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Productivity-Wage Gaps Among Age Groups: Does the ICT Environment Matter?

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Abstract This paper disentangles the age-productivity-wage nexus by estimating productivity and wage equations with longitudinal employer-employee panel data for Belgium. Results indicate that workers above 49 years are significantly less productive than their younger colleagues. Moreover, while relative productivities across age groups are not found to differ significantly between ICT and non ICT firms, the upward sloping age-wage profile appears to be somewhat steeper in ICT firms. Yet, whatever the ICT environment, findings show that young workers are paid below and older workers above their marginal productivity. This pattern is in line with the deferred payment model developed by Lazear (J Polit Econ 87:1261–1284, 1979).

Keywords Wages · Productivity · Ageing · Matched panel data · ICT

JEL Classification J14 · J24 · J31

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1 Introduction

The ageing of the European population is among the most salient demographic trends of recent decades and raises tough policy challenges, both from a social and economic point of view. In particular, the relative increase in the share of older people has led policy makers and economists to focus on the labour market participation of older workers. For instance, the increasing fiscal burden created by the observed demographic shifts motivated several governments to adopt policies designed to boost employment rates of older Europeans.

In order to provide sound policy advice, research has to explore the entire range of potential advantages and risks that may derive from an increased share of older people in the active labour force. According to standard economic theory, the employability of older workers depends on the comparison between the costs and benefits associated with their labour services. However, we know surprisingly little about such comparisons. How does the contribution of older workers to firm performance compare with the average remuneration of this demographic group? How does the productivity of older workers compare to the productivity of younger cohorts? These are the overarching questions we address in this paper. More precisely, our strategy consists in comparing the age-productivity profile and the age-wage profile of three age groups: workers younger than 30; between 30 and 49; and older than 49 years.

Several studies suggest that the labour productivity of different age groups is affected asymmetrically by the immediate environment in which workers are embedded at the firm level (Börsch-Supan et al. 2005; Bertschek and Meyer 2009). A consequential aspect of the firm environment that underwent significant change in the last decades is the intensity with which firms make use of information and communication technology (ICT) (see Autor et al. 1998). In particular, the implementation of ICT in production processes might affect the demand for different types of skills. For instance, the literature on the employment effects of technological change suggests that ICT could substitute for routine tasks and complement non-routine tasks (Acemoglu 2002; Bresnahan et al. 2002; Card and DiNardo 2002; Goos and Manning 2007; Kampelmann and Rycx 2011).

In addition to workers performing routine tasks, new technologies like ICT might also affect the employability of different age groups. For instance, Boockmann and Zwick (2004) observe an age bias of technological change given that innovative firms appear to employ fewer older workers than less technology-intense firms. Beckmann (2004) find a significant negative correlation between the share of older workers within firms and their productivity-wage bill ratio. This age bias appears to be distinct from skill bias since it has also been observed within occupational groups (Aubert et al. 2006). Age-biased technological change might be attributed to older workers difficulty in keeping up with the pace of changes in the work environment due to decreasing cognitive and learning capabilities. Firms might be reluctant to employ and train older workers given their shorter career horizon during which the training investments could be amortized. The effect of ICT on age is, however, by no means clear-cut. Indeed, it is also conceivable that certain types of technology (like improved user interfaces or the computerization of repetitive tasks) counter-act decreasing abilities and help ageing workers to maintain stable or even increasing levels of performance (Bartel and

Sichermann 1993). These opposing views have contradictory implications for older workers' incentives and access to on-the-job training and attitudes towards retirement decisions (Ahituv and Zeira 2002; Bartel and Sichermann 1993).

Given the policy challenges of demographic change and the unclear impact that recent waves of technological innovations could have on older workers' performance, the objective of this paper is twofold. First, we examine the relationship between age, wage and productivity for the overall workforce in the Belgian private sector in order to determine whether certain age groups are paid below or above their marginal productivity. To do so, we rely on detailed matched employer-employee panel data covering the period 1999–2006. Next, we investigate whether results vary according to the ICT environment of firms. Our data set does not comprise information on technological and innovative activities of firms. Therefore, we make use of the ICT taxonomy developed by O'Mahoney and van Ark (2003), which enables to classify firms according to the ICT capital intensity of industrial sectors at the NACE three-digit level. This methodology groups detailed industries based on whether they produce ICT goods and services and whether they intensively use ICT or not.

The present paper contributes to the existing literature in several ways. Firstly, empirical evidence regarding (i) the age-productivity-wage nexus and (ii) the role of the ICT environment on the productivity and remuneration of age groups is still very limited. Secondly, we add to the extant literature by looking at the effect of different age groups on productivity and wages in terms of hours instead of the inferior employment proxy of head counts. Thirdly, our access to a large employer-employee panel data set allows us to estimate a model controlling for a wide range of worker and firm characteristics. Finally, our estimates address several econometric issues such as the potential endogeneity of age shares, the existence of unobserved firm characteristics and the state dependence of firm productivity and wages.

Research questions addressed in this paper are particularly relevant for the Belgian economy. Like most OECD member countries, Belgium is facing the challenges associated with a rapidly ageing population. Projections suggest that the old age dependency ratio (i.e. the ratio of the number of persons aged 65 and more divided by the number of persons aged 15–64) will increase from around 26% in 2010 to almost 45% in 2050 (Giannakouris 2008). Belgium is also characterized by one of the lowest employment rates for workers aged 55–64 in the OECD area [35% in 2009 (OECD 2010)]. This situation is primarily due to the existence of attractive (to both employers and employees) early retirement schemes. Indeed, although the situation is progressively changing, it is still fairly common to retire early and to benefit from one of the various relatively generous schemes available (OECD 2003). The effective retirement age is currently about 5 years below the legal one at 65 years (OECD 2006). The low rate of employment among older workers can also be explained by the fact that employers are often reluctant to hire this category of workers. The point is that senior workers are generally considered to be less productive and more costly than their younger counterparts. This being said, the employment rate among people aged 15–24 is also quite low [25% in 2009 (OECD 2010)]. This is due to increasing years of schooling and the high unemployment rate among young people [22% in 2009 (OECD 2010)], particularly among those with a low level of education. Indeed, employers often complain that young workers are not sufficiently productive (because of a lack of skills and experience) and therefore prefer to hire somewhat older workers.

