Firm-level Labor Shares and Technology-driven Occupational Changes

Preliminary Draft

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Abstract

Technological advances have decreased labor demand for occupations with high routine task content and increased it for occupations that are either cognitively complex or require non-repetitive social interactions. Technology has also been one of the key drivers of the changes in the labor share of income. Our paper investigates whether the evolution of occupational employment shares and occupation-specific wage rates explains firm-level labor share dynamics. Using rich administrative data for Portugal, we show that the S-shaped dynamics of the aggregate labor share between 2004 and 2019 are mostly driven by changes in firms' labor share rather than value-added reallocation across the labor share distribution. Our findings suggest that firm-specific labor shares rise due to positive growth in hourly wages, particularly high among Routine Manual and Non-Routine Manual occupations. We also show that changes in task group employment shares have limited effects on the firm-level labor shares, due to the stabilization of occupational employment shares since 2010.

JEL codes: D33; J21; J31; O33

Keywords: labor share; occupational tasks; task-biased technological change

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1 Introduction

In this paper, we analyze the labor share dynamics at the firm-level, using rich administrative data on firms and their workers. In particular, we aim to assess how the transformations in the employment structure among occupational task groups have impacted the labor share at the firm level. For that purpose, we look at the evolution of employment shares and wages by task group, and compare them with the behavior of other labor share components.

The fall in the labor share of income (hereafter, labor share) has been widely documented in the past ten years. Recent empirical evidence suggests a downward trend in the aggregate labor share not only in the United States (Elsby et al., 2013; Karabarbounis and Neiman, 2014; Autor et al., 2020; De Loecker et al., 2020), but also in other advanced and developing countries (Dao et al., 2019). The striking evidence that aggregate labor shares were no longer constant, as assumed throughout the 20th century, boosted a new strand of literature.

Empirical evidence has suggested technological change as one of the most relevant drivers of lower labor shares. Acemoglu (2003), Jones (2005) and Irmen and Tabaković (2017) point at skill-biased technology change and factor-augmenting technical change. Karabarbounis and Neiman (2014)'s widely cited paper points at the fall of relative investment prices, under the assumption that the labor-capital elasticity is above one. At micro level, the role of markups and market concentration has also been identified as causing lower labor shares. Autor et al. (2020) document that larger firms are capturing a bigger share of value added due to higher investment in technology and innovation, and these "super-star firms" have lower labor shares. They also show that more concentrated industries have increased their patent activity, and have higher total factor productivity (TFP) growth. De Loecker et al. (2020) further prove that increasing markups are pushing firm-level labor share down.

Other authors have studied the impact of automation of routine tasks on income distribution, employment, and wages. These technological advances (either robot adoption or ICT implementation) have changed labor demand directed to occupations whose tasks are routine-intensive (Goos et al., 2014; Autor et al., 2015; Bárány and Siegel, 2018; Jaimovich et al., 2020), and they have changed firms' TFP in several countries (Autor and Salomons, 2018). Novel contributions show that (i) the impact of automation on employment, wages, and factor income distribution depends on the dialectic between job displacement and creation of new tasks (Acemoglu and Restrepo, 2018, 2019), (ii) even when automation doesn't entail an overall loss of employment or a decrease in mean wages, it generally decreases the labor share of income. The result holds for both aggregate- (vom Lehn, 2018), industry- (Autor and Salomons, 2018) and firm-level analysis in countries like Denmark (Humlum, 2019), France (Acemoglu et al., 2020), or Spain (Koch et al., 2021).

Despite being a burgeoning topic of research, only few papers provide broad firm-level evidence on the labor share dynamics. Apart from Autor et al. (2017, 2020) and De Loecker et al. (2020), on the role of markups and market concentration, Zhang (2019) demonstrates how firm-level heterogeneity and its evolution have contributed to the decline in the Chinese steel industry's share of labor. Kehrig and Vincent (2021) use plant-level U.S. data to decompose the aggregate labor share and to explore firm-level labor share dynamics. The authors observe that firms with lower labor shares are growing faster, not because they are low labor-share firms, nor because they pay lower wages, but because these firms present higher labor productivity. Kyyrä and Maliranta (2008) use data on Finnish firms to show that the decline in aggregate labor share relies on the reallocation of value added to lower labor-share firms, and Bloise et al. (2021) estimate firm-level determinants to explain the labor share heterogeneity across middle and large-sized units.

This paper aims to contribute to a more comprehensive knowledge of the micro-level dynamics of labor shares. We use Portuguese rich administrative employer-employee data, matched with corporations' financial statements, which covers private firms of all sizes and all non-financial industries except those in agriculture, fishing, and forestry. This contrasts with most works based on firm-level data, which rely on samples restricted to a specific sector (Kehrig and Vincent, 2021) or firm size (Bloise et al., 2021). We cover the period between 2004 and 2019. By decomposing the change in aggregate labor share, we assess the relative importance of within-firm transformations (which affect firms' labor share), between-firm transformations (which change the value-added distribution across firms with different labor shares), and firms' entry/exit dynamics. Going into further detail on the within-firm analysis, we discuss whether changes in the employment composition among task groups (Routine / Non-Routine, Manual / Cognitive) are quantitatively relevant to explain the dynamic of firm-specific labor shares. Furthermore, we evaluate the contribution of task group-specific wages and changes in firms' overall employment in explaining firm-level labor shares.

To the best of our knowledge, no other paper has analyzed the determinants of the labor share and its dynamics through the lens of the occupational composition of firm-level employment.

In the absence of microdata on robot purchases, we believe that changes in occupational employment shares may provide relevant insights on whether technology-based mechanisms are in play when it comes to firm-specific labor share dynamics.

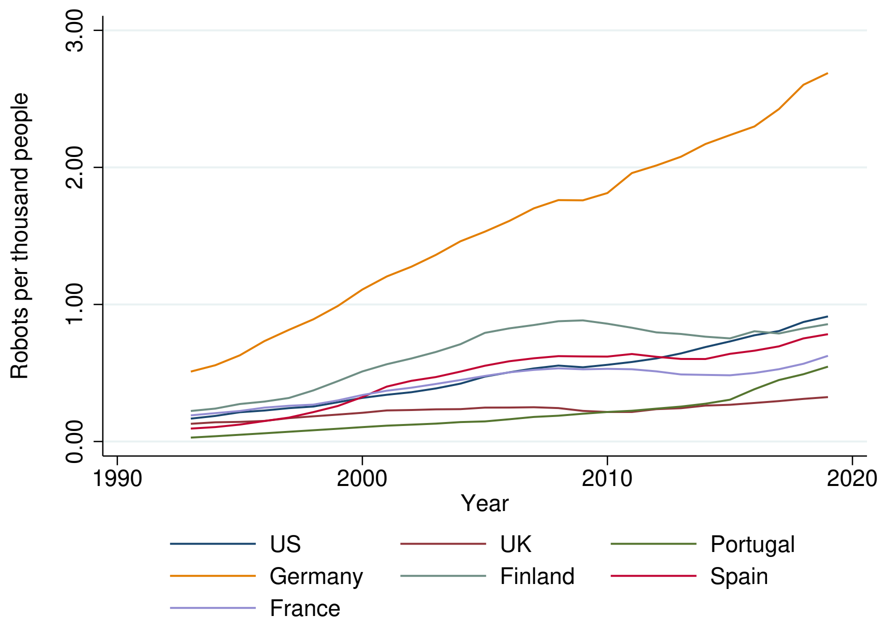
Portugal has experienced job polarization like other European countries (Goos et al., 2009; Cortes et al., 2020). Furthermore, despite Portugal's late take-off in the automation race, the number of robots by thousand people has been increasing since the late 2000s, and it is now close to what is observed in countries like France and has surpassed the UK (Figure 1). Portugal has also registered an aggregate labor share similar to the labor share in the U.K., U.S., and the European Union's average (around 60% of the GDP). It has faced an akin downward-trending labor share in the past thirty years (Autor and Salomons, 2018), irrespective of its cyclical variations.

In this paper, we cover a period in which these cyclical variations are especially important, given that Portugal faced a severe financial economic crisis between 2010 and 2014. We address these fluctuations by analyzing each stage of the labor share dynamics within the 2004-2019 period. Additionally, we discuss why the aggregate labor share based on firm-level data behaves differently than the labor share based on aggregate national accounts data, contributing to the debate on the labor share measurement (described in detail in Grossman and Oberfield (2021) and Siegenthaler and Stucki (2015))

The firm-level data reveals that the dynamics of the aggregate labor share between 2004 and 2019 is S-shaped (see Figure 2, below). To address firm heterogeneity, we look at micro-level labor share determinants. We find that firms employing a larger share of temporary employees and firms with higher expenses in labor services outsourcing have lower labor shares, as suggested by, e.g., Bloise et al. (2021). Using a proxy for unionization, based on the type of collective bargaining agreement predominant among workers in each firm, we show that firms with higher unionization have higher labor shares. This result is aligned with the contributions of Dimova (2019) and Bloise et al. (2021). Moreover, we find that firms in more concentrated industries and at the top of (within-industry) market share distribution have lower labor shares than their peers (consistent with Autor et al., 2017 and De Loecker et al., 2020).

We conclude that firms employing higher shares of non-routine cognitive workers exhibit, on average, higher labor shares, while firms employing a higher share of non-routine manual

Figure 1 – Robots by thousand people



Sources: IFR and World Bank Data; author's calculations.

workers exhibit lower labor shares. Given that these two task groups pay wages at the top and the bottom of the wage distribution, respectively, we infer that, when controlling for firm and industry characteristics, firms that pay on average higher wages exhibit higher labor shares. We discuss this result in light of what has been documented for other countries (e.g., Paul and Isaka, 2019; Kehrig and Vincent, 2021; Bloise et al., 2021).

A shift-share decomposition unveils that the S-shape pattern followed by the aggregate labor share between 2004 and 2019 is mostly driven by changes in surviving firms' labor share – the *within-firm* component – rather than by value-added reallocation towards higher labor share firms – the *between-firm* component. The limited role played by the *between* component contrasts with evidence found among Finnish firms (Kyyrä and Maliranta, 2008) and U.S. manufacturing firms (Kehrig and Vincent, 2021), but there are significant differences in the scope of the data used across studies. We also find that the extensive margin contributes negatively to the aggregate labor share since, on average, exiting firms have higher labor shares than entrants.

We then look in detail into the *within-firm* component and its drivers. We find that firm-specific labor shares between 2004 and 2019 have increased mostly due to the positive growth in hourly wages across task groups. Such increase in wages has been particularly strong among Routine Manual and Non-Routine Manual occupations. We also show that, although Portugal has experienced job polarization in the past thirty years, employment shares by task groups have stalled from 2010 onwards. Therefore, the impact of changes in task group employment shares has been limited in the past decade. Last but not least, we show that total labor costs are more persistent than changes in firms' value-added, which has contributed positively to the overall increase in the aggregate labor share.

The paper is organized as follows. Section 2 presents the data. Section 3 links macro trends with micro-level data. Section 4 explores why the task content of occupations may matter when discussing labor share dynamics at the firm level. Section 5 details the shift-share decomposition components and Section 6 summarizes the main take-outs.

2 Data

The data used in this paper covers private firms of all sizes and all non-financial industries, except those in agriculture, fishing, and forestry. It covers the period from 2004 and 2019. The final panel is based on two extremely rich administrative databases existent in Portugal: *SCIE* ("*Sistema de Contas Integradas das Empresas*"), a database that provides a large set of indicators at the firm level (namely balance sheet and financial statements' indicators), and *Quadros de Pessoal*, an employee-employer database which provides data on workers' characteristics. Both datasets result from compulsory surveys (to the Tax Authority and the Ministry of Labor, respectively), ensuring high levels of compliance and data accuracy.

SCIE covers potentially all establishments (including entrepreneurs and independent workers), except public or non-profit corporations and financial and insurance companies. From 2004 onwards, the dataset includes disaggregated annual data on income, expenditures, the total value added at market and factor cost prices, and a myriad of other balance sheet variables. It also provides detailed industry codes and the number of employees in each firm. Each unit is assigned a single identifier, which remains unchanged over time as long as the firm has activity in the surveyed year. We drop entrepreneurs and independent workers since their legal status exempts them from reporting balance sheet information (including labor costs).

