Aging Workforces and Technological Change:

Insights from Portugal's Labor Market

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Abstract

Title: Aging Workforces and Technological Change:. Insights from Portugal's Labor Market
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The shift in the structure of the labor force is affecting workers' productivity and firms' decisions. Can technology postpone the tipping point, avoiding an early downward inflection of productivity? This thesis examines the relationship between aging workforces, technological intensity, and productivity. It extends traditional analyses of productivity and aging by incorporating the dimension of technology intensity, providing a more granular understanding of how these elements interact across different sectors and age groups, with a focus on effects within firms. Using detailed firm-worker-technology data , it finds that in high technology-intensive firms, productivity increases with age, while in low-intensity firms, the age-productivity profile is flatter. It also finds that ICT training can have a role. These findings are particularly policy-relevant, suggesting that policy actions focused on training and technology can postpone the tipping point. While wage-setting norms may imply that wages continue to increase with age, worker productivity may not. However, technology and training can delay this tipping point, avoiding an early decline in productivity.

Resumo

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A mudança na estrutura da força de trabalho está a afectar a produtividade dos trabalhadores e as decisões das empresas. Poderá a tecnologia adiar o ponto de viragem, evitando uma inflexão descendente precoce da produtividade? Esta tese examina a relação entre o envelhecimento da força de trabalho, a intensidade tecnológica e a produtividade. Alarga as análises tradicionais da produtividade e do envelhecimento, incorporando a dimensão da intensidade tecnológica, proporcionando uma compreensão mais granular de como estes elementos interagem entre diferentes sectores e grupos etários, com foco nos efeitos dentro das empresas. Utilizando dados detalhados da empresa-trabalhador-tecnologia, conclui-se que nas empresas com elevada intensidade tecnológica, a produtividade aumenta com a idade, enquanto nas empresas de baixa intensidade, o perfil idade-produtividade é mais uniforme. Também considera que a formação profissional pode estar associada a aumentos do retorno da idade na produtividade. Estas conclusões são particularmente relevantes em termos de políticas públicas, sugerindo que as ações políticas centradas na formação e na tecnologia podem adiar o ponto de viragem. Embora as normas de fixação de salários possam implicar que os salários continuem a aumentar com a idade, a produtividade dos trabalhadores poderá não o fazer. No entanto, a tecnologia e a formação podem atrasar este ponto de viragem, evitando um declínio precoce da produtividade.

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1 Introduction

In recent decades, the increasing share of older individuals in the population has become a notable trend, driven by low fertility rates and higher life expectancy. This demographic transition is accelerating and significantly impacting the labor force composition, posing a challenge for many developed countries. As more older adults remain in the workforce, questions arise about the productivity of these workers compared to their younger counterparts. This shift in the structure of the labor force affects workers productivity, which in turn affects firms' decisions. A substantial body of literature examines wage-age profiles and productivity-age profiles. As workers age, there is an increasing mismatch between their productivity and earning profiles. After reaching a certain age - the tipping point - a negative or positive Wage-Productivity Gap might emerge. Addressing this gap is not straightforward, raising important questions about potential solutions.

This thesis examines the relationship between aging workforce, technological intensity, and productivity. Previous studies have focused either on the impact of technology on general workforce productivity or the implications of an aging workforce, without integrating the effects of rapid technological changes. By examining how technology intensity affects older workers, this thesis fills a critical gap. It extends traditional analyses of productivity and aging by incorporating the dimension of technology intensity, providing a more granular understanding of how these elements interact across different sectors and age groups, with a focus on effects within firms. While previous studies have acknowledged that productivity varies with age, they do not examine how these differences translate into earnings. By addressing how age-related changes in productivity correlate with earnings within technologically intense environments, this thesis highlights the potential of technology to alter the aging tipping point.

This is an interesting research question because the response is not straightforward. Aging significantly impacts worker-level productivity through various mechanisms. On one hand, aging can enhance productivity through accumulated experience and expertise (Levhari (1973), (**?**), Caplin et al. (2022)). On the other hand, aging can lead to declines in productivity due to physical and cognitive deterioration and skill obsolescence (Skirbekk (2008), Dinerstein, Megalokonomou, and Yannelis (2022), Aghion et al. (2022)). The net effect on productivity depends on various factors, including the adoption of technology and the specific skills in demand. Technology may alter the types of tasks required, and new tasks might demand different sets of skills and capabilities, causing the age-productivity profile to vary widely (Autor, Levy, and Murnane (2003)). Additionally, rapidly aging societies may have stronger incentives to adopt technology and automation due to the relative scarcity of middle-aged workers, which can potentially offset the negative effects of aging on productivity (Acemoglu and Restrepo (2022)).

Theoretically, in a perfectly competitive labor market, compensation is determined solely by productivity, so firms lack incentives to create a pay-productivity gap based on age. However, in imperfect labor markets, pay-productivity gaps can arise at different ages. This phenomenon can be explained by several models. Lazear (1979) discusses incentive-compatible models, while Becker (1964) focuses on human capital models. Imperfect labor-market models, including collective bargaining (Kuhn and Robert (1989)), and worker preferences (Neumark (1995)), also contribute to these gaps. Theoretically, there are various channels through which these gaps manifest. Young workers may accept low-paying jobs to be matched with high-productivity firms, a process known as sorting. Labor market rigidities, such as increased firing costs with tenure, also play a role. Additionally, firm-specific pay and retention policies, which anchor wages to aggregate productivity, can create and sustain these pay-productivity gaps.

Empirically, wage-productivity gaps related to age are challenging to estimate due to the need for comprehensive data and methodological complexities. Evidence on these gaps is mixed. Some studies find no significant wage-productivity gaps (Aubert and Crépon (2003), Dostie (2011), and Ours and Stoeldraijer (2011)), while others document significant differences in productivity for older workers (Hacgeland (1999), Ilmakunnas (2004)). Assessing wage-productivity gaps across different age groups is complex because age-productivity profiles vary widely across different occupations, industries, and over time. Göbel and Zwick (2012) find industry-specific factors influence productivity changes with age. Moreover, a worker's age can influence productivity, which is determined by both firm and worker characteristics. Hence, when analyzing the impact of age on productivity, it is essential to account for the collective dimension of labor productivity, which encompasses interactions between the firm's context and individual worker attributes. Additionally, aging can influence the technological choices of firms. Older workers can be more affected by technology adoption than younger ones, experiencing age-biased effects from ICT and innovative working practices (Aubert, Caroli, and Roger (2006); Behaghel, Caroli, and Roger (2014), Battisti, Dustmann, and Schönberg (2023)).

This thesis has three main findings. First, economy-wide estimates indicate an plateau shaped relationship between age and productivity, peaking at ages 45-49. Productivity increases rapidly in the early stages of the life cycle and slows down with age. Notably, there are differences between firms with varying levels of technological intensity. In high technology-intensive firms, productivity continues to increase with age, while low-intensity firms exhibit a flatter age-productivity profile.

Second, technological change delays the tipping point after which the wage-productivity gap turns negative. Using detailed firm-worker data and a set of different estimators, I analyze age-wage and age-productivity profiles at the firm level. The sample is split between firms in high and low technology-intensive sectors. The evidence shows that in high technology-intensive firms, productivity increases with age, while in low-intensity firms, the age-productivity profile is flatter.

Third, ICT training can help. Despite mixed empirical evidence on the effectiveness of training older workers (Armstrong-Stassen and Cattaneo 2010; Martin et al. 2014; Fleischmann et al. 2015; Leppel et al. 2012; Picchio and Van Ours 2013), this thesis shows that ICT training can be related to a delay the productivity inflection point. This finding is particularly policy-relevant, suggesting that policy actions focused on ICT training and technology can postpone the tipping point.

Section 1 explores the primary stylized facts that underpin the relationship between aging, productivity, and technology within the Portuguese context. Section 2 describes the data sources. Section 3 outlines the principal empirical methodologies employed. Section 4 details the findings of the analysis. Finally, Section 5 offers conclusions and implications of the study.

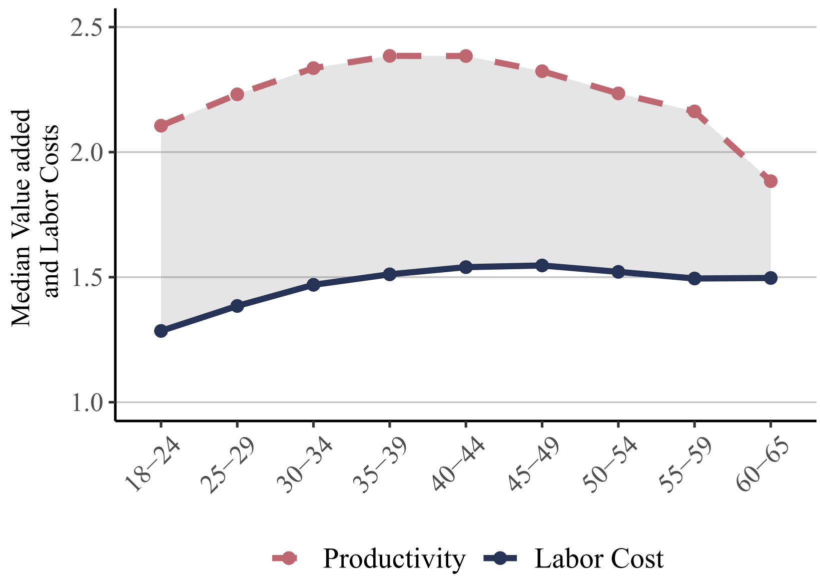
2 Stylized Facts

In this section, I present some stylized facts about the evolution of the Portuguese economy over the last 20 years. Firstly, I observe a correlation between the average age of the workforce and a gap between labor costs and productivity. Secondly, there has been a notable shift in the Portuguese private sector labor market, with older workers increasingly replacing younger ones, leading to a fast aging of the workforce. Lastly, this aging trend is predominantly occurring within economic units, such as firms and sectors, rather than being associated with worker mobility between sectors or firms.