Overall, most employers in Belgium draw on prime age workers (the 25–54 age group). This situation, accompanied by strong demographic changes, puts substantial pressure on public finances. To overcome this problem, policy makers aim to increase the employment rate essentially of older workers. Different strategies have been suggested to attain this goal [e.g. measures: (i) reforming early retirement schemes, (ii) creating incentives for older workers to remain in or return to work, (iii) encouraging firms to change their practices towards older workers, and (iv) raising the legal retirement age (OECD 2003)]. On any account, changes in the workforce age structure are likely to have important consequences for firms' productivity and wage bill. Yet, findings regarding the relationship between age, wage and productivity are still quite rare. Moreover, whether the ICT environment of firms affects whether certain age categories might be paid above or below their marginal productivity remains under-researched. The objective of this paper is to provide more empirical evidence on these important issues.

The structure of the paper is as follows: the next section provides an overview of the existing literature. Section 3 presents the estimation method used in this paper. Section 4 contains information on our data set and descriptive statistics. Regression results and robustness tests for the baseline model are discussed in Sect. 5. The impact of the ICT environment on the productivity and remuneration of age groups is scrutinised in Sect. 6. The final section concludes.

2 Review of the Literature

2.1 Age and Productivity

The theoretical literature on the relationship between age and productivity is ambiguous. While part of the literature underlines the positive impact that elderly and more experienced people might have on job performance, other theories suggest that older workers might be less productive and less efficient than younger ones.

The former strand of literature draws heavily on the predictions of the human capital model (Mincer 1974) and claims that older workers will perform better than younger ones since they have accumulated better know-how (Czaja and Sharit 1998). In particular, in jobs where verbal abilities and experience are more important than cognitive capacities and speediness, elderly workers might be more productive than their younger counterparts (Skirbekk 2003). Moreover, some authors stress that older workers are more likely to have correctly matched their job preferences with the employer's requirements (Johnson 1978) and are more likely to have been assigned to their best position in the firm organization (Jovanovic 1979).

By contrast, a second cluster of theories relies on the medical literature and expects ageing to be accompanied by a decline in mental elasticity and physical power and argues that this process may have a negative effect on productivity (Shepard 1999). Some authors also observe that older workers are likely to be less healthy, to suffer more from frequent or chronic diseases and to show higher rates of absenteeism and lower productivity (Ng and Feldman 2008).

In addition, other theories argue that older workers might be less motivated than younger ones since they will have a shorter time to benefit from better performance through promotions and career advancements (Tang and MacLeod 2006; Grund and Westergaard-Nielsen 2005). For the same reason older workers may have less incentives to invest in training and to acquire new competences. As a consequence, productivity might be higher in the beginning than in the end of the career, a pattern that could be further reinforced as skills acquired through formal education are expected to be state-of-the-art when graduates enter the labour markets but become more and more obsolete afterwards (Walewski 2008).

2.2 The Impact of Technology on Relative Productivity

Firms do not all use the same technologies and their economic activities do not require the same amount of investment in innovation. This implies that firms may need different types of skills. Indeed, one may expect that firms using new advanced technologies will employ individuals with strong cognitive skills and learning capabilities. Since such abilities are presumably decreasing over the worker's life cycle and innovative firms are also more likely to invest in on-the-job training programmes, it could be more profitable to employ a higher share of younger workers (Brooke 2003; Prskawetz et al. 2006). Older people may be less willing than younger workers to continuously update their competences due to inferior mental agility, processing speed and learning capabilities (Bartel and Sichermann 1993; Skirbekk 2003). Older workers may also fear new technology (Taylor and Rose 2005).

On the other hand, technology can benefit ageing workers in several ways. Firstly, as far as technological progress forces workers to train themselves, it might have a positive effect on older workers' performance since it induces them to update their skills and preserve their productivity (Bartel and Sichermann 1993). In addition, new technologies might boost productivity to the extent that they can compensate for disabilities and for physical or mental decline (eInclusion@EU 2007).

2.3 Empirical Literature

From an empirical perspective, results are not more clear-cut. This may be attributed at least partially to a lack of a direct measure of productivity (Aubert and Crépon 2003).

Many papers using matched employer-employee data find a hump-shaped relationship between age and productivity (De Koning 2005): productivity increases with age until the age of 50 and decreases thereafter. However, some studies found that productivity peaks at 55 years or more (Hellerstein and Neumark 1995; Hellerstein et al. 1999). Tang and MacLeod (2006) evaluate productivity growth in 10 Canadian provinces and find a negative and significant impact of the share of older workers (aged 55 and more) on productivity growth (measured by GDP). Using data from the ZEW ICT survey, Schleife (2008) reports that firms using ICT technology intensively employ smaller shares of older workers. However, in firms where older workers attend

ICT training programmes such composition effects cannot be observed. This suggests that training enhances older workers' productivity. Interestingly, the rise in productivity tends to decrease with the number of older workers trained, suggesting that firms may first select older employees for training who are more productive. The effect of computerization of occupations on older workers is studied by Friedberg (2003). He analyses data from the Current Population Survey and the Health and Retirement Study and concludes that impending retirement rather than ageing per se exerts a negative effect on the degree of computerization and on skills upgrading. In addition, Friedberg (2003) presents evidence that occupations affect significantly the ICT use of workers even after controlling for age differences between occupations.

Bertschek and Meyer (2009) analyse firm-level panel data for the German manufacturing and service industries and measure productivity by sales per worker. They find that older workers (aged 49 and more) are not less productive than prime age workers, while younger workers (aged less than 30) are less productive than prime age workers. They find that technological progress, proxied by the use of computers, has a positive impact on older workers productivity. They also stress that the higher productivity might not depend on the device itself, but on the fact that computer users are better qualified for using a computer. In line with these results, Göbel and Zwick (2009) find that older workers' productivity does not decrease dramatically with age. They use panel data from the German economy and measure productivity by value added per head. According to their analysis, productivity increases with the share of employees until the age of 50–55 years and decreases only slightly afterwards.

A less analysed but equally unresolved issue concerns the relationship between age, wage and productivity. Standard theory suggests that wages will in general reflect marginal productivity. By contrast, other models of wage determination, for instance based on incentive mechanisms and contract theory, predict a divergence between wages and productivity. The deferred payment model developed by Lazear (1979), for instance, asserts that younger workers might be paid below and older workers above their productivity so as to boost the loyalty and attachment of younger workers.

