The Effects of an Ageing Workforce on Firm Productivity:

Evidence from Portugal

Ricardo Figueiredo

Dissertation written under the supervision of Prof. Joana Silva

Dissertation submitted in partial fulfilment of requirements for the MSc in Economics, at the Universidade Católica Portuguesa, April 2021.

The Effects of an Ageing Workforce on Firm Productivity:

Evidence from Portugal

Ricardo Figueiredo

April 06, 2021

Supervisor: Joana Silva

Abstract

This thesis examines the relationship between the age structure of the workforce, labor productivity and wages at the firm level, using a longitudinal employer-employee data-set from Portugal for the period 2004-2018. It finds that labor productivity increases until the age of 55-59, whereas wages are ever increasing with age. This result is mainly driven by firms with a more skilled labor force, as less skill intensive firms show no significant increase in productivity from the age of 35-39. The relationship between age and productivity is positive among firms in technology intensive sectors, while it is mildly increasing from ages 35-39 to 50-54 and falls among older individuals. Overall, these results suggest that the adoption of technology in Portugal may be increasing older workers´ productivity rather than rendering them obsolete.

Keywords

Ageing; productivity; wages.

Os Efeitos do Envelhecimento da Força de Trabalho na Produtividade das Empresas:

O Caso Português

Ricardo Figueiredo

06 de Abril de 2021

Supervisor: Joana Silva

Resumo

Esta tese examina a relação entre a estrutura etária da força de trabalho, a produtividade do trabalho e os salários ao nível da empresa através de uma base de dados longitudinal que associa informação ao nível do trabalhador e da empresa de Portugal, entre o período 2004-2018. Descobre que a produtividade do trabalho aumenta até à idade de 55-59, enquanto os salários aumentam a um ritmo sempre crescente com a idade. Este resultado é impulsionado principalmente por empresas com uma força de trabalho mais especializada, enquanto as empresas menos especializadas não revelam nenhum aumento significativo na produtividade desde o grupo de idades 35-39 para a frente. As empresas em setores de alta tecnologia mostram uma relação positiva entre a idade e a produtividade, enquanto as empresas de baixa tecnologia revelam um crescimento brando desde as idades 35-39 até 50-54 e um decréscimo entre os indivíduos mais velhos. No cômputo geral, estes resultados sugerem que a adoção de technologias em Portugal pode estar a aumentar a produtividade dos trabalhadores mais velhos em vez de os tornar obsoletos.

Palavras-chave

Envelhecimento; produtividade; salários.

Acknowledgements

Above all, I would like to express my sincere gratitude to my advisor, Professor Joana Silva, who has helped me deeply throughout all of the stages of the thesis and guided me brilliantly throughout these months.

Second, I would like to thank all my colleagues in the Master in Economics, with a special emphasis to Martim Leitão, who has been a great friend and has taught me a lot during this journey.

Finally, I would like to thank my parents for giving me the opportunity to study at this school and at this level. They, alongside my brother, have showed unconditional support and I am truly grateful for all they have done for me.

Contents

1 Introduction

The rapid phenomenon of population ageing is seen as one of the most significant features of global demography (Bloom and Sousa-Poza 2013; Acemoglu and Restrepo 2017) and it is an increasing concern for most developed countries, which face a diminishing and ageing workforce having to sustain a growing share of pensioners. Population ageing is the event where there is a shift of the population from lower age groups to higher age groups, which can be translated into the workforce age structure. This phenomenon is mainly driven by low fertility rates combined with increasing life expectancy levels. These demographic trends along with the fact that people are working until later in life are contributing to an ageing workforce. This phenomenon has coincided with declining aggregate productivity. Could workforce ageing be partly responsible for the low productivity growth?

A number of theoretical explanations for such relationship have been advanced. One set of models emphasize the potential composition effects: the age distribution of the workforce affects the total human capital productivity. If older workers are assumed to be less productive, an increase in their share could slow productivity growth (Maestas, Mullen, and Powell 2016). Lower productivity could be the result of declining cognitive abilities, creativity, innovation, and the person's health over the years (Skirbekk 2004; Autor and Dorn 2009; Ilmarinen 2012).

A separate class of explanations focuses on *spillover effects*. In the presence of human capital spillovers due to experience, ageing could lead to higher productivity growth (Feyrer 2007). These effects would be particularly strong if older workers generate firm-specific human capital that is not easily replaced by the firm (Acemoglu and Restrepo 2017). In addition, older workers may have better social skills and to be more reliable and committed to the organization (Van Dalen, Henkens, and Schippers 2010; Göbel and Zwick 2012). Finally, Acemoglu and Restrepo (2017) suggest that the scarcity of younger and middle-aged labor can trigger the adoption of robotics technology that actually increases the aggregate output of the country.

On the other hand, older workers can fall victim to skill obsolescence. Innovations based on information technology change the skills required of many jobs, deeming some skills acquired prior to their existence as less important or not required at all (Desjonqueres, Machin, and Reenen 1999; Dickerson and Green 2004; Welch and Ureta 2002). Autor, Katz, and Kearney (2008) highlight that skill-biased technological involves firm restructuring which requires workers to adapt to new environments and skills, and it ultimately leads to the acceleration of skill obsolescence (Beckmann and Schauenberg 2007). Older workers are likely to be more vulnerable to these technological changes since they received their education less recently than younger workers. Additionally, older workers have less incentives to invest in training compared to younger workers since they will retire sooner and thus have less time to take advantage of that investment. This introduces the concept of age-biased technological change. In this context, the establishment of new technologies and innovative work practices is expected to negatively affect older workers more than the younger workers' productivity (Behaghel, Caroli, and Roger 2014; Hujer and Radic 2005).

Empirically, this relationship has been mainly studied at the aggregate level with mixed results. While Feyrer (2007) and Acemoglu and Restrepo (2017) find evidence consistent with countries with more ageing having higher productivity for the U.S., Maestas, Mullen, and Powell (2016) find that a state-level increase in the share of the population age 60 and older slows productivity growth significantly. Using sector-level data, Tipper (2012) regresses value added on the shares of workers in young, prime-aged or old age groups finding a positive relation. In contrast, Lallemand and Rycx (2009) find a negative relation, and Göbel and Zwick (2012) and Mahlberg et al. (2013) do not find a significant effect. In a more recent paper, Ozimek, DeAntonio, and Zandi (2018) study the effects of ageing on productivity in a cross-section of state-industry data for the U.S. The paper finds that an older workforce is associated with lower productivity with an average elasticity of productivity to the age 65 and older share of workers between 4.0 and 10.8. While this paper controls for country-level changes in industry productivity and state-level changes such as a growing dependency ratio, findings remain open to reverse causality and omitted variable bias.

In this thesis, I use a combination of high-quality administrative longitudinal matched employer-employee data with longitudinal firm-level financial information from Portugal over the 2004-2017 period to further examine the ageing-productivity relationship. Rather than focusing on the aggregate relationship, I focus on the firm-level relationship. Specifically, I examine the extent to which each firm's workforce age structure determines its productivity. Exploiting the richness of the data, I control for other workforce and firm specific characteristics, and for firm fixed-effects. The same model is estimated for wages and productivity allowing for a comparison of age-wage and age-productivity profiles.

Recognizing that the estimated fixed-effects could be biased if the shares of older workers are negatively correlated with productivity shocks and/or if some omitted variables are not constant over time, this models are also estimates in first-differences by the generalized method of moments (GMM). In this case, I instrument each age share with the corresponding level two and three years before, assuming that productivity shocks in a given period, even if correlated with the contemporaneous variations in shares of each age group in the workforce, would be uncorrelated with their past levels. To shed light on potential mechanisms driving the age-productivity relationship, I estimate the same regression separating firms by the intensity of skilled labor and also by how technology intensive the sector is. I find that firms with a more skilled workforce have a positive relationship between productivity and age, while in less skill intensive firms productivity increases with age until ages 30-34 and fall flat from then on. Second, I find that productivity increases with age among firms in high technology sectors while it registers a slight increase between ages 35-39 to 50-54 and a slight decline in the oldest age groups among firms in less technology intensive sectors. Overall, results are not supportive of the skill obsolescence hypothesis and are more consistent with the Acemoglu and Restrepo (2017) hypothesis.

This thesis is most closely related to the study of Cardoso, Guimarães, and Varejão (2011).

While previous studies of age wage and age-productivity profiles were based on cross-section data and broad age intervals (Hellerstein and Neumark 1995; Hellerstein, Troske, and Neumark 1999; Mahlberg et al. 2013)[1] or short panels of only few years where a limited number of workers move age brackets and identification is based on a small number of firms (Crépon, Deniau, and Pérez-Duarte 2002; Göbel and Zwick 2012)[2], the authors use Portuguese longitudinal matched employer-employee data (Quadros de Pessoal) spanning 22 years (1986 to 2008)[3]. The authors find that productivity increases until the age of 50-54, declining afterwards, whereas wages peak around the age of 40-44. My results are different, suggesting that productivity and wages increases until later ages. This finding is particularly sticking giving that I use a more consistent measure for productivity, which is value added per yearly worker-hour (as opposed to their sales per yearly worker-hour) which I compute by linking Quadros de Pessoal with Sistema de Contas Integradas das Empresas (SCIE), additional firm controls and cover the post 2008 period. This new result could be linked with the analysis of channels discussed above suggesting that technical progress in the 2000s could have contributed to increase older age workers productivity rather than rendering obsolete.

The remainder of the dissertation is divided into 5 sections. The next section contextualizes the analysis, going into detail about the ageing and declining productivity growth scenarios in Portugal. In section 3, the data is displayed and described. In Section 4, I explain the empirical approach. Section 5 presents the results and section 6 ends with the conclusions.

2 Institutional Context: Ageing in Portugal

Ageing is a crucial issue for the Portuguese labor force. The population is ageing rapidly and this trend is likely to continue in the future. The pressure on the workforce to sustain the social security system is increasing and fiscal sustainability is very much dependent on government intervention on the health and pension systems (Directorate-General for Economic and Financial Affairs 2018,OECD 2019).

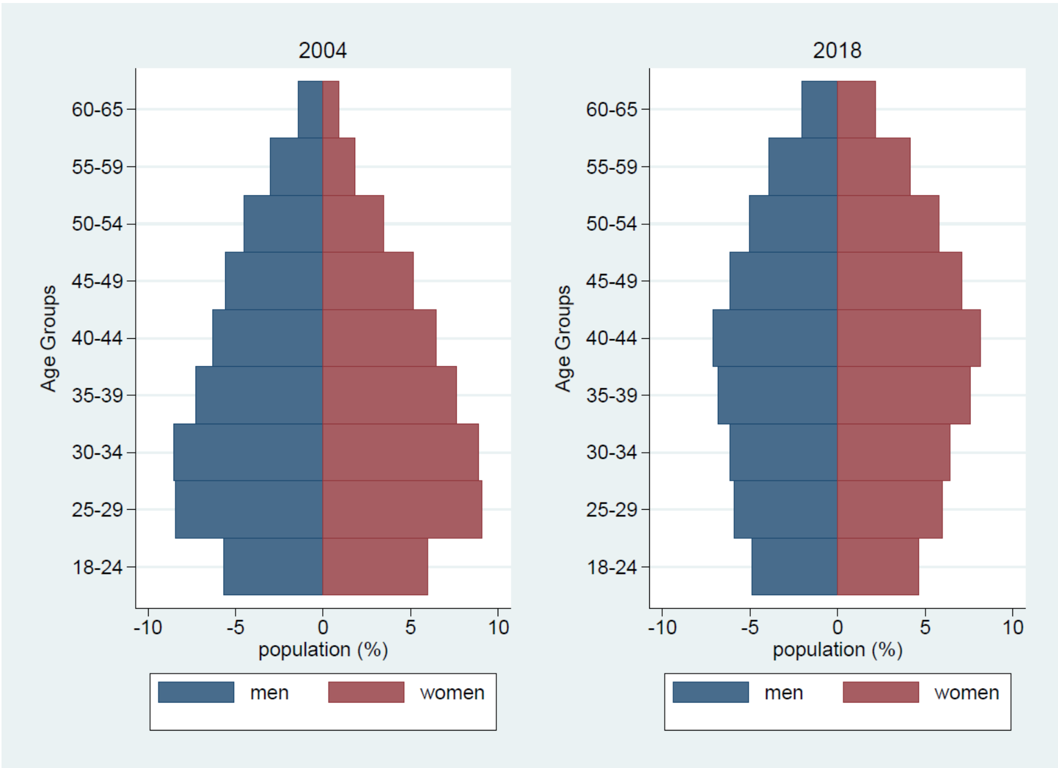
[1] This strand of the literature develops a firm-level analysis using matched employer-employee data. Hellerstein, Troske, and Neumark (1999) focus on a sample from the manufacturing sector of the USA. The authors regress firm's value added on shares of workers young, prime-aged and old. They find that productivity increases/decreases over the life-cycle according to the model specifications. Hellerstein and Neumark (1995) use data from Israel. They estimate the firm's output on shares of workers young, prime-aged and old. They find that productivity increases over the life cycle. Mahlberg et al. (2013) use data from Austria. They regress the firm's value added on the shares of workers who are young, prime-aged and old. They also separate firms in industry and construction sectors, and in the service sectors. They find no significant relation between older workers and productivity.

[2] This stand of the literature develops a firm-level analysis using longitudinal matched employer-employee data. Crépon, Deniau, and Pérez-Duarte (2002) use data from from France. They estimate the value added on the share of workers in certain age groups. They find an inverted U-shaped productivity profile with peak at 25-34 years old. Göbel and Zwick (2012) use data from Germany. The authors estimate firm's value added on shares of workers in certain age groups They also separate firms in metal manufacturing and service sectors. The results indicate no significant relation between age and productivity.

[3] Albeit data from years 1990 and 2001 are more limited as worker level data are not available.

In Portugal, much like in many other European countries, fertility rates have shown a declining trend from many years, falling well below replacement level[4]. In 1971 Portugal registered a total fertility rate of just about 3 while in 2019 that rate fell to under 1.5, having more than halved (see Appendix Figure A1). Life expectancy at birth, on the other hand, has been increasing at a faster rate than ever before, from around 72 years in 1980 to approximately 81 years of age in 2018 (see Appendix Figure A2). As a result, there is a shift of population from lower to higher age groups over time. Although the share of working age population has remained stable during the period under analysis, the average working age has increased substantially from 37 years old in 2004 to 40 years old in 2018.

Figure 1: Workers' Population Pyramids, Portugal (2004 and 2018)



Source: Computations made with *Quadros de Pessoal*

Naturally, these changes are translated into the workforce. Figure 1 presents the population pyramids for 2004 and 2018 in Portugal, calculated only with the active workers in the referenced years. It clearly shows the age structure differences in the Portuguese workforce, with the most representative age group changing from 25-29/30-34 years old in 2004 to 40-44 years old in 2018. The graph also registers a relative shrink of the younger workers' share and a consequent relative expansion of the older workers' share. Moreover, the share of female workers has also increased from 2004 to 2018.