Older labor force, lower productivity-labor cost gap Figure 1 illustrates the relationship between the average age of firms' workforce, labor productivity and labor costs. For each year I categorize firm observations into age bins according to the average age of its workforce. Next, I compute the median of the value added per labor hour and the median wage bill per labor hour for each age bracket and represent it graphically. It is possible to see that a higher average workforce age is related to higher labor productivity until the age of 40, after which starts to fall significantly. Contrary to the findings of Ours and Stoeldraijer (2011) for the Netherlands, the response of the average labor cost to average age is less significant than the one of productivity. However, it is observed that labor costs generally increase up to an average age of 45, after which it stabilizes. Most notably, Figure 1 illustrates that a higher average labor force age is related to a decreasing gap between productivity and labor costs, with the smallest gap observed when the firm's average workforce age is in the oldest age bracket.[1]

[1] However, it is important to note that this figure includes an unrestricted set of firms. Consequently, the firms being compared may not be directly comparable.

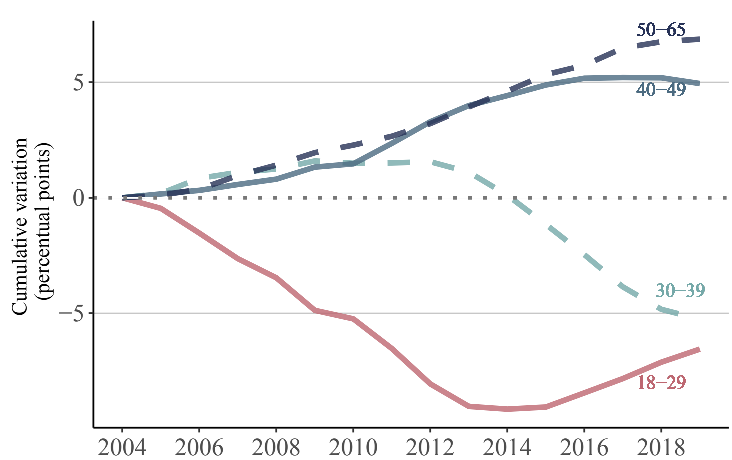
Figure 1: Median Value Added and Labor Costs by Age Group



Note: Each firm is allocated to an age bin according to its labor force average age. Productivity and Labor costs are measured by unit of labor. The scale is logarithmic. Own computations using QP data.

Labor force is getting older A second stylized fact addresses the significant demographic shift in the labor force over a brief 15-year period. During this time, the workforce has noticeably aged. Specifically, the average age within our sample increased from 37.2 in 2004 to 40.5 in 2019. This aging trend has reshaped the labor force, marked by a decline in the proportion of younger workers and an increase in the share of older workers, as illustrated in Figure 2.

Figure 2: Age composition of the labor force evolution (2004-2019)



Note: Own computations using QP data.

Decomposition of aggregate trends As it was demonstrated, the labor force aged significantly during the short period between 2004 and 2019. However, this piece of evidence does not directly show how this trend is related to changes in the composition of labor at the firm or industry level. Indeed, the aggregate change in the workforce's demographic structure may reflect shifts in the labor shares within economic units, between economic units or both. Hence, to better understand how this aggregate trend relates to the average firm labor demographic composition, I use a standard shift-share decomposition. The total variation in the employment share of age group j over the period 2004-2019, $\Delta l_j = l_{j,2019} - l_{j,2004}$, can be written as:

$$\Delta l_j = \underbrace{\sum_i \Delta\lambda_i \bar{l}_{i,j}}_{\Delta l_j^B} + \underbrace{\sum_i \bar{\lambda}_i \Delta l_{i,j}}_{\Delta l_j^W} \tag{1}$$

where Δl_j is the change in the overall share of employment for age group j between 2004 and 2019, Δl_j^W is the change in age group j's share of employment due to changes within economic units (firms or industries), Δl_j^B is the change in the share of age group j attributable to changes in the relative size of each economic unit, and i denotes different partitions of the aggregate economy - firms or industries[2].

Table 1 summarizes the results of the decomposition using equation 1 across four different age categories. The first and second columns display the share of labor hours in 2004 and the variation, in percentage points, of the relative size of each age category between 2004 and 2019, respectively. The subsequent columns contain the decomposition of the variation for firms and industries. In the bottom row, I report the weighted average contribution of each component to the overall variation[3].

Two main results that can be drawn from from Table 1. First, I find that the variation in the aggregate age composition of the labor force is occurring within firms, rather than through shifts in the economy's firm composition. This pattern is observed for all age categories and it suggests that aging is a phenomena verified across firms and across industries, and that an aging labor force is not related to a reconfiguration of the economy towards sectors and firms that tend to employ higher shares of workers. Second, I find evidence that the within variation is stronger than the total variation for all age categories. The within-firm component accounted on average for 114% of the total variation in the labor shares, which implies that the between variation is operating in

[2] $\Delta\lambda_i$ gives the change in the share of hours from economic unit i in the total amount of labor hours in the economy, Δl_j gives the change in the share of age group l within economic unit i's labor, $\bar{\lambda}_j$ gives the average share of hours of unit i, and $\bar{l}_j$ gives the average share of age group j in the labor force.

[3] The weighted average contribution of each component to the variations are computed as $\sum_j l_{j,2004} \times \Delta l_j^W / \Delta l_j$ and $\sum_j l_{j,2004} \times \Delta l_j^B / \Delta l_j$ for the within and between components, respectively.

Table 1: Decomposition of aggregate demographic trends, 2004-2019

	Share in 2004	Change	Firms Within	Firms Between	Industries Within	Industries Between
Age group						
18-29	29.11	-6.52	-8.22	1.69	-7.56	1.04
30-39	32.66	-5.24	-5.71	0.45	-5.70	0.47
40-49	23.45	4.95	5.28	-0.34	5.63	-0.67
50-65	14.78	6.86	7.80	-0.94	7.63	-0.77
Wgt. Avg. share in Change			1.14	-0.14	1.12	-0.12

Note: Same data as in Figure 1. Employment shares computed using the reported number of hours. A set of 22 distinct industries are considered (agriculture, extraction and contruction sectors are excluded).

an opposite direction, by increasing the share of young workers and reducing the share of older workers. This result is expected since firms that tend to employ above-average shares of young workers are firms that tend to have above-average hiring rates and productivity levels. Nevertheless, the between component is largely surpassed by the within variation, making it almost ineligible.

3 Data and Descriptive Statistics

To study the relationship between the age structure of the workforce, technology adoption and firm level outcomes I combine data from three different sources: a matched employer-employee data set, a firm-level balance sheet data set and a firm level ICT usage survey. All the three data sets are provided by *Instituto Nacional de Estatística (INE)*

Quadros de Portugal (QP) A rich longitudinal matched employer-employee data set for Portugal that is annually gathered by the Ministry of Labor, Solidarity, and Social Security. The data is collected through a mandatory survey from the universe of all private sector firms[4] (and respective employees) with at least one wage earner, and currently contains about 350,000 firms and 3 million workers. *QP* includes a detailed set of firm-level characteristics such as age, geographical location, industry affiliation, ownership, number of employees, among others. At the worker level it contains information regarding their demographic characteristics (age, gender, educational attainment), type of occupation, professional category, monthly hours worked (both regular and extra), nominal earnings (gross pay for normal hours of work, along with other regular benefits and premiums) and tenure. This data set is used for the period of 2004 to 2019 to create a set of detailed labor input and labor cost measures that are then collapsed at the firm level.

[4]Public administration and self employed workers are not covered by the survey.

Sistema de Contas Integradas das Empresas (SCIE) The SCIE is firm-level longitudinal data set that is compiled by Statistics Portugal and contains information on a wide variety of balance sheet and income statement variables since 2004. It covers nearly the universe of all Portuguese firms excluding non-market oriented, agricultural, insurance and financial sector firms. The data set includes variables such as value added, capital stock, intermediate goods, employment, wage bill, industry affiliation, not to mention others. It contains about 1 million observations by year. From this data set we are going to use the measure of output, value added at factor costs, the measure of capital, the measure of materials.

Inquérito à Utilização das Tecnologias de Informação e Comunicação nas Empresas (IUTIC) IUTIC is a yearly survey that gathers firm level information regarding the usage of ICT and related competences, and the incorporation of other technologies within firms. The survey is conducted by Statistics Portugal since 2004 as part of the Community Survey on ICT Usage and E-Commerce. For firms with more than 250 or turnover larger than 25 million euros, the survey is a census, and for firms that do not meet this criteria, it employs a stratified sample based on firm size, industry and turnover. The nature of this survey implies that the set of firms observed is not constant over the years, making it an unbalanced panel dataset. Additionally, the questionnaire is subject to significant changes across editions, which poses an additional limitation if we are interested in evaluating the longitudinal dimension. From this dataset we will focus on the answers given to four sets of questions on the share of computers users, the provision of ICT training to the firms workers, the usage of managerial software usage and the usage of more sophisticated technologies such as big data and cloud computing. The answer to the questions eleced will provide us an indication of a level of technological sophistication of the firm.

To construct the firm level panel database, I take several steps. I start by restricting the worker microlevel data for the period 2004-2019 to both full and part time employees, aged between 18 and 65 years, that earned earned[5] at least 80% of the national nominal minimum wage per reported hour of work. This data is then aggregated at the firm level to construct measures of labor cost — specifically, the average real wage per labor unit - and the detailed characteristics of workforce composition, such as age[6], tenure, educational attainment, occupational and gender shares. Employment is measured in full time equivalents (FTE) and, to assure reliability of the labor shares, firm-year observations for which the number of employees reduced by 5% following the worker level cleaning process are excluded. Furthermore, any firm-year observation with less than 5 FTE is also removed and, because of the poor quality of the data, firms in the agriculture, construction, and extraction sector are not considered.

[5]Wages are calculated as the sum of the base wage along with regular and non-regular benefits.

[6]We consider both nine (18-24, 25-29, 30-34, 35-39, 40-44 ,45-49, 50-54, 55-59, 60-65) and four age groups (18-29, 30-39, 40-49 and 50-65).