Using *SCIE* data on total labor costs (TLC) and value added at market prices (y), we are able to derive firm-specific labor shares in a giver year, defined as

$$l_{it} = \frac{TLC_{it}}{y_{it}}, \tag{1}$$

where i indexes each firm and t the year.[1] The aggregate labor share in each year (L_t) is given by the mean of all firm-level labor shares (l_{it}), weighted by each firm's value-added share on total value added (γ_{it}):

$$L_t = \sum_{i=1} \gamma_{it} l_{it} \tag{2}$$

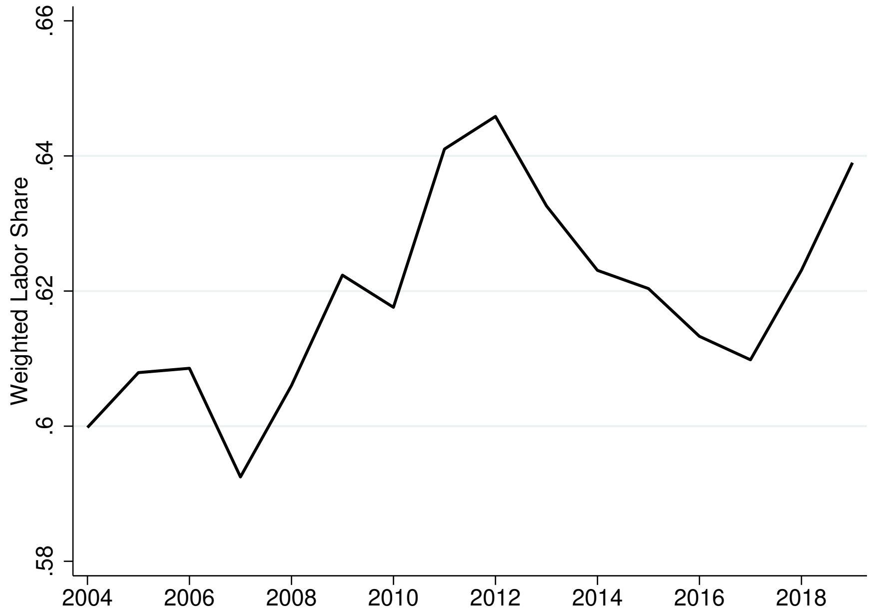
We drop firm-year observations with missing labor costs or missing value added. As in Kehrig and Vincent (2021) and Bloise et al. (2021), we also exclude observations at the bottom and top percentiles of the labor share distribution.

Figure 2 exhibits the aggregate labor share. Three distinct patterns arise: first, between 2004 and 2012, when the aggregate labor share rises; the second period, between 2013 and 2016, when the labor share falls; the third, characterized by a rebound, between 2017 and 2019. In 2010, Portugal fell into a deep economic crisis and, between 2010 and 2013, non-financial firms' value added decreased by 13%, recovering after that. The economic slump crosses two sub-periods and the behavior of the labor share during that time suggests that labor costs had a delayed adjustment in face of the fall in value added. To account for heterogeneous dynamics across the S-shaped labor share's performance, we run a decomposition exercise for each sub-period, in addition to the full 16-year period.

Until 2010, we can't disentangle labor costs assigned to board members fixed remunerations (mixed-income, as defined by the OECD) from labor costs paid to employees. Both are considered labor costs. Between 2010 and 2019 - when we are able to separate board members' and employees' payrolls -, the inclusion of the former raises the aggregate labor share by 5.5 p.p., on average. However, the dynamics of the labor share with or without corporations' mixed-income are similar. Figure 3 depicts the labor share when the numerator in equation 1 uses total labor costs (solid line) and when it excludes board members' labor remuneration (dashed line) - before any other cleansing operations. Since we are more interested in the dynamics of the labor share than its level, we choose to include all labor costs. This approach allows us to stretch the period of analysis back to 2004.

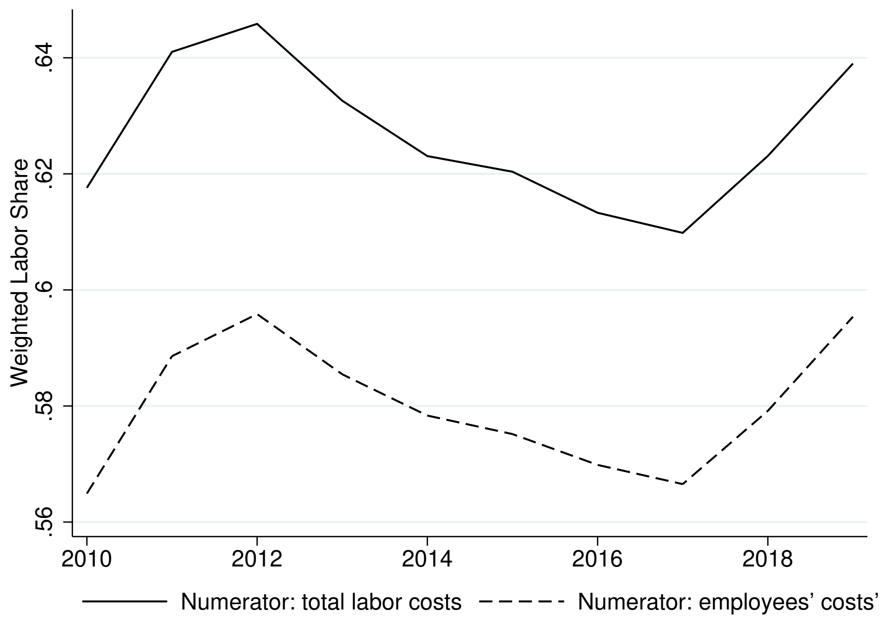
[1] The Statistics Office measures value added as the value of gross production less costs with intermediate goods.

Figure 2 – Aggregate Labor Share



Sources: SCIE; author's calculations.

Figure 3 – Aggregate Labor Share: total labor costs *vs.* employees' costs



Sources: SCIE; author's calculations.

Quadros de Pessoal, henceforth *QP*, covers potentially all employees in the private sector, from 1985 to 2019. It details each worker's gender, schooling, 3-digit occupation, monthly hours worked, monthly base, and total wage, among others. We exclude employees for whom we are missing wage, hours worked or occupation, and workers aged below 18 years old or above 68. To rule out misreporting information and outliers, we drop observations below the first and the last total wage percentile. Finally, we exclude workers employed in farming, fishing, and forestry.[2]

We use job titles at a 3-digit level to group occupations into four broad categories, according to the automation potential of the main task performed by each occupation, as suggested by Acemoglu and Autor (2011) and Cortes et al. (2020). If the occupation's main task is highly repetitive, it may be theoretically automated, and it falls into the group of routine tasks. Routine tasks can be cognitive (clerical and administrative jobs) or manual (production, operative, and assembly jobs). Routine Cognitive (RC) and Routine Manual (RM) occupations are usually middle-skilled and pay salaries in the middle of the wage distribution. If an occupation requires high adaptability (both at physical or cognitive level) and/or social interactions instead, it is considered non-routine. Likewise, non-routine occupations are divided into Non-Routine Cognitive (managerial, creative, professional, and technical jobs) and Non-Routine Manual occupations (drivers, janitors, personal care aide jobs). Non-Routine Cognitive (NRC) occupations are performed by highly skilled professionals and paid at the top of the wage ladder. Non-Routine Manual (NRM) occupations are performed by low-skilled workers and paid at the lowest wages (Autor et al., 2003; Cortes et al., 2017). The crosswalk matching 3-digit occupational job titles and occupational groups is presented in Appendix A and follows closely Cortes et al. (2017)'s crosswalk for U.S. occupations.

QP is based on a survey filled by the employers in October of each year, and the information retrieved from it reports to October only. This fact has three implications which are relevant to our work: first, the employer-employee match verified in October may not hold the full year; second, October's total hourly wage may not be constant over the year; third, the firm may be operating in October but not over the full year. To grasp how firm-level changes in the employment structure (by occupational groups) and in task-specific wages interact with the labor share, we need to extrapolate *QP*'s October data on wages and hours worked to

[2] *QP* also covers employees working in financial enterprises. As in the final panel we only keep firms present in both databases, workers employed in the financial sector are automatically excluded.

match SCIE's annual data on total labor costs. To build the final panel, we proceed as follows:

1. We match *QP* and *SCIE* databases in each year between 2004 and 2019, and drop firms that do not match. The panel has, at this stage, 463 thousand distinct firms.

2. We determine the hourly wage of each task group j by dividing total monthly wages (W_{jit}) by regular monthly hours worked (E_{jit}), both task group- and firm-specific, and adjust it to include other labor costs paid by the employer (e.g., employers' share of Social Security payments or other non-monetary benefits). These additional labor costs are firm and year-specific and we retrieve them from *SCIE*'s data as a share of total wage payroll (OCS_{it}). Hence, adjusted wage rates are given by:

$$w_{ijt}^{adj} = \frac{W_{jit}}{E_{jit}}\left(1 + OCS_{it}\right),$$

   where j indexes the task group.

3. Given that Portuguese workers are paid 14 times (one extra monthly payment as a Christmas bonus and another as a holiday bonus), we multiply the number of monthly hours worked (E_{jit}) by 14, and we obtain *QP*'s yearly labor costs.

$$TLC_{it}^{QP} = 14\sum_{j}^{4} w_{jit}^{adj} E_{jit}$$

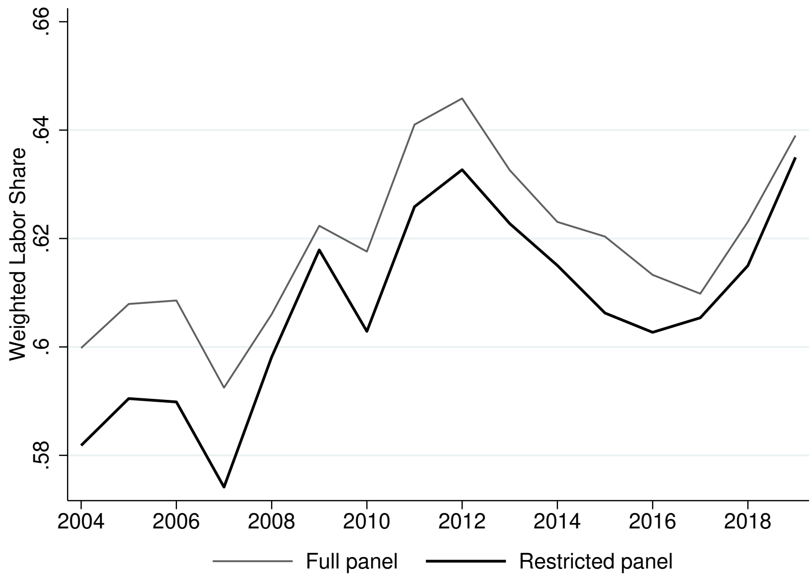
4. To the difference between the total labor costs reported in *SCIE* and the total labor costs based on *QP* data and own calculations we call *correction factor* ($cf_{it} = TLC_{it}^{SCIE}/TLC_{it}^{QP}$). The correction factor reflects within-year variations in wages and employment, caused by one (or a combination) of the factors described earlier. As a rule of thumb, we exclude firm-year observations for which the correction factor is below 0.5 or above 1.5 at the beginning or at the end of each sub-period.

As regards the 4th step above, we believe that for firms whose correction factor lies out of the [0.5, 1.5] range, *QP*'s data is unable to accurately represent their annual wage and employment structures. Although we lose many observations (around 47% of the whole universe of non-financial corporations), we gain data accuracy. The final panel has 179 781 firms in 2004 and 190 379 firms in 2019.[3] Among these firms, 21.6% continue operating for the full

[3]In each sub-period, we have a total of 262 335 (2004 - 2012), 221 690 (2013 - 2016), 225 958 (2017-2019)

period (survivors), 37.5% leave the market (exiters) and 41.0% enter the market (entrants).[4] Despite the restrictions imposed, the final panel includes more than 2 million workers each year. More importantly, the aggregate labor share features the same dynamics in both full and restricted datasets (except in 2017), as shown in Figure 4.

Figure 4 – Aggregate Labor Share: full and restricted panel



Sources: *SCIE* and *Quadros de Pessoal*; author's calculations. Note: The full panel series considers all firms that exist in both *QdP* and *SCIE* databases. The restricted panel series only considers firms whose correction factor lies between 0.5 and 1.5.

3 From macro to firm-level data

Several studies have documented the fall in the aggregate labor share in multiple countries (Elsby et al., 2013; Karabarbounis and Neiman, 2014; Autor et al., 2017; Dao et al., 2019; Dimova, 2019). A similar descending trend has been documented for Portugal: Autor and Salomons (2018) show a negative annualized change in log labor share in the 1990s and 2000s; Dimova (2019) argues that Portugal has the second-largest fall among the most advanced EU countries between 2002 and 2016, consistent with Lopes et al. (2021)'s

distinct firms.

