the coefficient estimates as almost not affected by the modification in the definition of markup. As a final robustness check, Table 4 presents the regression estimates of Eq.2 and Eq.3 substitutes the number of newly installed robots with the total stock of robots registered for each year in each sector. To differentiate from the previous one, this variable is labeled as $RobotS$. For all the variables, the resulting coefficients do not deviate significantly from the one obtained in the main specification. The coefficient associated with automation is slightly larger, being 0.001 and 0.002 in the results reported above.

2.2 Regression Estimates: TFP

The objective of this section is to analyze whether and to what extent the three explanations of the labor share decline may have contributed to the Spanish TFP slowdown. For what concerns Spain manufacturing TFP, as estimated by Gopinath

Table 5: Regression Estimate, Dependent variable TFP, standard error in parenthesis, $***p < 0.01, **p < 0.05, *p < 0.1$

	(1)	(2)
$Agg.markup$	-0.017	-0.005
	(0.019)	(0.016)
$std(markup)$	-0.027***	-0.024***
	(0.006)	(0.006)
PI	0.208**	0.205***
	(0.071)	(0.071)
$log\,(Robot)$	-0.003***	-.003***
	(0.001)	(0.001)
Controls	YES	YES
Year Dummies	YES	YES
Fixed Effects	YES	YES
Number of obs.	1,866	1,866

et al. (2017) it has shown a decline between a 7% and 12% relative to its efficient level from 1999 to 2012. This section presents the empirical investigation on the effects of automation, the relative price of investments, and markup on the TFP. The analysis is based on sectoral level data, more specifically they are sub-sectors of the manufacturing sector, as described above. The regression estimate takes into account both the aggregate markup, (computed as the cost-weighted average of firm-level markups, see Edmond et al. (2018)) and the markup standard deviation. Given the change in firm size distribution shown in Figure 2 the standard deviation of firm size is also considered as an independent variable. The control variables c plugged into the estimate include the lagged value of log TFP, yearly GDP growth, total sales in the sector, and a year dummy. Table 5 reports the estimation results. Columns one and two of the table report the estimate for the following regression equation is:

$$log\,(TFP_{jt}) = \alpha+\chi_1 markup_{jt}+\eta_1 sd(markup_{jt})+\chi_2 log\,(PI_{jt})+\chi_3 log\,(Robot_{jt})+\chi_4 c_{jt}+u_{jt} \tag{4}$$

The difference between the two columns consists of the weights used to aggregate markups. While the first columns uses the firm's production costs as weights, the second columns uses the firm's sales. Consistently in both estimates, the level of aggregate markup has a negative coefficient, but it is not significant. Differently, the standard deviation is significant and it has a negative sign, implying that the higher is the dispersion in the markup of firms operating in a specific sector the lower is the total factor productivity in that sector. This result is in line with what was found recently by Baqaee and Farhi (2020) and Reinelt and Meier (2020) for the US

economy. Further, notice that automation has a significant and negative effect on TFP, while the opposite is true for the relative price of investment.
The next section aims to provide a theoretical model able to replicate most of the results found in the empirical section.

3 Theoretical Model

This section considers an economic environment in which final consumption and investment goods are produced by using an intermediate good y which production function is characterized by CES technology. Firms in the intermediate sector operate under monopolistic competition. There is no aggregate uncertainty and all economic agents have perfect foresight. All payments in this economy are made in terms of the final consumption good, which is the numeraire. Individuals are heterogeneous with respect to entrepreneurial ability z and individual wealth a. Individual wealth evolves endogenously according to individual optimal saving decisions. Differently, entrepreneurial ability follows a stochastic process. Each individual retains her productivity with probability ψ while with probability $(1-\psi)$ she loses the current productivity and has to draw a new one. The new draw is from a time-invariant distribution with a cumulative density $\Omega(z) = 1 - z^{-\eta}$ and it is independent of her previous productivity level. Agents face a discrete choice relative to their occupation. According to their individual state, i.e. productivity and wealth level, individuals choose whether to be a worker or to be an entrepreneur and set up their own firms. The Individual who decides to be a worker offers the unit of labor whose she is endowed to the labor market and receives as compensation the equilibrium wage. Differently, the individual who decides to be an entrepreneur does not have access to the labor market and she only receives profits from running the firm. All the individuals have the same utility function:

$$U = E_t \int_{t=0}^{\infty} e^{-\rho t} u\left(c\right) dt \tag{5}$$

where ρ is the intertemporal discount factor and c is the level of consumption. Individuals can purchases consumption and investment goods x, from final good producers at their relative price. They use investment goods to accumulate wealth such that $\dot{a} = x - \delta a$.

3.1 Supply side

The output of the final goods sector is used for consumption and investment. The final goods sector is competitive, with final goods firms purchasing differentiated intermediate varieties from entrepreneurs. Each intermediate goods producer is the monopoly supplier of such a variety and thus has market power.

3.1.1 Final consumption good producers

Identical competitive producers use a faction of Y to produce final consumption and then sell it to the household at a price P^C. They produce final consumption with the technology:

$$C = Y^c \tag{6}$$

where Y^c is the fraction of input Y used in the production of the final consumption good. The consumption good producers purchase these inputs from perfectly competitive intermediate producers. Consumption good is the numeraire in the economy and it has a price of $P^C = 1$.