Table 2: Descriptive Statistics

	Main (2004-2019)		ICT Survey (2010-2019)	
Variable	Mean/Share	S.d.	Mean/Share	S.d.
Firm characteristics				
Av. sales per labor hour	66.509	426.117	78.517	494.543
Av. VA per labor hour	14.842	75.288	16.357	103.432
Av. hourly wage	5.320	2.819	5.531	2.803
Employment (log)	2.574	0.906	2.677	0.973
Capital stock (log)*	11.556	2.714	11.886	2.465
Intermediate goods (log)*	10.614	4.797	11.329	4.578
Av. firm age	17.428	14.486	21.388	14.741
Av. private capital	0.934	0.243	0.936	0.238
Detailed employment characteristics				
Males	0.546	0.310	0.580	0.293
STEM workers	0.059	0.161	0.071	0.168
Age group				
18-29	0.226	0.194	0.185	0.173
30-39	0.318	0.177	0.312	0.175
40-49	0.266	0.169	0.287	0.166
50-65	0.190	0.176	0.216	0.178
Education				
4 years	0.171	0.202	0.143	0.174
6 years	0.199	0.201	0.203	0.200
9 years	0.247	0.200	0.253	0.196
College	0.136	0.215	0.145	0.222
High School	0.243	0.216	0.253	0.209
Tenure (years)				
0-10	0.731	0.287	0.656	0.292
10-20	0.187	0.212	0.232	0.219
More than 20	0.082	0.163	0.111	0.183
Observations				
Firm × year	125,935		26,419	
Distinct firms	737,962		12,562	

Note:
Statistics related to the ICT Survey sample have been calculated using the provided sampling weights. *The variables Capital stock' and Intermediate goods are included only for the period 2010-2019, due to their unavailability in earlier years.

To incorporate data on the stock of capital, intermediate inputs and Value added at factor costs, the collapsed QP data is then merged with SCIE data through a unique firm identifier code present in both datasets. The Value added is then divided by the firm level total amount of labor to construct a measure of labor productivity. Value added outliers are discarded\footnote{Firms in the top 99% and bottom 1% by year-sector combination are trimmed.}. All monetary variables are deflated using the CPI of 2015.

For the analysis of the relationship between age profiles and the usage of digital technologies, I merge the IUTIC survey data to the main dataset using the firm identifier. Because there was a notable increase in the survey's coverage in 2010, I will exclusively use data from this survey post-2010. From this dataset, I will concentrate on specific questions that signal the intensity of ICT usage, the nature of its application, and the adoption of practices aimed at improving ICT-related skills among workers. These include the count of PC users within a firm (available for all used vintages of the survey), from which I create a variable that measures the share of computer users in proportion to firm size; the usage of CRM and ERC managerial software (not available for the 2016 and 2018), from which I will create a dummy variable indicating whether a firm employs such technology; the use of cloud computing and big data analytics (only available for the period 2016-2018), for which I create a dummy variable that denotes adoption; and the implementation of ICT skills training (available for the years 2014-2019), for which another dummy variable will be constructed.

Table 2 presents the sample sizes and summary statistics for the two final firm-level datasets. The main dataset includes approximately 125,935 firms and 737,962 year-firm observations. In contrast, the dataset merged with the ICT survey contains about 12,562 firms and 26,419 observations. This latter dataset exhibits attrition issues, with approximately 68% of firms appearing only once, and a balanced panel for merely 483 firms. Most employees fall within the 30-39 age category, and the majority have tenure of less than 10 years. There are notable differences between the two samples that suggest underlying temporal transformations. For instance, the share of older workers is larger in the sample that includes only observations post-2010, and the average share of STEM labor units has also increased significantly. A limitation of using this dataset is its reliance on sampling weights. Since I cannot extrapolate sampling weights for small firms, it will not be possible to use panel data estimators for smaller firms.

4 Empirical Model

The primary objective of this thesis is to estimate and compare the relative marginal productivity of workers across various age groups with their corresponding labor costs. This involves adopting an empirical approach where two firm-level equations are estimated: one for productivity and another for labor costs, both utilizing the same specifications. The goal is to conduct a comparative analysis of the coefficients from each equation, particularly focusing on those coefficients that pertain to age-related variables.

4.1 Productivity and Labor Costs Equations

Productivity Equation

To understand how labor productivity varies with the type of labor input by age, I use a conventional firm-level Cobb-Douglas production function augmented to include controls for firm-specific characteristics:

$$y_{it} = \beta_{QL} ln(QL)_{it} + \beta_k k_{it} + \delta X_{it} + \epsilon_{it} \tag{2}$$

where y_{it} defines output, measured as firm i's log value added at period t[7], k_{it} is the log stock of capital, QL_{it} is a quality of labor aggregate, X_{it} is a vector that includes industry, region and calendar time dummies as well as firm level characteristics such as firm's age, share of labor by educational group (the share of labor from employees with 4, 6, and 9 years of education, as well as the share of high school and college educated), the share of labor by gender, the share of labor by tenure group[8], and the share of capital owned by the private entities, and ϵ_{it} is an error term. As in Hellerstein, Neumark, and Troske (1999), Aubert and Crépon (2003), Ours and Stoeldraijer (2011), I assume that workers belonging to different age groups are perfect substitutes, although they may have varying marginal products.[9] The quality of labor aggregate can be written as:

$$QL = \sum_j \lambda_j(z) L_j = \lambda_0(z) L \left\{ 1 + \sum_{j>0} \gamma_j(z) l_j \right\} \tag{3}$$

where $l_j = \frac{L_j}{L}$ represents the share of labor units from the age group j[10], with L_j denoting the total

[7]As the measure of output, I consider value added at market prices, i.e. net of taxes and subsidies.

[8]I include tenure as a control variable to differentiate the impact of age from the accumulation of firm-specific experience. Similar to Göbel and Zwick (2012), I use tenure bins of 10 years to mitigate potential multicollinearity with the shares of age groups

[9]By using this approach, I am assuming the restriction that the relative marginal product of two different types of workers within a specific age group is equal to the relative marginal product of those two groups of workers within another age group. Hence, I impose that the relative marginal productivity of young blue collar workers to young white collar workers must be equal to the relative marginal product of old blue collar workers and old white collar workers. A second restriction has to do with the proportion of workers are contant across all other groups: I restrict blue collar workers to be equally represented in all occupations, education levels, marital status and so on. I impose such restrictions to not impose to many parameters in the model

[10]As noted in (**?**), I use both nine and four age categories. The latter applies when I integrate the main dataset with

labor units from that age group, and L representing the total labor units, and $\gamma_j(z) = (\frac{\lambda_j(z)}{\lambda_0(z)} - 1)$ is the relative marginal product of the age group j with respect to the representative group. The key addition to the existing literature is my assumption that the marginal productivity of each age group is a function of z, representing the labor-augmenting technology with heterogeneous effects across different age groups. Furthermore, I assume that z affects the marginal product of each age group in a way that the relative marginal product can change with technological intensity. By plugging Equation 3 into Equation **??** and log-linearizing I obtain the following expression:

$$y_{it} = \alpha + \beta_{\mathcal{L}}\mathcal{L}_{it} + \sum_{j>0} \gamma_j(z_i) l_{j,it} + \beta_k k_{it} + \delta X_{it} + \epsilon_{it} \tag{4}$$

where $\mathcal{L}_{it} = ln(L)_{it}$.

Labor Costs Equation

To be able to directly compare the production and the labor cost profiles results, I use an identical specification for both. Consequently, I use the following equation to estimate the relative labor costs associated with each age category of workers:

$$w_{it} = \alpha_w + \beta_{w,\mathcal{L}}\mathcal{L}_{it} + \sum_{j>0} \upsilon_j(z_i) l_{j,it} + \beta_{w,k} k_{it} + \delta_w X_{it} + \epsilon_{w,it} \tag{5}$$

where w_{it} is the mean log hourly labor cost of firm i in year t and $\upsilon_j(z_i)$ is the relative labor cost of age group j relative to the baseline age group, that measures the differential contribution of workers from age group j to the firms average hourly wage. This specification allows to study the existence of age contingent wedges between relative marginal products and the relative wage related to each age category by performing a comparison of the coefficients $\gamma_j(z)$ and $\upsilon_j(z)$.

4.2 Methodology

The coefficient estimates of Equation 4 derived from a pooled Ordinary Least Squares (OLS) estimator may suffer from bias due to at least two sources of misspecification in the production function. To see this, I will assume that the error term in Equation 4, ϵ_{it}, which can be interpreted as a Hicks-neutral productivity shock, can be decomposed into three components: a first component that captures the firm-specific persistence in productivity, α_i; a random unobservable productivity shock, ω_{it}; and an random noise η_{it} that I assume to be orthogonal to the input

the *IUTIC* dataset. Because there is a large drop in the number of observations, more aggregated categories are used to preserve data variability.

choices:

$$\epsilon_{it} = \alpha_i + \omega_{it} + \eta_{it} \tag{6}$$

The misspecification likely occurs because the two components are expected to influence input choices. The first potential source of bias and inconsistency of the OLS estimator concerns the unobserved fixed heterogeneity at the firm level, or α_i. This is the case, for instance, when the time invariant differences between types of firms are able to jointly explain the demographic composition of the workforce that it uses and the level of output that it produces. A feasible approach to remove this source of bias is by using a within estimator that could be implemented by differencing the variables in Equation 4. The second source of bias, called transmission bias (Griliches and Mairesse (1995)), is less trivial and more challenging to overcome. Contemporaneous correlation between the free input variables and ω_{it} might arise due to the fact that after observing a productivity shock - that is unobserved by the econometrician - a firm manager may be induced to change the free input choices. In particular, a positive (negative) productivity shock, ω_{it}, might induce increasing (decreasing) the amount of labor by hiring (laying off) workers[11]. Given that both hirings and layoffs predominantly target younger workers, it is likely that there is a positive correlation between ω_{it} and $l_{j,it}$[12]

To address the issues of simultaneity and unobserved heterogeneity in age-profile estimation, the literature suggest several methodologies. A widely adopted approach is to use a Generalized Method of Moments (GMM) estimator for Equation 4 in first differences, effectively removing firm-level fixed effects, and instrument the endogenous changes in the workforce's age composition between $t-1$ and t using the firm-level workforce's age structure in levels lagged two and three periods (Cardoso, Guimarães, and Varejão (2011), Ours and Stoeldraijer (2011)). The key assumption here is that, while ω_{it} may be correlated with changes in the labor force's age shares, it is expected to be uncorrelated with the age composition preceding any productivity shock. The equation to be estimated is given by:

$$\Delta y_{it} = \beta_{\mathcal{L}} \Delta \mathcal{L}_{it} + \sum_{j>0} \gamma_j(z_i) \Delta l_{j,it} + \beta_k \Delta k_{it} + \delta \Delta X_{it} + \Delta \epsilon_{it} \tag{7}$$

and the labor cost will be estimated using the same model, but using as dependent variable Δw_{it}. This method, however, has a large cost in terms of cross sections that are lost to construct the lags and the first differences.[13]. In this regard, the structure of the *IUTIC* dataset, which is will be used

[11] Negative shock other possibility: hiring less, and because hirings are overrepresented by younger workers, less younger workers

[12] The sign of the bias in $\gamma_j(z)$ is not that straightfoward to access since it depends on the response of other inputs to the productivity shock. This is only a good guess of the sign of the bias if I am to assume that the state variable is not reponsive to the productivity shock.