[4]These figures change across periods: in sub-period 1 we have 33.9%/35.4%/30.7%; in sub-period 2 we have 58.0%/17.8%/24.2%; and in sub-period 3 we have 66.5%/15.8%/17.8% of survivors/leavers/entrants.

findings based on two different wage share measures (wage share and adjusted wage share).[5]

Given the proliferation of evidence regarding the labor share overall decline, the S-shaped behavior documented in Figure 2 and the positive change between 2004 and 2019 – 5.3 percentage points in the final panel – may be surprising. The apparent divergency in labor share dynamics is due to two main factors. The first regards the relatively short period considered in our analysis: the labor share cyclicality in this period informs very little about long-term trends documented in other papers. The second factor regards methodological adjustments between macro data and firm-level data. When we compute the labor share using National Accounts data for non-financial corporations (total compensation of employees as a share of total value added) and compare it with our microdata-based labor share, we observe opposite dynamics between 2008 and 2012, as shown in Figure 5.[6] The methodological differences between national accounts data and firm-level data are the following: (1) national accounts estimate and comprehend the informal economy's value-added; (2) national accounts exclude the value-added stemmed from activities undertaken by Portuguese firms in foreign countries, and (3) national accounts exclude labor costs imputed to entrepreneurs.[7] To test which methodological differences contribute the most to explain the contrasting behavior of the labor share between 2008 and 2012, we compute an artificial labor share measure. We build this artificial measure using the total labor costs from our final panel of firms and the aggregate value added retrieved from the Portuguese national accounts. We plot it in Figure 6, together with the labor share based on data from the national accounts for non-financial corporations. Both follow the same U-shape behavior, which indicates that the informal economy sustained the fall in total value added reported by non-financial firms in their financial statements between 2008 and 2012.[8]

For last but not least, the adjustments undertaken to build the sample of firms also play a role in explaining the gap between the labor share based on macro data and the labor share based on microdata. However, these adjustments do not contribute for the divergent

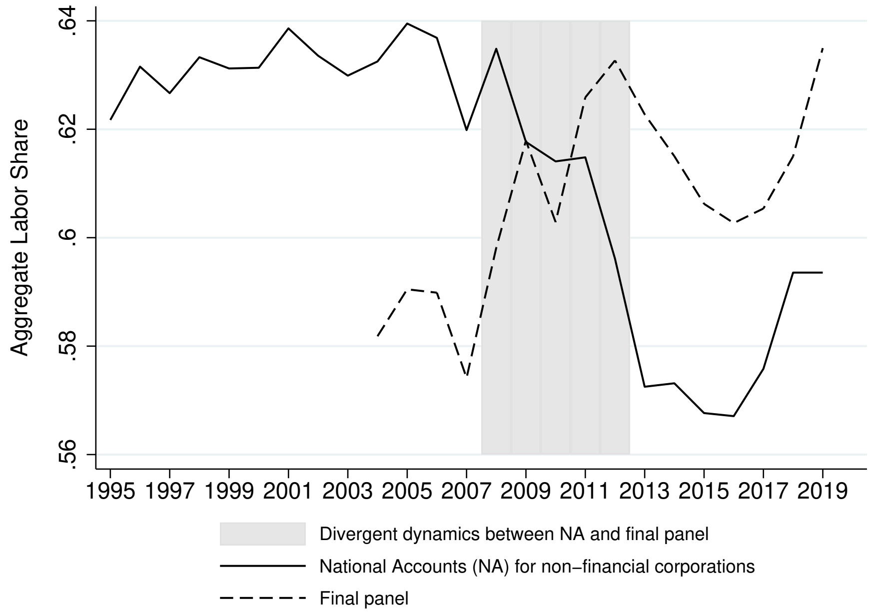
[5]The wage share differs from our measure of labor share by considering the compensation of employees only, thus excluding labor costs put up by owners. The adjusted wage share, as considered by AMECO , includes a part of the income earned by the self-employed as wage costs.

[6]The National Accounts data for non-financial corporations can be accessed here.

[7]Although we do not include income of independent workers in our final panel, we do include labor income paid to members of the firm's governing bodies.

[8]While national accounts for non-financial corporations register a fall in total value added of 2.4% between 2008 and 2012, SCIE's raw data reports a 15% decrease.

Figure 5 – Aggregate Labor Share: National Accounts vs. Firm-level data

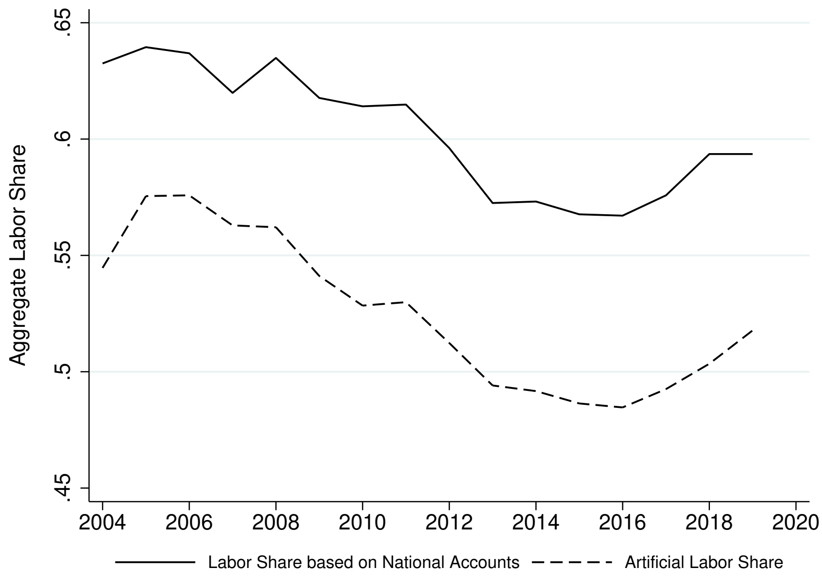


Sources: National Accounts of non-financial corporations and SCIE; author's calculations.

behavior between 2008 and 2012: as shown in Figure 4, all steps adopted to build the final panel do not change the dynamics of the aggregate labor share but only decrease its level.

One may inquire about the relevance of departing from a country- and industry-level to firm-level studies if, by doing so, we are constraint to a shorter period of analysis. Indeed, time constraints are shared by all of the (few) studies on labor share dynamics at the firm level (Bloise et al. (2021) for Italy, Siegenthaler and Stucki (2015) for Switzerland, Kyyrä and Maliranta (2008) for Finland), except Kehrig and Vincent (2021)'s, which covers a larger period of analysis by restricting the scope of their study to the manufacturing sector. Besides the need for a better in-depth knowledge on firm-specific labor share's determinants and dynamics, Bloise et al. (2021) and Siegenthaler and Stucki (2015) add other arguments. First, micro-level studies allow one to look at firm heterogeneity in characteristics suggested as labor share determinants: firm size (Dorn et al., 2017), industry (Elsby et al., 2013), automation and ICT adoption (Acemoglu and Restrepo, 2018) and outsourcing adoption (Bloise et al., 2021). Second, by using micro-level data we can assess whether changes in the aggregate labor share are due to changes in firm-level labor share or changes in the distribution of value-added across the labor share distribution (e.g., a larger share of value-added moving rightwards, across the labor share distribution). This effect, known as the

Figure 6 – Aggregate Labor Share: National Accounts vs. Firm-level data



Sources: National Accounts of non-financial corporations and SCIE; author's calculations.

composition effect, is key in Kyyrä and Maliranta (2008) and Kehrig and Vincent (2021). Micro-level data also allows one to account for firm dynamics, i.e., the role of exit/entry. Finally, by excluding self-employment, entrepreneurial income, and real state ownership, the labor share derived from firm-level data is free of measurement issues related to what should or shouldn't be acknowledged as labor compensation.[9] As described in the previous section, our final panel, despite excluding self-employment, considers firm owners' compensation as labor income. As such, we only partially address Elsby et al. (2013)'s concern with the impact of self-employment income on labor share long-term trends.

4 Does the employment structure by task-groups matter for the labor share?

Several recent studies have documented that technological advances have decreased demand for routine-intensive tasks and increased it for non-routine tasks (Acemoglu and Autor, 2011; Autor et al., 2003; Cortes et al., 2017; Autor and Salomons, 2018; Cortes et al., 2020). Al-

[9] Grossman and Oberfield (2021) summarize the debate around labor share measurement using macro data.

though many papers have theoretically proven that the replacement of routine tasks by machines may lead to a decrease in the labor share of income (Acemoglu and Restrepo, 2018; Autor and Salomons, 2018; Eden and Gaggl, 2018), only vom Lehn (2018) has decomposed the overall labor share into occupational labor shares, and looked at how they have changed across time. Based on cross-industry evidence, the author argues that the disappearance of routine occupations and abstract occupations with high routine content of routine explains the decline in the U.S. aggregate labor share.[10]

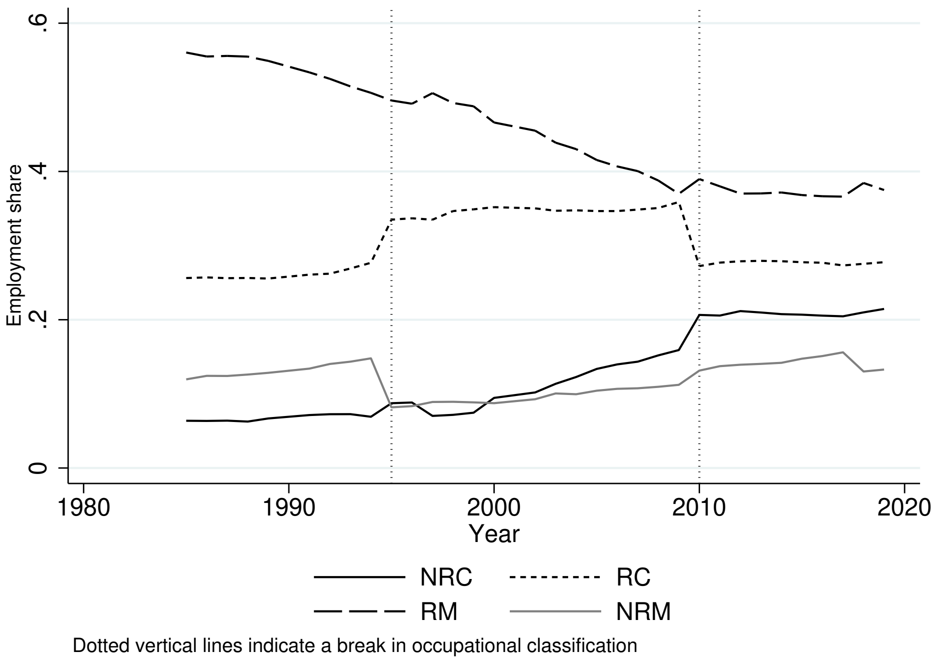
Employment reallocation between task groups also occurred in Portugal. The decline of labor demand for routine tasks - either cognitive or manual - and the increase in labor demand for non-routine tasks are similar to what has been observed in many developed countries (Goos et al., 2009). Figure 7 depicts how routine tasks and, in particular, routine manual tasks have been employing relatively fewer employees, while non-routine tasks have been consistently employing a larger share of employees. The period under analysis, 2004 to 2019, encloses one classification brake, in 2010, but if we inspect the evolution of task group shares prior and after that break, two patterns arise: (1) job polarization was mainly driven by the drop in routine-manual occupations and an increase in non-routine cognitive occupations until 2010, and (2) employment shares by task group have stabilized in the past decade.

For a given value-added, the employment distribution across task groups may affect the aggregate labor share through two different channels. The first channel stems directly from job polarization: the redistribution of employment from routine occupations, which wages lie in the middle of the wage ladder, either towards NRM occupations, that pay lower wages, or towards NRC occupations, at the top of the wage distribution. If workers move predominantly to better-paying occupations, the overall labor costs increase and so does the aggregate labor share. If workers move mostly to NRM occupations, the lowest-paid task group, labor costs decrease and so does the labor share. In the next section, where we decompose the labor share change at the firm level, we name this channel as *within-firm, between occupation* effect.

The second channel regards the relative wage growth in each task group. Fixing the value-added, positive wage rate growth always contributes to raising the labor shares. Since task groups are paid differently and have progressed differently over time, the magnitude of that

[10]vom Lehn (2018) defines three types of occupations - abstract, routine, and manual tasks – as suggested by David and Dorn (2013), instead of the four types of occupations we consider in this paper.

Figure 7 – Employment shares by task group



Sources: *Quadros de Pessoal* and author's calculations. Notes: Employment shares are computed as the share of workers in each task group over total employment in October of each year.

contribution also differs. If NRC and NRM wages increase by more than RC and RM wages, it positively reinforces the effect of job polarization in the labor share. On the contrary, if RM and RC wages increase by more than in the remaining task groups, then this second channel smooths the impact of the fall in routine occupations' labor share on the overall measure. We designate this channel as *within-firm, within task-group* effect.

Lower demand for routine occupations may not necessarily mean lower routine wages, in the presence of high unionization rates (Parolin (2020) argues that unionization rates are indeed higher among routine occupations). Cortes et al. (2020) show that, despite the substantial fall in routine manual jobs over the past 30 years in Portugal, this was the task group with the highest wage growth rate. Thus, the impact of the fall in routine employment on total labor costs may be, at least partially, offset by the growth in routine-specific wage rates - preventing the aggregate labor share from falling.