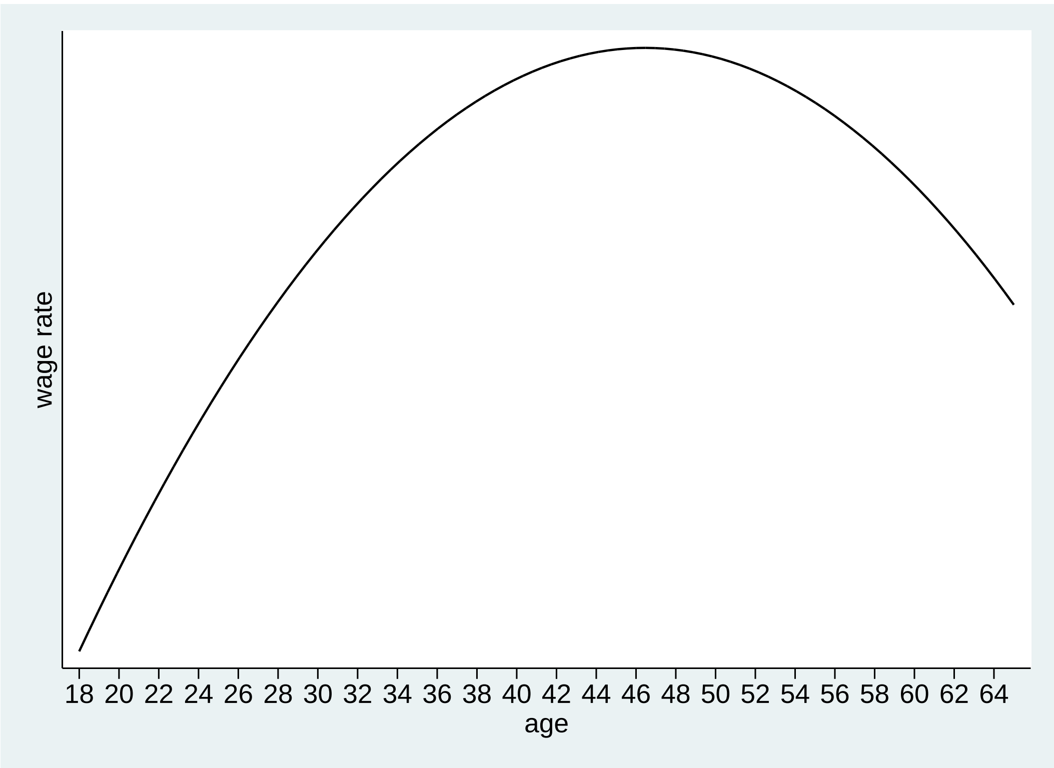
These changes in the population structure represent a threat to the pension plan system. In

[4] The total fertility rate is also used to indicate the replacement level fertility; in more developed countries, a rate of 2.1 is considered to be replacement level (Source: Statistics Portugal).

Portugal the pension system is a pay-as-you-go type of system in which current workers fund the retirement pensions of the current retirees. This system holds as long as the ratio of workers to retirees doesn't change or the productivity of the workers increases. Once common policy is to adjust the legal retirement age.

Until 2013, the legal retirement age in Portugal stood at 65 years old. By the end of the year, the Government determined that the retirement age should be conditional to the evolution of the longevity gains. According to the current legislation, about 2/3 of the longevity gains are converted into the legal retirement age. Looking at the population projections for the next decades, the life expectancy at 65 years old for Portugal will increase by approximately 5 years between 2018 and 2070, meaning that the retirement age is expected to increase by 3 years during that period (from 66 and 4 months in 2018 to 69 years and 4 months in 2070), as long as the legislation does not change in the meantime (*Boletim Económico Junho 2019*) (see Appendix Figure A3).

Figure 2: Age-Wage Workers' Profiles (Portugal, 2004-2018)

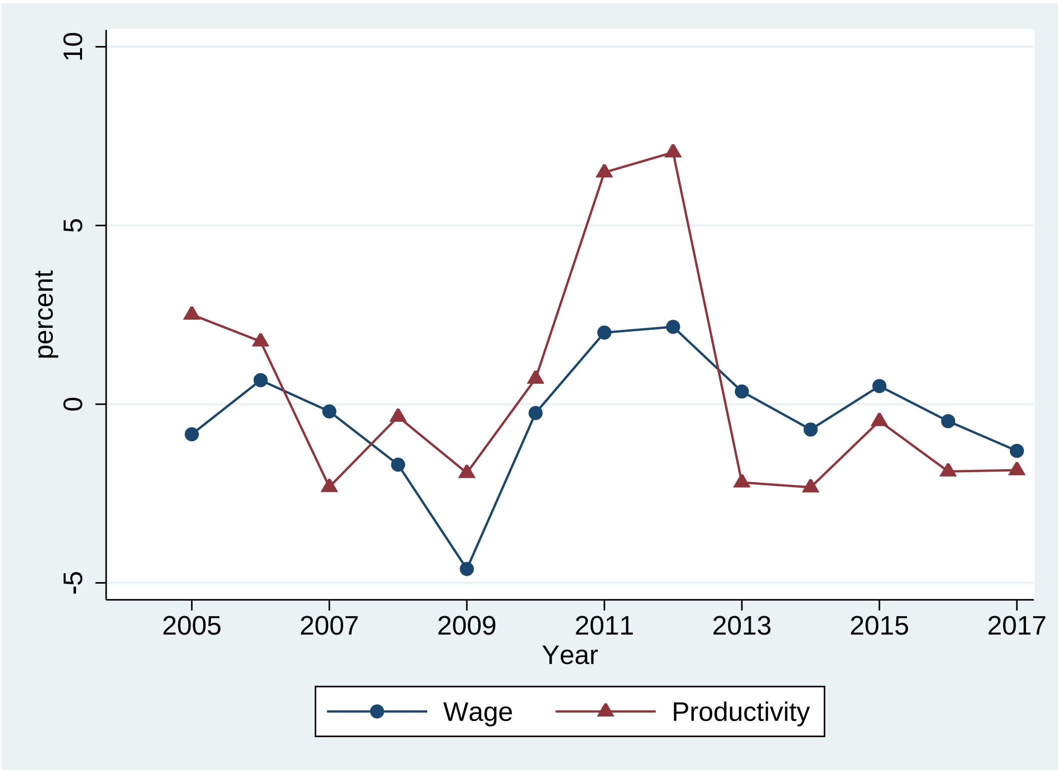


Source: Computations made with *Quadros de Pessoal*. Quadratic fit estimation of raw data.

Figure 2 presents the age-wage profiles of the workers included in the regression analysis. The graph depicts a quadratic fit of the data for the log of average wage rates in each year of age. Younger workers have, on average, lower wage rates than their older counterparts. Collectively speaking, wage rates are increasing up to the age of 47, decreasing afterwards. This result is, in fact, consistent with the literature. It is expected that younger workers earn less, as they are in the dawn of their careers. However, it is important to note that the outcome of this graph is a representation of the overall pattern of wages and does not render the exact values for each of the values for the average wage rates of the different ages.

Figure 3 depicts the wage and labor productivity growth in Portugal over the years 2004-2017. The graph shows that the Portuguese economy exhibits low wage and productivity growth, with the exception of the years after the crisis of 2007-2009, which show a very significant increase in value added per labor hour. The important question that is addressed here is whether or not this low productivity pattern is driven by the ageing phenomenon of the population.

Figure 3: Wage and labor productivity growth (Portugal, 2004-2017)



Source: Computations made with *Quadros de Pessoal*.

3 Data

In this section I describe the data. The databases used were collected from *Instituto Nacional de Estatística de Portugal* (INE), the Portuguese national statistics agency:

i *Quadros de Pessoal* (QP): gathers longitudinal information on all the workers in every firm and entity operating in Portugal each year. From this database I extract information on firm specific characteristics such as its location, age, industry, ownership of equity capital, sales and number of employees. As for the workers, the information drawn is their age, education, wage, gender, tenure and professional qualifications. The firms' and the workers' databases are then linked to create a longitudinal employer-employee data-set. The worker specific characteristics are then collapsed at the firmlevel to obtain the workforce characteristics.

ii *Sistema de Contas Integradas das Empresas* (SCIE): collects financial information for fiscal and accounting purposes from every firm and entity operating in Portugal each year. From this database I get the firms' value added data.

In QP, with the worker specific data, it is possible to obtain the share of workers with certain characteristics and average wages per hour worked in the firm. Worker level information is then collapsed by firm, so there is a unique observation for a firm in each year. The two data-sets, QP and SCIE, were then linked together through a unique identification number for each firm, which also makes it so it can be followed over time. The covered period of the data ranges from 2004 to 2018. However, the final year (2018) had to be dropped due to sales being reported only on the subsequent year[5].

In contrast to Cardoso, Guimarães, and Varejão (2011), where productivity is measured as total sales per labor unit, I measure productivity as value added per labor unit. To check the consistency of my results with theirs, I also use sales per worker-hour. The reason for this change is that sales capture the profitability of the firm, and not necessarily its productivity (Lieberman and Kang 2008).

The final observation of firms who run out of business is dropped. Furthermore, outlier observations for value added are removed[6] as well as sales outliers[7] have been dropped. Moreover, all monetary variables are in constant prices of 2015.

The workers considered in the analysis are 18-65 years old, wage-earners with a valid identification number. Wage outliers have also been dropped[8].

Firms in primary activities, such as agriculture, animal production, fishing and other related activities, as well as firms in the mining and construction sectors, have been dropped due to poor data quality. Furthermore, firms with 5 workers or less in at least one year (in the conditions specified above) have been dropped.

The final data-set contains 43,086 firms corresponding to about 350,000 firm-year observations in the period of 2004-2017. Table 1 presents the summary statistics. The average firm in the sample employs approximately 34 workers, of which 46% are women. The most represented age group, on average, is workers aged 35-39. One feature worth to mention is that, compared to the data presented by Cardoso, Guimarães, and Varejão (2011), education has increased significantly in the Portuguese labor market. While the share of workers with a university degree (highest level achieved) in their observations accounted for about 6% (1986-2008), that number has now doubled to 12% in the data presented in this study (2004-2018). Descriptive statistics

[5]Sales for year t are reported in year $t+1$

[6]Value added above 10 times the percentile 99 or below half the percentile 1.

[7]Sales above 10 times the percentile 99 or below half the percentile 1.

[8]Wages above 10 times the percentile 99 or below half the percentile 1.

Table 1: Summary Statistics

Variable	Mean or %	Std. Dev.
Employee Characteristics		
Share workers aged 18-24	0.089	0.112
Share workers aged 25-29	0.133	0.116
Share workers aged 30-34	0.160	0.114
Share workers aged 35-39	0.161	0.108
Share workers aged 40-44	0.147	0.105
Share workers aged 45-49	0.122	0.100
Share workers aged 50-54	0.094	0.093
Share workers aged 55-59	0.062	0.079
Share workers aged 60-65	0.033	0.056
Share workers w/ highest level university degree	0.120	0.189
Share workers w/ highest level high-school degree	0.218	0.207
Share workers w/ highest level 9 years education	0.254	0.207
Share workers w/ highest level 6 years education	0.217	0.212
Share workers w/ highest level 4 years education	0.178	0.205
Share female workers	0.402	0.291
Firm Characteristics		
Avg. hourly wage (euro)	5.378	2.282
Avg. sales per labor hour (euro)	63.693	104.608
Avg. value added per labor hour (euro)	14.883	17.134
Employment	34.431	67.580
Age of the firm	20.006	15.906
Lisbon	0.262	
Observations	350,708	

with the more detailed information can be found in the appendix table B1.

Appendix table D1 presents the statistics when separating firms by a ratio of skilled to unskilled workers in the firm. A worker has been classified as skilled when he's carrying either skilled or highly skilled labor in his occupation, and is considered unskilled when is carrying semi-skilled or unskilled labor. The type of labor that a worker is engaged in is reported in QP, under professional qualifications. The data displayed reveals that a firm with a skill ratio above the median has, on average, a higher volume of sales and value added per labor hour, as well as wage rates, compared to the firms with a ratio below the median. The employee characteristics are also quite different. The set of firms with a higher skill ratio have a more educated workforce and employ a smaller share of women, relative to the firms with a lower skill ratio.

The statistics for firms separated by high and low intensive technology firms are displayed in appendix table F1. The different technology intensive sectors are defined based on a definition by Statistics Portugal. On average, firms in the high technology sectors have higher wages, sales and value added per labor hour compared to those in the low technology sectors.

4 Empirical Approach

In this section I will explain the empirical approach used in the analysis. Following Cardoso, Guimarães, and Varejão (2011), I estimate one firm-level wage equation and two firm-level productivity equations that share a common specification. In my approach, I estimate another productivity equation, in addition to the one presented in their article, with a different and more accurate productivity measure. The purpose behind the similarity of the equations has to be with having the possibility to compare both results, with more recent data. Later, I estimate the same model with 2 additional distinct settings to test some hypotheses. I estimate the age-productivity and wage profiles of firms separated by a skilled to unskilled labor ratio and, in another analysis, separated by high and low technology intensive sectors.

The estimated firm-level wage equation is as follows:

$$\ln w_{i,t} = \alpha^w + \sum_{j-1} \beta^w (\frac{L_j}{L})_{i,t} + \sum_{m-1} \theta^w (\frac{L_m}{L})_{i,t} + \phi^w X_{i,t} + \varepsilon^w_{i,t} \tag{1}$$

where subscript i denotes the firm, subscript t denotes time, subscript j denotes age groups and subscript m denotes labor types (gender, highest education level achieved). The dependent variable w is the firm average hourly wage and L is total labor (in hours). L_j is the number of hours worked by employees in age group j, L_m is the number of hours worked by employees in group m. X is a vector of the firm-specific explanatory variables (employment, location, age, ownership of equity capital, industry and time) and ε is the firm specific error term. The firm average hourly wage for firm i at time t is calculated as:

$$w_{i,t} = \frac{\sum_z (bw + reg)_{z,i,t}}{\sum_z h_{z,i,t}} \tag{2}$$

where subscript z denotes the workers, bw is base wage, reg are regular transfers that are part of the worker's pay, such as food and transport allowances; and h are average monthly paid hours. Extra hours and extra pay are excluded from the computation.

The firm-level productivity equations are:

$$\ln s_{i,t} = \alpha^s + \sum_{j-1} \beta^s (\frac{L_j}{L})_{i,t} + \sum_{m-1} \theta^s (\frac{L_m}{L})_{i,t} + \phi^s X_{i,t} + \varepsilon^s_{i,t} \tag{3}$$

$$\ln v_{i,t} = \alpha^v + \sum_{j-1} \beta^v (\frac{L_j}{L})_{i,t} + \sum_{m-1} \theta^v (\frac{L_m}{L})_{i,t} + \phi^v X_{i,t} + \varepsilon^v_{i,t} \tag{4}$$

where the dependent variable s in equation (3) is the firm-average sales per yearly worker-hour, while the variable v in equation (4) refers to the firm-average value added per yearly worker-hour. The equations share the same explanatory variables and follow the same interpretation as in equation (1). The previously mentioned dependent variables are obtained by the following expressions:

$$s_{i,t} = \frac{sales_{i,t}}{12 * \sum_z h_{z,i,t}} \tag{5}$$

$$v_{i,t} = \frac{value\ added_{i,t}}{12 * \sum_z h_{z,i,t}} \tag{6}$$

where h carries out the same meaning as before mentioned and i, t and z are the subscripts for firm, time and worker, respectively; $sales$ is the total volume of sales of the year; gva stands for gross value added at factor cost. Furthermore and as previously mentioned in the data section, all monetary variables are in 2015 prices.

The most important explanatory variables in these equations are the age group shares. The other variables mainly act as controls for the workforce and firm characteristics. α is the marginal productivity of the omitted age group (35-39) and β is the effect of an increase in the share of age group j relative to the reference group; θ follows the same reasoning for labor type m. The coefficient phi for the log of the firm size can be interpreted as the total labor elasticity of output $E_{v,l} = \frac{dv}{dL} * \frac{L}{v}$. To be more accurate, the shares of workers with specific characteristics are calculated with yearly worker-hours, instead of number of workers. This means that, even if the firm has the same number of workers with certain distinct characteristics, the shares can be different, according to how many hours the groups have worked.