3.1.2 Final investment good producers

Similarly, identical competitive producers assemble the final investment good from intermediate inputs y and sell it to the household at a price P^X. They produce final investment with the technology:

$$X = \frac{1}{\xi} Y^X \tag{7}$$

where Y^X is the quantity of input y used in the production of the final investment good. The exogenous variable ξ denotes the technology level in the production of the consumption good relative to the investment good. A decline of ξ implies an improvement in the technology of producing the investment good relative to the consumption good. The price of final investment good P^X is then ξ which is also equal to the relative price of investment to consumption $\xi = \frac{P^X}{P^C}$

3.1.3 Final good aggregator

The final good producers, choose how much of each intermediate variety $y(i)$ to buy in order to maximize profits, taking the prices $p(i)$ of the inputs as given and subject to the Kimball production function.g

$$\int_\Omega \Upsilon \left(\frac{y(\omega)}{Y} \right) d\omega = 1 \tag{8}$$

where $y(\omega)$ is the quantity of variety i produced and ω is the measure of entrepreneurs. Following Klenow and Willis (2016) and Boar and Midrigan (2019) the aggregator Υ is:

$$\Upsilon\left(\frac{y}{Y}\right) = 1 + (\sigma - 1)\exp\left(\frac{1}{\varepsilon}\right)\varepsilon^{\frac{\sigma-\varepsilon}{\varepsilon}}\left[\Gamma\left(\frac{\sigma}{\varepsilon}, \frac{1}{\varepsilon}\right) - \Gamma\left(\frac{\sigma}{\varepsilon}, \frac{(y/Y)^{\frac{\varepsilon}{\sigma}}}{\varepsilon}\right)\right] \tag{9}$$

$\Gamma(\cdot, \cdot)$ is the upper incomplete gamma function, σ governs the average demand elasticity. This specification of the demand system nests the CES aggregator as a special case if $\varepsilon = 0$. The ratio $\frac{\varepsilon}{\sigma}$ determines how quickly markups increase with firm size. Moreover, it implies that markups are endogenous and heterogeneous among heterogeneous producers. The firm's optimal markup m is:

$$m\left(\frac{y}{Y}\right) = \frac{\sigma}{\sigma - \left(\frac{y}{Y}\right)^{\frac{\varepsilon}{\sigma}}} \tag{10}$$

Formally the final good producer solves:

$$\max_{y(\omega)} Y - \int_{\omega} p(\omega)\, y(\omega)\, d\omega$$

subject to Eq. 9.

The first-order condition for this problem implies that the optimal demand for each intermediate producer's product is:

$$p = \Upsilon'\left(\frac{y}{Y}\right) D \tag{11}$$

where D is an endogenously determined demand index.

3.1.4 Intermediate goods producers

Firms produce good y which can be used both for consumption and for investment purpose. Production function of firm in the sector is

$$y = z\left[\varkappa k^{\theta} + (1 - \varkappa)\, l^{\theta}\right]^{\frac{1}{\theta}} \tag{12}$$

The production technology is characterized by a constant return to scale. The parameter $\theta = \frac{\sigma_y - 1}{\sigma_y}$, where σ_y is the input elasticity of substitution. In the limiting case of $\sigma \to 1$ and then $\theta \to 0$, the function collapses to a Cobb-Douglas. Finally, $\varkappa \in (0, 1)$ is the distribution parameter, reflects capital intensity in production. A permanent change in $\varkappa$ is interpreted as an automation shock that makes output more capital intensive at the expense of labor. Producers of intermediate goods are subject to collateral constraints. More specifically, entrepreneurs' capital rental k is limited by a collateral constraint $k \leq \lambda a$, where λ measures the degree of credit frictions, with $\lambda \to \infty$ corresponding to perfect credit markets and $\lambda = 1$ to financial autarky. The profit-maximization problem of the producer of intermediate input y is:

$$\begin{aligned} \Pi &= \max_{p,k,l} py - (r+\delta) k - wl \\ s.t \quad k &\leq \lambda a \\ p &= \Upsilon' \left(\frac{y}{Y}\right) D \end{aligned} \tag{13}$$

where (14) is the demand faced by the entrepreneurs and it come from the profit maximization problem of the final aggregator. The Technical Appendix provides all the derivations.
The first order conditions of the problem for capital and labor are:

$$r + \delta + \mu = \phi \varkappa k^{\theta-1} z \left[\varkappa k^{\theta} + (1-\varkappa) l^{\theta}\right]^{\frac{1}{\theta}-1} \tag{14}$$

$$w = \phi (1-\varkappa) l^{\theta-1} z \left[\varkappa k^{\theta} + (1-\varkappa) l^{\theta}\right]^{\frac{1-\theta}{\theta}} \tag{15}$$

where ϕ is the marginal cost of production and μ is the Lagrangian multiplier associated to the collateral constraint. In the case of perfect credit, or for non financially constrained entrepreneurs $\mu = 0$, otherwise $\mu > 0$.

$$\mu = \max \left\{ w \frac{1}{\varkappa} \left(\frac{\varkappa}{1-\varkappa}\right)^{\frac{1}{\theta}} \left[\left(\frac{y}{z\lambda a}\right)^{\theta} - \varkappa\right]^{\frac{1-\theta}{\theta}} - (r+\delta), 0 \right\} \tag{16}$$

The value of μ is used as an indicator of the tightness of the borrowing constrained faced by the entrepreneurs: at the individual firm level, the higher the value of μ the further the optimal level of investment from the actual one. Noticing that $\theta < 0$, as λ tends to infinity, μ approaches negative values, and then it takes the value of 0. Similarly, μ increases in the productivity level z. Indeed, for a given value of wealth a, the more productive is the firm, the larger is the amount of capital desired, consequently the tighter is the credit constraint.