Proven as it is that differentiated occupational employment shares and wage growth rates may impact the aggregate labor share and that the Portuguese employment structure has become polarized, we aim to assess whether distinct employment distributions across task groups at firm-level lead to distinct labor shares. To investigate that hypothesis, we regress firms' labor share on the share of hours worked by each task group. The regression model includes a myriad of control variables that have been documented as determinants of labor share heterogeneity across firms. These factors are:(1) labor market institutions, such as the share of temporary contracts and unionization shares (Dimova, 2019; Bloise et al., 2021; Grossman and Oberfield, 2021); (2) market concentration and market power (Barkai, 2020; Autor et al., 2020); (3) outsourcing of labor-intensive activities (Bloise et al., 2021); and (4) internationalization (Panon, 2020; Bloise et al., 2021). As a proxy to firm-level *unionization*, we use the type of collective agreement which covers the largest share of workers employed in each firm.[11] To account for *market concentration*, we derive Herfindahl-Hirschman Index by detailed industry (NACE at 5-digit level). To measure *market power*, we assign each firm to a decile of sales' share within its industry (wherein the 1st decile we find firms with the lowest market share, and in the 10th decile firms with highest market shares). *Outsourcing* is derived as the share of expenditure on specialized labor services on total expenditure, and we use the share of exports on total sales as the internationalization measure (both retrieved from *SCIE* database). Other firm-specific controls include 3-year average log labor productivity (measured as the monthly average of value added by hour of labor employed), log number of employees, and dummies for contemporary and up to two lags of positive investment in software and industrial property as other firm-level control variables. We estimate the model

$$\log l_{it} = \beta_0 + \sum_{j}^{4} \beta_j \lambda_{jit} + \beta_5 \mathrm{HHI}_{st} + \delta \Omega_{it} + \epsilon_{it}, \tag{3}$$

with year and industry (at 2-digits level) fixed effects. In equation 3, i indexes each firm, j each of the four occupational groups, s 5-digit level industry codes and t the year; l_{it} is the firm's labor share, λ_{jit} depicts task j-employment share within the firm in each year, and HHI_{st} the Herfindahl-Hirschman index of the industry s to which firm i belongs to. Vector δ contains the estimates of all firm-level controls included in Ω_{it}, as described above.

[11] It is possible to have more than one collective agreement by firm if collective bargaining occurs between the firm (or employers' organizations) and multiple unions. There are four types of collective agreements in Portugal: firm-specific agreements ("Acordo de Empresa"), multi-firm agreements ("Acordo Colectivo de Trabalho"), industry-level agreements ("Contrato Colectivo de Trabalho") or extension ordinances ("Portaria de Extensão"), which administratively provides non-unionized workers the same labor conditions as workers covered by a collective agreement in the same firm or industry. Workers may not be covered by any collective labor agreement at all. In our regression model, we assume that firm-specific agreements translate the highest level of unionization, while the prevalence of no agreement at all is the lowest level of unionization.

Table 1 shows that firms' labor share increases as it employs a larger share of NRC occupations (which is the baseline category), in comparison with firms with larger employment shares in the remaining occupations. Firms with a larger share of employees in NRM occupations exhibit the lowest labor shares. Knowing that wages increase in the following order (1) non-routine manual, (2) routine manual, (3) routine cognitive, (4) non-routine cognitive (Figure 8), our estimates suggest that, as a firm employs more workers in higher paying task groups, its labor share tends to rise, when controlling for all remaining variables.[12]

Table 1 – Log labor share

	(1) log l_i	(2) log l_i
Share of Routine Cognitive	-0.453***	-0.390***
	(0.017)	(0.017)
Share of Routine Manual	-0.597***	-0.402***
	(0.016)	(0.020)
Share of Non-routine Manual	-0.643***	-0.435***
	(0.016)	(0.018)
Year FE	Yes	Yes
Industry FE	No	Yes
Observations	1,337,114	1,337,114
R2	0.786	0.820

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table shows the fixed-effects regression with robust standard errors of equation 3 on a sample restricted to the period 2010-2019. Observations are weighted using the share of each firm's value added in total value added. We restrict the period of analysis to 2010-2019, in order to include firm's share of labor outsourcing on total expenses, only available from 2010 onwards.

This result diverges from Kehrig and Vincent (2021)'s findings among U.S.'s manufacturing firms – where low labor share units do not pay, on average, lower wages than their peers. However, while their model only considers the relationship between wages and the labor share, equation (3) includes control variables which are statistically significant for firm's labor

[12]As robustness check, we adapt the estimation in equation (3) using firm log mean hourly wages (weighted by the share of each task group on firm employment) instead of task group employment shares. The positive coefficient associated with log mean hourly wages confirms the positive relation between wages and firm-level labor share.

share.[13] Indeed, if we perform a similar exercise as in Kehrig and Vincent (2021), which consists in running a linear regression of relative log wages, $\widetilde{w_{it}}$, such that $\widetilde{w_{it}} = \log\, w_{it} - \overline{\log\, w_{jt}}$ (where $\overline{\log\, w_{jt}}$ gives the weighted mean log wages of all firms j except their own, i), on firm-level labor share, we obtain a negative relationship between the two variables – indicating that low labor share firms do not pay lower wages than their peers. Figure 9 illustrates this result. Although the slope of the curve is steeper than the one reported for the U.S. (see Figure VI in Kehrig and Vincent (2021), p.1059), such negative correlation is consistent with other contributions in the literature (e.g., Bloise et al., 2021). The contrasting results we get from (i) the full model, expressed in equation (3), in which firms employing high-wage task groups have higher labor shares, and (ii) the empirical strategy suggested by Kehrig and Vincent (2021), in which firms paying high wages do not have lower labor shares, highlight the importance of controlling for firm and industry heterogeneity in multiple dimensions, such as, e.g., unionization and non-permanent employment, outsourcing of labor services, market concentration and market shares or technology adoption.

We find that most estimates from the regression model in equation (3) are consistent with existing literature: firms with larger share of non-permanent employment and labor outsourcing present lower labor shares (Bloise et al., 2021; Damiani et al., 2020); firms with firm-specific collective bargaining agreements – which we assume having higher rates of unionization – have higher labor shares; firms in more concentrated sectors have lower labor shares (as shown by Autor et al. 2020), and firms with the highest within-industry market shares are those with lowest labor shares.[14] Dummy variables for investment in industrial property and investment in software are not statistically significant. Firm-level labor shares seem to increase with firm size, and with the share of exports in total sales, which is not consistent with Paul and Isaka (2019), nor with Bloise et al. (2021)'s findings regarding lower labor shares among exporters (see the the full version of Table 1 in Appendix B).

From the estimation model expressed in equation (3) we also conclude that more productive firms exhibit lower labor shares. This piece of evidence complies with other studies that analyze firm-level labor share determinants (e.g. Paul and Isaka, 2019; Kehrig and Vincent, 2021; Bloise et al., 2021). The relationship between productivity and labor shares is also

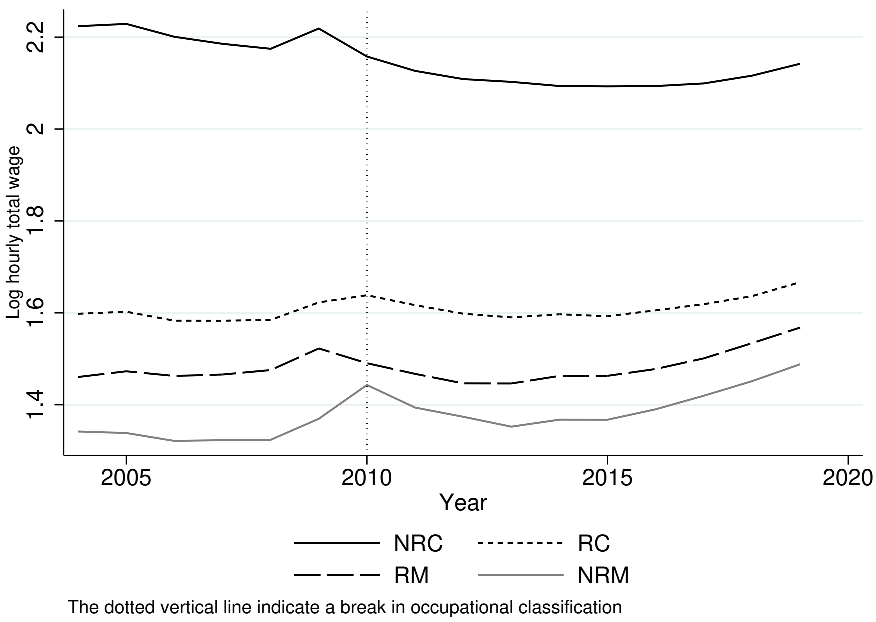
[13]For details on Kehrig and Vincent (2021) model see pages 1058-1059

[14]This result just holds in the regression with both year and industry fixed effects; moreover, the impact of market shares on the labor share is non-monotonic across market share deciles

explored at industry-level in other instances: Autor and Salomons (2018) show that higher total factor productivity has contributed to depress the aggregate labor share across countries; Autor et al. (2020) reveal that industries experiencing higher productivity growth have become more concentrated and, thus, have had the largest decreases in labor share.

In Figure 9, where we exhibit the correlation between relative wages and firm-level labor shares, we also plot the correlation between relative labor labor productivity and firm-level labor shares. Similarly to relative log wages, relative log labor productivity, $\widetilde{\frac{y_{it}}{E_{it}}}$, is given by $\widetilde{\frac{y_{it}}{E_{it}}} = \log \frac{y_{it}}{E_{it}} - \overline{\log \frac{y_{jt}}{E_{jt}}}$ (where $\overline{\log \frac{y_{jt}}{E_{jt}}}$ is the mean log labor productivity across firms j in each year t, excluding their own firm i). Consistently with the results from the full regression in equation (3), the graphic illustration depicts a strong negative correlation between firm-level labor share and relative labor productivity. Comparing the slopes of the fitted lines in both regressions, we conclude that differences in firm-level labor share are mostly determined by differences in relative labor productivity among firms, and not by differences in relative wages.

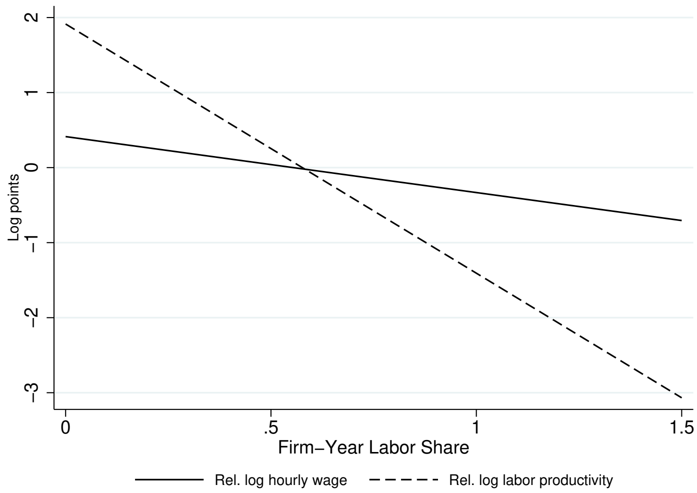
Figure 8 – Log hourly total wages by task group



Sources: *Quadros de Pessoal* and author's calculations. Notes: Log wages are based on total remuneration by regular hours worked. Within task-group means are weighted by the firm-task group-share employment in total task group employment.

The results arising from the regression analysis performed in this section shed light on firms'

Figure 9 – Log hourly total wages by task group



Sources: *Quadros de Pessoal*, *SCIE* and author's calculations. Notes: Relative log wages, $\widetilde{w_{it}}$, are given by the difference between the firm's log hourly wages and the mean log hourly wages paid by all the other firms. Relative log labor productivity, $\widetilde{\frac{y_{it}}{E_{it}}}$, is given by the difference between the firm's value added by hour employed and the mean log labor productivity of all other firms. Each line corresponds to the best-fitted line from a linear regression of log l_{it} on relative log productivity and relative log wage rates, respectively. Observations are weighted by their value added share, γ_{it}

heterogeneity and its impacts on firm-level labor shares. In particular, this exercise shows that, when controlling for firm- and industry-level characteristics, the employment structure by occupational groups is significant to determine the income distribution at the firm level and at a given year. However, it says little about the labor share dynamics, and how much the labor share has varied due to changes of each component of the labor share ratio, which is affected, among others, by the employment occupational composition. To that purpose, in the next section, we perform a detailed shift-share decomposition of the labor share.

5 Decomposition analysis

We implement our decomposition analysis into two steps. First, we decompose the change in the aggregate labor share to measure the role of composition effects *versus* the role of within-firm labor share changes (subsection 5.1). Then, we decompose within-firm changes to assess the role of task group-specific wage rate and employment variations and compare them with the contribution of value-added growth (subsection 5.2).