[13] If I use as instruments the lags of the levels for $t-2$ and $t-3$ a firm that is continuasly observed between $t=0$

for studying how technology intensity affects age profiles, imposes significant limitations on using this method. Due to high attrition, most firms do not have consecutive observations available[14]. Consequently, the effectiveness of using internal instruments is considerably reduced, leading to weak instruments. Despite these challenges, I implement this estimator as a benchmark.

To mitigate the identified sources of bias, I also adopt a control function approach, a technique originally pioneered by Olley and Pakes (1996) and subsequently refined by Levinsohn and Petrin (2003) and Ackerberg, Caves, and Frazer (2015). This method relies on a set of assumptions, one of which states that firm investment decisions can be represented as a monotonic function of both observed state variables, like capital, and the unobserved productivity shock, ω_{it}. Based on this *scalar unobservability* assumption, the function can be inverted, allowing ω_{it} to be expressed as an unknown function, $\phi_{it}(.)$, of observables, namely capital and investment. Then, by incorporating $\phi_{it}(.)$ into the production function and approximating it using a polynomial, generally of the third order, I can identify the labor parameters. Since capital features in both the function of unknown form and the production function, a second step is needed to determine the capital parameters. Wooldridge (2009) demonstrates that the coefficients for both capital and labor can be estimated simultaneously using a single-stage GMM estimator.

The initial Olley and Pakes (1996) estimator, however, presents some limitations. Notably, the existence of capital adjustment costs may compromise *scalar unobservability* assumption, and the original estimator does not consider the possibility of firm-specific persistence in productivity. To address these issues, I will adopt the approach suggested by Levinsohn and Petrin (2003), which uses intermediate inputs as a proxy for the productivity shock instead of relying on investment. Additionally, I will incorporate the Lee, Stoyanov, and Zubanov (2019) extension, which accounts for potential firm-specific persistence in productivity. This estimator, known as the control function estimator with fixed effects (CFE-FE), can be implemented in a single step, similar to the method described by Wooldridge (2009). The equation to be estimated is as follows:

$$y_{it} = \alpha_i + \sum_{j>0} \gamma_j(z_i) l_{j,it} + f(k_{it-1}, m_{it-1}) + \delta_W W_{it} + \zeta_{it} \tag{8}$$

where $f(.)$ represents a function of unknown form that will be approximated using a third-degree polynomial of (k_{it-1}, m_{it-1}), and $W_{it} = \mathcal{L}_{it} + k_{it} + X_{it}$. To address the issue of persistence in productivity, this model is estimated in first differences. Moreover, the moment conditions considered are $E(\Delta\zeta_{it}|S_{it})$, where S_{it} is the set of excluded instruments, namely

and $t = 3$, will only have available the first difference between $t = 3$ and $t - 2$.

[14] As afore mentioned, largely because the survey employs a stratified sample focusing only on firms that meet specific size and turnover criteria.

$(\mathcal{L}_{it-2}, k_{it-1}, m_{it-2})$, along with their powers and products, all of which are predetermined relative to $\Delta\zeta_{it}$. Again, labor costs will be estimated with the same model, using Δw_{it} as the dependent variable

5 Results

5.1 Age profiles under different estimation techniques

In this section, I present parameter estimates from the productivity and labor cost equations for the Portuguese economy, covering the period from 2004 to 2019. These estimates are generated using Ordinary Least Squares (OLS) and the Generalized Method of Moments (GMM-IV). Due to the lack of capital stock data before 2010, estimates from the Control Function Estimator with Fixed Effects (CFE-FE) are limited to the period from 2010 to 2019.[15]

The first and forth columns in Table 3 and Figure 4a display the estimated coefficients for the productivity and earnings specifications using the OLS for equation 3. The obtained results for the production specification indicate a non-negative relationship between workforce's age and labor productivity. This finding diverges from the commonly reported inverted U-shaped age-productivity profile using pooled OLS estimator (Aubert, Caroli, and Roger (2006), Ours and Stoeldraijer (2011), and Dostie (2011)). Indeed, the point estimates indicate that increasing the share of older workers up to the age category of 45-49 is related with higher average productivity per unit of employment at the firm level. Beyond this age, the benefits of employing a greater share of older workers, relative to the reference category (workers aged 18-24), stabilize, resulting in a plateau-shaped profile.[16]

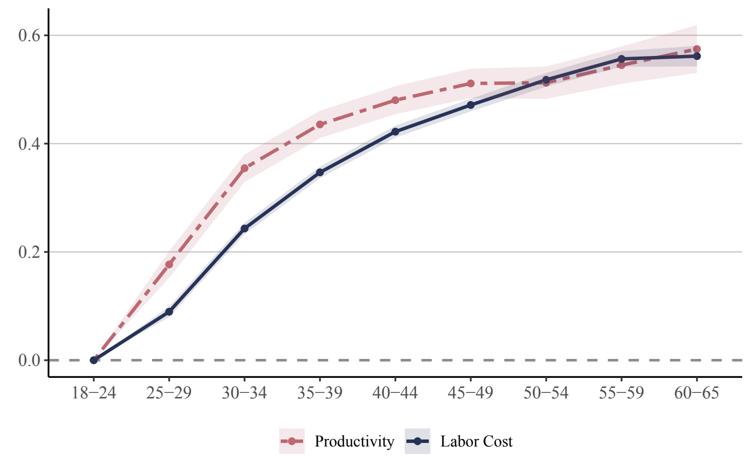
Turning to wage dynamics, the estimated OLS age-labor cost profile shows that as the proportion of older workers increases, average firm wages also rise, reaching a peak in the 55-59 age bracket before stabilizing (see the fourth column of Table 3 and Figure 4a). These results diverge from typical worker-level earnings regressions, which often observe a downturn in the earnings profile at later stages of the lifecycle.

When considering these two patterns together, it becomes evident that, up to a certain point, higher experience levels are linked to rises in both productivity and wages. However, the delayed response of labor costs relative to productivity gains calls into question the hypothesis of deferred

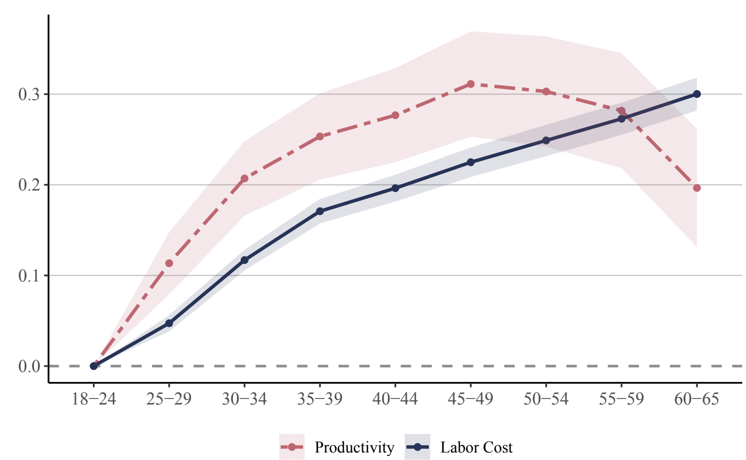
[15] In the Appendix section, I demonstrate that the profiles produced by each estimator remain consistent when the analysis is limited to the period from 2010 to 2019 across all models.

[16] This result indicates that fixed heterogeneity, which explains time invariant different productivity levels across firms, is a likely source of bias. In fact, firms that do not employ workers in the older age group exhibit a average labor productivity that is approximately 9.4% percent lower compared to firms that hire workers of this category.

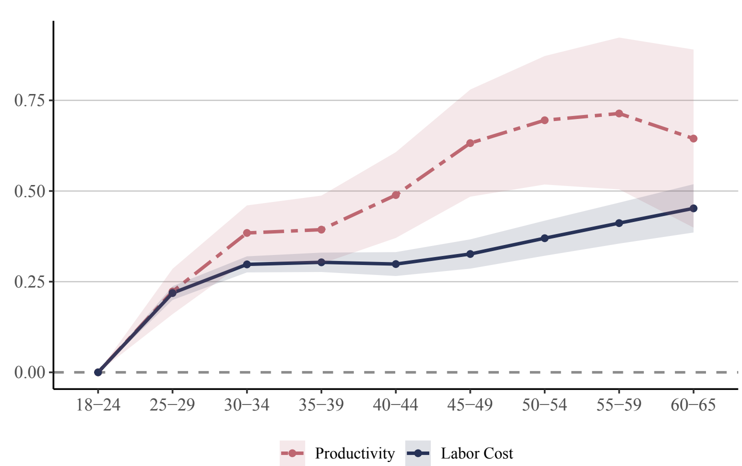
Figure 3: Production and labor cost age profiles - Baseline parameter estimates



(a) OLS



(b) CFE-FE



(c) GMM-IV

compensation across the lifecycle. Notably, the productivity profile only aligns with labor costs after the age of 30-34, leading to a late convergence around the age of 50-54. This discrepancy creates an age-dependent productivity-labor cost gap, that peaks at the age of 30-34. To quantify this gap, on average, and assuming all else remains constant, increasing the proportion of workers aged 30-34 at the expense of the reference category (workers aged 18-24) leads to an approximate 0.355% increase in productivity average firm level productivity, but only a 0.243% increase in average labor costs.