Aubert and Crépon (2003) quantify productivity with value added in the French manufacturing, service and commerce sectors and find that individual productivity grows until the age of 40 and stagnates afterwards. They also examine the possible divergence between productivity and remuneration, finding no evidence of a productivity-wage gap for elderly people, except for workers older than 55 years. van Ours and Stoeldraijer (2011) use matched worker-firm panel data for the Dutch manufacturing sector and proxy productivity with value added. Once they address the endogeneity of age shares, they observe that both productivity and wage costs increase with age and find no strong evidence for productivity-wage gaps. Ilmakunnas and Maliranta (2005) analyse Finnish manufacturing plant data and specify different productivity equations using value added and sales as proxies of productivity. They observe productivity-wage gaps that increase with age, a finding that they impute to strong seniority effects in wage setting. A significant productivity-wage gap is also found by Cardoso et al. (2011), but here it has the opposite sign. Using Portuguese firm-level panel data and measuring productivity with total sales per worker, the authors observe that productivity peaks around the age of 50 and then remains relatively constant. In contrast, wages are found to be quite flat after the age of 29 and to decline after 50. Accordingly, their estimates suggest that the contribution of older workers to firm productivity exceeds their wages.

The empirical evidence for the Belgian economy is quite limited. Lallemand and Rycx (2009), employing cross-sectional matched employer-employee data for the private sector and using value added per capita to proxy productivity, find that young workers are significantly more productive than older ones. They also assess the potential effect of ICT on the relationship between ageing and performance. Their findings show that the proportion of young workers is larger in firms using ICT intensively and that age-structure effects on productivity are weaker in firms that are less exposed to ICT. Yet, these results should be taken with caution in particular because (i) firm unobserved fixed effects are not controlled for and (ii) instruments used to address the endogeneity of the firm's age structure may not be the most appropriate.

The relationship between age, productivity and labour costs has been examined by Vandenberghe and Waltenberg (2010) on the basis of Belgian firm-level panel data. Addressing the problem of endogeneity and controlling for fixed firm effects, their results suggest that older workers are less productive than prime age workers by between 20 and 40%, and that this productivity differential is not compensated by lower relative labour costs. Their findings thus suggest that firms based in Belgium are *a priori* not willing to employ more older workers. Although rather compelling, their results do not account for some important control variables that are either missing or only available in broad categories in their data (e.g. the composition of the workforce according to education skills, previous training and occupations). Moreover, given the focus on labour costs rather than on workers' wages, the paper principally deals with the consequences of population ageing on the labour demand for people of different age groups. The question whether young and older workers are "paid what they are worth" (i.e. whether workers are paid according to their marginal productivity) is thus only indirectly tested and deserves to be re-examined with more detailed information on remuneration and on workforce compositions. This is the first objective of the present paper. However, we also want to investigate with firm-level panel data whether the relationship between age, wage and productivity depends on the ICT environment of firms [an issue that has not been investigated by Vandenberghe and Waltenberg (2010)].

3 Methodology

The test developed in this article is based on the separate estimation of a value added function and a wage equation at the firm level. The value added function yields parameter estimates for the average marginal product of each workers' age group, while the wage equation estimates the respective impact of each age category on the average wage paid by the firm. Given that both equations are estimated with the same set of firms, age groups and covariates, the parameters for marginal products and wages can be compared and conclusions on age productivity-wage gaps can be drawn. This technique was pioneered by Hellerstein et al. (1999) and refined by Aubert and Crépon (2003); van Ours (2009); Göbel and Zwick (2009); van Ours and Stoeldraijer (2011) and others.

Equation (1) is a function linking a range of inputs of firm i to its value added Y_i.

$$Y_i = F(K_i, QL_i) \tag{1}$$

where K_i represents the firm's capital stock and QL_i is a quality of labour term. The latter allows introducing a heterogeneous labour force into the value added function.

There is an abundant econometric literature on the estimation of relationships as the one depicted in Eq. (1). In an attempt to reflect more accurately the production process inside the firm, specialists in the field have proposed specifications allowing e.g. for production inefficiencies or different elasticities of substitution between the factors of production. Since our focus is not on the production process itself, but rather on the comparison between productivities and wages for a set of workers' age groups, we use a simple Cobb–Douglas version of Eq. (1), with substitution elasticities equal to one and the assumption of firms operating at the efficiency frontier. This restriction appears to be unproblematic as previous firm-level studies have shown that productivity coefficients obtained with a Cobb–Douglas structure are robust to other functional specifications (see, for instance, Hellerstein and Neumark 2004). Equation (2) is the basic (Cobb–Douglas) value added function:

$$\log(Y_i) = \log(A_i) + \alpha \log(K_i) + \beta \log(QL_i) \tag{2}$$

where A_i is a constant. The parameters α and β are the respective marginal productivities of each input factor. QL_i can be written as:

$$QL_i = L_i \left(1 + (\theta_{i,j} - 1) \sum_{j=1}^{G} \frac{L_{i,j}}{L_i} \right) \tag{3}$$

where L_i is the total labour force of the firm i and $L_{i,j}/L_i$ the proportion of total labour force in age group j. Substituting Eq. (3) into (2) allows for different marginal productivities for each of the G age categories. If for age group j the parameter θ_j is bigger (smaller) than unity, then this group has a higher (lower) marginal impact on productivity than the reference age category. If all groups have θ's equal to one, then Eq. (3) becomes $QL_i = L_{i,}$ i.e. labour is perfectly homogeneous.

As for the wage equation, Aubert and Crépon (2003) show that the average wage of firm i can be expressed as:

$$\overline{w}_i = \frac{\sum_{j=1}^{G} w_{i,j} L_{i,j}}{\sum_{j=1}^{G} L_{i,j}} = w_{i,0} \left(\sum_{j=1}^{G} \frac{w_{i,j}}{w_{i,0}} \frac{L_{i,j}}{L_i} \right) = w_{i,0} \left(1 + \sum_{j-\{0\}}^{G} \left(\frac{w_{i,j}}{w_{i,0}} - 1 \right) \frac{L_{i,j}}{L_i} \right) \tag{4}$$

where $w_{i,j}$ is the average wage of $L_{i,j}$ and $j = 0$ the reference age category with the wage $w_{i,0}$. Similar to the interpretation of θ in the production function, if the ratio w_j/w_0 is bigger (smaller) than unity, then the marginal impact of age group j on the average wage in the firm is higher (lower) compared to the reference age category.

Comparing marginal productivities and wage differentials across age groups boils down to comparing θ_j with the corresponding w_j/w_0.