The different workforce-specific characteristics considered are age, gender and highest level of education achieved. Age groups are defined by intervals of 5 years, from 18 to 65, with the first (18-24) and last (60-65) group being the exceptions. Age group 35-39 is omitted. The gender description of the workforce is contemplated in the analysis through the female share and the highest level of education achieved is divided into 5 categories: 4, 6, and 9 years of schooling, high-school and university degrees. Illiterate workers and blank observations are omitted. The firm-specific characteristics included are employment (log of the total number of workers), age (calculated in years since the creation of the firm), ownership of equity capital (dummies for public and foreign ownership, with private omitted) and location (dummy that has the value 1 if the company is located in the Lisbon district and 0 otherwise). There are also controls for the industry (18 dummies) and time (13 dummy variables).

I will first estimate equations (1), (3) and (4) by Pooled Ordinary Least Squares (OLS) . OLS estimates are likely to be biased in this case, however, because that would require all the regressors to be uncorrelated with the error term, which is unlikely because we cannot control for all establishment characteristics, meaning there could be an unobserved factor. I will then estimate the equation with firm Fixed Effects (FE), which will aim to solve the heterogeneity bias, but not the endogeneity problem. According to Cardoso, Guimarães, and Varejão (2011), both ”positive and negative productivity shocks are expected to lead to the hiring and firing of workers, with younger workers being over-represented in both flows”. This would lie on the assumption that older workers would be less likely to be hired and more likely to be fired, in the corresponding scenarios.

In order to account for endogeneity in the model, I will estimate equations (1), (3) and (4) in first differences by the Generalized Method of Moments (GMM). Just as in Cardoso, Guimarães, and Varejão (2011), the workers' age shares are instrumented through their corresponding lags of two and three years. The implicit assumption is that a productivity shock in one period would not be correlated with the variations in the levels of labor shares of two and three periods before, the authors state. The difference GMM model corrects endogeneity by transforming all regressors through differencing and also removes fixed effects. For instruments validity, I will perform the Hansen J Test of over identifying restrictions. This way, I estimate the three following equations by GMM:

$$\Delta \ln w_{i,t} = \sum_{j-1} \beta^w \Delta(\frac{L_j}{L})_{i,t} + \sum_{m-1} \theta^w \Delta(\frac{L_m}{L})_{i,t} + \phi^w \Delta X_{i,t} + \Delta\varepsilon^w_{i,t} \tag{7}$$

$$\Delta \ln s_{i,t} = \sum_{j-1} \beta^s \Delta(\frac{L_j}{L})_{i,t} + \sum_{m-1} \theta^s \Delta(\frac{L_m}{L})_{i,t} + \phi^s \Delta X_{i,t} + \Delta\varepsilon^s_{i,t} \tag{8}$$

$$\Delta \ln v_{i,t} = \sum_{j-1} \beta^v \Delta(\frac{L_j}{L})_{i,t} + \sum_{m-1} \theta^v \Delta(\frac{L_m}{L})_{i,t} + \phi^v \Delta X_{i,t} + \Delta\varepsilon^v_{i,t} \tag{9}$$

where $(\frac{L_j}{L})_{i,t}$ instrumented through $(\frac{L_j}{L})_{i,t-n}$ with $n = 2, 3$. All the equations estimated, from OLS to FE to GMM, account for clustering and robustness at the firm level.

I then estimate the previously mentioned equations conditioning with skill ratio. I separate firms in 2 different sets, above and below the median of skilled to unskilled workers ratio. This ratio is calculated by dividing the number of workers who are engaged in skilled and highly skilled labor by the number of workers who are in semi-skilled and non-skilled labor in each firm for each year. This information is taken from the professional qualifications of the workers that are reported in QP. The median is calculated only after collapsing the mean of the ratios by firm. Firms with no workers in each of the specifications are not accounted in the calculation of the ratio. However, the firms with no skilled labor are then integrated into the set of firms below the median and firms with no non-skilled labor are integrated into the set of firms above the median of the ratio.

The final setting is when firms are separated by high and low technology intensive sectors. The industries considered to be engaged in high technology intensive activity are based on a definition by Statistics Portugal. I estimate the same equations as in the other settings and derive the age-wage and age-productivity profiles of each set of firms.

5 Results

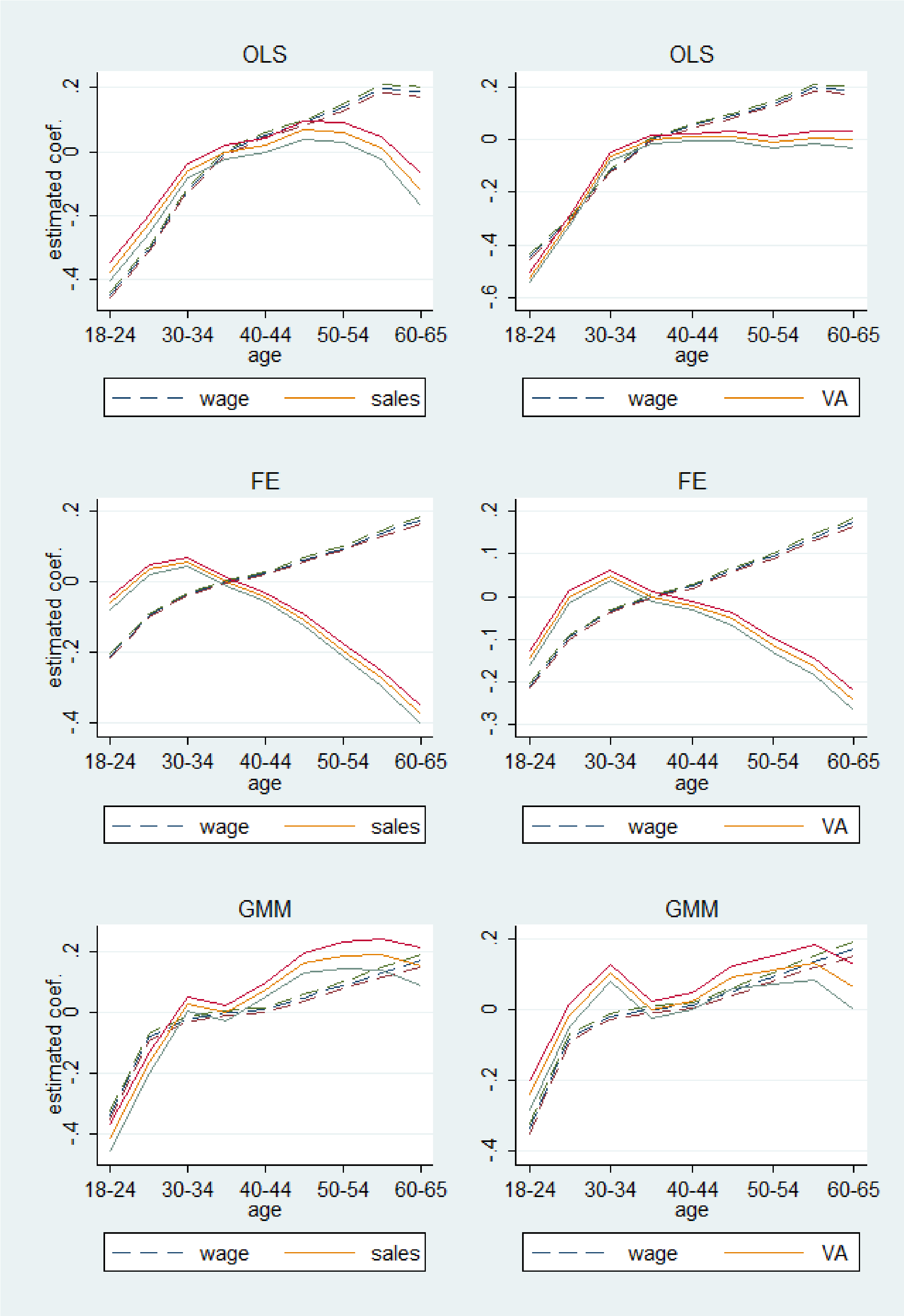
Figure 4 draws the wage and productivity profiles of the estimations with OLS, FE and GMM. The left column presents three graphs that illustrate the age-wage and age-productivity profiles using sales per yearly worker-hour as the productivity measure across the different estimation methods. The right column shows the equivalent graphs using the gross value added per yearly worker-hour as the productivity measure instead. Table 2 reproduces the results of the results of the main estimation on average wages and labor productivity.

From the OLS estimations on wages, I find that the average hourly wages within the firm are increasing with a higher share of older workers, only declining in the last age group of 60-65 (see panel 1 in figure 4 and column 1 in table 2). On average, a firm with a higher share of younger workers tends to pay their workers less per hour than a firm with a higher share of older workers. A firm with a higher share of workers aged 55-59 tends to pay the highest wages per labor hour. In contrast to Cardoso, Guimarães, and Varejão (2011), in which wages are increasing with a larger share of older workers up to the age group of 50-54, I find that the downturn in wages happens on the succeeding age group share of 55-59 years old.

As for the productivity function, the OLS results differ with productivity measures. In the sales specification, productivity is increasing with a higher share of older workers up until the age group of 45-49 and decreasing in the subsequent age groups, depicting an inverted U-shape profile (see panel 1 of figure 4 and column 4 in table 2). This result is close to the one from Cardoso, Guimarães, and Varejão (2011), in the way that productivity shows an inverted U-shape profile, yet they exhibit a steeper decline in productivity and starting from a younger age group. With the value added specification, however, productivity is also increasing up to the age group of 35-39, but it seems to stabilize from then on (see panel 2 in 4 and column 7 in 2), not showing the decline that is portrayed with the sales productivity measure. Hence, labor productivity does not seem to lower when employing older workers rather than middle-aged workers. Nevertheless, a higher share of younger workers has, on average, a negative impact on firm productivity.

Looking at the evolution of average wages and productivity together, it is clear that wages increase alongside productivity until productivity stops increasing. This is when the average hourly wages keep increasing but the productivity does not follow. On average and keeping everything else constant, when a firm replaces workers aged 45-49 for workers aged 35-39 (reference group), the average hourly wage decreases by 0.09%, average sales per yearly worker-hour decrease by 0.068% and average value added per yearly worker-hour decreases by 0.012%, per percentage point change. If the firm instead replaces the workers aged 60-65 by those aged 35-39, the decrease in average wages would be of 0.187%, and the average sales would increase by 0.119% per percentage point change, with no significant change in the average value added.

Figure 4: Wage, sales (left column) and value added (right column) cost functions: OLS, FE and GMM estimation (Portugal, 2004-2018)



Source: Computations made with *Quadros de Pessoal* and SCIE. Note: the plots without legend represent 95% confidence intervals.

Table 2: Panel estimation results on average wages and labor productivity (average sales and value added)

	Wages			Sales			Value Added		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Employment(log)	0.052***	0.004*	-0.013***	0.043***	-0.263***	-0.686***	0.008***	-0.160***	-0.500***
	(0.001)	(0.002)	(0.002)	(0.004)	(0.006)	(0.006)	(0.003)	(0.005)	(0.007)
Share workers aged 18-24	-0.446***	-0.209***	-0.336***	-0.375***	-0.060***	-0.410***	-0.524***	-0.145***	-0.241***
	(0.009)	(0.006)	(0.014)	(0.030)	(0.018)	(0.045)	(0.020)	(0.016)	(0.041)
Share workers aged 25-29	-0.304***	-0.095***	-0.078***	-0.224***	0.036**	-0.163***	-0.309***	0.000	-0.017
	(0.008)	(0.005)	(0.011)	(0.027)	(0.015)	(0.034)	(0.018)	(0.014)	(0.031)
Share workers aged 30-34	-0.118***	-0.034***	-0.019**	-0.058***	0.058***	0.030	-0.064***	0.050***	0.103***
	(0.007)	(0.004)	(0.008)	(0.022)	(0.012)	(0.024)	(0.015)	(0.012)	(0.023)
Share workers aged 40-44	0.053***	0.024***	0.010	0.020	-0.044***	0.078***	0.010	-0.021*	0.024
	(0.007)	(0.004)	(0.008)	(0.022)	(0.012)	(0.023)	(0.015)	(0.011)	(0.023)
Share workers aged 45-49	0.090***	0.063***	0.050***	0.068**	-0.105***	0.164***	0.012	-0.052***	0.090***
	(0.009)	(0.006)	(0.011)	(0.029)	(0.016)	(0.033)	(0.019)	(0.015)	(0.031)
Share workers aged 50-54	0.138***	0.095***	0.092***	0.061*	-0.193***	0.190***	-0.010	-0.113***	0.112***
	(0.010)	(0.006)	(0.013)	(0.032)	(0.018)	(0.043)	(0.021)	(0.017)	(0.040)
Share workers aged 55-59	0.198***	0.139***	0.133***	0.013	-0.272***	0.194***	0.008	-0.165***	0.132***
	(0.012)	(0.008)	(0.016)	(0.036)	(0.021)	(0.052)	(0.024)	(0.020)	(0.049)
Share workers aged 60-65	0.187***	0.175***	0.172***	-0.119**	-0.376***	0.154**	0.000	-0.244***	0.062
	(0.016)	(0.009)	(0.021)	(0.051)	(0.027)	(0.063)	(0.033)	(0.024)	(0.063)

Continuation of Table 2									
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share workers university	1.200***	0.335***	0.280***	1.565***	0.113***	0.076**	1.424***	0.020	-0.027
	(0.016)	(0.013)	(0.013)	(0.051)	(0.035)	(0.032)	(0.034)	(0.031)	(0.034)
Share workers high-school	0.506***	0.140***	0.086***	0.783***	0.147***	0.077***	0.657***	0.072***	0.020
	(0.015)	(0.011)	(0.011)	(0.048)	(0.029)	(0.027)	(0.032)	(0.026)	(0.029)
Share workers 9 years school	0.241***	0.102***	0.041***	0.334***	0.115***	0.032	0.276***	0.052**	-0.027
	(0.015)	(0.010)	(0.011)	(0.046)	(0.028)	(0.026)	(0.031)	(0.025)	(0.027)
Share workers 6 years school	0.112***	0.052***	0.009	-0.023	0.023	-0.021	0.105***	0.006	-0.039
	(0.015)	(0.010)	(0.011)	(0.047)	(0.028)	(0.025)	(0.031)	(0.024)	(0.027)
Share workers 4 years school	-0.015	0.015	-0.023**	-0.081*	0.021	-0.079***	-0.050	0.010	-0.063**
	(0.015)	(0.010)	(0.011)	(0.047)	(0.028)	(0.027)	(0.031)	(0.024)	(0.029)
Share female workers	-0.128***	-0.012***	-0.008***	-0.265***	-0.041***	-0.028***	-0.229***	-0.038***	-0.028***
	(0.004)	(0.003)	(0.002)	(0.014)	(0.008)	(0.006)	(0.008)	(0.007)	(0.005)
Age of the firm	0.001***			0.003***			0.003***		
	(0.000)			(0.000)			(0.000)		
Public Ownership	0.025			-0.447***			-0.160**		
	(0.020)			(0.084)			(0.067)		
Foreign Ownership	0.249***			0.349***			0.245***		
	(0.021)			(0.073)			(0.055)		

Continuation of Table 2									
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lisbon	0.077***			0.043***			0.066***		
	(0.003)			(0.009)			(0.006)		
Constant	1.175***	1.509***	0.000	2.834***	4.440***	-0.014***	2.199***	3.088***	-0.004***
	(0.016)	(0.012)	(0.000)	(0.051)	(0.033)	(0.001)	(0.033)	(0.029)	(0.001)
Observations	350,708	350,708	220,518	350,708	350,708	220,518	350,708	350,708	220,518
R-squared	0.592	0.925	0.019	0.399	0.910	0.159	0.318	0.793	0.086
F statistic	1372.7***	492.42***	108.36***	639.74***	222.67***	1056.8***	583.05***	230.3***	450.93***
Hansen-J Statistic			15.68**			26.789***			17.963**
Endogeneity Test			324.73***			132.52***			88.64***
Kleinberger-Paap rk LM			3560.6***			3560.6***			3560.6***
Kleinberger-Paap rk Wald			353.92***			353.92***			353.92***

Education refers to the highest level achieved. The OLS regression includes controls for the industry (18 dummy variables) and time (13 dummy variables); the FE regression includes controls for time (13 dummy variables). In the GMM regression, the equation is estimated in first differences, with the shares of worker ages lagged 2 and 3 periods used as instruments. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The fixed effects estimation results convey a fundamentally similar to the one drafted by the OLS estimation for the age-wage profile. Wages are increasing with the share of older workers. The age-productivity profile through sales also presents the inverted U-shape pattern, but the decrease starts from the age group of 35-39, meaning that, on average, having a larger share of workers aged 30-34 would yield a higher result on average sales per labor hour. The age-productivity profile with the value added specification draws a very similar outcome, but with a slightly less steep decrease from the age group of 35-39 onward (see row 2 in figure 4 and columns 2, 5 and 8 in table 2). These results are quite similar the ones presented by Cardoso, Guimarães, and Varejão (2011), with a small change in the slope of the functions.