To address potential biases from the endogeneity of workforce demographic composition and fixed firm heterogeneity, I applied the two aforementioned estimators. The findings using the CFE-FE estimator are presented in the second and fifth columns of Table 3 and in Figure 4b. Consistent with the OLS results, the CFE-FE estimates indicate that, after controlling for the response of inputs to productivity shocks and fixed firm-specific characteristics, an increase within a firm in the share of older workers leads to an increase in average productivity, peaking in the age bracket of 45-49. However, the results indicate that productivity follows an inverted U-shaped pattern. Specifically, after the age of 45-49, productivity begins to decline, experiencing a notable decrease in the final age bracket considered. In opposition to this, the labor cost profile follows a positive monotonic relationship with age, resulting in an age-dependent labor costs-productivity gap. This gap is similar to that observed in OLS results, where there is a distinct positive difference between productivity and labor costs, particularly for younger workers. Nonetheless, this gap narrows in the age bracket of 50-54, suggesting that older workers are able to capture a larger share of their marginal product as earnings.

To verify the validity of the CFE-FE estimator, I conducted two tests. First, I applied the Hansen J-test of overidentifying restrictions, to checks whether the excluded instruments are uncorrelated with the error term, implying correct exclusion from the regression equation. In both specifications, the test did not reject the null hypothesis, indicating that the instruments are orthogonal to the error term and thus valid. Additionally, I used the Kleibergen-Paap LM statistic to assess underidentification, which tests if the excluded instruments are sufficiently correlated with the endogenous regressors. The instruments passed this test, indicating they are not weak and effectively address endogeneity.

The results yielded by the GMM-IV estimator, that can be found in the third and sixth columns of Table 3, diverge partially from those obtained using OLS and the CFE-FE. First, according to the estimates, productivity continues to grow until reaching the 55-59 age bracket, after which it begins to diminish (as one can visualize in Figure 4c). However, the usage of internal instruments, namely the lagged levels of inputs, lead to a significant fall in the precision of the estimates. Likewise, the large confidence intervals of the estimated parameters do not allow us to reject the hypothesis of a plateau shaped productivity profile after the age of 40-44, as it was found for the OLS estimates.

Second, wage adjustments appear to be less responsive to age. While during the initial stages of a worker's career there are high increments in both earnings and productivity, suggesting the effect of on the job training at the beginning of a career, wages seem to stop growing after the age of 30-34, leading to an increasing earnings wedge, that only diminishes at the last age category considered. Contrary to the remaining methods, the GMM-IV estimates suggest that this wedge increases with age in a later stage of the lifecycle. This findings are consistent with the predictions of Glover and Short (2020), that suggests that due to the lack of labor market dynamism of older workers, employers may have monopsony power, allowing them to get an age increasing share of the marginal product of older workers.

To confirm the validity of the GMM approach, I applied the same set of tests previously used to validate the CFE-FE estimator. Additionally, I conducted an endogeneity test using the Durbin-Wu-Hausman test, which is considers as the null hypothesis that the demographic composition of the labor force, presumed endogenous within the model, is in fact exogenous. The rejection of this null hypothesis for both specifications suggests that the age composition of the labor force is indeed endogenous, confirming the necessity of using techniques like GMM to properly account for these internal dynamics within the data.

Overall, estimates indicate that productivity generally increases with age before reaching a plateau, with this trend varying based on the approach used to address potential endogeneity. Notably, the CFE-FE model reveals early occurrences of gaps between productivity and labor costs, supporting human capital theory. In contrast, the GMM IV model shows that these gaps appear later in the career lifecycle. This difference is evident in the age-contingent labor cost productivity wedges observed in the data.

Table 3: Baseline parameter estimates of the production and labor cost function

	Productivity			Labor Costs		
	OLS	CFE-FE	GMM-IV	OLS	CFE-FE	GMM-IV
Age group						
25-29	0.177***	0.113***	0.223***	0.090***	0.047***	0.219***
	(0.013)	(0.018)	(0.032)	(0.005)	(0.005)	(0.010)
30-34	0.355***	0.207***	0.384***	0.243***	0.117***	0.298***
	(0.013)	(0.0211)	(0.039)	(0.005)	(0.006)	(0.011)
35-39	0.435***	0.253***	0.393***	0.347***	0.171***	0.303***
	(0.013)	(0.024)	(0.048)	(0.005)	(0.007)	(0.014)
40-44	0.480***	0.277***	0.489***	0.422***	0.196***	0.299***
	(0.013)	(0.027)	(0.060)	(0.006)	(0.008)	(0.017)
45-49	0.511***	0.311***	0.632***	0.471***	0.225***	0.326***
	(0.014)	(0.030)	(0.075)	(0.006)	(0.008)	(0.021)
50-54	0.512***	0.303***	0.695***	0.518***	0.249***	0.370***
	(0.015)	(0.031)	(0.090)	(0.006)	(0.009)	(0.025)
55-59	0.545***	0.282***	0.714***	0.556***	0.273***	0.412***
	(0.018)	(0.032)	(0.107)	(0.007)	(0.009)	(0.029)
60-65	0.575***	0.197***	0.645***	0.562***	0.300***	0.452***
	(0.023)	(0.033)	(0.125)	(0.010)	(0.009)	(0.034)
Education group						
4 years	-0.123**	0.039	0.092	0.048**	0.010	0.049**
	(0.053)	(0.103)	(0.087)	(0.020)	(0.022)	(0.021)
6 years	0.084	0.119	0.196**	0.222***	0.070***	0.100***
	(0.052)	(0.103)	(0.087)	(0.020)	(0.022)	(0.021)
9 years	0.237***	0.114	0.299***	0.344***	0.120***	0.161***
	(0.052)	(0.102)	(0.090)	(0.020)	(0.022)	(0.022)
High school	0.624***	0.104	0.357***	0.593***	0.174***	0.239***
	(0.052)	(0.103)	(0.094)	(0.020)	(0.022)	(0.023)
College	1.342***	0.111	0.309***	1.270***	0.372***	0.447***
	(0.053)	(0.105)	(0.097)	(0.021)	(0.023)	(0.025)
Tenure group						
0-10	0.300***	-0.181*	0.398***	-0.114***	-0.154***	-0.088***
	(0.067)	(0.097)	(0.077)	(0.026)	(0.021)	(0.019)
10-20	0.481***	-0.044	0.288***	-0.018	-0.095***	-0.059***
	(0.067)	(0.094)	(0.074)	(0.026)	(0.019)	(0.018)

Table 3: Continuation

	Productivity			Labor Costs		
	OLS	CFE-FE	GMM-IV	OLS	CFE-FE	GMM-IV
Tenure group						
20-30	0.317***	0.0046	0.159**	0.012	-0.0364*	-0.011
	(0.069)	(0.0908)	(0.071)	(0.027)	(0.019)	(0.018)
30-40	0.183**	-0.001	0.091	0.024	-0.012	0.012
	(0.072)	(0.086)	(0.067)	(0.028)	(0.018)	(0.016)
Log of employment	0.101***	0.875***	-0.473***	0.063***	1.018***	-0.016***
	(0.002)	(0.040)	(0.006)	(0.001)	(0.012)	(0.002)
Share of male labor	0.423***	0.104***	0.102***	0.240***	0.102***	0.128***
	(0.006)	(0.016)	(0.013)	(0.003)	(0.004)	(0.004)
Observations	710,156	238,080	328,003	710,156	238,080	328,003
R-squared	0.297	0.021	0.059	0.616	0.763	0.0289
Number of firms	121,557	54,136	59,402	121,557	54,136	59,402
Hansen-J Statistic	-	0.365	10.53	-	2.123	29.69***
Endogeneity Test	-	-	100.8***	-	-	428.8***
Kleinberger-Paap kr LM	-	82.20***	3614***	-	82.20***	3614***

Note: The OLS estimation includes controls for industry, year, region (NUTS II), capital ownership and firm age. The CFE-FE is estimated in first differences. Coefficients for the polynomials incliuded in the estimation were not included in this table. The GMM-IV is estimated in first differences, with the shares of workers ages lagged 2 and 3 periods used as instruments.

5.2 Heterogeneity in the Age Profiles

5.2.1 Sector comparisons and Techies

In the preceding subsection, the baseline estimates relied on the assumption that the effects of aging on a firm's average labor costs and productivity are consistent across all industries and firm types. However, as previously discussed, varying levels of technological intensity within firms can significantly change these impacts. To gain a more detailed understanding of how a more ICT-intensive environment influences the relationship between productivity and earnings over the lifecycle, this subsection introduces two extensions to explore how technology shapes age-related productivity and labor cost profiles.

Initially, I allow age profiles to vary based on the nature of tasks performed across different sectors. By categorizing sectors according to their technological intensity and comparing those with lower versus higher levels of technological engagement, I seek to study the implications of technological adoption on productivity across age groups. Following this sectoral analysis, I shift focus to the firm level charateristics, where the proportion of STEM-skilled labor (or "Techies") is used as a proxy for technological intensity, following the steps Harrigan, Reshef, and Toubal (2021). I estimate the age productivity and labor cost profiles using the same set of estimators as in the previous subsection.

Results

Figure 5 displays the age productivity and labor cost profiles for firms categorized into high and low technology-intensive sectors. The details are provided in Table 4 Significant differences emerge between these two industry groups. The three graphs illustrate the profiles using the three estimation methods previously considered. The left column contains the point estimates for the productivity specification, while the right column presents the estimates for labor costs.