3.2 Individual problem

The occupational choice problem follows Buera (2009). Agents $i(a,z)$ who decide to be entrepreneur obtain as income the realized profit $M(a,z) = \Pi(a,z)$. The occupational choice of the agent is then defined as $oc(a,z) = 1$ and labor and capital demand is $l(a,z), k(a,z) > 0$. Differently, the income of an agent $i(a,z)$ who decide to be worker is given by the wage $M(a,z) = w$. Her occupational choice, capital and labor demand are $oc(a,z), l(a,z), k(a,z) = 0$. The agent chooses consumption

c and investment x in order to maximize her utility, subject to the period budget constraint.

$$M(a,z)=\max\left[w,\Pi(a,z)\right]$$

the utility maximization problem is the following:

$$\max_{c} E_t \int_{t=0}^{\infty} e^{-\rho t} u(c)\, dt$$

s.t. the budget constraint:

$$c(a,z)+\xi\dot{a}(a,z)=M(a,z)+ar+\delta(1-\xi)a$$

Or, equivalently, recalling the law of motion for wealth accumulation, the budget constraint can be written as

$$c(a,z)+\xi x(a,z) \quad = \quad M(a,z)+(r+\delta)a \tag{17}$$

where

$$x_t=\dot{a}+\delta a$$

Writing the problem recursively, the first order condition is:

$$u'(c)=\frac{1}{\xi}v'(a,z) \tag{18}$$

3.3 Equilibrium

As in standard Ayagari model, individuals' consumption-saving decision and the evolution of the joint distribution of their income and wealth can be summarized with two differential equations:

- Hamilton-Jacobi-Bellman (HJB) equation

$$\rho v(a,z)=\max_{c}\left\{u(c(a,z))+\begin{bmatrix} v'(a,z)\left(\frac{1}{\xi}(M(a,z)+\right. \\ \left.(r+\delta)a-c(a,z))-\delta a\right)+ \\ (1-\psi)\left[\Omega(z)\int_z v(a,z)-v(a,z)\right]\end{bmatrix}\right\} \tag{19}$$

- Kolmogorov Forward (or Fokker-Planck):

$$0=-\partial_a\left[g(a,z)s(a,z)\right]+(1-\psi)\left[\int_z \Omega(z)g(a,z)-g(a,z)\right] \tag{20}$$

  where $s(a,z)$ is the saving function:

$$s(a,z)=\frac{1}{\xi_t}\left(M(a,z)-c(a,z)+(r_t+(1-\xi)\delta)a\right)$$

Finally, capital and labor market clearing conditions and the aggregate resource constraint are:

$$
\begin{aligned}
K &= \int_{(a,z):oc(a,z)=1} k(a,z)\, g(da,dz) = \int_{(a,z)} a g(da,dz) && (21) \\
L &= \int_{(a,z):oc(a,z)=1} l(a,z)\, g(da,dz) \\
&= 1 - \int_{(a,z):oc(a,z)=1} g(da,dz) && (22) \\
Y &= \int_{(a,z):oc(a,z)=1} y(a,z)\, g(da,dz) \\
&= \int_{(a,z)} c(a,z)\, g(da,dz) + \xi \int_{(a,z)} x(a,z)\, g(da,dz) && (23)
\end{aligned}
$$

4 Quantitative Analysis

This section describes the strategy followed to calibrate the model's parameters. Furthermore, it specifies the way in which structural changes in the relative price of investments, automation, and markup are introduced in the model. The aim of the quantitative analysis is twofold. First, it analyzes the long-run effect of the structural changes on the main macroeconomic variables: consumption, output, capital, factor shares, aggregate markups, wages, and real interest rate. The analysis is presented by first considering one structural change at the time and then by hitting the economy with all of them at the same time. Second, it analyzes the effects of the same shocks on the TFP, and it quantifies the TFP losses disentangling the contribution of firms' dynamics from that of capital misallocation.

The algorithm used to solve the system of partial differential equations that characterizes the model is based on a finite difference method, as in Achdou et al. (2020). It is possible to summarize the algorithm by describing its three main steps. The first step solves the HJB equation for a given vector of prices r and w and aggregate variables D and Y. The second step solves the Kolmogorov-Forward (KF) equation for the evolution of the joint distribution of entrepreneurial ability and wealth. The third and final step iterates, and repeats the first two steps, updating at each iteration the vector of prices, to find the prices and corresponding aggregates that satisfy the equilibrium conditions of the model.