The results in the GMM estimation for wages are also consistent with the OLS and FE estimations: the average hourly wage is increasing with a higher share of older workers. As for the productivity profiles, it differs from the previous estimation methods. Overall, the age-productivity profile for sales manifests an increasing trend, with a slight decline from the age groups of 30-34 to 35-39 and also from 55-59 to 60-65. The productivity profile with the value added specification also presents an increasing trend, but with a significant decrease from the age groups of 30-34 to 35-39 and also from 55-59 to 60-65 (see row 3 in figure 4 and columns 3, 6 and 9 in table 2).

To verify the validity of the GMM approach, I perform the Hansen-J test of over-identifying restrictions. For the sales equation, the test rejects the null hypothesis for any conventional significance level. In both the wage and the value added equations, the Hansen-J statistic fails to reject the null hypothesis at a 10% significance level, suggesting the instruments used are not correlated with the error term and thus the over-identifying restrictions are valid. Nevertheless, the test performs poorly in higher significance levels which indicates that the instrument set is not the most suitable. However, the endogeneity test rejects the null hypothesis for any conventional significance values, which means that the endogenous variables (share of workers' age groups) should be treated as such.

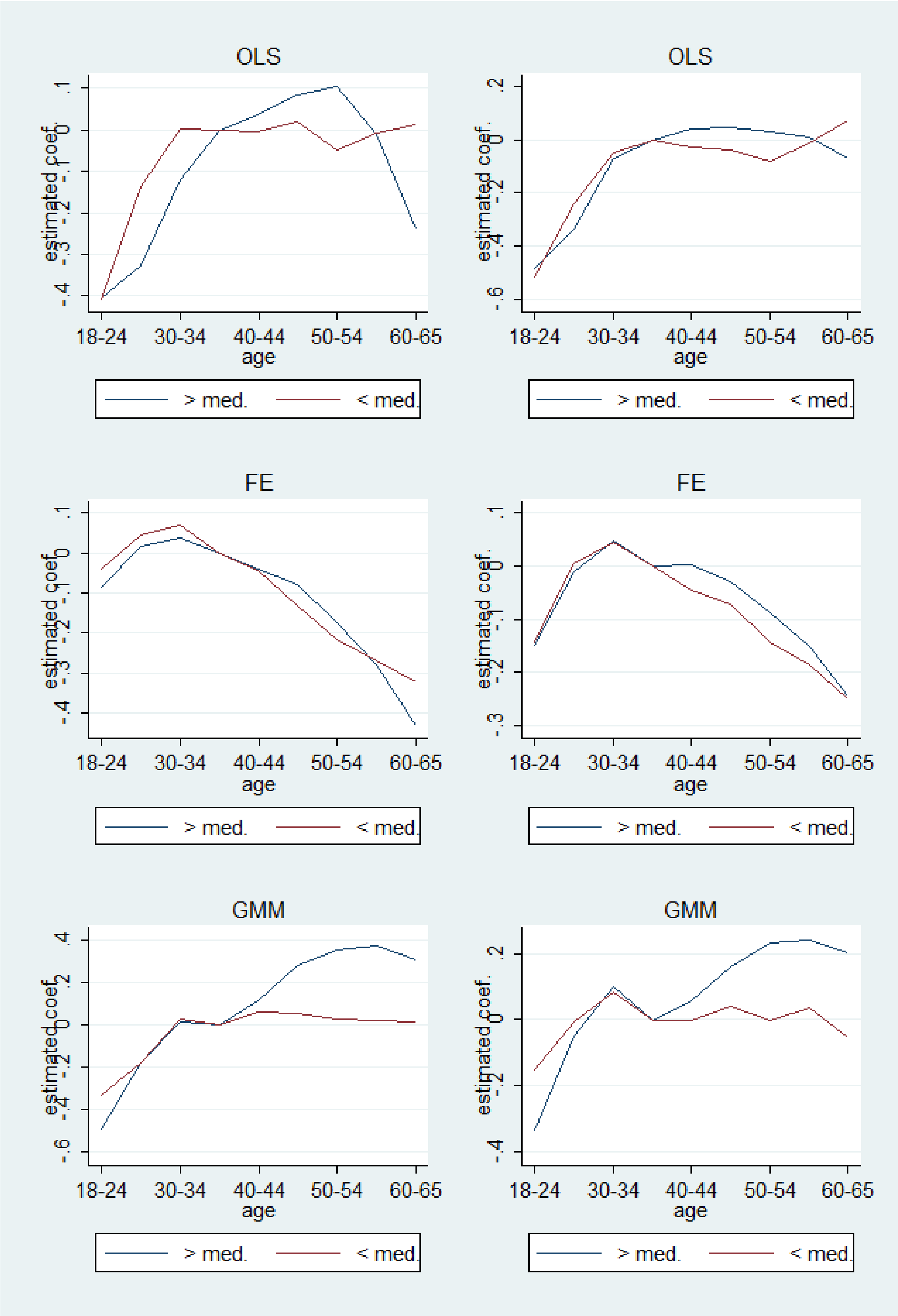
The first important result that is systematically robust across estimation methods is that firms with a higher share of younger workers tend to have lower average hourly wages. One other consistent result is that productivity tends to be lower with a larger group of the youngest workers, rising rapidly alongside wages as the cohort grows older in the firm. The GMM estimation underlines that the decline in productivity in the other estimation methods (in the OLS and the FE estimations in the sales specification and the FE estimation in the value added specification) might be a wide-eyed result, as the age-productivity shows an increasing trend under this preferred specification method (GMM). In addition, on average, the more educated the group of workers is, the higher wages and higher productivity the firm presents. This is an important result in line with the literature (Kampelmann et al. 2018).

I follow Cardoso, Guimarães, and Varejão (2011), yet I find some different results. The age-wage profiles show increasing trends and the age-productivity profiles present an inverted U-shape in the OLS and FE estimations, with the GMM estimation differing. The peaks of the productivity profiles (sales) are different, since they find that productivity peaks with a higher share of workers aged 40-44 while I find that it peaks with a higher share of workers aged 45-49. This might be just the consequence of the evolution of the Portuguese labor force as it grows older. It is also important to highlight the specification with value added as a productivity measure. The results are fundamentally the same, with only slight differences, but it expectantly presents more accurate results on productivity, since sales is more of a profitability measure. These results are also broadly consistent with the work by Göbel and Zwick (2012), which finds that while the OLS estimates point to an inverted U-shaped age-productivity profile, the difference GMM estimations show hardly no differences in productivity with higher shares of different age groups.

Figures 5 and appendix figure C1 draw the age-productivity and age-wage profiles for firms separating by high and low skilled to unskilled labor ratio firms. The left column of figure 5 presents three graphs illustrating the age-productivity profiles using sales as the productivity measure across all three estimation methods considered in the analysis: OLS, FE and GMM. The right column shows the equivalent graphs using the value added productivity measure. Tables C1, C2 and C3 indicates the estimation results in detail.

The age-wage profile is fundamentally equivalent to the one reproduced without the skill ratio specification, which means that firm average wages tend to increase with a higher share of older workers in the workforce, regardless of their workforce being composed of more high skilled or more low skilled workers. However, the age-productivity profiles are not quite the same when firms are separated by this skill ratio.

Figure 5: Sales (left column) and value added (right column) age profiles separating high from low skilled to unskilled workers' ratio firms: OLS, FE and GMM estimations (Portugal, 2004-2018)



Source: Computations made with *Quadros de Pessoal* and SCIE.

The OLS estimations show that, on average, firms with a skilled to unskilled worker ratio reveal the inverted U-shaped productivity profile (sales) mentioned previously, having a very significant increase in productivity as they employ more older workers until the age group of 50-54, when productivity declines rapidly with a higher share of workers after that aged 55 and older. The results for the firms with a lower skilled to unskilled worker ratio reveal the same increase in average productivity in the youngest age groups, until the age group of 30-34, when productivity tends to stabilize. Results for the productivity profiles of firms separated by the skill ratio using value added are more similar than those using sales. Firm productivity tends to increase in the younger age groups up until the age group of 35-39 in both sets of firms. Yet firms with a higher skill ratio keep slightly increasing productivity with a higher share of older workers until the age of 45-49, declining in the consequent age groups, while firms with a lower skill ratio show the opposite trend: a small decline with a higher share of older workers until the age of 50-54 followed by an rise in average productivity with a higher share of workers aged 55 and older (see panels 1 and 2 in figure 5 and columns 1 and 4 in appendix tables C2 and C3). The hypothesis that productivity would decline faster in firms with a more skilled labor force is verified with the sales specification. The intuition behind this result is that skilled work requires more complex cognitive abilities, which are bound to decrease with age.

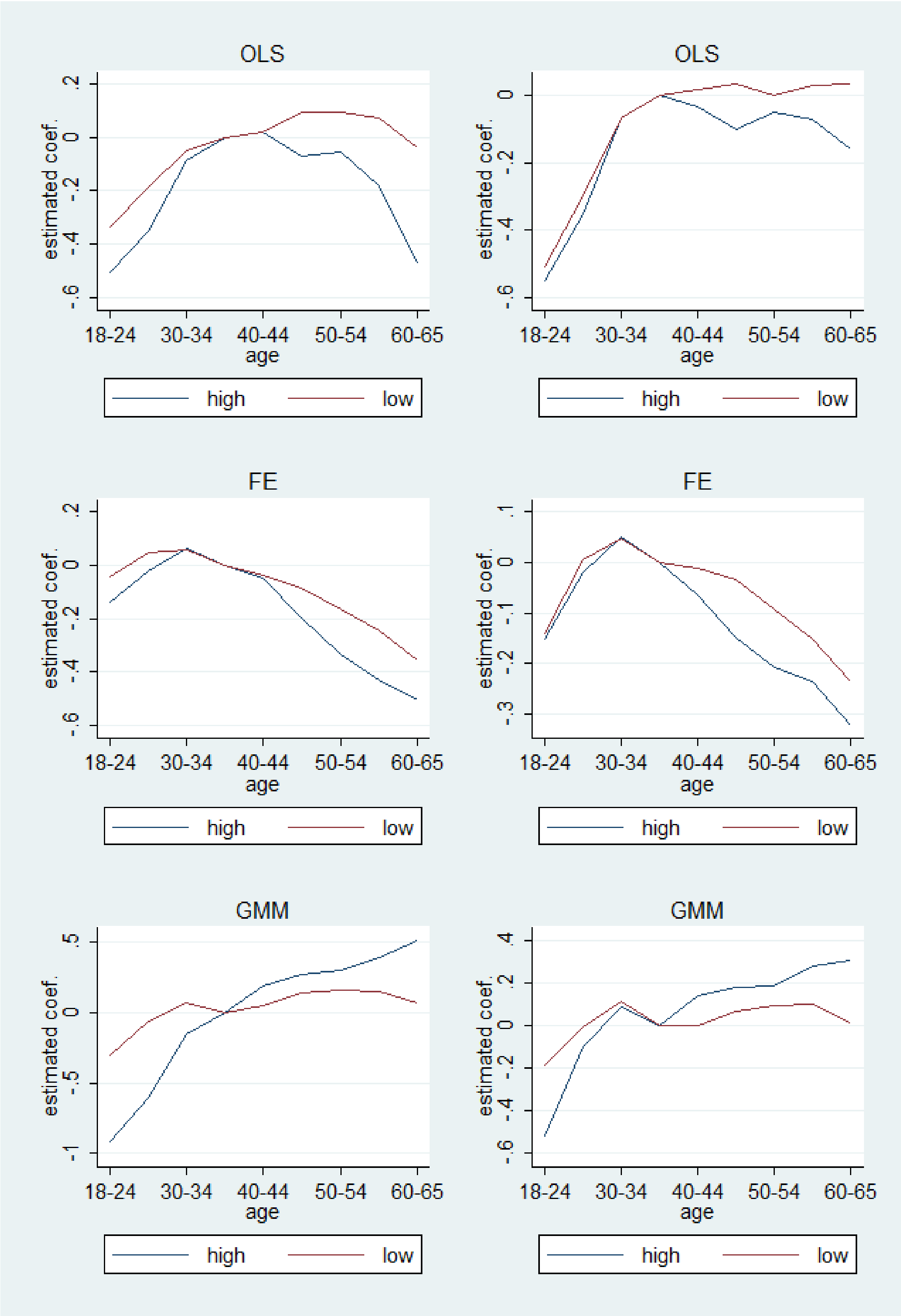
When using the more adequate estimation method (GMM), the results diverge significantly. The increases in productivity in the higher shares of younger workers remain unchanged, but firms with a higher skill ratio present a notable increase in productivity by employing a higher share of older workers starting from the age group of 35-39. There is also a small decrease in the age group of 60-65. Firms with a lower skill ratio, on the other hand, see no important changes in average productivity by having a larger share of older workers from the age group of 35-39 onward.

This change in the evolution of firm average productivity when separating firms with relatively high and low skilled to unskilled workers ratio is relevant to address. The important decrease in average firm productivity (for firms with a higher skill ratio) seen in the OLS estimations can perhaps confirm the phenomenon of skill obsolescence in skilled work. However, this decrease is not as marked in the GMM estimation, which is the preferred estimation method. Another important finding in the GMM results is that the average firm productivity is upwards driven mainly by workers aged 40-44 and older in firms with higher skill ratio, while the lower skilled firms present a fundamentally flat age-productivity profile from the age of 35-39.

Figure 6 displays the age-productivity profiles of firms separated by high and low technology intensive sectors (sales in the left column; value added in the right column). Appendix figure E1 presents the corresponding age-wage profiles. These graphs are obtained from the estimations in tables E1, E2 and E3.

The age-wage profiles are inherently similar to the ones presented in the main estimation. On average, wages are positively related to the age structure of the workforce. The age-productivity profiles, however, highlight some differences between the two sets of firms.