4 Data and Descriptive Statistics

Our empirical analysis is based on a combination of two large data sets covering the years 1999–2006. The first, carried out by Statistics Belgium, is the 'Structure of Earnings Survey' (SES). It covers all firms operating in Belgium that employ at least 10 workers and with economic activities within sections C to K of the NACE Rev. 1 nomenclature.[1] The survey contains a wealth of information, provided by the management of firms, both on the characteristics of the latter (e.g. sector of activity, number of workers, level of collective wage bargaining) and on the individuals working there (e.g. age, education, tenure, gross earnings, paid hours, sex, occupation).[2] The SES provides no financial information. Therefore, it has been merged with a firm-level survey, the 'Structure of Business Survey' (SBS). The SBS, also conducted by Statistics Belgium, provides information on financial variables such as firm-level value added and gross operating surplus (per hour and per worker). The coverage of the SBS differs from that of the SES in that it does not cover the whole financial sector (NACE J) but only Other Financial Intermediation (NACE 652) and Activities Auxiliary to Financial Intermediation (NACE 67). The merge of the SES and SBS data sets has been carried out by Statistics Belgium using firms' social security numbers.

Three filters have been applied to the original data set. The first derives its rationale from neoclassical productivity theory, which relies on the assumption that prices are economically meaningful. This is why we deleted firms that are publicly controlled and/or operating in predominantly public sectors from our sample. All regressions are therefore applied to privately controlled firms only.[3]

Second, we have eliminated firms with less than 10 observations, the reason for this being our use of average values at the firm level. In order to assure that averages (like, for instance, the proportion of employees in a specific occupation) are based on a minimum number of observations, we filtered out firms that provided information on less than ten employees.[4] This selection criterion leads to an average number of observations per firm in each year that is equal to 35.

In addition to applying these two filters, the final sample on which our estimations are based consists only of firms that are observed in at least three consecutive years due to the inclusion of lagged differences in our models (see Sect. 5). This leads to a bias towards big firms because of the sample design of the SES in which big firms

[1] It thus covers the following sectors: (i) mining and quarrying (C), (ii) manufacturing (D), (iii) electricity, gas and water supply (E), (iv) construction (F), v) wholesale and retail trade, repair of motor vehicles, motorcycles and personal and household goods (G), (vi) hotels and restaurants (H), (vii) transport, storage and communication (I), (viii) financial intermediation (J), and ix) real estate, renting and business activities (K).

[2] For more details on the SES see Appendix A.

[3] More precisely, we eliminate firms for which public financial control exceeds 50%. This exclusion reduces the sample size by less than 4%.

[4] This selection is unlikely to affect our results as it leads to a small drop in sample size.

are more likely to stay in the sample for several consecutive years than small firms (see Appendix A).

Our final sample consists of an unbalanced panel of 1,735 firms yielding 5,459 firm-year-observations during the 6-year period (1999–2006). It is representative of all medium-sized and large firms employing at least 10 employees within sections C to K of the NACE Rev. 1 nomenclature, with the exception of large parts of the financial sector (NACE J) and almost all the electricity, gas and water supply industry (NACE E).

The definition of earnings we use in the estimation correspond to the total gross wages, including premia for overtime, weekend and night work, performance bonuses, commissions and other premia. The work hours correspond to the total remunerated hours in the reference period (including paid overtime hours). The firm's value added per hour is measured at factor costs and calculated with the total number of hours effectively worked by the firm's employees. All variables in the SES-SBS are not self-reported by the employees, but provided by the firm's management and therefore more precise compared to employee or household surveys.

Table 1 sets outs the means and standard deviations of selected variables. We observe that firms have a mean value added per hour worked of 55.51 Euros and that workers' mean gross hourly wage stands at 17.24 Euros. The age structure of the workforce within firms is on average composed by: 21% of workers younger than 30 years, 63% of prime aged workers (between 30 and 49 years) and 16% of older workers (with at least 50 years). We also find that 24% of workers are women, 54% are blue collar[5], 33% have a low level of education (i.e. lower secondary at most), 34% work less than 38 h per week, and 96% have an open-ended employment contract. Moreover, almost 90% of workers in our sample are employed in relatively big firms (i.e. firms with at least 100 employees) essentially concentrated in the manufacturing sector (61%), hotels and restaurants (13%), wholesale and retail trade, repair of motor vehicles, motorcycles and personal and household goods (10%), construction (10%) and real estate, renting and business activities (9%).

A simple way to explore the age-wage-productivity nexus in our data is to look at the age-wage and age-productivity relationships at the firm level. Figure 1a charts the quadratic prediction plots for value added and average wages as a function of the shares of three age groups: below 30, 30–49, and above 49 years. In the vicinity of the sample means for the age groups (21, 63 and 16%, respectively), the curves for value added and average wage have a relatively similar shape. Both firm-level value added and average wages appear to decrease with the proportion of workers below 30 years. As for prime age workers, value added increases until the share of this group reaches around 65% and decreases for higher shares, while the average wage in the firm increases with the share of prime age workers. Finally, the proportion of older workers has a positive effect on firm-level value added until they reach a share of around 30%. The firm wage peaks on average when this group represents around 45% of the firm's labour force. To make the comparison between value added and wages more explicit, Fig. 1b plots the difference between the two as a function of age shares.

[5] Blue-collar occupations include "Craft and related trades workers", "Plant and machine operators, and assemblers", and "Elementary occupations".

Table 1 Descriptive statistics for firms (1999–2006)

Variables	All firms		ICT		Non-ICT	
	Mean	SD	Mean	SD	Mean	SD
Value added per hour (2004 Euros)	55.51	207.15	59.76	63.10	53.50	247.58
Hourly wage (2004 Euros)	17.24	4.82	18.70	5.63	16.55	4.21
Age structure						
Share of workers <30 years	0.21	0.13	0.23	0.14	0.21	0.12
Share of workers between 30 and 49 years	0.63	0.12	0.62	0.13	0.63	0.12
Share of workers >49 years	0.16	0.11	0.15	0.12	0.17	0.11
Share of female workers	0.24	0.21	0.31	0.22	0.21	0.20
Education						
Lower education	0.08	0.16	0.04	0.10	0.10	0.17
Lower secondary education	0.25	0.27	0.16	0.22	0.30	0.28
General upper secondary school	0.18	0.22	0.20	0.21	0.17	0.22
Technical/artistic/professional upper secondary school	0.22	0.24	0.19	0.22	0.23	0.25
Short higher education	0.16	0.16	0.23	0.19	0.13	0.13
Long higher education or university	0.11	0.14	0.18	0.19	0.08	0.10
Occupations						
Managers	0.04	0.07	0.05	0.08	0.03	0.06
Professionals	0.11	0.19	0.22	0.26	0.07	0.11
Technicians and associate professionals	0.09	0.15	0.12	0.18	0.08	0.13
Clerical support workers	0.18	0.19	0.21	0.21	0.14	0.15
Service and sales workers	0.04	0.15	0.06	0.18	0.03	0.12
Craft and related trades workers	0.23	0.31	0.15	0.25	0.26	0.31
Plant and machine operators, and assemblers	0.22	0.30	0.14	0.24	0.28	0.31
Elementary occupations	0.09	0.19	0.05	0.13	0.10	0.21
Working time						
Part time (<20 work hours per week)	0.01	0.06	0.01	0.04	0.01	0.06
Medium time (20 to 38 h per week)	0.33	0.40	0.38	0.42	0.31	0.39
Full time (>38 work hours per week)	0.66	0.41	0.61	0.43	0.68	0.40
Not standard (i.e. non open-ended) employment contract	0.04	0.10	0.04	0.09	0.04	0.10
Number of employees per firm						
$\leq$ 19	0.01		0.01		0.00	
20–49	0.03		0.04		0.02	
50–99	0.08		0.10		0.07	
100–199	0.18		0.20		0.17	
200–499	0.44		0.39		0.47	
$\geq$ 500	0.27		0.27		0.27	
Firm age						
$\leq$ 1 year	0.00		0.00		0.00	