5.1 Aggregate labor share decomposition

To perform the first level decomposition, we rely on Melitz and Polanec (2015), who proposes a dynamic Olley-Pakes decomposition to account for the contributions of entering and exiting firms in the aggregate labor share dynamics. This approach addresses the problem of composition bias that may arise from the fact that a large portion of Portuguese firms existing in a given year exit the market after a short period.[15] It is then helpful to divide firms into three groups - survivors, entrants, and exiters. The size of these groups varies from sub-period to sub-period.[16] The aggregate labor share is given by equation 2. For the first and last year of the period (t_0 and $t+m$), we can rewrite this equation as a function of the value-added share of each group of firms – survivors (S), entrants (E) and exiters (X) –, and the intra-group labor share, such that:

$$\begin{aligned} L_{t_0} &= \Gamma^S_{t_0} L^S_{t_0} + \Gamma^X_{t_0} L^X_{t_0} = L^S_{t_0} + \Gamma^X_{t_0}\big(L^X_{t_0} - L^S_{t_0}\big) \\ L_{t+m} &= \Gamma^S_{t+m} L^S_{t+m} + \Gamma^E_{t+m} L^E_{t+m} = L^S_{t+m} + \Gamma^E_{t+m}\big(L^E_{t+m} - L^S_{t+m}\big), \end{aligned} \tag{4}$$

where Γ^z_t ($z \in \{S, X, E\}$) represents the value added of firms in group z as a share of total value added in year $t \in t_o, t+m$, such that $\Gamma^z_t = \sum_{i\in z} y^z_{it}/Y_t$, and L^z_t is the weighted average of intra-group firm-specific labor shares, $L^z_t = \sum_{i\in z} \gamma^z_{it} l^z_{it}$. The overall change between $t+m$ and t_0 is given by:

$$\Delta L = \underbrace{\Delta L^S}_{\text{Survivors' contribution}} + \underbrace{\Gamma^E_{t+m}\big(L^E_{t+m} - L^S_{t+m}\big)}_{\text{Entrants' contribution}} - \underbrace{\Gamma^X_{t_0}\big(L^X_{t_0} - L^S_{t_0}\big)}_{\text{Exiters' contribution}}$$

$$\Delta L = \underbrace{\overbrace{\sum_{i\in S} \overline{\gamma^s_i} \Delta l^s_i}^{\text{within-firms}} + \overbrace{\sum_{i\in S} \Delta \gamma^s_i \overline{l^s_i}}^{\text{between-firms}}}_{\text{Survivors' contribution}} + \underbrace{\Gamma^X_{t+m}\left(\sum_{i\in E} \gamma^E_{i,t+m} l^E_{i,t+m} - \sum_{i\in S} \gamma^S_{i,t+m} l^S_{i,t+m}\right)}_{\text{Entrants' contribution}} - \underbrace{\Gamma^X_{t_0}\left(\sum_{i\in X} \gamma^X_{i,t_0} l^X_{i,t_0} - \sum_{i\in S} \gamma^S_{i,t_0} l^S_{i,t_0}\right)}_{\text{Exiters' contribution}} \tag{5}$$

where the index i refers to the firm, and the upper bar indicates time averages.[17] The first term of the shift-share decomposition corresponds to the contribution of *within-firm changes*

[15] According to Eurostat data, only about a third of Portuguese firms born in t-5 are still operating at time t. The EU's average 5-years survival rate is 44%.

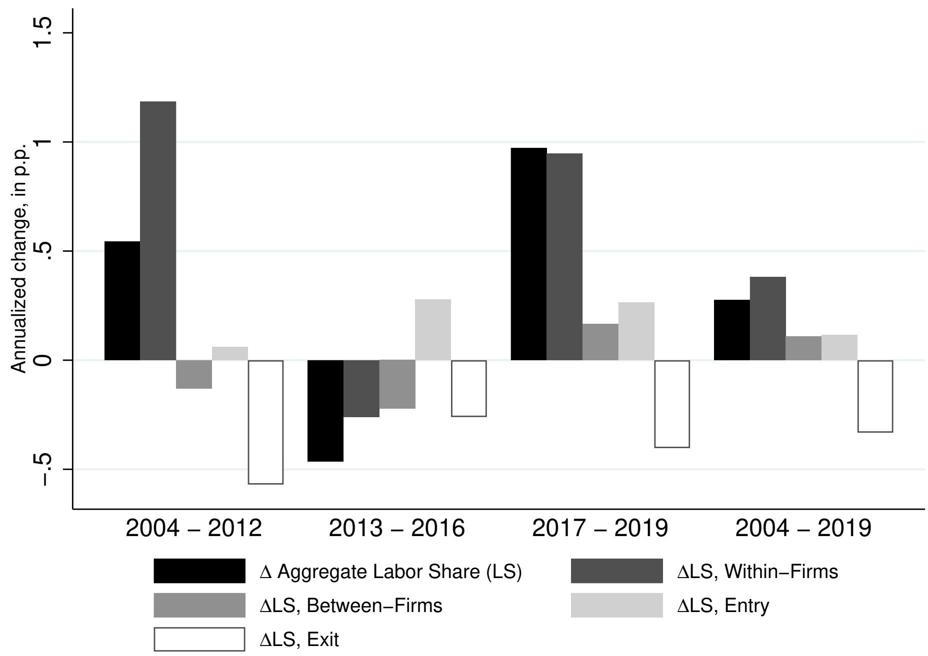
[16] As expected, firms are much more likely to survive during 3 years than 9 years. Between 2004 and 2019 we find the lowest share of surviving firms.

[17] E.g. $\overline{\gamma_i} = \frac{1}{2}\big(\gamma_{i,t_0} + \gamma_{i,t+m}\big)$.

- i.e., changes in firms' "raw" labor shares (as called by Kehrig and Vincent (2021)) - to the aggregate dynamic, keeping the distribution of value-added across firms constant. The second term corresponds to the contribution of *between-firm changes*. It reflects the reallocation of value-added across the labor share distribution. Both within- and between-firms changes arise from continuing firms, which we call survivors for simplicity. The last two terms combine the *net entry* effect in the labor share, weighted by exiters' and entrants' share in total value added at t_0 and $t + m$, respectively.

Given the swinging dynamics of the labor share between 2004 and 2019, we run the decomposition analysis not only for the full 16-year period but also for three well-defined sub-periods, each one corresponding to different segments of the S-shape described in Section 2. Indeed, between 2004 and 2012, the aggregate labor share increased by 4.7 p.p.; between 2013 and 2016, it decreased by 1.9 p.p., and between 2017 and 2019 it bounced back 2.8 p.p.. Figure 10 plots the contribution of *between-firms, within-firms, entry* and *exit* in each sub-period.

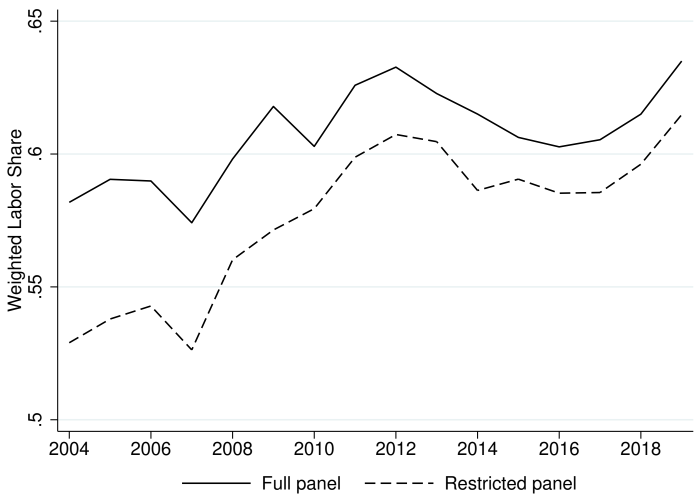
Figure 10 – Decomposition of the aggregate labor share



Sources: *Quadros de Pessoal* and *SCIE*; author's calculations.

The first insight we retrieve from the graph regards the negative impact net entry has on the labor share in most periods (except in the second period, when it has barely any impact). Such negative impact means that closing firms have higher labor shares than entrants. As such, the extensive margin decreases the overall labor share. The contribution of exiters to push down the labor share is consistent with Kyyrä and Maliranta (2008) andAutor et al. (2020)'s findings for Finland and the U.S., respectively. In particular, Autor et al. (2020) estimate a negative contribution from exiting firms of 2.8 p.p. for a period of similar length (1997-2012). The decomposition exercise for Portugal doubles these figures (5.3 p.p. between 2004 and 2019), although the aggregate labor shares move in different directions in Portugal and in the U.S. over this particular period. However, while U.S. entrants also tend to have high labor shares (offsetting the negative impact of exiters) (Autor et al., 2020; Kehrig and Vincent, 2021), Portuguese incomers tend to set their labor costs relatively low (to their output value). As a result, the net entry effect is rather negative. To illustrate the importance of the extensive margin, we compute the aggregate labor share among firms who survive the whole 2004-2019 period and the aggregate labor share based on the total sample. Figure 11 shows that the labor share among surviving firms grew by 8.6 percentage points between 2004 and 2019, while the aggregate labor share increased by much less – 4.4 p.p. –, especially at the beginning of the period.

Figure 11 – Aggregate Labor Share with and without entry/exit



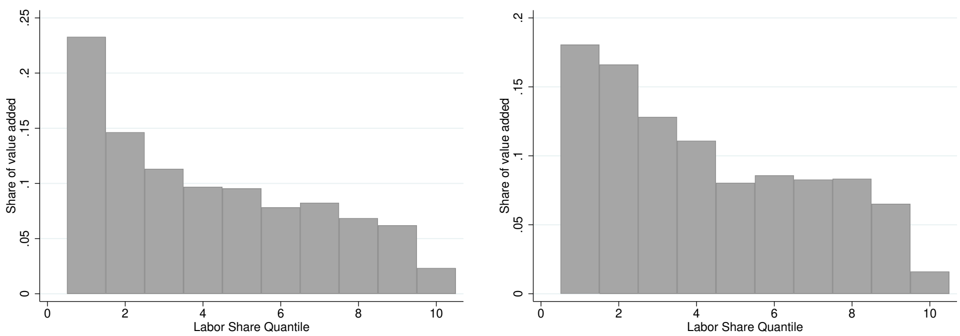
Sources: SCIE; authors' calculations.

The second take-out from Figure 10 concerns the relatively modest contribution of value-added reallocation between survivors. The behavior of the *between-firms* component has been erratic across sub-periods, contributing negatively until 2016, and positively in the last, shortest period. The overall contribution is positive but modest: it explains 1.7 p.p. of the total 4.4 p.p. aggregate labor share's increase between 2004 and 2019.

For a better understanding of how value-added has moved to higher labor share firms, we plot its distribution across labor share deciles at the beginning (Figure 12a) and the end of the period (Figure 12b). To construct this graph, we compute the value-added share by labor share deciles, so that in the first bin we have the cumulative value-added of the 10% lowest labor share firms and in the last bin we have the cumulative value-added share of the 10% highest labor share firms. Looking at Figure 12 we notice that the positive *between-firms*' contribution comes mostly from the value-added reallocation from the first labor share decile towards the second and third deciles. The top half of the labor share distribution remains barely unchanged.

Figure 12 – Value added distribution by labor share quantiles

(a) 2004 **(b)** 2019



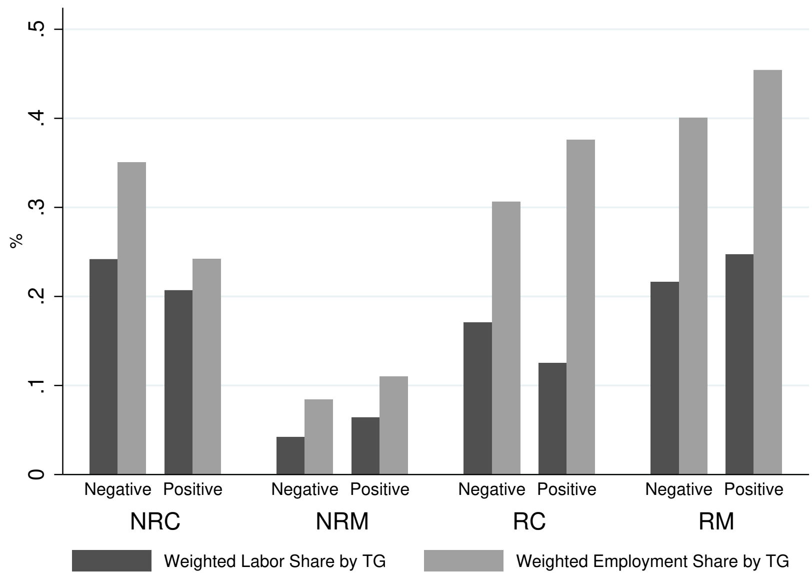
Source: *SCIE database*, autor's calculations.