4.1 Calibrated and Estimated Parameters

Calibration is at yearly bases. Some of the parameters are calibrated by following common practices in the literature. The utility function is assumed to be a standard CRRA $u(c) = \frac{c^{1-\alpha}}{1-\alpha}$ with parameter $\alpha = 1.5$, see for example Buera (2009). As in Buera et al. (2015) the depreciation rate of capital is $\delta = 0.06$. The probability to maintain the current productivity at the individual level is $\psi = 0.894$, such that the exit rate of the economy is 10%. The parameter of the collateral constraint $\lambda = 3$ targets an external credit to capital ratio of 0.30, which is in the range of previous studies. Zetlin-Jones and Shourideh (2017) for UK firms and Crouzet and Mehrotra (2020) for US firms report debt to capital ratio for entrepreneurs of 0.35. Midrigan and Xu (2014) reports a ratio of 0.30 for Korea in the period 1991-1996. In the initial state, the price of investments ξ is normalized to 1. On the other hand, other parameters are calibrated to match specific moments from Spain's economy in 1993. This is the first year available on many variables. The tail parameter of the Pareto distribution, η, is set equal to 2.9 to target the share of income held by households at the top 10% of the income distribution observed in Spain in 1993, which is equal to 0.35 (World Inequality Database). In the production function, the parameter $\varkappa = 0.09$ targets the aggregate labor share, equal to 0.73. This value is taken from AMECO data-set for the time series for the Aggregate Labor share in the manufacturing Industry, computed as the compensation per employee as a percentage of nominal gross value added per person employed in the year 1993. The elasticity of demand σ_ϵ is set equal to 14.2 to match aggregate mark-up, computed as sales-weighted average, which is equal to 1.28 (De Loecker et al. (2020)). The individual discount factor $\rho = 0.49$ is set to obtain an initial interest rate equal to 0.1 (FRED, Interest Rates, Government Securities, Treasury Bills for Spain). These values are summarized in Table 6.

Finally, the value for elasticity of substitution between capital and labor is estimated using the firm-level database.[7] The value estimated is $\sigma = \frac{1}{1-\theta} = 0.817$, so that $\theta = -0.224$.

Calibration of Structural Changes: To calibrate the permanent shocks to automation, markup, and the relative price of investments the reference year is 2016, due to data availability of the investment price, which is computed using KLEMS data.

The parameter $\varkappa$ in the production function is used to simulate the increase in automation. This parameter is calibrated by targeting the change in capital intensity induced by the increase in the stock of robots. To do the estimated elasticity of capital intensity to the stock of robots is estimated. In particular, the following strategy

[7] Details on this estimation are reported in the Appendix.

Table 6: Calibration, Spain 1993

Parameter	Value	Target	Data	Model
ρ	0.41	Interest rate	0.10	0.10
λ	3.1	External credit to GDP	0.45	0.46
η	3.7	Top 10% Income share	0.34	0.32
ψ	0.894	Exit rate	0.10	0.10
$\varkappa$	0.09	Labor share	0.73	0.73
σ_ϵ	9.5	Aggregate Markup	1.28	1.28

is implemented: first, using the database, the elasticity of capital intensity with respect to the number of robots (which is our proxy for automation) is estimated. The estimated elasticity is the average over the period 2001 to 2016. Thus, it is assumed that this average elasticity didn't change relative to the average elasticity between 1993 to 2016. The estimated coefficient for the elasticity of automation on the capital intensity found with the data sample is 0.23. The reported number of robots per worker is 9.23 times larger in 2016 than in 1993. Then, to simulate the increase in automation the parameter of the production function $\varkappa$ is changed to target an increase in capital intensity of 1.68 relatives to its initial level (see Appendix A.2 for details).

The elasticity of substitution among consumption goods is set to obtain a value for aggregate markup of 1.34 (De Loecker et al. (2020)).

Finally, the relative price of investments is normalized to 1 in the first steady-state, while is set equal to 0.68 in the second steady-state to capture the decline in the aggregate relative price experienced in the manufacturing sector between 1995 and 2016 (the first and the last available data in KLEMS database).

4.2 Structural Changes and Macroeconomics Aggregates

Table 7 reports the effects on some of the main economic aggregates for each one of the three structural changes simulated by the model. The first column, reports the value of labor, capital, and profit share in the initial steady state of the economy, as well as the aggregate markup and the prices of production inputs.

The second column presents the changes observed in the model economy after a decline in the relative price of investment. The change in the investment price has positive effects on all the aggregates, especially on capital which increases by almost 50%. This is directly connected to the fostering effect of the relative price on investment. Profit, capital and labor shares remain unchanged, as well as the aggregate markup. Some effect is instead observed in the factor prices, with wages going up,

Table 7: Main Aggregates

	Initial S.S.	Inv. P.	Autom.	Markup	All
ΔC	-	2.0%	23.4%	-34.2%	-18.01%
ΔY	-	1.9%	24.1%	-34.2%	-17.49%
ΔK	-	46.5%	68.2%	-32.6%	- 64.75%
Labor share	0.73	0.73	0.67	0.69	0.64
Capital share	0.05	0.05	0.10	0.05	0.10
Profit share	0.22	0.22	0.23	0.26	0.26
Aggregate Markup	1.28	1.27	1.28	1.34	1.34
Δw	-	2.14%	22.1%	-82.4%	-79.3%
r	0.1	0.08	0.12	0.15	0.15

and rental rate of capital going down. The increase in saving and the subsequent abundance in the capital supply pushes down the interest rate. On the other hand, given that in the model capital and labor are complementary, the increase in capital leads to an increase in labor demand, putting upward pressure on the price of this factor. These dynamics in prices allow capital and labor share to remain at the initial steady-state value, although the capital per worker ratio in the economy changed. Overall, in the model, the decline in the relative price of investments does not entail a transformation in the structural characteristics of the economy, but it modestly shifts total output upward.