Figure 6: Sales (left column) and value added (right column) age profiles separating firms by high and low technology intensive sectors: OLS, FE and GMM estimations (Portugal, 2004-2018)



Source: Computations made with *Quadros de Pessoal* and SCIE.

The OLS estimations show that, on average, productivity is lower with a higher share of younger workers, but it increases at a fast pace towards prime-age. In high technology firms, productivity peaks earlier and presents a more steep decrease in productivity with an older workforce, relatively to low technology firms. This result verifies the hypothesis that firms in high technology sectors are more likely to see their productivity decrease with a more aged workforce. The underlying assumption is that older workers are usually more vulnerable to technological change, due to the acceleration of skill obsolescence, as well as older workers being perceived as less flexible and open to innovation.

The GMM estimation, however, displays a different pattern. High technology firms show an increasing trend of productivity with age, while low technology firms present a more flat age-productivity profile. Productivity increases faster in the early stages of the life cycle and slows down with age. This result contradicts the hypothesis previously described and is supportive of the hypothesis of Acemoglu and Restrepo (2017) that the scarcity of young labor can trigger the adoption of robotics technology that actually increases the aggregate output of the economy.

5.1 Robustness Checks

Following Mahlberg et al. (2013), as a robustness check for the main estimations, I re-estimate the model with the tenure variable. I specify 5 different ranges of years of tenure: below 1, between 1 and 2, between 2 and 5, between 5 and 10 and above 10 (reference group). Table 3 displays the short results of the estimation just with the age effects. The results for the age-wage and age-productivity profiles are quite similar with and without the tenure variable, which makes me believe in the robustness of the estimates.

As an additional check, I estimate the wage and productivity equations only for the firms in the manufacturing sectors (see table 4 below). The results seem consistent with the ones presented in the main estimation.

Table 3: Age effects on firm average wages and labor productivity (average sales and value added) with tenure shares

	Wages			Sales			Value Added		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share workers aged 18-24	-0.339***	-0.169***	-0.164***	-0.280***	-0.032	-0.328***	-0.318***	-0.042**	-0.026
	(0.014)	(0.009)	(0.030)	(0.045)	(0.025)	(0.092)	(0.029)	(0.021)	(0.092)
Share workers aged 25-29	-0.213***	-0.078***	0.042**	-0.194***	0.016	-0.123*	-0.189***	0.011	0.166***
	(0.012)	(0.008)	(0.021)	(0.039)	(0.020)	(0.063)	(0.025)	(0.018)	(0.063)
Share workers aged 30-34	-0.083***	-0.031***	0.034***	-0.126***	0.039**	0.050	-0.047**	0.047***	0.184***
	(0.010)	(0.006)	(0.013)	(0.031)	(0.017)	(0.040)	(0.021)	(0.015)	(0.040)
Share workers aged 40-44	0.055***	0.026***	-0.027**	0.079**	-0.030*	0.101***	0.057***	-0.004	0.024
	(0.010)	(0.006)	(0.012)	(0.031)	(0.017)	(0.036)	(0.021)	(0.015)	(0.037)
Share workers aged 45-49	0.094***	0.070***	0.007	0.140***	-0.070***	0.228***	0.067***	-0.024	0.094*
	(0.012)	(0.008)	(0.017)	(0.038)	(0.021)	(0.052)	(0.025)	(0.019)	(0.052)
Share workers aged 50-54	0.134***	0.102***	0.032	0.126***	-0.148***	0.235***	0.048*	-0.074***	0.105
	(0.012)	(0.008)	(0.022)	(0.042)	(0.024)	(0.068)	(0.027)	(0.021)	(0.069)
Share workers aged 55-59	0.178***	0.139***	0.042	0.093**	-0.199***	0.272***	0.050	-0.111***	0.134
	(0.014)	(0.010)	(0.027)	(0.047)	(0.028)	(0.083)	(0.031)	(0.025)	(0.085)
Share workers aged 60-65	0.147***	0.175***	0.080**	-0.047	-0.259***	0.328***	0.019	-0.159***	-0.005
	(0.019)	(0.012)	(0.033)	(0.063)	(0.034)	(0.098)	(0.040)	(0.030)	(0.103)

Table 4: Age effects on firm average wages and labor productivity (average sales and value added) for manufacturing firms

	Wages			Sales			Value Added		
	OLS	FE	GMM	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Share workers aged 18-24	-0.317***	-0.196***	-0.348***	-0.136***	-0.023	-0.708***	-0.191***	-0.056**	-0.333***
	(0.013)	(0.009)	(0.019)	(0.050)	(0.029)	(0.068)	(0.029)	(0.024)	(0.060)
Share workers aged 25-29	-0.165***	-0.099***	-0.124***	0.047	0.039	-0.441***	-0.004	0.016	-0.132**
	(0.012)	(0.008)	(0.017)	(0.045)	(0.026)	(0.056)	(0.027)	(0.022)	(0.052)
Share workers aged 30-34	-0.072***	-0.043***	-0.050***	0.063*	0.058***	-0.130***	0.025	0.014	-0.004
	(0.010)	(0.007)	(0.012)	(0.036)	(0.021)	(0.042)	(0.023)	(0.018)	(0.038)
Share workers aged 40-44	0.023**	0.026***	0.020*	0.032	-0.022	0.186***	-0.037*	-0.027	0.053
	(0.010)	(0.007)	(0.011)	(0.036)	(0.021)	(0.039)	(0.022)	(0.018)	(0.036)
Share workers aged 45-49	0.059***	0.064***	0.072***	0.155***	-0.105***	0.324***	-0.024	-0.056**	0.166***
	(0.012)	(0.009)	(0.015)	(0.045)	(0.026)	(0.054)	(0.027)	(0.022)	(0.051)
Share workers aged 50-54	0.087***	0.094***	0.127***	0.180***	-0.205***	0.455***	-0.060*	-0.111***	0.346***
	(0.013)	(0.010)	(0.020)	(0.050)	(0.030)	(0.071)	(0.030)	(0.026)	(0.065)
Share workers aged 55-59	0.130***	0.123***	0.160***	0.093	-0.305***	0.453***	-0.057*	-0.140***	0.339***
	(0.016)	(0.012)	(0.024)	(0.057)	(0.035)	(0.088)	(0.035)	(0.032)	(0.083)
Share workers aged 60-65	0.128***	0.165***	0.186***	-0.152*	-0.394***	0.539***	-0.142***	-0.226***	0.366***
	(0.022)	(0.015)	(0.034)	(0.083)	(0.045)	(0.112)	(0.049)	(0.041)	(0.113)

6 Conclusion

In this thesis, I analyse the relationship between the age composition of the workforce with wages and productivity at the firm level, using a longitudinal employer-employee data-set from Portugal for the period 2004-2018. The main estimation includes all the firms in the data-set and then I estimate the same model separately for firms with a high and low skill ratio; and for firms in high and low technology intensive sectors. The hypotheses are that cognitive abilities, as well as flexibility and adaptation to technological advances, are declining with age, due to skill obsolescence.

Summing up the wage regressions results, I find a positive relationship between average hourly wages and the age of the workforce in the firm level. The productivity ageing results show that firm productivity is usually lower in firms with a larger share of young workers, and average productivity increases considerably from employing prime-aged workers (30-34 to 45-49) rather than young workers (18-24 and 25-29). Overall, the OLS estimations show a considerable negative effect of the share of older workers (55-59 and 60-65), especially for firms with a more skilled labor workforce. However, the GMM estimations show that this decrease in average firm productivity is quite small, relative to OLS. When separating firms by high and low technology sectors, I find different results across estimation methods. In high technology firms, the OLS and FE estimations argue that productivity decreases steeply when employing a higher share of older workers, while GMM shows that productivity is increasing with age. Firms in low technology sectors have more flat age-productivity profiles and productivity seems to increase slightly until the age of 50-54 and fall thereafter. Overall, the preferred estimation method (GMM) shows that the productivity contributions of an older workforce are in line with their influence in wages. In conclusion, firms with an older workforce bear a higher wage bill, but there is no indication that an ageing workforce leads to a decline in labor productivity. Moreover, the technology separation estimation suggests that the adoption of technology in Portugal may be increasing older workers' productivity rather than rendering them obsolete.

Future work in this topic could focus on a specific sector where productivity is expected to be more affected by ageing effects. Furthermore, my analysis excludes workers older than 65 years old. Although relatively small, the share of workers with these ages starts to become more and more relevant as years go by. It would be interesting to study their impact on firm productivity, having in mind that old age is a changing concept with time. As life expectancy increases, old age should increase simultaneously.

References

Acemoglu, Daron, and Pascual Restrepo. “Secular Stagnation? The Effect of Aging on Economic Growth in the Age of Automation”. *American Economic Review* 107, no. 5 (May 2017): 174–79.

Autor, David, and David Dorn. “This Job Is ”Getting Old”: Measuring Changes in Job Opportunities Using Occupational Age Structure”. *American Economic Review* 99, no. 2 (May 2009): 45–51.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. “Trends in U.S. Wage Inequality: Revising the Revisionists”. *The Review of Economics and Statistics* 90, no. 2 (May 2008): 300–323.

Behaghel, Luc, Eve Caroli, and Muriel Roger. “Age-biased Technical and Organizational Change, Training and Employment Prospects of Older Workers”. *Economica* 81, no. 322 (2014): 368–389.

Cardoso, Ana Rute, Paulo Guimarães, and José Varejão. “Are Older Workers Worthy of Their Pay? An Empirical Investigation of Age-Productivity and Age-Wage Nexuses”. *De Economist* 159, no. 2 (June 2011): 95–111.

Crépon, Bruno, Nicolas Deniau, and Sébastien Pérez-Duarte. “Wages, Productivity and Worker Characteristics : A French Perspective” (May 2002).

Desjonqueres, Thibaut, Stephen Machin, and John van Reenen. “Another Nail in the Coffin? Or Can the Trade Based Explanation of Changing Skill Structures Be Resurrected?” *Wiley, The Scandinavian Journal of Economics* 101, no. 4 (1999): 533–554.

Dickerson, Andy, and Francis Green. “The growth and valuation of computing and other generic skills”. *Oxford Economic Papers* 56, no. 3 (July 2004): 371–406.

Feyrer, James. “Demographics and Productivity”. *The Review of Economics and Statistics* 89, no. 1 (2007): 100–109.

Göbel, Christian, and Thomas Zwick. “Age and Productivity: Sector Differences”. *De Economist* 160, no. 1 (Mar. 2012): 35–57.

Hellerstein, Judith, Kenneth Troske, and David Neumark. “Wages, Productivity, and Worker Characteristics: Evidence from Plant-Level Production Functions and Wage Equations”. *Journal of Labor Economics* 17 (Feb. 1999): 409–46.

Hellerstein, Judith K., and David Neumark. “Are Earnings Profiles Steeper Than Productivity Profiles? Evidence from Israeli Firm-Level Data”. *Journal of Human Resources* 30, no. 1 (1995): 89–112.

Kampelmann, Stephan, et al. “Does education raise productivity and wages equally? The moderating role of age and gender”. *IZA Journal of Labor Economics* 7 (Dec. 2018).

Lallemand, Thierry, and François Rycx. “Are Older Workers Harmful for Firm Productivity?” *De Economist* 157, no. 3 (Sept. 2009): 273–292.

Lieberman, Marvin, and Jina Kang. “How to Measure Company Productivity Using Value-Added: A Focus on Pohang Steel (POSCO)”. *Asia Pacific Journal of Management* 25 (Feb. 2008): 209–224.

Maestas, Nicole, Kathleen J Mullen, and David Powell. “The Effect of Population Aging on Economic Growth, the Labor Force and Productivity”. *National Bureau of Economic Research*, no. 22452 (July 2016).

Mahlberg, Bernhard, et al. “Ageing, productivity and wages in Austria”. *Labour Economics* 22 (June 2013): 5–15.

Ozimek, Adam, Dante DeAntonio, and Mark Zandi. “Aging and the Productivity Puzzle”. *unpublished* (Sept. 2018).

Skirbekk, Vegard. “Age and Individual Productivity: A Literature Survey”. *Vienna Yearbook of Population Research* 2 (2004): 133–153.

Van Dalen, Hendrik P., Kène Henkens, and Joop Schippers. “How do employers cope with an ageing workforce? Views from employers and employees”. *Demographic Research* 22 (2010): 1015–1036.

Welch, Finis, and Manuelita Ureta. “The obsolescence of skill”. *Research in Labor Economics* 21 (Sept. 2002).

Other Sources

Beckmann, Michael, and Bernd Schauenberg. *Age-biased technological and organizational change: firm-level evidence and management implications*. Working papers, 2007/05. Faculty of Business and Economics - University of Basel, Apr. 2007.

Bloom, David E, and Alfonso Sousa-Poza. *Ageing and Productivity: Introduction*, Feb. 2013.

Hujer, Reinhard, and Dubravko Radic. *Age and skill biased technological change: A multiple treatment approach using a linked employer employee dataset*, Nov. 2005.

Tipper, Adam. *Labour productivity, real wages, and workforce age structure*. Paper presented at the 53rd New Zealand Association of Economists Conference, June 2012.

Documents and Reports

Banco de Portugal. *Boletim Económico Junho 2019*. Banco de Portugal, June 2019.

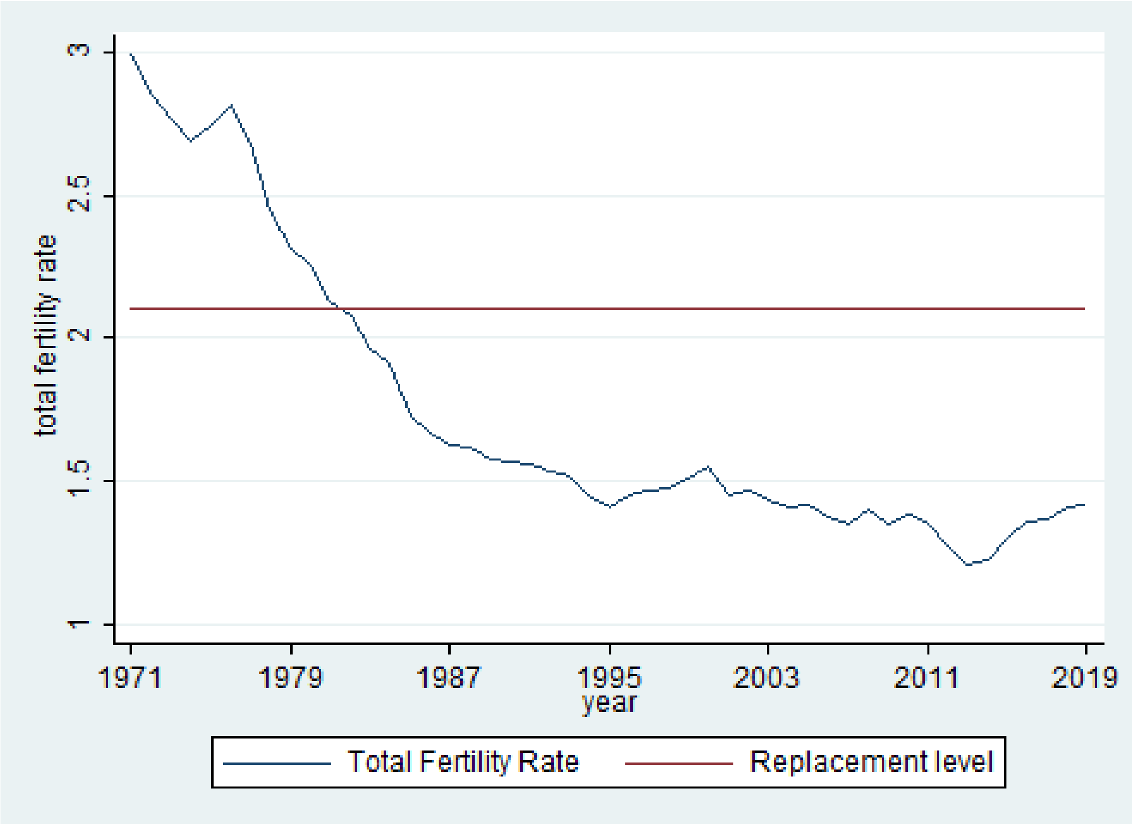
Directorate-General for Economic and Financial Affairs. *The 2018 Ageing Report - Economic & Budgetary Projections for the 28 EU Member States (2016-2070)*. European Commission, 2018.