There is a notable variation in age productivity profiles across different types of industries. The OLS estimates reveal that firms within each industry by technology intensity demonstrate a plateau-shaped productivity profile, similar to the results obtained considering the pooled industries estimate. Nevertheless, there is one major distinction between the two sets of firms. Even though both industry types start with similar productivity slopes, productivity ceases to increase at a much younger age category in the low technology sector compared to the high technology sector. This could be attributed to the nature of tasks performed in each sector. In sectors with lower technology intensity, workers often engage in tasks that demand greater physical abilities, which tend to depreciate faster than cognitive abilities, thus negatively affecting productivity earlier. In particular, in the low technology sector, productivity increases only up to the age of 30-34, after which it grows at a significantly reduced rate and eventually stabilizes. In contrast, in the high technology sector, the age productivity profile continues to rise until the age of 45-49 before it plateaus.

Similar to productivity, the decomposition of earnings profiles by sector also yields similar shaped profiles as the ones obtained in the pooled industry estimates. Apparently in the low technology sector, average wages are less responsive to the age of the workers, resulting in less steep curve for most age categories when compared to the one for technoloigy intensive industries. The shape of the labor cost profiles mirrors those estimated for the pooled industries in the earlier subsection, suggesting a general trend across different technological intensities.

The CFE results delineate distinct productivity profiles for the two sets of industries. In general, there seems to be a weaker response of average firm productivity to workers' age, leading to a much flatter productivity profile across the sectors. However, in high technology intensity sectors, a clear tipping point is observed. Increasing the share of older workers significantly boosts average productivity levels up to the age bracket of 45-49 years. Beyond this point, productivity begins to decline, albeit less markedly than what was observed in the pooled sectors' estimation.

Regarding earnings profiles, the low productivity sector displays a quasi-linear relationship between age and labor costs, with a flatter slope than that observed in the high-intensity sector for a substantial portion of the life cycle. By contrast, in the high-intensity sector, there appears to be a two stages pattern of earnings growth. The first phase, extending up to the age category of 35-39, is characterized by a strong positive response of earnings to age, suggesting that in the early stages of the life cycle in highly technologically firms, there is a robust response of earnings to age. However, after this age bracket, earnings growth dampens, and the slope of the labor cost profile becomes similar to that estimated for the low technology intensity sectors.

This contrast likely highlights fundamental differences in how age influences productivity across sectors. In the low technology sector, the weak relationship between age and productivity suggests that wage growth is predominantly driven by seniority. In contrast, in the high technology sector, the compensation structure significantly benefits younger workers, where increases in productivity due to greater experience directly result in substantial wage increases. However, after reaching the age bracket of 34-39, the rate of earnings growth begins to slow, even though productivity continues to rise until the age of 45-49.

The GMM-IV estimator reveals distinct patterns across sectors. In the analysis of age productivity profiles, results indicate that productivity increases persist until the later age bracket of 55-59, enhancing the average productivity level of firms, particularly in high-technology intensity sectors. In contrast, the low technology intensity sector displays a much weaker link between productivity and age. The almost flat shape of the productivity profile in these sectors underscores the minimal influence of age on productivity, corroborating the findings from the CFE-FE estimator that differences in the type of tasks performed might explain the varying productivity patterns across sectors.

Regarding labor cost profiles, the results are consistent across both sectors and align closely with those observed in the pooled analysis of sectors. The relationship between wages and age remains subdued, as previously noted. However, an interesting observation emerges in the high technology intensity sector, where earnings in the early stages of a career increase at a relatively higher rate compared to the low technology intensity sector. This trend mirrors the CFE-FE findings and highlights a sector-specific dynamic where early career earnings in high-tech environments outpace those in less technologically advanced settings. After reaching the age bracket of 30-34, the earnings growth in high-tech sectors tends to plateau, aligning with the nearly flat age earnings profile observed in the low technology intensity sector.

The results obtained by analyzing firm-level characteristics, specifically by estimating separate profiles for firms with a positive labor share of STEM-skilled workers, are consistent with those derived from comparisons between high-technology and low-technology sectors. This consistency underscores the significance of a firm's internal use of specific technologies as a crucial driver of differences in productivity and labor cost profiles across sectors. This analysis suggests that the observed variations in productivity profiles are more attributable to differences within the firms themselves, rather than the sectors to which they belong. By focusing on firms with varying levels of ICT usage, proxied by the share of STEM workers, I find that the differences in both productivity and earnings profiles are primarily driven by the characteristics of the firms in each sector, rather than by the sectors themselves.

5.2.2 ICT usage

In this subsection, I explore how specific firm-level attributes related to ICT usage influence the relationship between the demographic composition of the labor force and productivity and labor costs. Using a more narrowly defined sample from the *IUTIC* survey, I differentiate firms based on their ICT intensity, which allows to better understand how profiles vary with technological intensity beyond the sector-based comparisons.

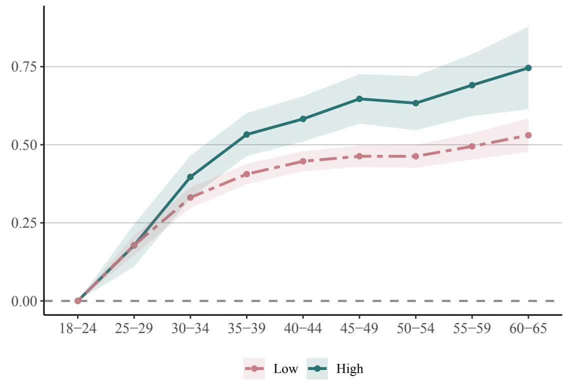
To study how the adoption of specific types of ICT is related to differences in age profiles, I have adapted Equation 4 (and subsequent equations for remaining estimation methods) to allow for differing age productivity profiles based on specific technology usage. This is achieved by letting the parameter $\gamma_j(z_i)$, the relative marginal product of age group j, to vary with the technology intensity indicator, z_i. In particular, I consider a specification where $\gamma_j(z_i)$ is defined as $\gamma_j(z_i) = \gamma_j + \gamma_{j,tech} \times tech_{it}$, with $tech_{it}$ being a dummy variable indicating the usage of specific technologies by firm i in period t, that serves as a proxy for z_i. Accordingly, Equation 4 becomes:

$$y_{it} = \alpha + \beta_{tech} tech_{it} + \sum_{j>0} \gamma_j l_{j,it} + \sum_{j>0} \gamma_{j,tech} l_{j,it} \times tech_{it} + \delta P_{it} + \rho_{it} \tag{9}$$

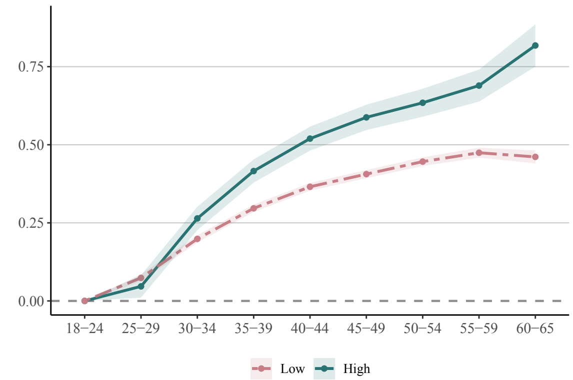
where P_{it} is a vector that includes the same set of controls present in Equation 4. As before, for the labor cost equation I will consider the same specification, using w_{it} as the dependent variable. In such specification, the relative labor cost of each age group will be defined as $\upsilon_j(z_i) = \upsilon_j + \upsilon_{j,tech} \times tech_{it}$.

I will estimate three different sets of equations, in which $tech_{it}$ will have different meanings. In the first specification, I will define $tech_{it}$ as a dummy variable for firm i in year t that takes value one if the firm ranks within the top 25 percent of its sector on the share of computer users in its labor force for that year. Conversely, it will take a value of zero if the firm falls within the bottom

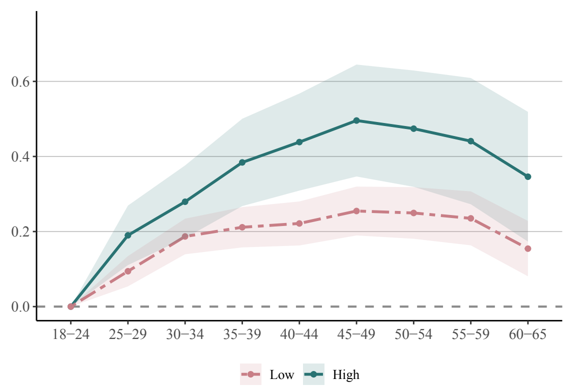
Figure 4: Producitivy and labor cost age profiles - High versus low technology intensity sectors



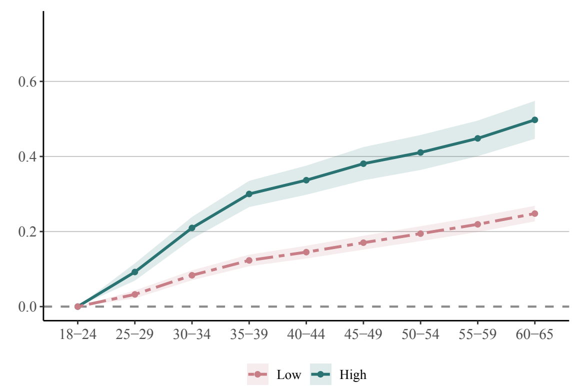
(a) Age Productivity Profiles (OLS)



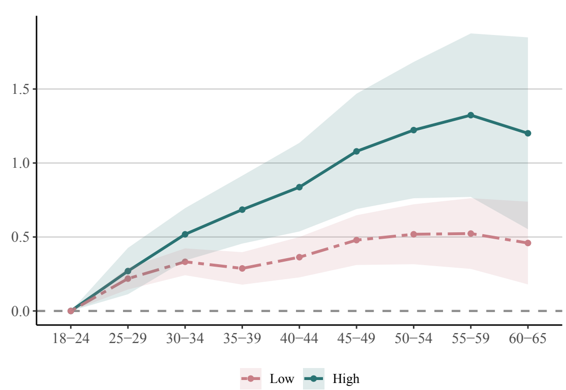
(b) Age Labor Cost Profiles (OLS)



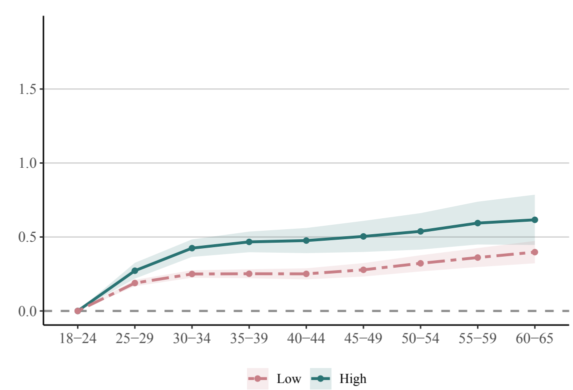
(c) Age Productivity Profiles (CFE-FE)



(d) Age Labor Cost Profiles (CFE-FE)



(e) Age Productivity Profiles (GMM-IV)



(f) Age Labor Cost Profiles (GMM-IV)

25 percent of its sector in terms of computer usage in year of the observation. Firms that do not fall into these categories, i.e. those between the 25th and 75th percentiles, will be excluded from this analysis. I impose this exclusion to test how widely different intensities of PC usage are related to different shapes in the productivity profile.