The third column shows the changes in the model economy induced by the rise in automation. As can be seen from the table, automation generates positive effects on all aggregates, qualitatively equal to the ones generated by the decline of the relative price of investments, although much larger in magnitude. A striking difference compared to the previous column is the opposite effect on the price of capital, since higher automation leads to a rise of r. In this case, indeed, the price dynamic reflects the rise in the demand of capital induced by the new technology, rather than the increase in the supply, as in the previous case. On the other side, the effect on wage goes in the same direction, taking place again the complementarity of the two production inputs. Moreover, the automation shock induces changes in the relative share of income. The labor share declines, by about 6 percentage points, and capital share gains all the points lost by labor share, such that the profit share doe not move. Also, as before, the aggregate markup is not affected by this change in the production function.

The next simulation considers the fall in the consumption elasticity of substitution and the subsequent increase in aggregate markup, the results of this simulation are shown in the third column of the table. Among the three permanent shocks consid-

Table 8: Firms Dynamics and TFP

	Initial S.S.	Inv. P.	Autom.	Markup	All
Fraction of Entrep.	5.63%	5.98%	5.70%	10.92%	12.12%
Exit Rate	10.4%	10.4%	10.5%	9.6%	9.7%
std(markup)	-	-19%	3%	70%	29%
ΔTFP	-	-0.55%	-2.90%	-11.54%	-13.76%

ered, it is the only one that causes a negative variation in consumption, output, and capital. Moreover, for each of the aggregate variables examined here, the magnitude of the effect is significantly larger compared to previous columns. The increase in the firm's markup pushes significantly downward firms' output and upward the prices of the final goods, generating the drop in aggregate demand reported in the tables. Looking a the relative shares of income, it is clear that only profit share gains, mainly at the expenses of labor share, which declines by 4 percentage points, while capital share remains unchanged. The fall of labor share is partially driven by the lowering of the equilibrium wage, which falls by almost 30 percent. The interest rate slightly declines as well. Finally, the last column of the table reports the values registered in an economy where all the structural changes just examined took place at the same time. In this economy, the dominant effect is the one stemming from the decline in household consumption elasticity. Indeed, as in the case of markup shock only (column 3), all the aggregates register a negative variation, though smaller in magnitude thanks to the contribution of the other two shocks, which goes in the opposite direction and then partially compensate the negative impact of the increased markup. Similarly, also the effect on the factors' share is, to some degree, a linear combination of each shock individually simulated. The labor share declines by 9 percentage points (it drops by 6 in the case of automation and by 4 in the case of markup). The labor share declined is half compensated by the increase in the capital share and half by the increase in the profit share.

4.3 Structural Changes and TFP Losses

This Section aims to rationalize a link between TFP and the long-run trends found to be responsible for the labor share decline. Furthermore, this section also tries to disentangle the role of firm dynamism from that of capital misallocation in affecting the TFP in response to the stimulated structural changes. To this scope, Table 8 shows how the three changes impact the fraction of entrepreneurs active in the economy, the exit rate, firms' distribution, and, in the last row, total factor productivity. According to the model results, all the structural changes considered have a negative