Table 1 continued

Variables	All firms		ICT		Non-ICT	
	Mean	SD	Mean	SD	Mean	SD
2–4 years	0.01		0.01		0.01	
5–9 years	0.05		0.07		0.05	
≥10 years	0.93		0.92		0.94	
Sector (%)						
Mining and quarrying (C)	0.01		0.00		0.01	
Manufacturing (D)	0.61		0.47		0.68	
Electricity, gas and water supply (E)	0.00		0.00		0.00	
Construction (F)	0.10		0.00		0.15	
Wholesale and retail trade (G)	0.10		0.26		0.02	
Hotels and restaurants (H)	0.13		0.00		0.02	
Transport, storage and communication (I)	0.07		0.06		0.08	
Financial intermediation (J)	0.01		0.04		0.00	
Real estate, renting and business activities (K)	0.09		0.17		0.05	
Number of observations	5,459		1,889		3,570	
Number of firms	1,735		666		1,096	

Count of ICT and non-ICT firms exceeds the number of all firms due to firms that changed category during the observation period. Monetary values in 2004 Euros

Around the respective sample means, this difference becomes smaller as the share of older workers in the firm increases, while the opposite holds for younger workers. The share of prime age workers is related to increases in the gap between value added and average wages until it reaches around 60%, and decreases thereafter.[6]

Comparing levels of age shares, value added and average wages across firms can be problematic as all three variables might be affected simultaneously by unobserved firm characteristics like idiosyncratic production processes, an advantageous geographic location or a profitable patent. A solution to this problem is to look at year-to-year changes as is done in Fig. 2: computing changes eliminates by definition time-invariant firm characteristics. Figure 2 plots non-parametric curves and actual year-to-year changes for each of the three age groups and the two variables of interest (firm-level value added and average wages). In our sample, the curves have slightly different shapes if they are based on changes instead of levels. Again, the proportion of younger workers in a firm appears to be clearly negatively related to the average wage paid by the firm, while this relationship appears to be positive for the respective shares of prime age and older workers. However, the links between age shares and value added cease to be parallel to the impact on wages. Indeed, for all three age groups the relationship between age shares and value added appears to be flat. However, Figs. 1 and 2 should be interpreted with caution: in contrast to the regression results presented in the next section, they do not control for observable firm characteristics such as the firm's educational or occupational composition.

6 We thank an anonymous referee for the suggestion to include Fig. 1b in this section.

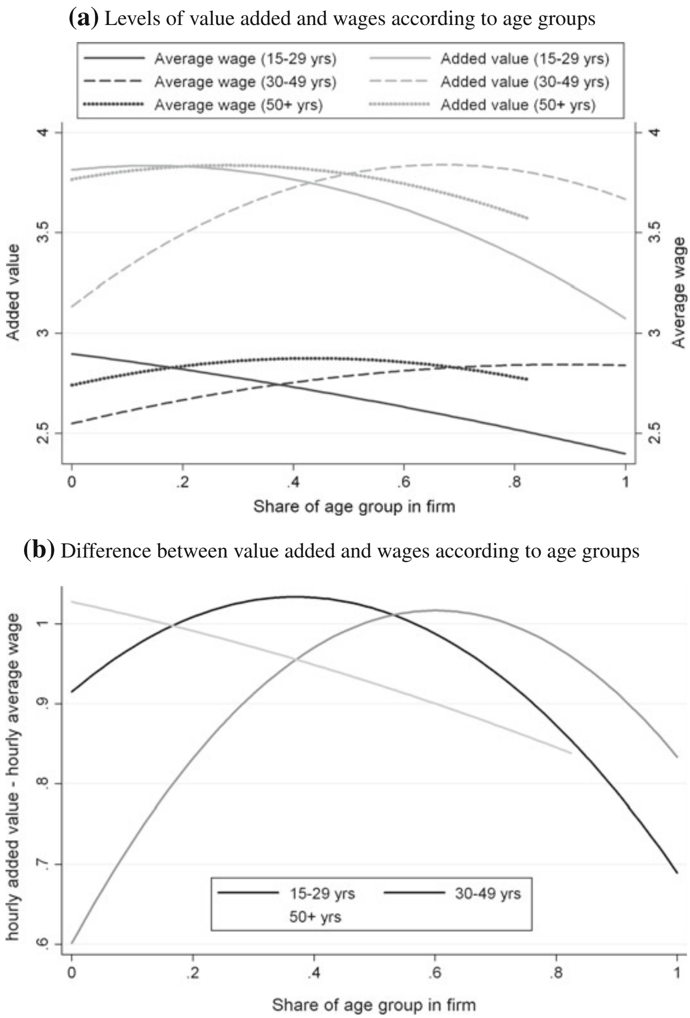

Fig. 1 Firm-level value added, earnings and age groups (1999–2006). Figure 1a shows quadratic prediction plots of firm-level value added and average wage as a function of age groups within firms. Figure 1b shows quadratic prediction plots of the difference between value added and average wage as a function of age groups within firms. Earnings deflated with CPI; earnings and value added per hour and in log. In 80% of firms, the share of the 15–29 years group lies in the interval [0.06, 0.38]; the share of the 30–49 years in the interval [0.47, 0.78]; and the share of 50+ workers in the interval [0.03, 0.31]

5 Specification and Results

5.1 Functional Specifications of the Model

In this section we describe the three different specifications of the Eqs. (2) and (4) that we estimated.