The relatively low importance of the *between-firm* decomposition component contrasts with what has been found for other countries. Kehrig and Vincent (2021) and Autor et al. (2020) document a “dramatic” reallocation of value-added from the middle of the labor share distribution towards the bottom of the distribution from 1967 and 2012 in the U.S. and Kyyrä and Maliranta (2008) shows that this is the most relevant effect in explaining the fall in the Finnish's labor share.

We can characterize firms that become more relevant in the value-added distribution, both in terms of their employment structure and also in terms of their task group-specific labor shares, as suggested by vom Lehn (2018). To this purpose, we derive the weighted average of employment and labor shares by task group among firms that increased their value-added share on overall output, and among firms which became relatively smaller. Figure 13 reveals that units moving up in the value-added distribution ($\Delta\gamma_{it} > 0$) employ, on average, a smaller share of NRC occupations than firms with $\Delta\gamma_{it} \leq 0$, but employ a larger share of workers in all other task groups. In terms of task group-specific labor shares, Figure 13 also shows that firms with $\Delta\gamma_i > 0$ have, on average, smaller NRC and RC labor shares than firms whose γ_{it} fell.

If firms that, on average, employ fewer NRC workers (which, simultaneously, are those with higher labor shares) drive the positive contribution of between-firms, then we can conclude that NRC-intensive firms have become less productive (relatively to firms that employ more of other task groups).

Figure 13 – Employment and labor shares by task group



Sources: SCIE; authors' calculations. Note: Task group-specific labor shares and employment shares are averaged over 2004-2019, so that the firm's value added weight is the only variable allowed to change. Both variables are weighted by the firm's value added share in 2004. "*Negative*" stands for $\Delta\gamma_i \leq 0$ and "*Positive*" for $\Delta\gamma_i > 0$

Comparing with other studies performing similar decomposition exercises, a major difference stands out: within-firm labor share variations play a much bigger role than in other countries, even when we account for composition differences between datasets.[18] In sum, from Figure

[18]When we restrict our panel to firms with more than 20 employees to match Kyyrä and Maliranta (2008), to 50 employees to match Bloise et al. (2021), or to manufacturing firms only to match Kehrig and Vincent (2021),

10, we observe that the change in survivors' unweighted average labor share is actually the main driver of aggregate labor share growth in all sub-periods we consider in our analysis.

5.2 Firm-level labor share decomposition

Thanks to the richness of our datasets, we can go further in the decomposition analysis and infer about the relative importance of each of the four forces that compose the firm-level labor share: (1) task group-specific wage rate (w_{jit}), (2) employment shares by task group (λ_{jit}), (3) employment level (E_{it}) and (4) value-added level (y_{it}). To that purpose, we rewrite firm-level labor share as

$$l_{it} = \frac{\sum_j^4 w_{jit}\lambda_{jit}E_{it}}{y_{it}}, \tag{6}$$

where $j \in \{\text{NRC, RC, RM, NRM}\}$. The shift-share analysis of the within-firms component is then given by:

$$\Delta l_i = \underbrace{\sum_{j=1}^{4} \Delta w_{ji} \frac{\overline{\lambda_{ji}}\,\overline{E_i}}{\overline{y_i}}}_{\text{WF, within-task groups}} + \underbrace{\sum_{j=1}^{4} \Delta \lambda_{ji} \frac{\overline{w_{ji}}\,\overline{E_i}}{\overline{y_i}}}_{\text{WF, between-task groups}} + \underbrace{\sum_{j=1}^{4} \Delta E_i \frac{\overline{w_{ji}}\,\overline{\lambda_{ji}}}{\overline{y_i}}}_{\text{WF, employment level}} - \underbrace{\overline{l_{it}} \frac{\Delta y_i}{\overline{y_i}}}_{\text{WF, distribution}} \tag{7}$$

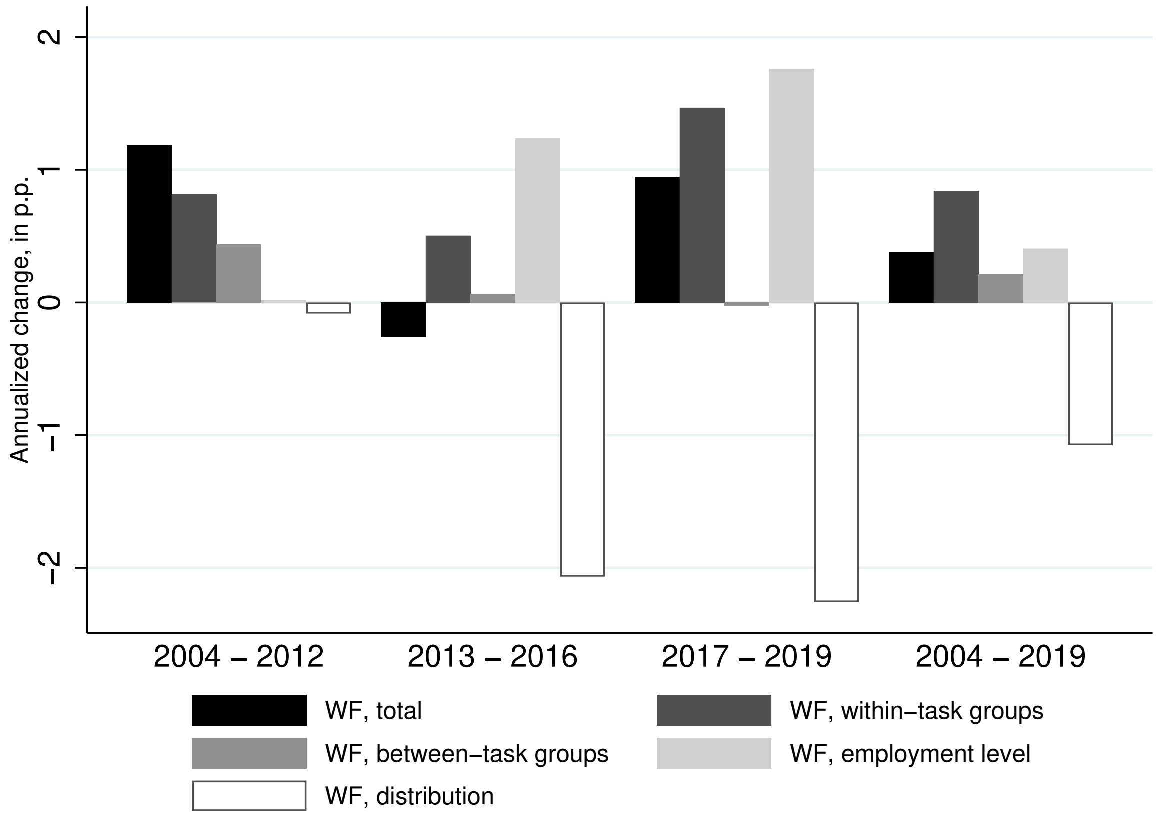
To keep the notation light, we omit the superscript S that indexes surviving firms. The mechanics of how each term acts upon the firm's labor share, everything else constant, are the following:

- *WF, within-occupations:* l_i increases if the wage rate in all occupations increase, decreases if the wage rate in all occupations decrease, and may increase or decrease if wage rates vary in opposite directions across occupations;
- *WF, between-occupations:* l_i increases if the firm's employment structure shifts towards better-paying task groups (e.g. from RC to NRC), and decreases if the firm shift its employment to lower-paying occupations;
- *WF, employment level:* l_i increases if the employment level increases, and decreases otherwise;
- *WF, distribution:* l_i increases if the firm's value added drops, and decreases otherwise.

Figure 14 plots the contribution of each component of the within-firm decomposition, in each one of the three sub-periods and in the full 2004-2019 period.

the role of within-firm changes still offsets the role of between-firm changes.

Figure 14 – Decomposition of within-firm changes in firm-level labor share



Sources: *SCIE* and *Quadros de Pessoal*, author's calculations.

Changes in wages - *within-firms, within-task groups* - have always operated in workers' favor. Its positive impact on the labor share was especially strong in the most recent years and more modest between 2013 and 2016, when the economic crisis was still impacting wage growth. To illustrate wage growth heterogeneity between task groups, we plot the contribution of each task group to the overall *within-firms, within-task groups* (WF-WTG) effect, such that WF-WTG$_j$ $= \sum_{i=1} \gamma_i (\Delta w_{ji} \overline{\lambda_{ji} E_i} / \overline{y_i})$ (Figure 15). WF-WTG$_j$ reflects not only the wage rate increase between 2004 and 2019, but also the volume of employment in each occupation. Routine occupations, both cognitive and manual, are the largest contributors to the overall effect - since, on average, they represent a larger share of total employment. We notice, however, that NRM occupations had the highest wage growth rates in all sub-periods, closely followed by RM occupations (Figure 16). As shown before, workers in these two task groups earn the lowest wages, and a large share of workers employed in manual occupations earn the minimum wage, which has been increasing the overall mean.[19]

Figure 15 – Task group contribution to WF-WTG, 2004-2019

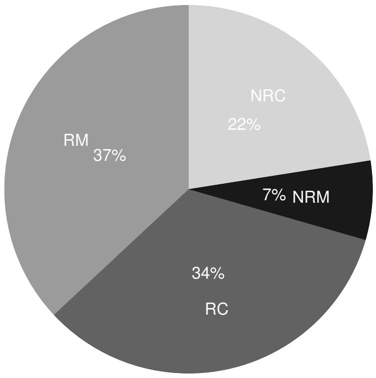
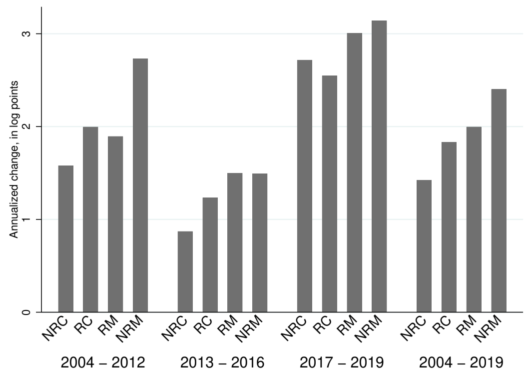


Figure 16 – Mean log hourly wage growth by task group



Sources: *SCIE* and *Quadros de Pessoal*, author's calculations. Notes, left figure: The contribution of each task group is given by the share of $(\Delta w_{ji}\overline{\lambda_{ji}E_i})/\overline{y_i}$, weighted by the mean of each firm's value added on total value added, $\overline{\gamma_i}$, $j \in \{\text{NRC, RC, RM, NRM}\}$, on the WF-WTG effect. Notes, right figure: Log hourly wages are in nominal terms, and only surviving firms are considered. The mean log hourly wage growth is weighted by the firm-, task group-employment share in task group-employment at t_0.

Despite the large number of papers documenting the impact of task-replacing technologies on the labor market (see, e.g., (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018; Downey, 2021; Humlum, 2019; Bessen et al., 2019), its specific effect on wages is unclear, and the results depend on the methodology adopted and the country under analysis. Graetz and Michaels (2018) find that robots adoption has positive effects on wages, based on industry data for 17 countries, and Dinlersoz and Wolf (2018) show that automated U.S. establishments pay higher wages than their competitors. Heterogenous wage outcomes among workers in different occupations are described by Dauth et al. (2019), Humlum (2019), and Böhm (2020).[20] Acemoglu and Restrepo (2020), on the other hand, estimate that the increase in the stock of robots has decreased wages in local U.S. labor markets.

[19]The minimum wage increased, on average, 3.4% each year between 2004 and 2019, while mean total wages increased by 2.4% in the same period. Between 2004 and 2019, the share of RM and NRM workers paid the minimum wage has increased from 0.8% and 0.7%, respectively, to 44.5% and 45.4%, respectively.

[20]Böhm (2020) describes a polarization effect in wages in the U.S., with wages paid to abstract and manual non-routine tasks rising and wages paid to routine tasks falling. Dauth et al. (2019) also shows differentiated wage outcomes among German workers, especially between those who stay in plants that automate and those who are displaced. Finally, Humlum (2019) documents an increase in average wages in Denmark, but a fall in workers' wages employed in manufacturing.

Cortes et al. (2020) show that task groups account for about a substantial proportion of wage variation, after controlling for other individual characteristics. In the presente paper, we have also shown that task groups are paid differently (Figure 8). However, we have not yet determined whether firms' adoption of task-replacing technologies affects the wages they pay. To that purpose, we look at firms' investment in industrial property and software.[21] Industrial property includes firms' investment in patents, while investment in software partially reflects ICT investment.[22] We take these variables as measures of technology adoption, although they come with limitations. First, these two types of investment are highly concentrated in firms with high value-added: 46% and 48% of these investments, respectively, are performed by firms in the last decile of the value-added distribution. Figure 21, in Appendix B illustrates the skewness in both distributions. Most firms report null investment in industrial property or software (only 6.1% and 28.7% of the firms reported positive average expenses between 2010 and 2019 in each type of investment, respectively). Second, by definition, investment in software excludes expenses in hardware and software when acquired together with the respective hardware, ignoring what may be an important fraction of ICT investment. Third, the SCIE database only informs about investment in industrial property and software from 2010 onwards.