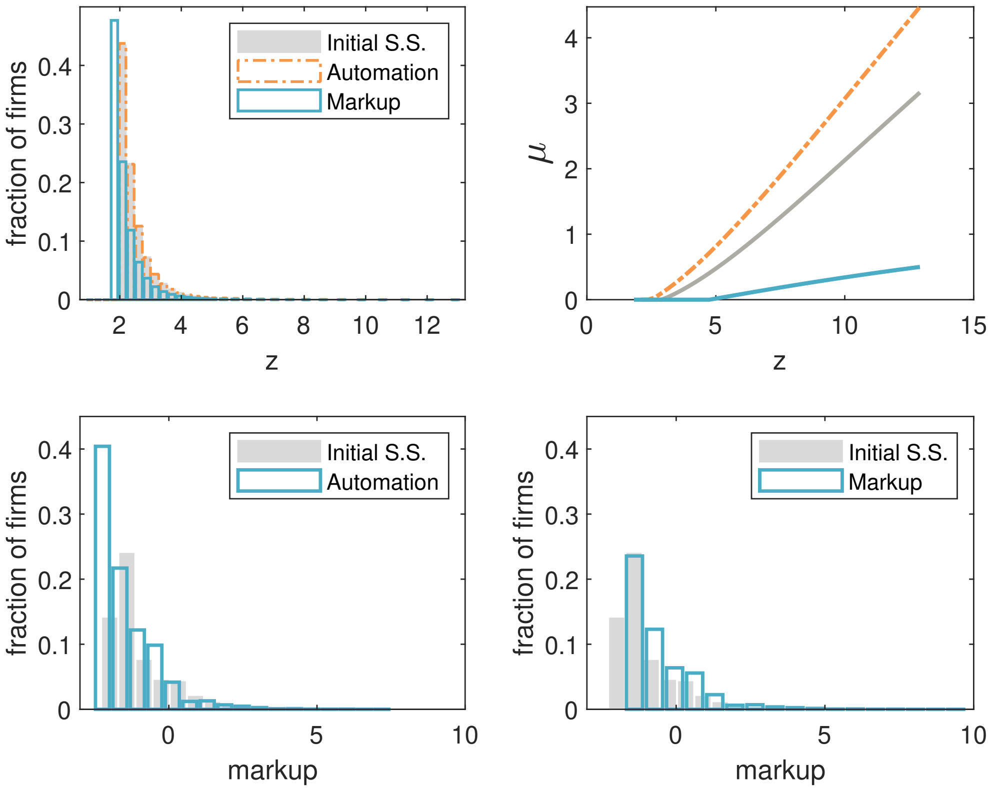

Figure 3: Firms' size distribution (Top left panel). Entrepreneur's financial wedge, for a given level of wealth a (Top right panel). Firms' markup distribution (Bottom panels)

effect on aggregate productivity, though they significantly differ in magnitude. The effects of the change in the relative price of investment on TFP are almost negligible but still negative. In this case, the decline of TFP is linked to the general equilibrium feature of the model and, in particular, to the drop of interest rate induced by this structural change through the increase in saving. The channel through which it affects TFP is similar to the one highlighted by Gopinath et al. (2017), lower interest rate on capital favors less productive investment and, consequently, it negatively impacts TFP. On the other hand, both the increase in automation and the increase in markup have a considerable effect on aggregate productivity. Moreover, the increase in aggregate markup induces a decline in TFP which is almost three times the one induced by the increase in automation. Finally, the last column shows that even for this class of variables the effects of three shocks sum up, with the values of the variables being almost linear in the shocks.

The next paragraph focuses on the mechanics of the model leading to increased automation and markup to reduce aggregate TFP. In the model there are two mechanisms through which the structural changes affect the TFP: (i) the intensive margin mechanism, that is the allocation of capital among entrepreneurs; (ii) the extensive margin mechanism, that is the distribution of firms and their dynamism. In the case of higher markup, the decline of TFP is mainly due to the extensive margin mechanism, i.e. dynamic in the entrepreneurs' distribution. As it is shown in figure 3 left panel, in the economy with higher markup the fraction of entrepreneurs with lower productivity significantly increases, and the distribution moves to the left. Indeed, higher profitability induces less productive entrepreneurs to enter the market, lowering total factor productivity. Furthermore, it also reduces firms' dynamism, as can be seen from the decrease in the exit rate. This change in the firms' distribution and its effect on TFP is in accordance with what emerged from the firm-level data analysis presented above in figure 2 and with the results of the regression estimates. Indeed, as found from the empirical analysis, what matters for TFP is the dispersion of firms' size and markup rather than the level of markup per se. Table 8 reports the change in the standard deviation of markup induced by the three structural changes relative to the value registered in the initial steady state. The larger change is by far the one generated by the increase in markup, in this case, the standard deviation increase by 70%, while in the case of an increase in automation it increases just by 3 percentage points. The bottom panels of figure 3 show the distribution of markup. When this figure is compared with Figure 2 computed from the data, it can be noticed that the change in markup is the only one that generates a dynamic close to the one observed in our sample. In fact, as in the data, in the model economy with higher aggregate markup, the firm's markup distribution is shifted to the right, it is more dispersed and it reports a fatter tail.

The right panel in figure 3 shows, for the three economies, the financial wedge faced by a constrained entrepreneur as a function of entrepreneurial ability. In the model, the financial wedge is measured by the distance between the optimal level of capital desired by firms and the actual level of capital, which can be lower than the optimal one due to financial constraints faced by the entrepreneurs. Therefore, in the case of perfect allocation of capital the wedge is zero, while capital misallocation increases as the desired level of capital versus the feasible level of capital diverge. As it is clear from the figure the intensive margin mechanism operates by reducing capital misallocation and therefore contributing to improving the TFP in case of structural changes in markups. The latter result is explained by the wealth effect induced by the increased profits of entrepreneurs that increase their possibility to save thus ultimately resulting in being less financially constrained. Moreover, the drop in interest rate further reinforces this channel, reducing entrepreneurs' financial wedge. Nonetheless, the extensive margin effect more than compensates the intensive margin one, and the TFP losses generated are larger than under the automation permanent shocks. A very different picture emerges in the case of automation shock. In this case, the firms' distribution almost overlaps with the one corresponding to the initial steady-state, so that the extensive margin mechanism remains mute. Neither the exit rate nor the fraction of entrepreneurs change significantly after the increase in automation. Differently, the higher level of automation induces a decline in TFP by rising capital misallocation. As shown in figure 3, for the same level of wealth, the rise in automation importantly rises the financial wedge compared to the initial state, resulting in more capital misallocation and then lower TFP. In this case, the automation shock increases the marginal productivity of capital, especially for those entrepreneurs with a high ability to increase their desired demand for capital. However, due to financial constraints, they cannot increase their stock of capital up to the desired level. Notice that the results for the structural change in the relative price of investments are not reported in the figures since it negligibly affects the TFP.