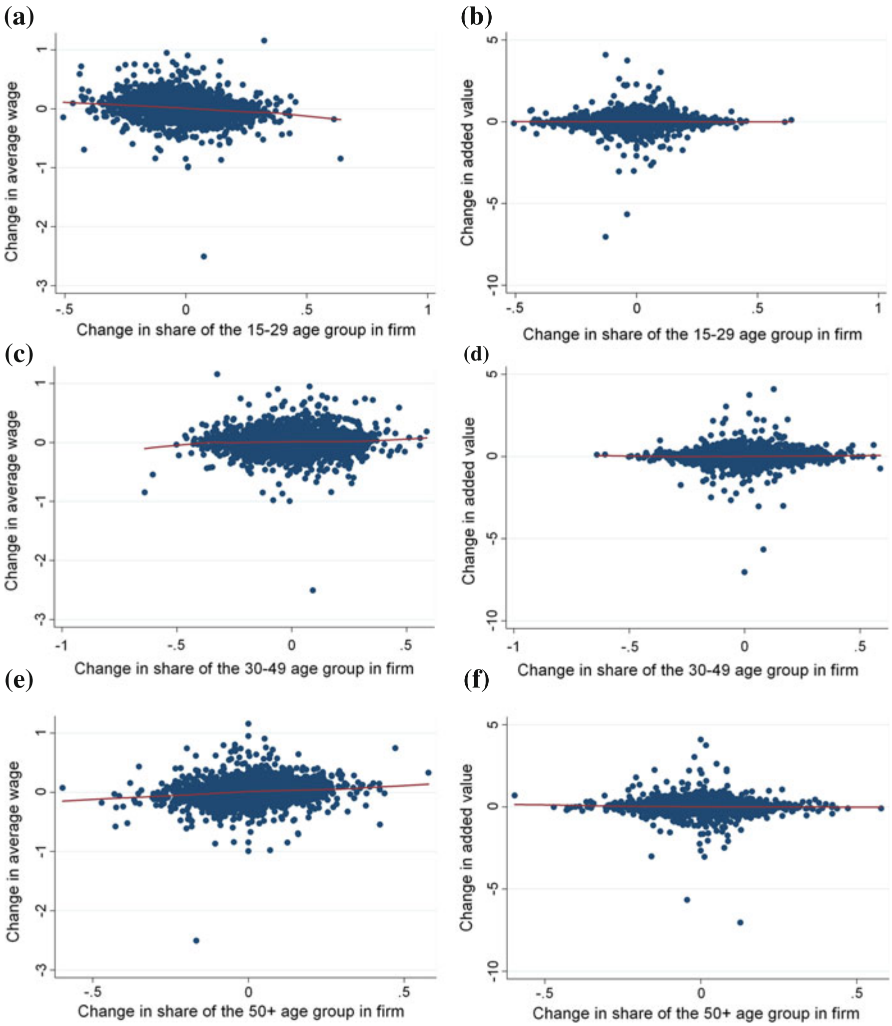

Fig. 2 Changes in firm-level value added, earnings and age groups (1999–2006). **a** Average wage and 15-29 age group, **b** Value added and 15–29 age group, **c** Average wage and 30–49 age group, **d** Value added and 30–49 age group, **e** Average wage and 50+ age group, **f** Value added and 50+ age group. *Notes* Figures show scatter plots and non-parametric, locally weighted smoothing curves of year-to-year changes (bandwidth = 0.8). Earnings deflated with CPI; earnings and value added per hour and in log

The model formed by Eqs. (5) and (6) is our baseline specification and similar to the model in Hellerstein et al. (1999). The β_j (with $j = 1, 2$) in Eq. (5) is the relative marginal impact of age group j [note that β_j corresponds to $\theta_j - 1$ in Eq. (3)]. In Eq. (6), β_j^* is the relative marginal impact of age share j on the average wage (β_j^* corresponds to $w_j/w_0 - 1$ in Eq. 4). The terms $\varepsilon_{i,t}$ and $\varepsilon_{i,t}^*$ represent the error terms.

$$\log\,(Value\ Added/Hours)_{i,t} = \alpha + \beta_1 A_{1i,t} + \beta_2 A_{3i,t} + \lambda X_{i,t} + \varepsilon_{i,t} \tag{5}$$
$$\log\,(Total\ Wages/Hours)_{i,t} = \alpha^* + \beta_1^* A_{1i,t} + \beta_2^* A_{3i,t} + \lambda^* X_{i,t} + \varepsilon_{i,t}^* \tag{6}$$

The dependent variable in Eq. (5) is the total value added by the firm i in period t, divided by the total number of work hours (taking into account paid overtime hours) that have been declared for the same period. The dependent variable in Eq. (6) is firm i's average hourly gross wage (including premia for overtime, weekend or night work, performance bonuses, commissions and other premia). It is obtained by dividing the firm's total wage bill by the total number of work hours. Hence, the dependent variables in the estimated equations are firm averages of value added and wages on an hourly basis. The main independent variables are the shares of hours worked by each age category in total work hours, ($A_{1i,t}$, $A_{2i,t}$, $A_{3i,t}$). This is a better employment indicator than the number of employees in each age category since it takes into account age differences in working time. We split employees of a firm into three age groups (i.e. <30, 30–49, 50+) and consider the share of prime age workers ($A_{2i,t}$) as our reference category. These age categories provide a good representation of the different stages in the individual life cycle. Indeed, as noted by Malmberg et al. (2005), one may suppose that workers younger than 30 years are more healthy, mobile and motivated individuals. The middle-aged workers might (i) have heavier family responsibilities, (ii) be more experienced and (iii) hold important management responsibilities. Workers older than 49 years of age could (i) have a good knowledge of themselves (e.g. they know how to be productive with a minimum of effort), (ii) have a better matching of their abilities with their job preferences, (iii) be less motivated to learn and (iv) suffer a weakening of their health.

In addition to the age shares in total work hours, we also included the vector $X_{i,t}$. It contains a set of variables controlling for observable characteristics of the firm and its labour force. More precisely, it includes 5 dummies for the size of the firm (i.e. the number of employees), 3 dummies for the firm vintage age,[7] respectively 5 and 7 dummies for the educational and occupational composition of the workforce, the proportion of female employees, shares of part-time and medium-time workers, the fraction of workers with an open-ended employment contract and 7 dummies for the years of observations. Since the firms' capital stock is not available in the SES-SBS data set, capital is proxied with dummy variables for nine economic sectors at the one-digit level of the NACE nomenclature. This is likely to compensate for the omission of capital since the latter tends to be correlated with the type of activity of the firm. Given the results reported in the empirical literature, van Ours and Stoeldraijer (2011) argue that the omission of the exact capital stock does not affect the estimates of production functions on firm-level data since the corresponding productivity effects tend to be small (see Hellerstein et al. 1999; Aubert and Crépon 2003; Dostie 2011).[8]

7 Our data set does not provide the firm age directly, which is why we proxied this variable with the seniority of the firm's most senior employee.