To overcome some of these limitations, we restrict the estimation of the impact of investment in industrial property and software on individual wages to firms that reported positive investment at least once in the period 2010-2019. We estimate two models:

$$\ln\, w_{kt} = \sum_{\tau=1}^{3} \Phi_\tau \ln\, X_{i,t-\tau+1} + \sum_{\tau=1}^{3} \Psi_\tau \ln\, X_{i,t-\tau+1} \times \text{Routine}_{\,kt} + \epsilon_{kt}, \tag{8}$$

where X is either investment in industrial property or investment in software. k indexes individual workers at time t, i indexes firms, and τ indexes the number of time lags (up to three). *Routine* is a dummy variable that takes the value 1 if the worker is employed in RM and RC occupations and 0 otherwise. To address firms' heterogeneity, namely in terms of size, productivity, industry, and other firm-specific characteristics, we include firm fixed effects, together with year fixed effects. Table 2 displays the estimates for both models and

[21] According to Portuguese accounting rules, "industrial property" includes investment in patents, copyrighting, etc. (Carvalho et al., 2010). Software investment includes software purchased without any physical part (hardware).

[22] OECD defines ICT as "the acquisition of equipment and computer software (...). ICT has three components: information technology equipment; communications equipment; and software".

shows that (1) routine workers employed in firms that invest more in patents or copywriting have wages 0.9 to 1.6% lower than non-routine co-workers, (2) routine workers employed in firms that invest more in software have wages 0.8 to 1.3% lower than their non-routine co-workers, (3) firms that invest more in each technology pay higher wages (regardless of the worker's occupation), and (4) past investments impact contemporaneous wages, but while the effect of software adoption on wages disperses as the number of lags increases, the effect of patent adoption becomes stronger. These estimates suggest that technology-related investments have an overall positive impact on log wages, but their gains are disproportionally distributed between routine and non-routine workers.

Table 2 – Log hourly total wages

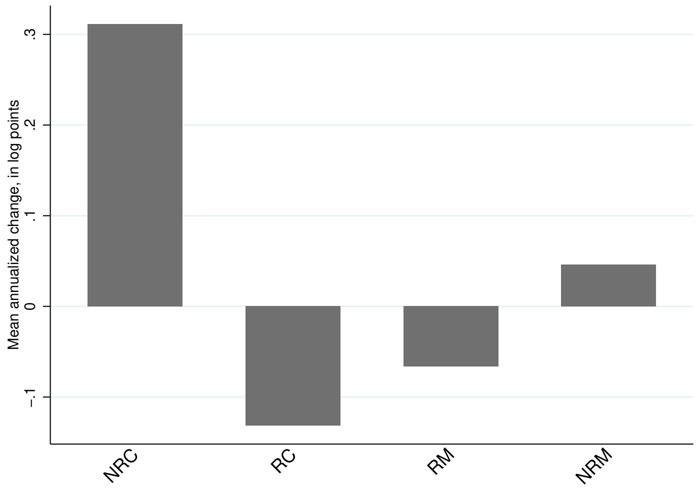
	ln w_{kt} X = Ind. Property	ln w_{kt} X = Software
Ln Investment X_t	0.009***	0.008***
	(0.000)	(0.000)
Ln Investment X_{t-1}	0.006***	0.007***
	(0.000)	(0.000)
Ln Investment X_{t-2}	0.008***	0.007***
	(0.000)	(0.000)
Ln Investment X_{t-3}	0.011***	0.005***
	(0.000)	(0.000)
Routine × Ln Investment X_t	-0.013***	-0.013***
	(0.000)	(0.000)
Routine × Ln Investment X_{t-1}	-0.009***	-0.011***
	(0.000)	(0.000)
Routine × Ln Investment X_{t-2}	-0.010***	-0.009***
	(0.000)	(0.000)
Routine × Ln Investment X_{t-3}	-0.016***	-0.008***
	(0.000)	(0.000)
Firm FE	Yes	Yes
Year FE	Yes	Yes
Observations	2 471 721	2 471 721
R2	0.463	0.518

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We now return to the within-firm decomposition (Figure 14) to look at the role of *between-task groups* dynamics, i.e., changes in surviving firms' employment shares by task groups. Its contribution is considerably more modest than the *within-task group*'s - 0.002 p.p. per year, on average - and most of the long-difference effect comes from the first sub-period (2004-

2012).[23] This result is not unexpected, considering the stabilization of the employment shares by task group already identified in the previous section (and displayed in Figure 5). Having explored the mechanism through which changes in the firms' employment structure may affect labor shares, we aim to assess whether these changes, despite small, are aligned with the literature on the impact of technology adoption in routine tasks.[24] In Figure 17 we plot the employment share change by task group (averaged across firms, and weighted by each firm's share on occupation employment in 2004). The graph suggests that, first, job polarization is a phenomenon that occurs in continuing firms and not (only) at the margins, i.e., entrants do not employ disproportionally more non-routine occupations, nor exiters employ disproportionally more routine workers in relation to survivors.[25] Second, it suggests that the positive contribution of the *within-firms, between-task groups* effect over 2004-2019 relies on the substancial increase in the share of NRC occupations among surviving firms. Since this is the highest-paying task group then, everything else equal, job polarization has positively contributed to rising surviving firms' labor shares.

Figure 17 – Average annualized changes in employment shares among surviving firms



Sources: *SCIE*, *Quadros de Pessoal*, and author's calculations.

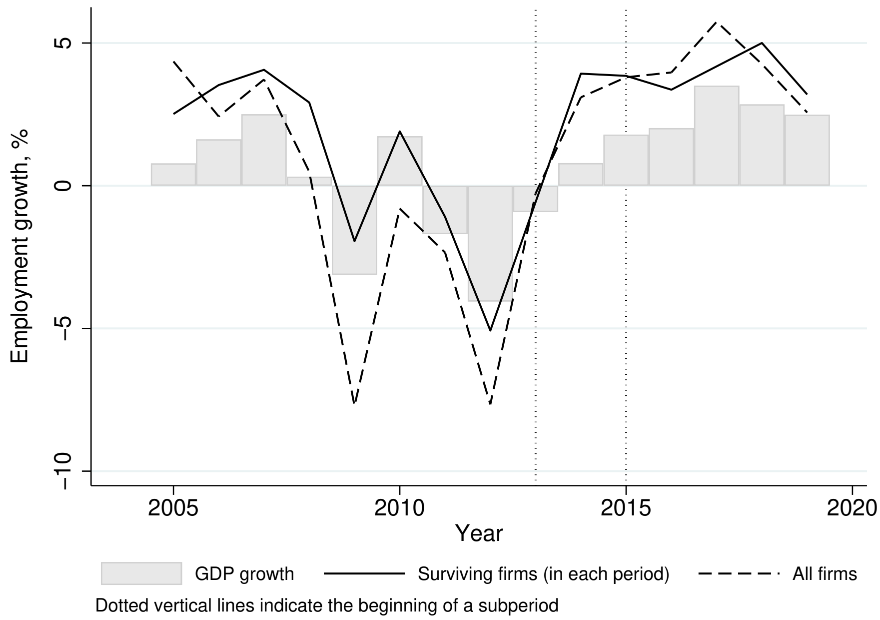
[23]To account for the revision in occupations' classification, which happened in 2010, we compute the between-occupations contribution defining different sub-periods - 2004-2009 and 2010-2016. We notice that the average annualized change between 2004 and 2016 decreases by half, which means that the classification break partially explains why this effect is much larger in the sub-period 2004-2012 than in the remaining periods.

[24]Dauth et al. (2019) and Humlum (2019) show that robot-adopting firms reduce employment in routine tasks, but increase it in tasks with higher abstract content.

[25]Replicating the same graph for different periods give the same polarization effect, although less pronounced.

The *within-firm, employment level* component from equation 7 reflects the variations in the number of employees among survivors, keeping wages, occupational shares, and value-added unchanged. Changes in surviving firms' employment levels in each sub-period seem to respond closely to business cycles, but in periods of economic recession, a considerable part of job losses are driven by the extensive margin (i.e., job losses from exiting firms are greater than job created by new firms). Figure 18 plots the employment growth rate, considering both within-sub-periods balanced and full panels, and the GDP growth rate.

Figure 18 – Employment growth rate and GDP growth



Sources: Employment growth - *Quadros de Pessoal* and author's calculations; GDP growth - World Bank Data. Note: The solid line series considers only firms that operate the full sub-period 2004-2012, 2013-2016, 2017-2019 (firms included in this series may, or may not, endure the full 16-year period). For the dashed line series, we compute the employment growth rate based on the full panel, i.e., we include survivors and firms that exit/entry between 2004 and 2019. Both series use changes in hours worked.

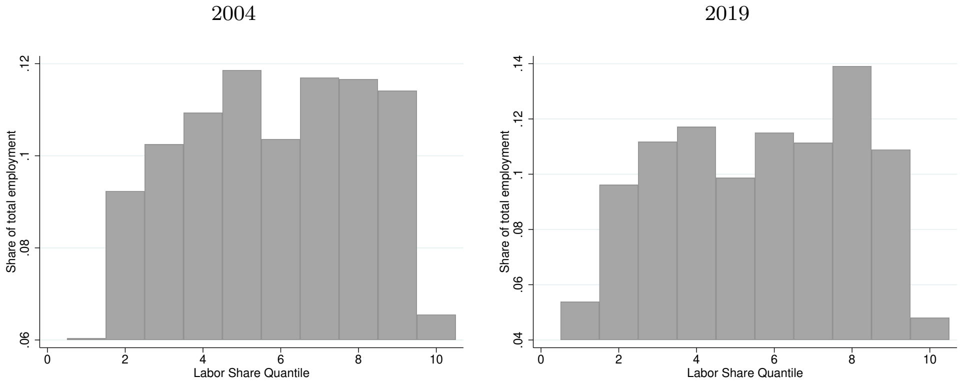
Besides other non-technological related reasons able to explain micro-level employment dynamics, such as industry-specific non-technological trends or firm-specific shocks, a strand of literature has studied the impact of technology adoption on employment, both at the industry and firm level. As for the effect of technology on wages, the empirical evidence in the literature has reached multiple results, depending on the type of technology and the level of analysis. At the industry level, several contributions show that even when automation displaces workers in a particular industry, there are positive productivity spillovers to other industries that may push the aggregate employment level up (Autor and Salomons, 2018; Aghion et al., ming; Dauth et al., 2019). In contrast, evidence for France and the U.S. shows that, when a firm automates, its competitors face job losses, causing a decline in employment in the industry they belong to (Acemoglu and Restrepo, 2020; Acemoglu et al., 2020). Other authors argue that the use of robots benefits only a group of workers (e.g., high-skilled workers or workers performing non-routine tasks) while displacing others, but find no effect on aggregate employment (Graetz and Michaels, 2018; Dauth et al., 2019; Humlum, 2019). Last but not least, studies using firm-level data report positive impacts from automation on firm-level employment: Acemoglu et al. (2020) show that French manufacturing firms adopting robots increase employment by 10.9%, and Koch et al. (2021) find that their counterparts increase employment by the same percentage.

It is not in the scope of this paper to assess whether an automation event drives changes in the employment level since our data does not allow us to identify spikes in technology adoption (identification strategy suggested by Bessen et al. (2019) and Humlum (2019)). However, by looking at the distribution of employment across the labor share distribution at the beginning and end of the period, we conclude that the employment reallocation towards firms with higher labor shares was meager. Figure 19 displays the survivors' employment share by labor share deciles and shows that the distribution is similar in both years - the cumulative employment share up to the 7th decile is exactly 70.4% in 2004 and 2019, but there is a slightly higher concentration in the 8th decile, in 2019. The figure also shows that Portuguese employment is dispersed across the labor share distribution, similarly to what Kehrig and Vincent (2021) found for the U.S. in 2012.

The last *within-firm* component of the labor share decomposition among survivors translates changes in firms' value-added. Since the final panel includes negative value-added observations, theoretically the *distribution* effect could positively contribute to the firm's labor share in some firms. Since in most cases they report positive value-added, such effect counterbalances the growth in total labor costs in most of the periods for which we run the decomposition analysis.