5 Conclusions

This paper combines firm-level data and sectoral-level data of Spain's manufacturing sector to empirically investigate the relative contribution of automation, price markup, and the investment price in the decline of the labor income share. At the same time, it investigates the effects of these variables on TFP. The main findings are that both automation and markup, particularly its dispersion, play a significant role in explaining the labor share decline and, at the same time, they negatively affect TFP. On the contrary, the decline of the investment price is not a driver of the labor share. The effect of the investment price on labor share is consistent with the estimated value of input elasticity of substitution between capital and labor, which is lower than one in our sample of firms. The second part of the paper introduces a model with firm heterogeneity and dynamics, imperfect competition, and financial market frictions to rationalize the empirical findings. The results of the theoretical model well replicated the findings of the empirical investigation. More specifically, in the model as in the data, the rise in automation and markup plays a relevant role in the decline of the labor share. Furthermore, the model shows that in the economy the financial frictions generate substantial capital misallocation and TFP losses, which turn out to be particularly relevant in case of an increase in the markups dispersion. Finally, the model also replicates the dynamics of the labor share and markup distributions observed in the data, as well as the observed increase in the number of small firms and the overall decline observed in business dynamism.

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Appendices

A Parameter Estimates

A.1 Input Elasticity of Substitution Estimation

The firm-level database is used to estimate the Input Elasticity of Substitution in the production function. Then, following Raval (2011), and the first-order conditions for capital and labor of the CES production function under cost minimization imply that:

$$\log\left(\frac{rk}{wl}\right) = -\left(1-\sigma_y\right)\log\left(\frac{w}{r}\right) + A$$

In the case of a Cobb-Douglas production function firms adjust their capital-labor ratio proportionately to any change in factor prices, such that the factor cost ratio $\log\left(\frac{w}{r}\right)$ does not change. Differently, an increase in the wage generates a decline in the factor cost ratio $\sigma_y < 1$, which means that firms do not increase capital enough to compensate for the rise in wages.
And our results estimates are:

Table 9: Dependent variable $\log\left(\frac{rk}{wl}\right)$, standard error in parenthesis, $***p < 0.01, **p < 0.05, *p < 0.1$

$\log\left(\frac{w}{r}\right)$	-0.183***
	(.0016)
Constant	1.069***
	(.0113)

Then, the model is calibrated with the following elasticity of substitution:

$$\sigma_y = 1 - 0.183 = 0.817$$

A.2 Automation Shock

Capital intensity is used as the instrument through which automation revels in the model. The data are used to document the effect of automation (proxied by the number of robots per worker) on firms' capital intensity. Given the nature of the data, it is implicitly assumed that the elasticity of capital intensity to robots remains unchanged over the entire time period considered in the model, and in particular that it is the same in 1993 as it is in our sample which starts from the year 2001.

Table 10: Dependent $log\left(\frac{k}{l}\right)$, standard error in parenthesis, $***p < 0.01, **p < 0.05, *p < 0.1$

$log\,(Robot)$	0.233***
	(.0027)
$controls$	-16.654***
	(4.347)
Constant	5.190***
	(.0189)

The first step is to estimate the coefficient of the elasticity of automation on capital intensity, in doing this firm's size is used as control:

$$log\left(\frac{k}{l}\right) = \alpha + \beta log\,(Robot) + controls$$

The estimation results are reported in Table 10. Hence, the equation above yields

$$log\left(\frac{k}{l}\right)_t - log\left(\frac{k}{l}\right)_{t0} = \beta\left[log\,(Robot)_t - log\,(Robot)_{t0}\right]$$

which can be simplified to: $log\left[\frac{\left(\frac{k}{l}\right)_t}{\left(\frac{k}{l}\right)_{t0}}\right] = \beta log\left[\frac{Robot_t}{Robot_{t0}}\right]$, leading to

$$\frac{\left(\frac{k}{l}\right)_t}{\left(\frac{k}{l}\right)_{t0}} = \left(\frac{Robot_t}{Robot_{t0}}\right)^{\beta}$$

In our data $t0 = 1993$ and $t = 2016$ and $\left(\frac{Robot_t}{Robot_{t0}}\right) = 9.23$. Then, in the model the ratio of capital intensity between initial and final steady state is: $\frac{\left(\frac{k}{l}\right)_t}{\left(\frac{k}{l}\right)_{t0}} = (9.23)^{0.233} = 1.68$