8 For the modalities of all control variables and corresponding descriptive statistics see Table 1.

Estimating Eqs. (5) and (6) yields insight into the shape and significance of age-productivity and age-wage profiles, but it does not allow to test directly whether the difference between the value added and wage coefficients for a given age group is statistically significant. A simple method to obtain a test for the significance of productivity-wage gaps has been proposed by van Ours and Stoeldraijer (2011). We apply a similar approach and estimate a model in which the difference between firm i's hourly value added and average wage is regressed on the same set of explanatory variables as in Eqs. (5) and (6). This produces age coefficients that measure directly the size and significance of each age group productivity-wage gap.

We have estimated Eqs. (5) and (6), as well as the productivity-wage gap, with two different methods. The baseline regression is a pooled Ordinary Least Squares (OLS) estimator with robust standard errors [we use a Huber/White/sandwich estimate of variance, i.e. the errors are robust to heteroscedasticity and serial correlation (see Wooldridge 2002)]. This estimator is based on both the cross-section variability between firms and the longitudinal variability within firms over time.

Pooled OLS estimators of value added models have been criticized for their potential "heterogeneity bias" (Aubert and Crépon 2003; p. 116). This bias is due to the fact that firm productivity depends to a large extent on firm-specific, time-invariant characteristics that are not measured in micro-level surveys. As a consequence, the age coefficients of these estimators might be biased since unobserved firm characteristics may affect simultaneously the firm's level of value added and its workforce age composition. This is referred to as a problem of spurious correlation and could be caused by factors such as an advantageous location, firm-specific assets like the ownership of a patent or other firm idiosyncrasies. One way to deal with unobserved time-invariant heterogeneity of firms is to estimate Eqs. (5) and (6), as well as the productivity-wage gap, in first differences (with heteroscedasticity and serial correlation robust standard errors). First differences do not estimate the *level* of productivity of firm i, but the *change* in productivity. Time-invariant heterogeneity is by definition not linked to changes in productivity and therefore controlled for. Since the first differences estimator eliminates firm characteristics that remain unchanged during the observation period, time-invariant control variables are not included in this specification.

In addition to pooled OLS and first differences estimations, we have carried out a series of robustness tests to examine whether our results are sensitive to: a) the potential endogeneity of the workforce age structure, b) the inclusion of dynamics in the model, c) the use of long differences in age share variables and d) the use of a smaller set of control variables. The outcome of these tests (reported in Sect. 5.3.) shows that the main conclusions presented in the next section are robust to alternative specifications.

5.2 Estimation Results

We first estimate Eqs. (5) and (6), as well as the productivity wage gap, by pooled OLS. Results regarding the age-productivity profile are presented in the second column of Table 2. They show that workers younger than 30 are significantly less productive than prime age and older workers. In contrast, the productivity of workers older than

49 is not found to differ significantly from that of middle-aged workers. The regression coefficient associated to the share of young workers is equal to −0.17. This means that if the fraction of younger workers within a firm increases by one unit (i.e. one percentage point), productivity decreases on average by 0.17% (i.e. −0.17* 0.01 = −0.0017 = −0.17%). Regression coefficients for the shares of young and older workers can thus be roughly interpreted as elasticities between productivity and fractions of workers by age groups. Yet, one should keep in mind that a change in one group of (young, prime age or older) workers modifies the incidence of workers in the other groups (van Ours and Stoeldraijer 2011). Turning to the relationship between age and wage, results show (see column 3 of Table 2) that a one percentage point increase in the share of young workers decreases mean hourly wages within firms on average by 0.32%. On the opposite, mean hourly wages are found to increase on average by 0.11% following a one percentage point increase in the fraction of older workers. Findings thus support the existence of a significant upward sloping age-wage profile. The comparison of estimates for the age-productivity and age-wage profiles suggests that young workers are paid below their marginal productivity while workers older than 49 would be overpaid.[9] Results from the productivity-wage gap regression (reported in column 4 of Table 2) support this hypothesis. Indeed, the impact of the share of young (older) workers on the productivity-wage gap is found to be significantly positive (negative).

However, these results should be interpreted with caution. Indeed, they may suffer from the fact that time-invariant unobserved workplace characteristics are not accounted for. Indeed, the Breusch and Pagan (1980) Lagrangian multiplier is 4735.88 for the value added and 4060.36 for the wage equation, which is why we refute the adequateness of pooled OLS for the estimation of Eqs. (5) and (6). We therefore re-estimated the model, as well as the productivity-wage gap, in first differences. Results for the age-wage profile are not very different than those in the OLS regression (see column 6 of Table 2). They again highlight that average hourly wages within firms increase significantly and monotonically with mean workers' age. Yet, the regression coefficient associated to the share of young workers drops from −0.32 to −0.15 while that for the fraction of older workers increases from 0.11 to 0.15. Findings for the age-productivity profile after controlling for firm fixed effects are quite different from those obtained with OLS (see column 5 of Table 2). Indeed, results now show that workers

[9] It can be argued that comparing β_j (the estimate for the relative marginal productivity of age group j) with β_j^* (the estimate for the difference in relative pay for age group j) may lead to imprecise conclusions as β_j underestimates differences in relative productivities given that $\beta_j = \beta\left(q_j - 1\right)$, whereas $\beta_j^* = w_j/w_0 - 1$ (see section 3). Indeed, Vandenberghe and Waltenberg (2010) propose to compare β_j^* with $\beta_j/\beta = q_j - 1$ in order to adjust the estimates of the relative productivities of the different age groups for total labour productivity β [see Eq. (2)]. Unfortunately, our data do not allow to estimate β directly. In order to guarantee the anonymity of firms in the SES-SBS, Statistics Belgium provides information on the total number of employees per firm only in 6 thresholds. As a result, firm size is basically a time-invariant variable (in our data set) which disappears in first differences specifications. Since values of β have been estimated to range between 0.6 and 0.8 (Vandenberghe and Waltenberg 2010; van Ours and Stoeldraijer 2011), our estimates should therefore be interpreted as lower bounds for differences in relative productivities. Given that in most specifications discussed in this paper β_j and β_j^* have opposite signs, the proposed adjustment would further increase the magnitude (but not necessarily the significance) of the estimated productivity-wage gaps. We are grateful to an anonymous referee for having pointed out this issue.