In the second specification, I define $tech_{it}$ as a dummy variable that takes a value of one if firm i reports using CRM or ERP software.[17] The rationale behind this specification is that the usage of such types of software indicate a working environment characterized by a broader use of technology and a higher integration of tasks through ICT.In the third specification, $tech_{it}$ is defined as a dummy variable that assumes the value of one if firm i reports offering ICT training to its workers. The underlying idea is that the potential negative impacts of ICT on skill depreciation or obsolescence can be mitigated by active training. I will estimate these two final specifications using the OLS estimator due to the insufficient number of observations for the other estimators, which resulted in non-significant outcomes. As a control group, I will include firms that appeared in at least two periods of the survey and reported not using managerial software or undergoing ICT training during that time.

Results

Figure 5 illustrates the estimates for productivity and labor cost specifications considering potential heterogeneity in each profile according to the ICT intensity of the firm that is proxied the percentile share of PC users. It features three graphs in the right column, each displaying age-productivity profiles for distinct estimation methods, while the left column shows the corresponding labor cost profiles. The point estimates in each graph are labeled *Low* indicates γ_j, and *High* represents $\gamma_j + \gamma_{j,tech}$ for both productivity and earnings profiles. Detailed numerical estimates are available in Table 5.

The ICT intensity level appears to be connected to the dynamics of productivity and labor cost across workers age. First, by looking at the OLS results (Table 5) one can clearly see that for high ICT intensity firms, productivity increases with age until the oldest age bin. In contrast, low ICT intensity firms present an early tipping point at the bracket of 40-49, after which it starts to fall.[18]

The OLS estimates for the age productivity profile, displayed in Figure 7a, indicate that age productivity profiles vary significantly between firms in the top 25 percentile and bottom 25 percentile of PC usage. In firms with lower PC usage intensity, the age productivity profile

[17] CRM software assists businesses in managing and analyzing customer interactions by consolidating all customer-related data onto a single platform. ERP software provides a comprehensive system for organizations to integrate and manage essential business functions such as accounting, purchasing, project management, and supply chain activities.

[18] Due to the use of more aggregated age groups in this section, it is difficult to precisely define the shape of the age productivity profile within the oldest category. However, the magnitude of the point estimates suggests that the tipping point occurs at a later age in high ICT intensity firms compared to those with low ICT intensity.

exhibits a pronounced inverse U-shape, peaking in the 40-49 age bracket. Conversely, in firms with relatively high PC usage, older workers' contributions to average productivity appear to increase with age up to the last age bracket considered. This finding suggests that although firms with higher ICT intensity might exhibit a bias against older workers, the marginal product of older employees tends to be substantially higher than that of their younger counterparts, relative to firms with lower ICT intensity. As pointed about before, this pattern likely emerges due to the type of tasks performed in each type of firm. In environments with high ICT intensity, although the pressure from new technologies may disadvantage older workers, the tasks are generally less susceptible to cognitive capacities depreciation over an employee's life cycle compared to more physical tasks. This allows older workers' capabilities to remain relatively resilient as they age.

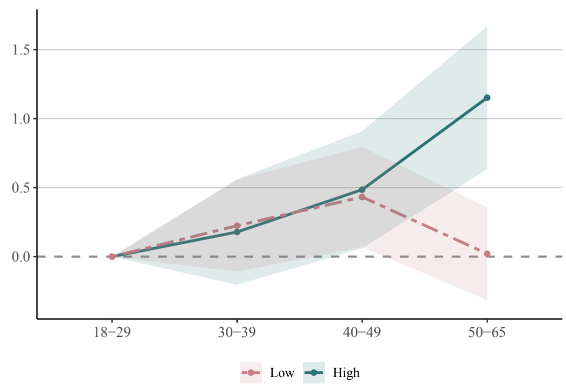
Earning profiles, displayed in Figure 7b, closely mirror the respective age productivity profiles in shape, though the magnitude of the point estimates differs significantly. These estimates are substantially smaller, indicating a less pronounced response in average earnings over the lifecycle, consistent with previous observations.

The productivity profile estimates derived from the CFE-FE model are illustrated in Figure 6c. Despite the reduced sample size, due to reliance on variables lagged by two periods which leads to less distinct profiles because of low statistical power, clear patterns still emerge. Technology usage not only appears to elevate the productivity profiles, suggesting greater productivity gains with age, but it also alters their overall shape. However, aside from the 40-49 age group in firms with high-intensity PC usage, the point estimates are not statistically significant. This finding is consistent with the results obtained using the OLS estimator, though the large size of the point estimates here indicates a lack of precision. Similarly, the earnings profiles highlight that an increased proportion of older workers correlates with higher average labor costs, especially in technologically intensive firms where the effect on average earnings is more pronounced.

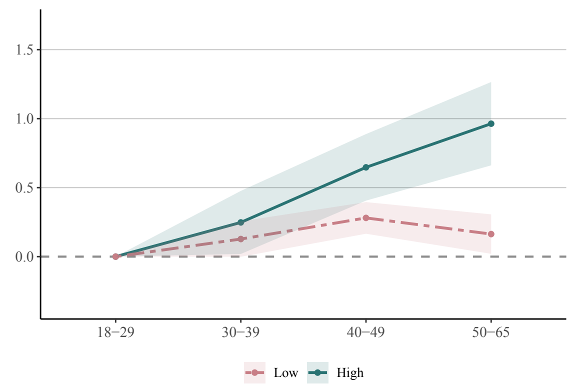
The results for the final specification on labor productivity are presented in Figure 6c. These findings indicate that, similar to firms with a higher share of PC users and those utilizing managerial software, the age productivity profiles of firms that engage in ICT training also tend to reach a tipping point at a later stage. Although the data does not provide direct evidence that ICT training definitively shapes age productivity profiles, it suggests that firms actively using such training tend to experience a delayed peak in productivity. This observation underscores the potential role of technology-enhanced training in extending the productive years of an aging workforce.

The findings of this analysis clearly indicate that the intensity of ICT adoption plays a significant role in shaping the dynamics of age-related productivity and labor cost profiles. This relationship

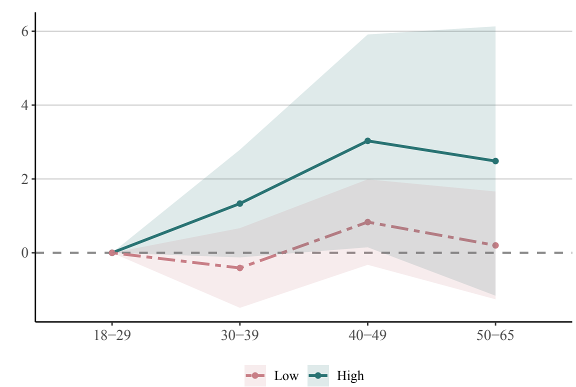
Figure 5: Production and labor cost age profiles by PC usage intensity



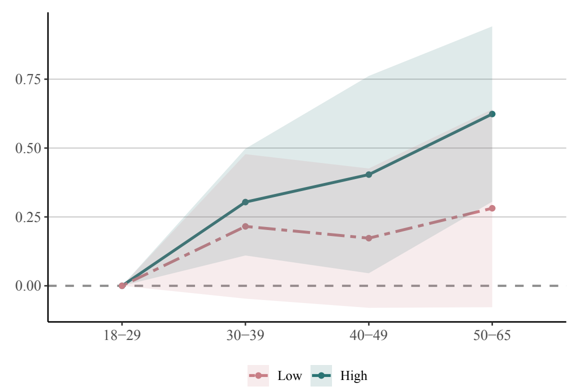
(a) Age productivity profiles (OLS)



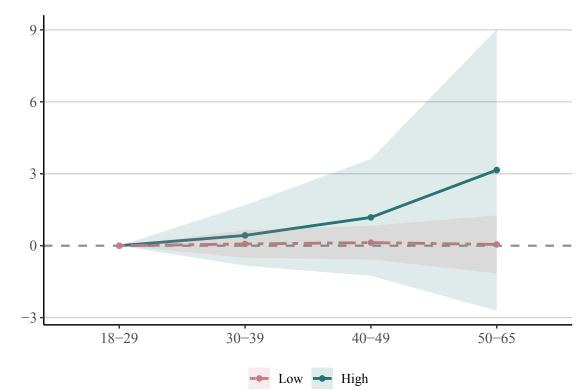
(b) Age labor cost profiles (OLS)



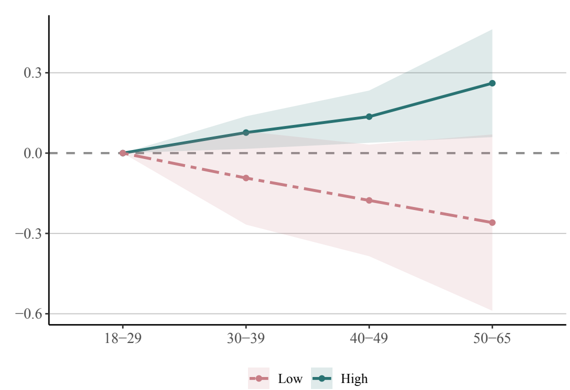
(c) Age productivity profiles (CFE-FE)