Ilmarinen, Juhani. *Promoting active ageing in the workplace*. European Agency for Safety and Health at Work, 2012.

OECD. *OECD Economic Surveys: Portugal*. OECD, Feb. 2019.

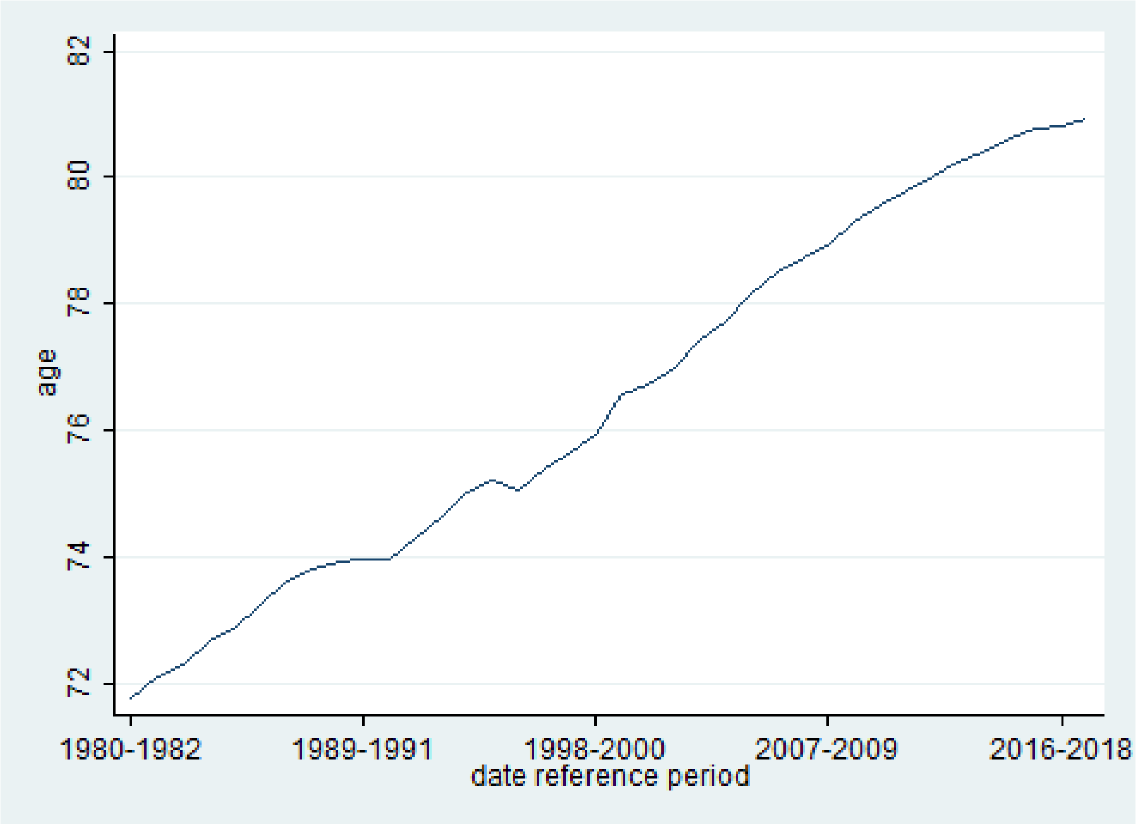
A Population graphs: Ageing in Portugal

Figure A1: Total Fertility Rates in Portugal (1971-2019)



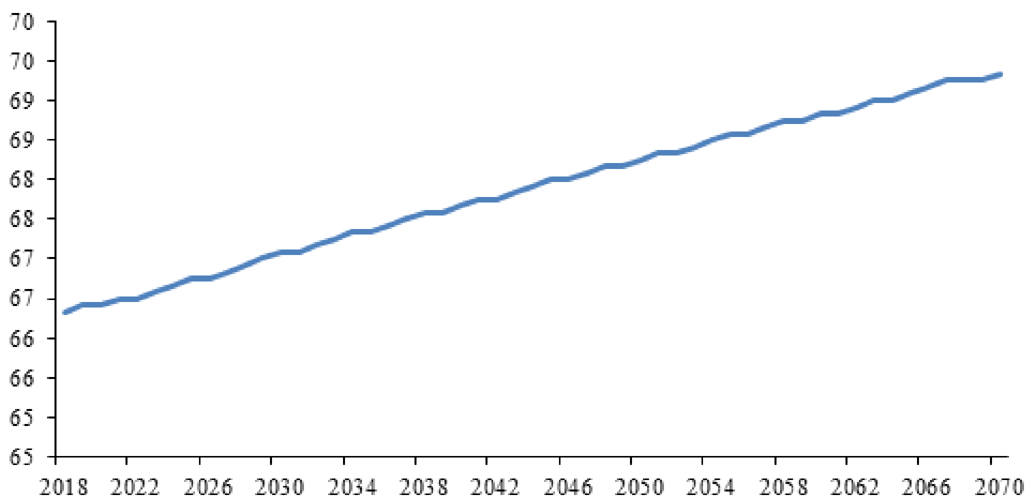
Source: Statistics Portugal

Figure A2: Life Expectancy at Birth (1980-2019)



Source: Statistics Portugal (Computations according to the 2007 methodology - Years)

Figure A3: Retirement age projections according to longevity gains (2018-2070)



Source: Banco de Portugal

B Descriptive Statistics

Table B1: Descriptive Statistics

Variable	Mean or %	Std. Dev.
Employee Characteristics		
Share workers aged 18-24	0.089	0.112
Share workers aged 25-29	0.133	0.116
Share workers aged 30-34	0.160	0.114
Share workers aged 35-39	0.161	0.108
Share workers aged 40-44	0.147	0.105
Share workers aged 45-49	0.122	0.100
Share workers aged 50-54	0.094	0.093
Share workers aged 55-59	0.062	0.079
Share workers aged 60-65	0.033	0.056
Share workers w/ highest level university degree	0.120	0.189
Share workers w/ highest level high-school degree	0.218	0.207
Share workers w/ highest level 9 years education	0.254	0.207
Share workers w/ highest level 6 years education	0.217	0.212
Share workers w/ highest level 4 years education	0.178	0.205
Share female workers	0.402	0.291
Firm Characteristics		
Avg. hourly wage (euro)	5.378	2.282
Avg. sales per labor hour (euro)	63.693	104.608
Avg. value added per labor hour (euro)	14.883	17.134
Employment	34.431	67.580
Age of the firm	20.006	15.906
Industry		
Textiles, clothing, leather	0.118	
Wood, cork, furniture	0.042	
Paper, printing	0.019	
Chemicals, rubber, plastic	0.022	
Other non-metallic mineral prod.	0.025	
Metals, machinery	0.078	
Other manuf.	0.014	
Trade, repairs	0.281	
Hotels, restaurants	0.109	
Transport, communication	0.051	
Financial intermediation	0.010	

Continuation of Table B1		
Variable	Mean or %	Std. Dev.
Real estate, renting and business activities	0.091	
Education	0.020	
Health, social serv.	0.036	
Sewage, refuse disposal	0.008	
Membership orgs.	0.005	
Recreational, cultural, sports activ.	0.006	
Other household, personal serv.	0.007	
Food, bev.	0.058	
Ownership of equity capital		
Public	0.001	
Foreign	0.003	
Private	0.996	
Lisbon	0.262	
Observations	350,708	

C Estimations with skill ratio separation

Table C1: Panel estimation results on average wages separating by skilled to unskilled workers' ratio

	Skill ratio > median			Skill ratio <= median		
	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Employment(log)	0.052***	-0.001	-0.013***	0.055***	0.011***	-0.011***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Share workers aged 18-24	-0.443***	-0.243***	-0.366***	-0.405***	-0.172***	-0.302***
	(0.013)	(0.009)	(0.019)	(0.013)	(0.008)	(0.020)
Share workers aged 25-29	-0.324***	-0.116***	-0.096***	-0.249***	-0.074***	-0.068***
	(0.011)	(0.007)	(0.015)	(0.012)	(0.008)	(0.016)
Share workers aged 30-34	-0.130***	-0.041***	-0.024**	-0.095***	-0.032***	-0.023*
	(0.009)	(0.006)	(0.010)	(0.010)	(0.007)	(0.012)
Share workers aged 40-44	0.070***	0.034***	0.014	0.031***	0.015**	0.017
	(0.009)	(0.006)	(0.010)	(0.010)	(0.007)	(0.012)
Share workers aged 45-49	0.108***	0.073***	0.071***	0.063***	0.055***	0.040**
	(0.012)	(0.008)	(0.014)	(0.013)	(0.008)	(0.016)
Share workers aged 50-54	0.169***	0.108***	0.124***	0.089***	0.082***	0.072***
	(0.014)	(0.009)	(0.018)	(0.014)	(0.009)	(0.020)
Share workers aged 55-59	0.216***	0.152***	0.154***	0.166***	0.123***	0.126***
	(0.016)	(0.010)	(0.023)	(0.016)	(0.011)	(0.024)
Share workers aged 60-65	0.160***	0.186***	0.199***	0.226***	0.163***	0.160***
	(0.023)	(0.013)	(0.029)	(0.020)	(0.014)	(0.030)

Continuation of Table C1						
	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Share workers university	1.117***	0.303***	0.237***	1.185***	0.381***	0.341***
	(0.025)	(0.019)	(0.019)	(0.023)	(0.019)	(0.019)
Share workers high-school	0.477***	0.129***	0.062***	0.427***	0.134***	0.105***
	(0.024)	(0.016)	(0.017)	(0.019)	(0.014)	(0.015)
Share workers 9 years school	0.215***	0.089***	0.025	0.208***	0.100***	0.053***
	(0.023)	(0.016)	(0.016)	(0.018)	(0.013)	(0.014)
Share workers 6 years school	0.083***	0.037**	-0.008	0.094***	0.056***	0.022
	(0.023)	(0.015)	(0.016)	(0.018)	(0.013)	(0.014)
Share workers 4 years school	-0.044*	-0.000	-0.043**	-0.008	0.025*	-0.007
	(0.024)	(0.015)	(0.017)	(0.018)	(0.013)	(0.015)
Share female workers	-0.112***	-0.005	-0.003	-0.124***	-0.020***	-0.014***
	(0.005)	(0.004)	(0.003)	(0.005)	(0.004)	(0.003)
Age of the firm	0.001***			0.001***		
	(0.000)			(0.000)		
Public ownership	0.068**			0.023		
	(0.035)			(0.024)		
Foreign ownership	0.234***			0.274***		
	(0.027)			(0.036)		

Continuation of Table C1						
	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Lisbon	0.098***			0.040***		
	(0.004)			(0.004)		
Constant	1.185***	1.603***	-0.001**	1.183***	1.404***	0.002***
	(0.025)	(0.017)	(0.001)	(0.020)	(0.015)	(0.001)
Observations	194,170	194,170	122,745	156,538	156,538	97,773
R-squared	0.615	0.930	0.021	0.524	0.906	0.021
F statistic	948.44***	257.03***	56.51***	455.68***	247.05***	57.83***
Hansen-J Statistic			12.026			5.666
Endogeneity Test			166.25***			141.56***
Kleinberger-Paap rk LM			1870.7***			1721.6***
Kleinberger-Paap rk Wald			175.46***			179.32***

Education refers to the highest level achieved. The OLS regression includes controls for the industry (18 dummy variables) and time (13 dummy variables); the FE regression includes controls for time (13 dummy variables). In the GMM regression, the equation is estimated in first differences, with the shares of worker ages lagged 2 and 3 periods used as instruments. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table C2: Panel estimation results on average sales separating by skilled to unskilled workers' ratio

	Skill ratio > median			Skill ratio <= median		
	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Employment(log)	0.056***	-0.250***	-0.673***	0.028***	-0.278***	-0.699***
	(0.006)	(0.009)	(0.009)	(0.006)	(0.009)	(0.009)
Share workers aged 18-24	-0.404***	-0.085***	-0.495***	-0.408***	-0.039	-0.332***
	(0.041)	(0.025)	(0.062)	(0.044)	(0.025)	(0.064)
Share workers aged 25-29	-0.327***	0.016	-0.183***	-0.136***	0.045**	-0.180***
	(0.036)	(0.020)	(0.047)	(0.041)	(0.022)	(0.050)
Share workers aged 30-34	-0.120***	0.039**	0.010	0.001	0.071***	0.025
	(0.029)	(0.016)	(0.032)	(0.033)	(0.018)	(0.037)
Share workers aged 40-44	0.035	-0.039**	0.112***	-0.005	-0.043**	0.056
	(0.029)	(0.017)	(0.031)	(0.033)	(0.019)	(0.036)
Share workers aged 45-49	0.085**	-0.079***	0.280***	0.020	-0.132***	0.051
	(0.039)	(0.021)	(0.045)	(0.042)	(0.024)	(0.050)
Share workers aged 50-54	0.104**	-0.175***	0.352***	-0.048	-0.217***	0.026
	(0.043)	(0.025)	(0.059)	(0.047)	(0.027)	(0.063)
Share workers aged 55-59	-0.012	-0.281***	0.369***	-0.008	-0.270***	0.018
	(0.049)	(0.029)	(0.073)	(0.052)	(0.031)	(0.076)
Share workers aged 60-65	-0.238***	-0.431***	0.307***	0.013	-0.320***	0.011
	(0.069)	(0.038)	(0.088)	(0.073)	(0.037)	(0.089)

Continuation of Table C2						
	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Share workers university	1.412***	0.069	0.114**	1.638***	0.166***	0.053
	(0.074)	(0.045)	(0.048)	(0.073)	(0.052)	(0.043)
Share workers high-school	0.736***	0.124***	0.114***	0.714***	0.142***	0.035
	(0.070)	(0.038)	(0.042)	(0.063)	(0.043)	(0.035)
Share workers 9 years school	0.329***	0.087**	0.047	0.295***	0.113***	0.011
	(0.069)	(0.037)	(0.040)	(0.061)	(0.041)	(0.034)
Share workers 6 years school	-0.077	-0.016	-0.012	0.034	0.042	-0.034
	(0.069)	(0.036)	(0.039)	(0.061)	(0.041)	(0.033)
Share workers 4 years school	-0.138**	0.007	-0.079*	-0.049	0.021	-0.080*
	(0.070)	(0.036)	(0.042)	(0.061)	(0.040)	(0.034)
Share female workers	-0.187***	-0.030***	-0.027***	-0.385***	-0.052***	-0.027***
	(0.020)	(0.010)	(0.008)	(0.019)	(0.011)	(0.008)
Age of the firm	0.002***			0.003***		
	(0.000)			(0.000)		
Public ownership	-0.609***			-0.299***		
	(0.133)			(0.109)		
Foreign ownership	0.340***			0.375***		
	(0.093)			(0.104)		