B Model Derivations: Entrepreneur's Problem

The entrepreneur's problem is solved in two steps: first, taking the optimal quantity y as given, the optimal demand for capital and labor that solve the firm's cost minimization problem, taking into account the borrowing con trained faced by the entrepreneur:

$$\min_{k,l} C = wl + Rk \tag{24}$$

$$y = z\left[\varkappa k^{\theta} + (1-\varkappa)\,l^{\theta}\right]^{\frac{1}{\theta}} \tag{25}$$

$$k \leq \lambda a \tag{26}$$

The Lagrangian of the problem is:

$$L(k, l; \phi, \mu) = wl + Rk - \phi \left\{ y - z \left[\varkappa k^{\theta} + (1-\varkappa) l^{\theta} \right]^{\frac{1}{\theta}} \right\} - \mu (k - \lambda a)$$

and the First Order conditions are:

$$\begin{aligned} \frac{\partial L}{\partial k} &= 0 : R + \mu = \phi \varkappa k^{\theta-1} z \left[\varkappa k^{\theta} + (1-\varkappa) l^{\theta} \right]^{\frac{1}{\theta}-1} && (27) \\ \frac{\partial L}{\partial l} &= 0 : w = \phi (1-\varkappa) l^{\theta-1} z \left[\varkappa k^{\theta} + (1-\varkappa) l^{\theta} \right]^{\frac{1-\theta}{\theta}} && (28) \end{aligned}$$

and the transversality conditions:

$$\begin{aligned} y - z \left[\varkappa k^{\theta} + (1-\varkappa) l^{\theta} \right]^{\frac{1}{\theta}} &= 0 \\ \mu (k - \lambda a) &= 0 \end{aligned}$$

Manipulating the system of equations above, yields the following expression for the marginal cost of productions ϕ:

$$\phi = \frac{R+\mu}{z\varkappa} \left[\varkappa + (1-\varkappa) \left(\frac{w}{R+\mu} \frac{\varkappa}{1-\varkappa} \right)^{\frac{\theta}{\theta-1}} \right]^{\frac{\theta-1}{\theta}}$$

Case $\mu = 0$: When the borrowing constraint Eq. 26 is not binding, $\mu = 0$ and from equations above the derived optimal demand of capital and labor is:

$$\begin{aligned} k &= \phi \frac{\varkappa y}{R} \left[\varkappa + (1-\varkappa) \left(\frac{w}{R} \frac{\varkappa}{1-\varkappa} \right)^{\frac{\theta}{\theta-1}} \right]^{-1} \\ l &= \left(\frac{w}{R} \frac{\varkappa}{1-\varkappa} \right)^{\frac{1}{\theta-1}} k \end{aligned}$$

Case $\mu > 0$: When Eq. 26 is binding $\mu > 0$, formally:

$$\mu = \max \left\{ w \frac{1}{\varkappa} \left(\frac{\varkappa}{1-\varkappa} \right)^{\frac{1}{\theta}} \left[\left(\frac{1}{\lambda a} \right)^{\theta} \left(\frac{y}{z} \right)^{\theta} - \varkappa \right]^{\frac{1-\theta}{\theta}} - (r+\delta), 0 \right\} \tag{29}$$

Then the capital demand then is constrained by the level of wealth of the entrepreneur:

$$k = \lambda a \tag{30}$$

and the subsequent optimal demand of labor is:

$$l = \left[\left(\frac{y}{z} \right)^{\theta} - \varkappa \left(\lambda a \right)^{\theta} \right]^{\frac{1}{\theta}} \left(\frac{1}{1 - \varkappa} \right)^{\frac{1}{\theta}} \tag{31}$$

The second step of the solution is to compute the optimal level of production, taking into account the relative demand faced by the entrepreneur. Formally the firm solves:

$$\max_{y} \Pi = p\left(y\right) y - C\left(y\right)$$

with F.O.C.

$$p' \left(\frac{y}{Y} \right) \frac{y}{Y} + p \left(\frac{y}{Y} \right) = \phi$$

note that the optimality condition of the final producer profit maximization give Eq 11. Then, F.O.C. are rewritten as:

$$\Upsilon''\left(q\right) Dq + \Upsilon'\left(q\right) D = \phi \tag{32}$$

where

$$\Upsilon' \left(\frac{y}{Y} \right) = \frac{\sigma - 1}{\sigma} \exp \left(\frac{1}{\epsilon} - \frac{\left(\frac{y}{Y} \right)^{\frac{\epsilon}{\sigma}}}{\epsilon} \right) \tag{33}$$

and

$$\Upsilon'' \left(\frac{y}{Y} \right) = -\frac{\sigma - 1}{\sigma^2} \exp \left(\frac{1 - \left(\frac{y}{Y} \right)^{\frac{\epsilon}{\sigma}}}{\epsilon} \right) \left(\frac{y}{Y} \right)^{\frac{\epsilon}{\sigma} - 1} \tag{34}$$

$$= -\Upsilon' \left(\frac{y}{Y} \right) \frac{\left(\frac{y}{Y} \right)^{\frac{\epsilon}{\sigma} - 1}}{\sigma} \tag{35}$$

Finally, plugging into Eq. 32 Eq. 33 and 34, and rearranging:

$$\Upsilon' \left(\frac{y}{Y} \right) D = \frac{\sigma}{\sigma - \left(\frac{y}{Y} \right)^{\frac{\epsilon}{\sigma}}} \phi \tag{36}$$

Note that $\frac{\sigma}{\sigma - \left(\frac{y}{Y} \right)^{\frac{\epsilon}{\sigma}}}$ is firm's markup, and then this condition resembles the canonical optimal price choice, given that $p = \Upsilon' \left(\frac{y}{Y} \right) D$:

$$p = \frac{\sigma}{\sigma - \left(\frac{y}{Y} \right)^{\frac{\epsilon}{\sigma}}} \phi \tag{37}$$