(d) Age labor cost profiles (CFE-FE)

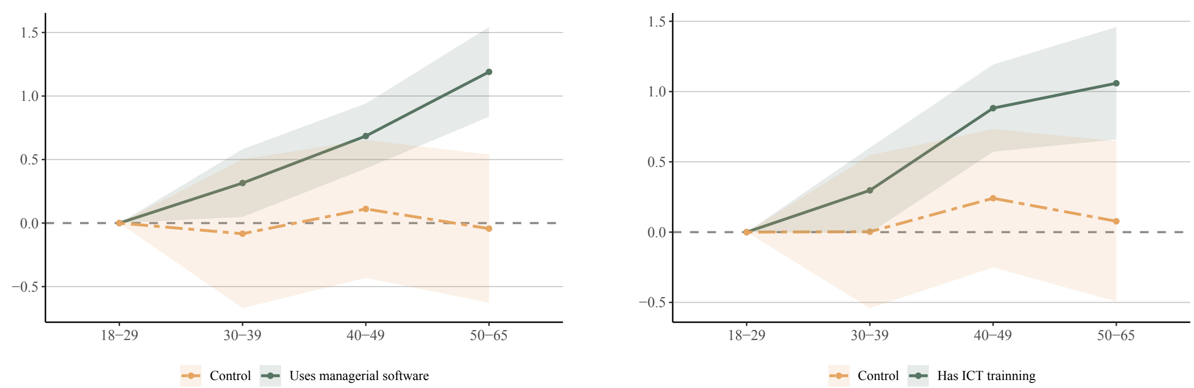


(e) Age productivity profiles (GMM-IV)



(f) Age labor cost profiles (GMM-IV) reveals how technological integration within workplaces not only boosts overall productivity but also shifts the economic value assigned to workers across different age groups. These insights highlight the critical interplay between technology adoption and workforce dynamics, suggesting that ICT can significantly alter traditional perceptions of age-related productivity and compensation. This understanding points to the potential for technology to rejuvenate the productivity contributions of an aging workforce and adjust compensation structures in a way that reflects the evolving technological landscape.

Figure 6: Production and labor cost age profiles by PC usage intensity



(a) Age productivity profiles (ICT trainning)

(b) Age labor cost profiles (Managerial Software)

6 Conclusion

This thesis has explored the relationship between aging workforces, technological intensity, and productivity. The growing proportion of older individuals within the workforce is a significant trend, and this research has identified a tipping point at which a Wage-Productivity Gap emerges, potentially influencing firm decision-making. The findings suggest that higher levels of technological intensity are associated with a delayed occurrence of this tipping point, meaning the wage-productivity gap becomes negative later. Additionally, ICT training appears to be linked to a similar delay in reaching this tipping point. However, it is important to note that these observations do not necessarily imply causation.

This thesis focuses on within firm effects and offers a new methodological approach. Results are robust to different specifications and measures of technology intensity. They are also consistent with economy and sector wide wage-age and productivity-age profiles. They are policy-relevant, suggesting that policy actions focused on ICT training and technology can postpone the tipping point. While wage-setting norms may imply that wages continue to increase with age, worker productivity may not. However, technology and training can delay this tipping point, avoiding an early decline in productivity.

Future research should investigate further the effects of training and the extent to which different types of technology adoption lead to different effects.

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A Appendix

Table 4: Baseline parameter estimates of the production and labor cost function - High technology intensity against low technology intensity sectors

	Productivity						Labor Costs					
	Low Tech. Intensity			High Tech. Intensity			Low Tech. Intensity			High Tech. Intensity		
	OLS	CFE-FE	GMM-IV	OLS	CFE-FE	GMM-IV	OLS	CFE-FE	GMM-IV	OLS	CFE-FE	GMM-IV
Age group												
25-29	0.178***	0.094***	0.219***	0.178***	0.190***	0.270***	0.074***	0.033***	0.189***	0.047**	0.092***	0.272***
	(0.016)	(0.021)	(0.037)	(0.035)	(0.041)	(0.080)	(0.006)	(0.005)	(0.011)	(0.018)	(0.012)	(0.027)
30-34	0.331***	0.187***	0.332***	0.397***	0.279***	0.518***	0.199***	0.083***	0.250***	0.264***	0.210***	0.425***
	(0.017)	(0.024)	(0.046)	(0.035)	(0.049)	(0.090)	(0.006)	(0.007)	(0.013)	(0.019)	(0.015)	(0.030)
35-39	0.406***	0.211***	0.288***	0.533***	0.384***	0.685***	0.297***	0.123***	0.252***	0.416***	0.300***	0.467***
	(0.016)	(0.027)	(0.056)	(0.035)	(0.059)	(0.117)	(0.006)	(0.008)	(0.016)	(0.019)	(0.018)	(0.036)
40-44	0.447***	0.222***	0.364***	0.583***	0.438***	0.837***	0.366***	0.145***	0.251***	0.520***	0.337***	0.476***
	(0.017)	(0.030)	(0.070)	(0.037)	(0.066)	(0.153)	(0.006)	(0.009)	(0.019)	(0.020)	(0.020)	(0.043)
45-49	0.463***	0.255***	0.479***	0.647***	0.496***	1.079***	0.406***	0.170***	0.278***	0.588***	0.381***	0.504***
	(0.017)	(0.033)	(0.086)	(0.040)	(0.076)	(0.199)	(0.007)	(0.009)	(0.023)	(0.021)	(0.023)	(0.054)
50-54	0.463***	0.249***	0.518***	0.633***	0.474***	1.222***	0.446***	0.194***	0.322***	0.634***	0.411***	0.538***
	(0.019)	(0.035)	(0.103)	(0.044)	(0.079)	(0.235)	(0.007)	(0.010)	(0.028)	(0.023)	(0.024)	(0.063)
55-59	0.495***	0.235***	0.523***	0.691***	0.441***	1.323***	0.474***	0.219***	0.361***	0.689***	0.448***	0.594***
	(0.021)	(0.037)	(0.122)	(0.051)	(0.086)	(0.282)	(0.008)	(0.011)	(0.033)	(0.026)	(0.024)	(0.074)
60-65	0.531***	0.154***	0.459***	0.746***	0.346***	1.201***	0.461***	0.248***	0.398***	0.818***	0.498***	0.616***
	(0.027)	(0.038)	(0.143)	(0.068)	(0.088)	(0.331)	(0.011)	(0.011)	(0.039)	(0.034)	(0.026)	(0.087)
Log of employment	0.092***	0.800***	-0.495***	0.099***	0.953***	-0.418***	0.054***	0.985***	-0.011***	0.070***	1.046***	-0.024***
	(0.002)	(0.049)	(0.007)	(0.005)	(0.072)	(0.014)	(0.001)	(0.015)	(0.002)	(0.002)	(0.023)	(0.004)
Observations	438,269	172,582	237,837	111,123	45,943	62236	438269	172,582	237,837	111,123	45,943	62236
Number of firms	83,577	39,866	44,143	21,417	10,619	11,392	83,577	39,866	44,143	21,417	10,619	11,392
Hansen-J Statistic	-	1.11	14.63*	-	0.25	5.96	-	4.59	15.62*	-	1.1	10.66
Endogeneity Test	-	-	49.30***	-	-	49.57***	-	-	226.1***	-	-	111.21***
Kleinberger-Paap kr LM	-	58.74***	2710***	-	17.02***	597.93***	-	58.74***	2710***	-	17.02***	597.93***

Note: The OLS estimation includes controls for industry, year, region (NUTS II), capital ownership and firm age. The CFE-FE is estimated in first differences. Coefficients for the polynomials incliuded in the estimation were not included in this table. The GMM-IV is estimated in first differences, with the shares of workers ages lagged 2 and 3 periods used as instruments.

Table 5: Parameter estimates of the production and labor cost function - High against low PC usage intensity

	Productivity						Labor Costs					
	Bottom 25 %			Top 25 %			Bottom 25 %			Top 25 %		
	OLS	CFE-FE	GMM-IV	OLS	CFE-FE	GMM-IV	OLS	CFE-FE	GMM-IV	OLS	CFE-FE	GMM-IV
Age group												
25-29	0.224	-0.411	0.073	0.179	1.334*	0.429	0.127*	0.289***	-0.093	0.248**	0.316***	0.077**
	(0.170)	(0.551)	(0.213)	(0.195)	(0.744)	(0.338)	(0.066)	(0.108)	(0.089)	(0.117)	(0.089)	(0.031)
30-34	0.432**	0.832	0.129	0.485**	3.031**	1.180**	0.281***	0.263**	-0.177*	0.647***	0.376**	0.136***
	(0.185)	(0.591)	(0.255)	(0.217)	(1.470)	(0.543)	(0.059)	(0.116)	(0.106)	(0.123)	(0.174)	(0.050)
35-39	0.021	0.201	0.052	1.152***	2.485	3.156***	0.163**	0.317**	-0.260	0.963***	0.662***	0.261**
	(0.172)	(0.745)	(0.403)	(0.265)	(1.861)	(1.120)	(0.073)	(0.146)	(0.168)	(0.154)	(0.174)	(0.103)
Observations	5,002	837	1003	3195	1,900	2,477	5,002	837	1003	3,195	1,900	2,477
Number of firms	1542	263	313	1221	600	777	1542	263	313	1221	600	777
Endogeneity Test	-	-	4.87	-	-	93.49***	-	-	19.04***	-	-	14.07***
Kleinberger-Paap kr LM	-	2.936	5.349**	-	0.897	11.81***	-	1.969	5.349**	-	5.472	11.81***

Note: The OLS estimation includes controls for industry, year, region (NUTS II), capital ownership and firm age. The CFE-FE is estimated in first differences. Coefficients for the polynomials incliuded in the estimation were not included in this table. The GMM-IV is estimated in first differences, with the shares of workers ages lagged 2 and 3 periods used as instruments.