Continuation of Table C2						
	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Lisbon	0.086***			-0.006		
	(0.013)			(0.013)		
Constant	2.698***	4.517***	-0.021***	3.110***	4.376***	-0.008***
	(0.074)	(0.044)	(0.002)	(0.068)	(0.048)	(0.002)
Observations	194,170	194,170	122,745	156,538	156,538	97,773
R-squared	0.413	0.911	0.147	0.395	0.906	0.172
F statistic	373.73***	128.21***	531.09***	279.76***	100.07***	547.9***
Hansen-J Statistic			20.118***			13.765*
Endogeneity Test			111.72***			39.036***
Kleinberger-Paap rk LM			1870.7***			1721.6***
Kleinberger-Paap rk Wald			175.46***			179.32***

Education refers to the highest level achieved. The OLS regression includes controls for the industry (18 dummy variables) and time (13 dummy variables); the FE regression includes controls for time (13 dummy variables). In the GMM regression, the equation is estimated in first differences, with the shares of worker ages lagged 2 and 3 periods used as instruments. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table C3: Panel estimation results on average value added separating by skilled to unskilled workers' ratio

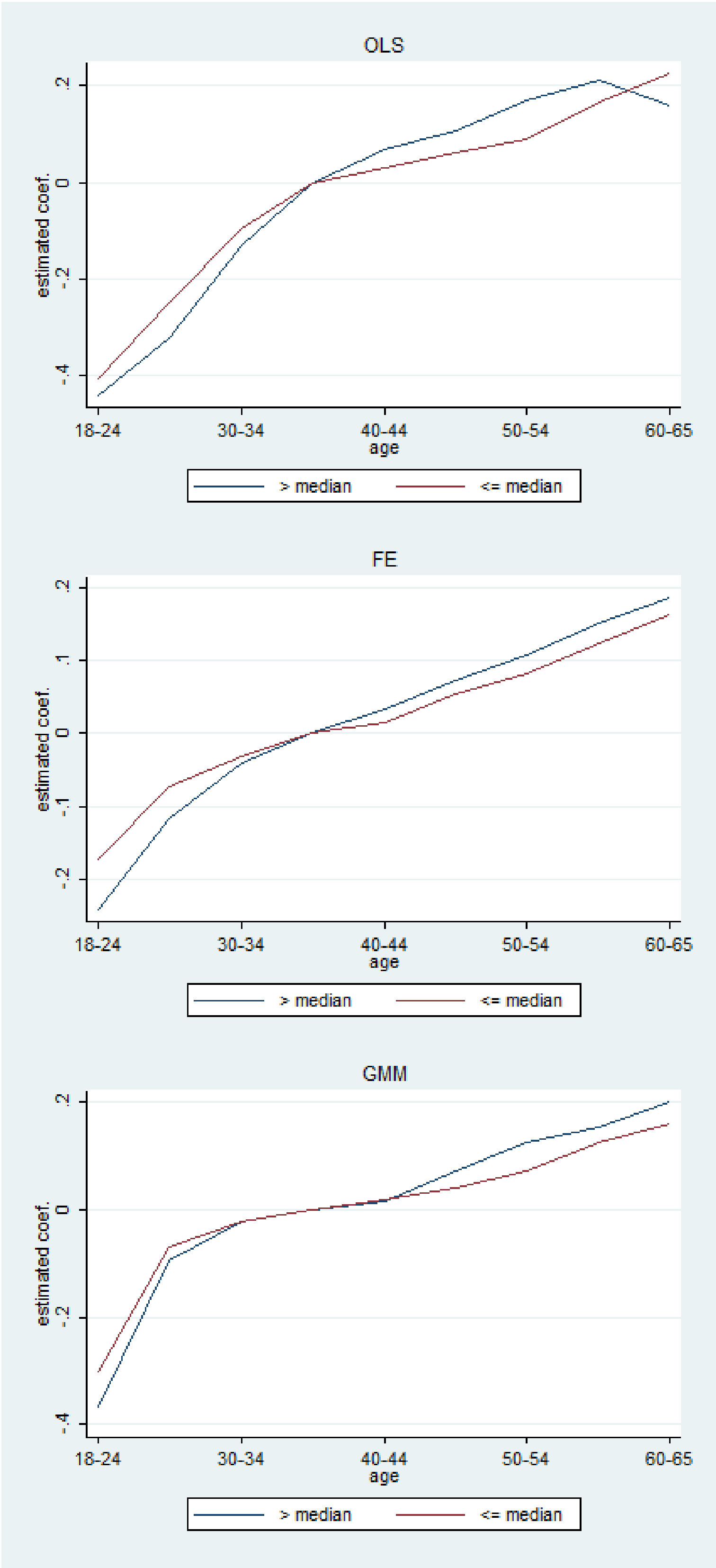
	Skill ratio > median			Skill ratio <= median		
	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Employment(log)	0.009**	-0.156***	-0.479***	0.007*	-0.165***	-0.524***
	(0.004)	(0.007)	(0.010)	(0.004)	(0.008)	(0.009)
Share workers aged 18-24	-0.482***	-0.149***	-0.335***	-0.518***	-0.144***	-0.153**
	(0.027)	(0.022)	(0.057)	(0.029)	(0.024)	(0.060)
Share workers aged 25-29	-0.338***	-0.011	-0.049	-0.242***	0.005	-0.006
	(0.024)	(0.018)	(0.042)	(0.028)	(0.021)	(0.048)
Share workers aged 30-34	-0.070***	0.047***	0.101***	-0.051**	0.044**	0.083**
	(0.019)	(0.015)	(0.029)	(0.024)	(0.018)	(0.036)
Share workers aged 40-44	0.040**	0.002	0.059*	-0.028	-0.044**	-0.002
	(0.020)	(0.015)	(0.030)	(0.023)	(0.018)	(0.034)
Share workers aged 45-49	0.047*	-0.030	0.158***	-0.040	-0.072***	0.040
	(0.025)	(0.019)	(0.043)	(0.028)	(0.022)	(0.047)
Share workers aged 50-54	0.029	-0.088***	0.232***	-0.081***	-0.142***	-0.004
	(0.028)	(0.022)	(0.054)	(0.031)	(0.026)	(0.059)
Share workers aged 55-59	0.007	-0.150***	0.243***	-0.013	-0.187***	0.038
	(0.032)	(0.027)	(0.068)	(0.036)	(0.030)	(0.072)
Share workers aged 60-65	-0.068	-0.243***	0.203**	0.075	-0.250***	-0.054
	(0.045)	(0.034)	(0.088)	(0.048)	(0.035)	(0.090)

Continuation of Table C3						
	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Share workers university	1.328***	0.017	-0.010	1.439***	0.037	-0.037
	(0.054)	(0.043)	(0.048)	(0.048)	(0.048)	(0.047)
Share workers high-school	0.649***	0.081**	0.014	0.554***	0.049	0.031
	(0.051)	(0.037)	(0.041)	(0.041)	(0.036)	(0.040)
Share workers 9 years school	0.279***	0.060*	-0.036	0.228***	0.028	-0.020
	(0.050)	(0.035)	(0.040)	(0.039)	(0.034)	(0.037)
Share workers 6 years school	0.080	0.004	-0.070*	0.106***	0.001	-0.010
	(0.050)	(0.035)	(0.040)	(0.039)	(0.034)	(0.037)
Share workers 4 years school	-0.079	0.026	-0.106**	-0.035	-0.007	-0.024
	(0.051)	(0.035)	(0.043)	(0.039)	(0.034)	(0.038)
Share female workers	-0.219***	-0.024***	-0.026***	-0.230***	-0.052***	-0.032***
	(0.011)	(0.009)	(0.008)	(0.012)	(0.010)	(0.008)
Age of the firm	0.002***			0.003***		
	(0.000)			(0.000)		
Public ownership	-0.268**			-0.056		
	(0.112)			(0.082)		
Foreign ownership	0.249***			0.215***		
	(0.072)			(0.076)		

Continuation of Table C3						
	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Lisbon	0.095***			0.026***		
	(0.008)			(0.009)		
Constant	2.166***	3.129***	-0.009***	2.262***	3.045***	0.001
	(0.053)	(0.041)	(0.002)	(0.043)	(0.040)	(0.002)
Observations	194,170	194,170	122,745	156,538	156,538	97,773
R-squared	0.362	0.808	0.078	0.237	0.761	0.093
F statistic	418.03***	127.36***	206.53***	178.01***	108.53***	270.69***
Hansen-J Statistic			17.785**			16.125**
Endogeneity Test			74.767***			26.241***
Kleinberger-Paap rk LM			1870.7***			1721.6***
Kleinberger-Paap rk Wald			175.46***			179.32***

Education refers to the highest level achieved. The OLS regression includes controls for the industry (18 dummy variables) and time (13 dummy variables); the FE regression includes controls for time (13 dummy variables). In the GMM regression, the equation is estimated in first differences, with the shares of worker ages lagged 2 and 3 periods used as instruments. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure C1: Age-wage profiles separating high from low skilled to unskilled workers' ratio firms: OLS, FE and GMM estimations (Portugal, 2004-2018)



Source: Computations made with *Quadros de Pessoal*

D Descriptive Statistics - separating firms by skill ratio

Table D1: Descriptive Statistics - separating firms by skill ratio

Skill ratio	> median		≤ median	
Variable	Mean or %	Std. Dev.	Mean or %	Std. Dev.
Employee Characteristics				
Share workers aged 18-24	0.082	0.110	0.096	0.112
Share workers aged 25-29	0.135	0.121	0.131	0.112
Share workers aged 30-34	0.167	0.118	0.151	0.108
Share workers aged 35-39	0.168	0.111	0.153	0.103
Share workers aged 40-44	0.150	0.108	0.144	0.101
Share workers aged 45-49	0.119	0.101	0.124	0.098
Share workers aged 50-54	0.090	0.093	0.098	0.093
Share workers aged 55-59	0.059	0.077	0.067	0.080
Share workers aged 60-65	0.030	0.055	0.036	0.058
Share workers w/ highest level education				
University degree	0.139	0.210	0.096	0.156
High-school degree	0.239	0.218	0.192	0.189
9 years	0.250	0.207	0.260	0.206
6 years	0.213	0.220	0.224	0.202
4 years	0.151	0.193	0.211	0.215
Share female workers	0.364	0.292	0.449	0.284
Firm Characteristics				
Avg. hourly wage (euro)	5.780	2.528	4.879	1.815
Avg. sales per labor hour (euro)	70.548	113.802	55.189	91.222
Avg. value added per labor hour (euro)	16.311	18.664	13.112	14.833
Employment	30.589	48.658	39.196	85.171
Age of the firm	19.850	15.519	20.199	16.372
Industry				
Textiles, clothing, leather	0.124		0.110	
Wood, cork, furniture	0.038		0.048	
Paper, printing	0.020		0.016	
Chemicals, rubber, plastic	0.012		0.034	
Other non-metallic mineral prod.	0.014		0.039	
Metals, machinery	0.098		0.054	
Other manuf.	0.013		0.015	
Trade, repairs	0.336		0.213	

Continuation of Table D1				
Variable	Mean or %	Std. Dev.	Mean or %	Std. Dev.
Hotels, restaurants	0.062		0.167	
Transport, communication	0.079		0.017	
Financial intermediation	0.016		0.004	
Real estate, renting and business activities	0.098		0.081	
Education	0.010		0.032	
Health, social serv.	0.028		0.046	
Sewage, refuse disposal	0.004		0.012	
Membership orgs.	0.006		0.004	
Recreational, cultural, sports activ.	0.005		0.007	
Other household, personal serv.	0.006		0.009	
Food, bev.	0.031		0.092	
Ownership of equity capital				
Public	0.001		0.002	
Foreign	0.004		0.002	
Private	0.996		0.996	
Lisbon	0.286		0.233	
Observations	194,170		156,538	

E Estimations with technology intensity separation

Table E1: Panel estimation results on average wages separating firms by high and low technology intensive sectors

	High tech sectors			Low tech sectors		
	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Employment(log)	0.041***	-0.010**	-0.020***	0.055***	0.008***	-0.011***
	(0.003)	(0.005)	(0.005)	(0.001)	(0.002)	(0.002)
Share workers aged 18-24	-0.535***	-0.282***	-0.462***	-0.432***	-0.191***	-0.308***
	(0.025)	(0.016)	(0.034)	(0.010)	(0.006)	(0.015)
Share workers aged 25-29	-0.358***	-0.127***	-0.108***	-0.292***	-0.088***	-0.072***
	(0.022)	(0.016)	(0.030)	(0.009)	(0.006)	(0.012)
Share workers aged 30-34	-0.137***	-0.024*	-0.001	-0.115***	-0.037***	-0.024***
	(0.018)	(0.013)	(0.022)	(0.007)	(0.005)	(0.009)
Share workers aged 40-44	0.053***	0.029**	0.020	0.052***	0.023***	0.008
	(0.019)	(0.013)	(0.021)	(0.007)	(0.005)	(0.008)
Share workers aged 45-49	0.060**	0.048***	0.061**	0.094***	0.065***	0.047***
	(0.024)	(0.016)	(0.029)	(0.009)	(0.006)	(0.011)
Share workers aged 50-54	0.141***	0.077***	0.110***	0.136***	0.097***	0.087***
	(0.027)	(0.017)	(0.035)	(0.011)	(0.007)	(0.014)
Share workers aged 55-59	0.191***	0.121***	0.146***	0.200***	0.138***	0.128***
	(0.030)	(0.020)	(0.044)	(0.012)	(0.008)	(0.018)
Share workers aged 60-65	0.066	0.157***	0.208***	0.210***	0.175***	0.163***
	(0.042)	(0.025)	(0.056)	(0.016)	(0.010)	(0.022)

Continuation of Table E1						
	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Share workers university	1.241***	0.364***	0.245***	1.199***	0.328***	0.288***
	(0.051)	(0.034)	(0.034)	(0.017)	(0.014)	(0.014)
Share workers high-school	0.712***	0.129***	0.074**	0.474***	0.139***	0.089***
	(0.049)	(0.030)	(0.030)	(0.015)	(0.011)	(0.012)
Share workers 9 years school	0.364***	0.064**	0.008	0.221***	0.106***	0.049***
	(0.048)	(0.029)	(0.030)	(0.015)	(0.011)	(0.011)
Share workers 6 years school	0.220***	0.032	-0.015	0.096***	0.054***	0.016
	(0.048)	(0.029)	(0.030)	(0.015)	(0.011)	(0.011)
Share workers 4 years school	0.071	0.015	-0.061**	-0.027*	0.015	-0.014
	(0.049)	(0.028)	(0.031)	(0.015)	(0.011)	(0.012)
Share female workers	-0.222***	-0.100***	-0.080***	-0.120***	-0.009***	-0.006***
	(0.013)	(0.018)	(0.014)	(0.004)	(0.003)	(0.002)
Age of the firm	0.000			0.001***		
	(0.000)			(0.000)		
Public ownership	-0.030			0.025		
	(0.050)			(0.021)		
Foreign ownership	0.286***			0.242***		
	(0.056)			(0.022)		

Continuation of Table E1						
	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Lisbon	0.085***			0.073***		
	(0.007)			(0.003)		
Constant	1.319***	1.734***	-0.002*	1.168***	1.461***	0.001**
	(0.050)	(0.034)	(0.001)	(0.016)	(0.012)	(0.000)
Observations	61,616	61,616	40,668	289,092	289,092	179,850
R-squared	0.486	0.900	0.020	0.599	0.929	0.021
F statistic	252.94***	72.40***	28.38***	1246.1***	430.67***	82.67***
Hansen-J Statistic			8.744			19.430**
Endogeneity Test			93.368***			229.19***
Kleinberger-Paap rk LM			621.13***			2942.0***
Kleinberger-Paap rk Wald			53.375***			300.96***