Kehrig and Vincent (2021) focus on firms at the bottom of the labor share distribution and show that these firms were those performing better in terms of value-added growth (increasing their relative importance in total value-added and, thus, causing the fall in U.S. aggregate labor share). The evidence found for U.S.'s manufacturing labor shares suggests

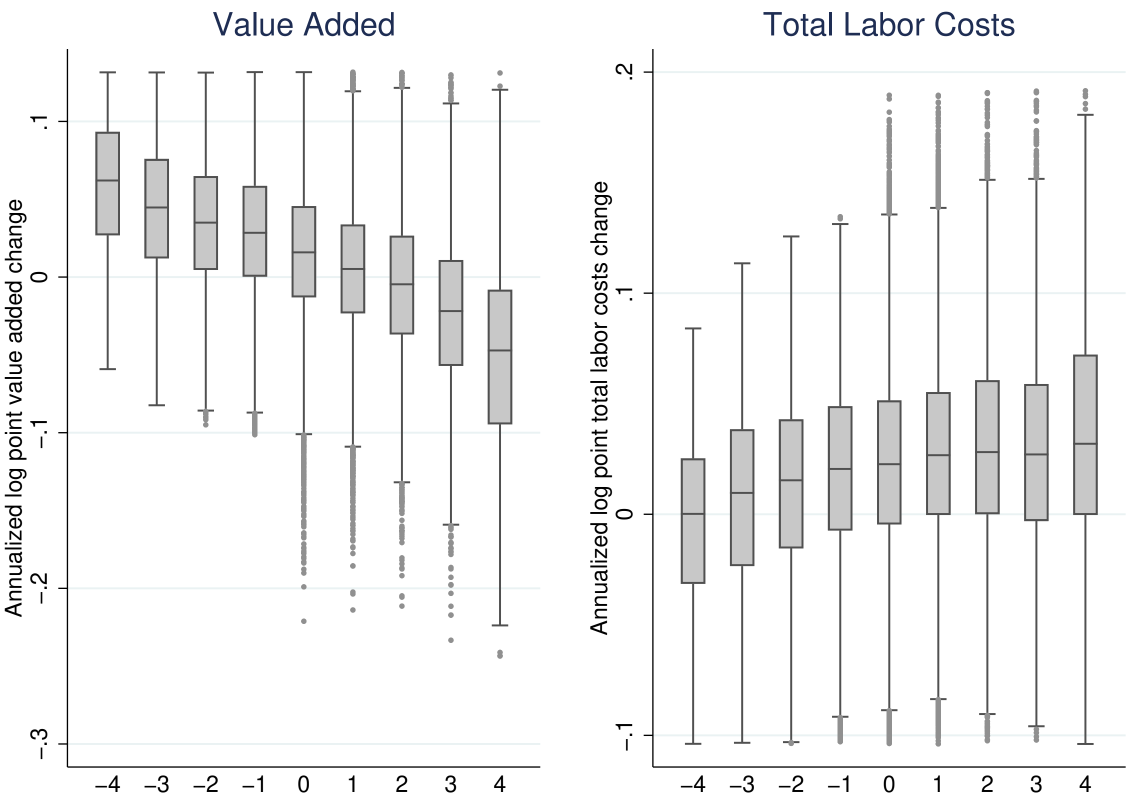
Figure 19 – Employment distribution by labor share deciles



Source: *SCIE* database, autor's calculations. As in Kehrig and Vincent (2021), Figure III, we sum the firms' employment shares by labor share decile. We only consider firms that operate the full 2004-2019 period. The 1st decile hosts firms with the lowest labor shares, and the 10th decile firms with the highest labor shares.

that, at a given year, low labor share firms reported strong value-added growth the previous period, so as in the period immediately after, and wage and employment adjustments were comparatively small. The evidence we find for Portugal suggests that, when we consider all firms and the full 2004-2019 period, employment and, especially, wages adjust enough to offset the negative impact of value-added growth on the labor share, leading the latter to grow. Nonetheless, we find heterogeneity among firms in different segments of the labor share distribution. To fully grasp which effect – changes in value-added or changes in total labor costs – influences firms' movements over the labor share distribution the most, we split surviving firms by quintiles of the labor share distribution in 2004 and 2009, and then by the number of quintiles they moved up or down in the labor share distribution ($\text{shift}_i = lq_i^{2019} - lq_i^{2004}$). As an example, a firm that was initially in the 4th quintile and, in 2019, is found to be in the 3rd quintile assumes the position -1 along the x-axis in Figure 20. In the left graph, we plot the changes in value-added (in annualized log points) between 2004 and 2019 for firms in each position. In the figure from the right, we plot the annualized log point changes in total labor costs. It is clear that, on average, firms that move up the labor share distribution have registered lower (or negative) value-added growth rates, and firms that move down the distribution have, on average, sharper value-added growth rates. At the same time, most firms have increased their total labor costs, regardless of how many quintiles they move up or down in the labor share distributions (e.g., at least 50% of the firms that have jumped from the highest quintile to the 1st quintile registered positive total labor costs growth rates). As *within-firm* effects contribute positively to the increase of the aggregate labor share, one must expect that a larger aggregate value-added share is concentrated in firms whose value-added grew by less than their labor costs. To confirm that expectation, in Table 3 we display the value-added growth and the total labor costs weighted means by the number of shifts, and the value-added share of firms in each bin. We conclude that 77.5% of the total value-added among survivors is concentrated in firms whose labor costs grew by more than their value-added, which explains the overall positive *within-firms* effect.

Figure 20 – Value-added and total labor costs changes and firm reallocation along the labor share distribution between 2004 and 2019



Sources: *SCIE*; author's calculations. Notes: For firms in each shift $\in [-4, 4]$ we compute their value-added growth and total labor costs growth. Both measures are in annualized log points, and are unweighted.

6 Conclusion

In this paper we investigate the labor share dynamics at the firm level and, in particular, the role of occupational employment changes and occupational wage changes in those dynamics. We apply a 2-step shift-share analysis: first, we decompose the aggregate labor share and,

Table 3 – Share of value added, value-added growth and total labor costs growth by quintiles variation

$l_q^{2019} - l_q^{2004}$	Value-added share	Value-added growth	Total labor costs growth
-4	0.008	0.057	-0.006
-3	0.024	0.029	-0.003
-2	0.055	0.027	0.007
-1	0.137	0.023	0.014
0	0.474	-0.001	0.011
1	0.165	-0.002	0.024
2	0.073	-0.020	0.020
3	0.049	-0.071	-0.009
4	0.014	-0.083	0.008

Notes: For each shift $\in [-4, 4]$ we compute (1) the share of value added on total value added among survivors, (2) the weighted mean of the value-added growth and (3) the weighted mean of total labor costs growth (as weights we use the share of value added among survivors in 2004). Both (2) and (3) are in annualized log points.

second, we decompose firm-specific labor shares. Using firm-level Portuguese data that provides detailed information on employees' occupations, we conclude that the S-shaped dynamic of the aggregate labor share between 2004 and 2019 is mostly driven by changes in firms' labor share – the *within-firm* component – rather than by value-added reallocation towards higher labor share firms. More specifically, our findings suggest that firm-specific labor shares have been rising due to positive growth in occupational wage rates, which have been especially strong in Routine Manual and Non-Routine Manual occupations. Although Portugal has been following a job polarization pattern in the long term, employment shares by task groups have stalled from 2010 onwards. Therefore, the impact of changes in task group employment shares has been limited in the past decade. Last but not least, we show that changes in total labor costs are more persistent than changes in firms' value-added, which has contributed positively to the overall increase in the aggregate labor share.

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Appendix A - Occupational groups and job titles cross-walk

Table A.1 – Mapping of detailed occupation codes to broad task groups

Broad Occupation	**Occupation Classification Coding**	
	1995 - 2009	**2010-2017**
Non-Routine Cognitive	211 - 221, 312, 313, 321, 112 - 131, 222 - 311, 314, 315, 322 - 339, 345, 347, 515	111 - 132, 134, 141, 143, 221 - 243, 261 - 265, 312, 313, 315 - 332, 333, 335 - 343, 133, 142, 211 - 216, 251, 252, 311, 314, 331, 351
Routine Cognitive	341 - 344, 411 - 512, 514, 521 - 523	334, 352, 411 - 441, 511, 521 - 524
Routine Manual	711 - 745, 811 - 834, 916 - 933	711 - 754, 811 - 835, 911 - 933, 961
Non-Routine Manual	516, 911 - 915	512 - 516, 941 - 952, 962

Appendix B - Estimation results from Section 3

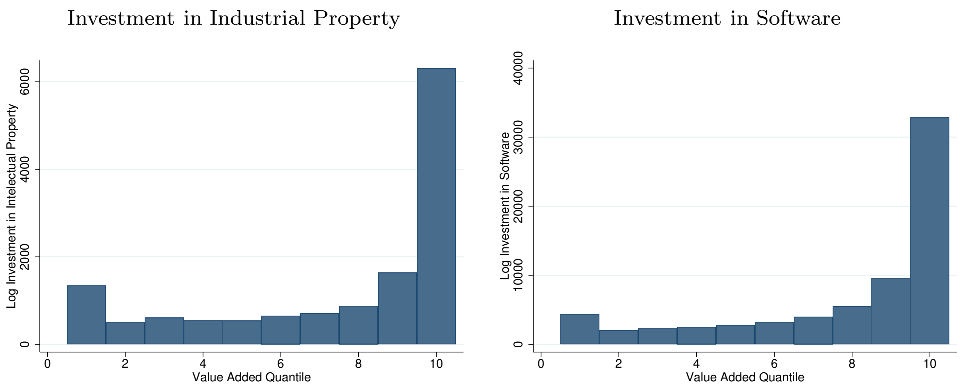
Table B.1 – Table of results from the log labor share regression (equation (3))

	(1) Log labor share	(2) Log labor share
Firm size, productivity and export share		
Log Firm Employment	0.039***	0.059***
	(0.004)	(0.004)
3-y Mean Log productivity	-0.690***	-0.644***
	(0.009)	(0.010)
Share of Exports on Total Sales	0.176***	0.137***
	(0.016)	(0.014)
Investment in technology		
Dummy for industrial property investment	-0.040	0.009
	(0.031)	(0.029)
Dummy for software investment 1 lag	-0.029	-0.010
	(0.028)	(0.029)
Dummy for software investment 2 lags	-0.037	-0.027
	(0.029)	(0.028)

	(1) Log labor share	(2) Log labor share
Dummy for software investment	0.021	0.011
	(0.013)	(0.010)
Dummy for software investment 1 lag	0.005	0.001
	(0.011)	(0.009)
Dummy for software investment 2 lags	0.006	0.005
	(0.012)	(0.009)
Employment composition by task groups		
Share of Routine Cognitive Hours Worked	-0.453***	-0.390***
	(0.017)	(0.017)
Share of Routine Manual Hours Worked	-0.597***	-0.402***
	(0.016)	(0.020)
Share of Non-routine Manual Hours Worked	-0.643***	-0.435***
	(0.016)	(0.018)
Labor relations		
Share of Outsourced Services on Total Expenses	-0.324***	-0.411***
	(0.057)	(0.061)
Share of Non-Permanent workers	-0.069***	-0.136***
	(0.017)	(0.012)
Dummy for Multi-firm Agreement Predominance	-0.330***	-0.043
	(0.062)	(0.064)
Dummy for Industry-level Agreement Predominance	-0.182***	-0.133***
	(0.040)	(0.035)
Dummy for Extension ordinance Predominance	-0.160***	-0.159***
	(0.043)	(0.037)
Dummy for No Agreement Predominance	-0.201***	-0.150***
	(0.043)	(0.038)
Industry concentration and market share		
Herfindahl index 5 digits industry	-0.091	-0.174***
	(0.048)	(0.045)
Decile of sales share, 5dig=2	-0.497***	-0.296**
	(0.115)	(0.095)
Decile of sales share, 5dig=3	-0.402***	-0.248***
	(0.061)	(0.048)
Decile of sales share, 5dig=4	-0.375***	-0.221***
	(0.061)	(0.048)
Decile of sales share, 5dig=5	-0.419***	-0.281***
	(0.068)	(0.057)
Decile of sales share, 5dig=6	-0.366***	-0.242***
	(0.060)	(0.048)
Decile of sales share, 5dig=7	-0.374***	-0.262***
	(0.061)	(0.049)
Decile of sales share, 5dig=8	-0.380***	-0.281***
	(0.060)	(0.048)
Decile of sales share, 5dig=9	-0.378***	-0.288***
	(0.061)	(0.048)
Decile of sales share, 5dig=10	-0.351***	-0.322***
	(0.061)	(0.048)
Constant	2.316***	1.914***
	(0.084)	(0.076)
Year	Yes	Yes
Industry	No	Yes
Observations	1.34e+06	1.34e+06
R2	0.786	0.820

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 21 – Investment in Industrial property and in software by value added deciles in 2019



Sources: SCIE; authors' calculations. Note: To build both graphs, we first ranked the value added data, split it into 10 equally large bins, and then computed the sum of log investment of each type by bin.