Education refers to the highest level achieved. The OLS regression includes controls for the industry (18 dummy variables) and time (13 dummy variables); the FE regression includes controls for time (13 dummy variables). In the GMM regression, the equation is estimated in first differences, with the shares of worker ages lagged 2 and 3 periods used as instruments. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table E2: Panel estimation results on average sales separating firms by high and low technology intensive sectors

	High tech sectors			Low tech sectors		
	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Employment(log)	0.038***	-0.251***	-0.607***	0.046***	-0.268***	-0.704***
	(0.009)	(0.014)	(0.015)	(0.005)	(0.007)	(0.007)
Share workers aged 18-24	-0.508***	-0.140***	-0.913***	-0.334***	-0.044**	-0.303***
	(0.074)	(0.047)	(0.110)	(0.033)	(0.019)	(0.049)
Share workers aged 25-29	-0.351***	-0.022	-0.609***	-0.188***	0.048***	-0.061*
	(0.068)	(0.038)	(0.092)	(0.030)	(0.016)	(0.036)
Share workers aged 30-34	-0.088*	0.062**	-0.157**	-0.050**	0.057***	0.071***
	(0.052)	(0.031)	(0.065)	(0.024)	(0.013)	(0.026)
Share workers aged 40-44	0.020	-0.046	0.186***	0.021	-0.039***	0.048*
	(0.053)	(0.033)	(0.062)	(0.025)	(0.013)	(0.025)
Share workers aged 45-49	-0.068	-0.195***	0.265***	0.096***	-0.084***	0.137***
	(0.068)	(0.041)	(0.088)	(0.032)	(0.017)	(0.036)
Share workers aged 50-54	-0.053	-0.332***	0.302***	0.095***	-0.163***	0.158***
	(0.072)	(0.045)	(0.111)	(0.036)	(0.020)	(0.046)
Share workers aged 55-59	-0.182**	-0.431***	0.388***	0.075*	-0.242***	0.146***
	(0.078)	(0.054)	(0.138)	(0.040)	(0.023)	(0.056)
Share workers aged 60-65	-0.471***	-0.505***	0.514***	-0.036	-0.356***	0.071
	(0.112)	(0.066)	(0.173)	(0.056)	(0.029)	(0.067)

Continuation of Table E2						
	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Share workers university	1.585***	0.193**	0.037	1.564***	0.095**	0.074**
	(0.138)	(0.091)	(0.082)	(0.055)	(0.038)	(0.034)
Share workers high-school	1.064***	0.070	0.042	0.737***	0.155***	0.081***
	(0.127)	(0.076)	(0.071)	(0.051)	(0.032)	(0.029)
Share workers 9 years school	0.382***	0.007	0.007	0.330***	0.132***	0.037
	(0.121)	(0.073)	(0.069)	(0.050)	(0.030)	(0.027)
Share workers 6 years school	0.227*	-0.070	-0.135*	-0.058	0.042	0.006
	(0.119)	(0.073)	(0.070)	(0.050)	(0.030)	(0.026)
Share workers 4 years school	-0.049	-0.047	-0.281***	-0.073	0.040	-0.034
	(0.121)	(0.074)	(0.073)	(0.051)	(0.030)	(0.028)
Share female workers	-0.157***	-0.067	-0.056*	-0.277***	-0.041***	-0.024***
	(0.047)	(0.047)	(0.032)	(0.014)	(0.007)	(0.006)
Age of the firm	-0.000			0.004***		
	(0.001)			(0.000)		
Public ownership	-1.005***			-0.415***		
	(0.148)			(0.088)		
Foreign ownership	0.546**			0.306***		
	(0.224)			(0.072)		

Continuation of Table C2

Variable	OLS (1)	FE (2)	GMM (3)	OLS (4)	FE (5)	GMM (6)
Lisbon	0.042*			0.040***		
	(0.022)			(0.010)		
Constant	3.248***	4.618***	-0.023***	2.826***	4.410***	-0.012***
	(0.127)	(0.085)	(0.003)	(0.055)	(0.036)	(0.001)
Observations	61,616	61,616	40,668	289,092	289,092	179,850
R-squared	0.181	0.853	0.114	0.426	0.918	0.168
F statistic	45.70***	33.41***	172.38***	673.13***	202.06***	889.53***
Hansen-J Statistic			16.251**			18.369**
Endogeneity Test			82.856***			79.940***
Kleinberger-Paap rk LM			621.13***			2942.0***
Kleinberger-Paap rk Wald			53.375***			300.96***

Education refers to the highest level achieved. The OLS regression includes controls for the industry (18 dummy variables) and time (13 dummy variables); the FE regression includes controls for time (13 dummy variables). In the GMM regression, the equation is estimated in first differences, with the shares of worker ages lagged 2 and 3 periods used as instruments. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table E3: Panel estimation results on average value added separating firms by high and low technology intensive sectors

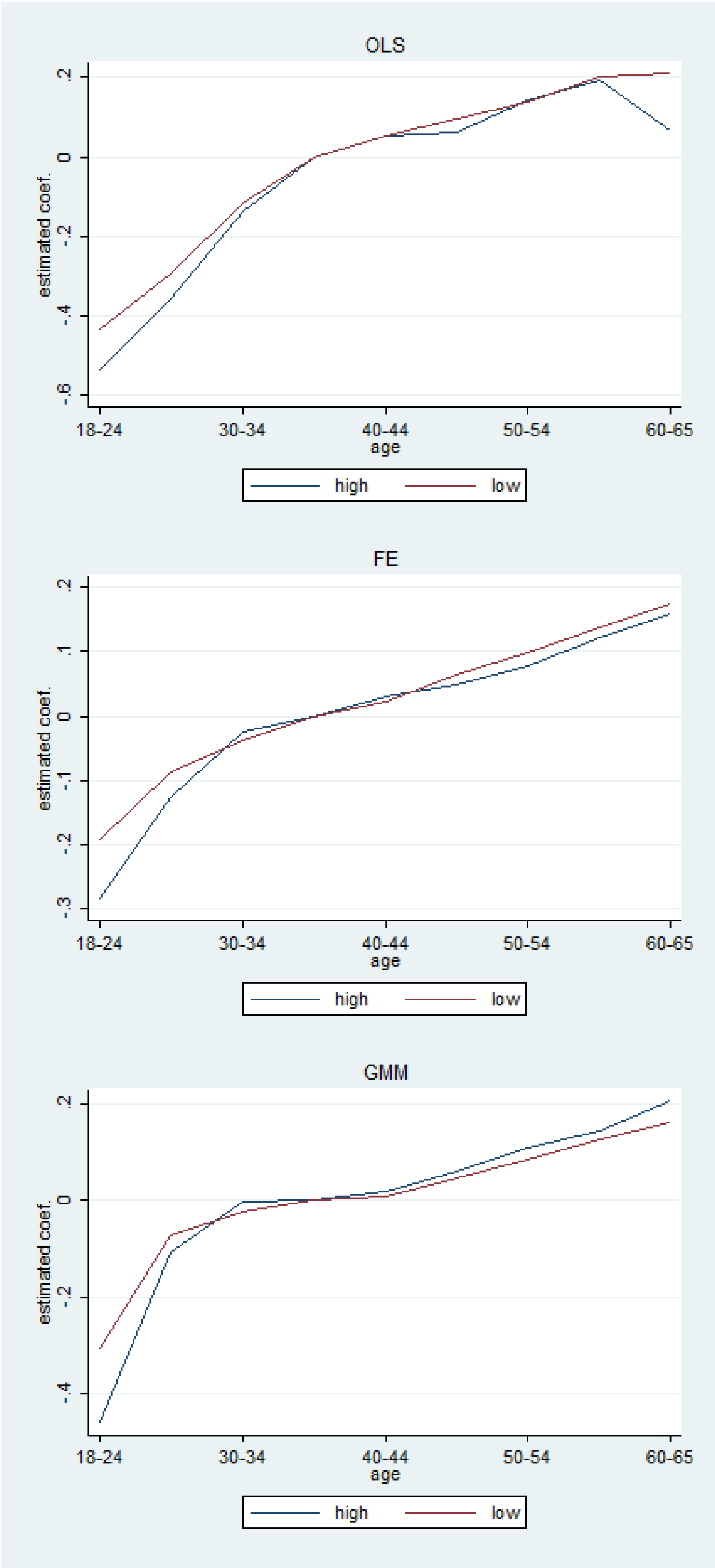
	High tech sectors			Low tech sectors		
	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Employment(log)	0.024***	-0.145***	-0.408***	0.005*	-0.163***	-0.522***
	(0.006)	(0.012)	(0.017)	(0.003)	(0.006)	(0.007)
Share workers aged 18-24	-0.549***	-0.151***	-0.519***	-0.510***	-0.140***	-0.187***
	(0.049)	(0.041)	(0.096)	(0.022)	(0.017)	(0.046)
Share workers aged 25-29	-0.352***	-0.020	-0.098	-0.298***	0.007	-0.005
	(0.046)	(0.034)	(0.080)	(0.020)	(0.015)	(0.034)
Share workers aged 30-34	-0.066*	0.050*	0.084	-0.065***	0.049***	0.110***
	(0.037)	(0.028)	(0.057)	(0.016)	(0.013)	(0.025)
Share workers aged 40-44	-0.032	-0.065**	0.140**	0.018	-0.012	-0.003
	(0.038)	(0.029)	(0.056)	(0.017)	(0.012)	(0.025)
Share workers aged 45-49	-0.099**	-0.147***	0.178**	0.035*	-0.033**	0.066*
	(0.047)	(0.036)	(0.077)	(0.020)	(0.016)	(0.035)
Share workers aged 50-54	-0.049	-0.207***	0.183*	0.001	-0.093***	0.093**
	(0.050)	(0.040)	(0.098)	(0.023)	(0.019)	(0.044)
Share workers aged 55-59	-0.072	-0.235***	0.277**	0.030	-0.152***	0.096*
	(0.056)	(0.048)	(0.120)	(0.026)	(0.022)	(0.055)
Share workers aged 60-65	-0.158*	-0.322***	0.307**	0.034	-0.234***	0.014
	(0.082)	(0.064)	(0.153)	(0.036)	(0.026)	(0.069)

Continuation of Table E3						
	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Share workers university	1.252***	0.113	-0.075	1.453***	0.001	-0.014
	(0.086)	(0.073)	(0.083)	(0.037)	(0.035)	(0.037)
Share workers high-school	0.760***	0.031	-0.032	0.642***	0.077***	0.035
	(0.079)	(0.056)	(0.071)	(0.034)	(0.029)	(0.031)
Share workers 9 years school	0.333***	-0.032	-0.134*	0.265***	0.066**	-0.004
	(0.076)	(0.053)	(0.068)	(0.033)	(0.027)	(0.030)
Share workers 6 years school	0.191**	-0.056	-0.130*	0.088***	0.019	-0.016
	(0.075)	(0.053)	(0.068)	(0.033)	(0.027)	(0.029)
Share workers 4 years school	0.018	-0.025	-0.217***	-0.060*	0.020	-0.029
	(0.076)	(0.054)	(0.074)	(0.034)	(0.027)	(0.031)
Share female workers	-0.289***	-0.051	-0.086**	-0.219***	-0.038***	-0.023***
	(0.029)	(0.044)	(0.036)	(0.008)	(0.007)	(0.005)
Age of the firm	0.001			0.003***		
	(0.000)			(0.000)		
Public ownership	-0.523***			-0.137*		
	(0.142)			(0.070)		
Foreign ownership	0.443*			0.213***		
	(0.226)			(0.047)		

Continuation of Table E3						
	OLS	FE	GMM	OLS	FE	GMM
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Lisbon	0.052***			0.069***		
	(0.014)			(0.006)		
Constant	2.411***	3.331***	-0.009***	2.206***	3.036***	-0.003*
	(0.081)	(0.066)	(0.003)	(0.036)	(0.032)	(0.001)
Observations	61,616	61,616	40,668	289,092	289,092	179,850
R-squared	0.191	0.757	0.060	0.321	0.795	0.091
F statistic	65.50***	34.55***	49.14***	544.67***	196.21***	435.95***
Hansen-J Statistic			12.578			12.728
Endogeneity Test			46.542***			62.054***
Kleinberger-Paap rk LM			621.13***			2942.0***
Kleinberger-Paap rk Wald			53.375***			300.96***

Education refers to the highest level achieved. The OLS regression includes controls for the industry (18 dummy variables) and time (13 dummy variables); the FE regression includes controls for time (13 dummy variables). In the GMM regression, the equation is estimated in first differences, with the shares of worker ages lagged 2 and 3 periods used as instruments. Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure E1: Age-wage profiles separating firms by high and low technology intensive sectors: OLS, FE and GMM estimations (Portugal, 2004-2018)



Source: Computations made with *Quadros de Pessoal*

F Descriptive Statistics - separating firms by technology intensity

Table F1: Descriptive Statistics - separating firms by technology intensity

Skill ratio	High tech		Low tech	
Variable	Mean or %	Std. Dev.	Mean or %	Std. Dev.
Employee Characteristics				
Share workers aged 18-24	0.075	0.095	0.092	0.115
Share workers aged 25-29	0.124	0.110	0.135	0.118
Share workers aged 30-34	0.158	0.110	0.160	0.114
Share workers aged 35-39	0.163	0.103	0.161	0.109
Share workers aged 40-44	0.148	0.099	0.147	0.106
Share workers aged 45-49	0.126	0.096	0.121	0.101
Share workers aged 50-54	0.101	0.093	0.092	0.093
Share workers aged 55-59	0.070	0.081	0.061	0.078
Share workers aged 60-65	0.035	0.056	0.032	0.057
Share workers w/ highest level education				
University degree	0.126	0.192	0.118	0.188
High-school degree	0.206	0.185	0.220	0.211
9 years	0.252	0.190	0.255	0.210
6 years	0.225	0.194	0.216	0.216
4 years	0.181	0.199	0.177	0.207
Share female workers	0.223	0.204	0.440	0.293
Firm Characteristics				
Avg. hourly wage (euro)	6.105	2.378	5.223	2.231
Avg. sales per labor hour (euro)	60.816	89.242	64.306	107.589
Avg. value added per labor hour (euro)	17.918	20.305	14.236	16.307
Employment	41.732	63.654	32.875	68.286
Age of the firm	22.145	15.796	19.550	15.892
Industry				
Textiles, clothing, leather	0		0.141	
Wood, cork, furniture	0		0.051	
Paper, printing	0		0.023	
Chemicals, rubber, plastic	0.126		0	
Other non-metallic mineral prod.	0		0.031	
Metals, machinery	0.444		0	

Continuation of Table F1				
Variable	Mean or %	Std. Dev.	Mean or %	Std. Dev.
Other manuf.	0.078		0	
Trade, repairs	0		0.341	
Hotels, restaurants	0		0.132	
Transport, communication	0.293		0	
Financial intermediation	0.060		0	
Real estate, renting and business activities	0		0.110	
Education	0		0.024	
Health, social serv.	0		0.044	
Sewage, refuse disposal	0		0.010	
Membership orgs.	0		0.006	
Recreational, cultural, sports activ.	0		0.007	
Other household, personal serv.	0		0.009	
Food, bev.	0		0.071	
Ownership of equity capital				
Public	0.000		0.001	
Foreign	0.003		0.003	
Private	0.997		0.996	
Lisbon	0.244		0.266	
Observations	61,616		289,092	