Table 2 Estimation results for entire sample

Dependent variable	Pooled OLS			First differences		
	Value added per hour worked (ln)	Mean wage per hour worked (ln)	Value added-wage gap (ln)	Value added per hour worked (ln)	Mean wage per hour worked (ln)	Value added-wage gap (ln)
Share (Age <30)	−0.17***	−0.32***	0.15***	0.03	−0.15***	0.17***
	(0.06)	(0.02)	(0.06)	(0.04)	(0.02)	(0.05)
Share (Age >50)	0.00	0.11***	−0.11*	−0.12**	0.15***	−0.26***
	(0.07)	(0.03)	(0.06)	(0.05)	(0.02)	(0.05)
F statistic	47.89	192.31	9.68	1.55	48.85	17.85
R squared	0.29	0.67	0.07	0.01	0.32	0.06
Number of observations	5,459	5,459	5,459	5,459	5,459	5,459
Number of firms	1,735	1,735	1,735	1,735	1,735	1,735

***,**,*significant at the 1, 5 and 10% level. Robust standard errors are reported between brackets. We control for worker characteristics that include the educational and occupational composition of the firm's workforce (6 and 8 categories, respectively), share of female employees, working time (3 categories) and share of non-standard work contracts. We control for firm characteristics that include size (5 dummies), firm vintage age (3 dummies) and industry (8 dummies), but in the first differences estimations they are dropped since they are time invariant. We also control for year dummies (7)

older than 49 are significantly less productive than prime age and young workers. Moreover, we find no evidence anymore for the fact that young workers would be less productive than prime age workers. Overall, our results lend support to the existence of a mechanism of deferred compensation over the life-cycle (Lazear 1979). Indeed, results from our productivity-wage gap regression (see column 7 of Table 2) again highlight the "underpayment" of workers younger than 30 and the "overpayment" of workers older than 49.

5.3 Robustness Tests

An array of tests has been carried out to assess the robustness of the results presented in the previous section. The main results stand up to a range of alternative specifications.

5.3.1 Potential Endogeneity of Age Shares

A first issue to consider is the potential endogeneity of the workforce age structure. The point is that any unobserved productivity shock might generate correlated changes in the workforce age structure and labour productivity that are not due to the ageing of the workforce per se. For example, one might expect that a firm undergoing a negative productivity shock would prefer not to hire new individuals, which would increase the age of the workforce. Hence, the correlation that we could find, using first differences estimations, between a decrease of firm productivity and the rise of the share of older workers could be purely spurious. A way to address this simultaneity problem is to use instruments that are correlated with the problematic explanatory variables and uncorrelated with the exogenous shocks (i.e. the error term).

To explore the acuteness of the simultaneity problem in our data, we have estimated Eqs. (5) and (6), as well as the productivity-wage gap, in first differences and instrumented the (differenced) age shares with the one-period lag of the level of these shares. In other words, the lagged level of age shares is assumed to be correlated with future values of the instrumented variables but not with the exogenous shocks.[10] We estimated the IV first-differenced equations using the Generalized Method of Moments (GMM) with a Newey-West variance-covariance matrix and standard errors that are robust to heteroscedasticity and serial correlation. This IV approach has been applied to productivity and wage equations by Aubert and Crépon (2003) and is now standard in the literature (van Ours 2009; Göbel and Zwick 2009). To examine the reliability of our results, we have computed the usual diagnostic tests for instrumental variables. First, the Kleibergen-Paap statistic for under-identification tests whether the equation is identified, i.e. whether the excluded instruments are all relevant. The null hypothesis in this test is that the equation is underidentified. Second, the Kleibergen-Paap statistic for weak identification is a Wald F statistic testing whether the excluded instruments are sufficiently correlated with the endogenous regressors (the null hypothesis being weak identification). Since a rejection rule for this test has yet to be established, we rely on the "rule of thumb" that weak identification is problematic for F-statistics smaller than 10 (van Ours and Stoeldraijer 2011). Finally, we compute an endogeneity test with the null hypothesis that the age shares can actually be treated as exogenous. The test is based on the difference of two Sargan–Hansen statistics: one for the equation in which the age shares are treated as endogenous, and one in which they are treated as exogenous. If the null hypothesis of this test cannot be rejected, then instrumentation is actually not necessary.

The results in Appendix B indicate that under- and weak identification is unproblematic in our case: we reject the hypothesis of under-identification at the one percent level and the Kleibergen-Paap statistics for weak identification are above 10. Moreover, we cannot reject the hypothesis that age shares can actually be treated as exogenous: the corresponding p-values are 0.78 (value added), 0.87 (wage) and 0.74 (productivity-wage gap). This means that instrumentation is actually not necessary since there appears to be no endogeneity in the age shares once we control for time-invariant unobserved firm characteristics by taking first differences. The results for GMM-IV reported in Appendix B should therefore be read with the disclaimer that the IV estimates are less efficient compared to our baseline model in first differences and that instrumentation is actually not necessary in our case.

5.3.2 Dynamic Specification

Another problem to consider is the potential state dependence of the dependent variable. To do so, we estimate a dynamic version of our models in first differences by

[10] We have experimented with a larger set of instruments, for instance by including lags of age shares for $t-2$ and $t-3$. However, only the smaller set including one-period lags passed the test of weak identification.

including one-period lag of the dependent variable among the regressors. In other words, we allow the dependent variable to be not only related to contemporary inputs, but also to be a function of its own value in the previous period (Arellano and Bond 1991; Göbel and Zwick 2009). The lagged dependent variable is found to be highly significant in the three regressions and the "goodness of fit" of our models is improved (see Appendix C). This being said, results still confirm conclusions from the static specification. However, the size of the regression coefficients associated to the age share variables is somewhat reduced. Indeed, the detrimental effect of older workers on firm productivity drops from −0.12 to −0.09. Moreover, mean hourly wages are now found to increase (decrease) on average by 0.13% following a one percentage point increase in the fraction of older (younger) workers. Overall, this leads to a (slightly) smaller "overpayment" ("underpayment") of older (young) workers. More precisely, dynamic results suggest that a one percentage point increase in the share of workers younger than 30 (older than 49) increases (decreases) the productivity-wage gap within firms on average by 0.15% (0.21%).

5.3.3 Changes in Age Shares May Need Time to Affect Productivity

The observed contrast between productivity and wage equations could reflect that the dynamics of changes in a firm's age composition work differently for productivity than for wages. Imagine, for instance, that a firm replaces older workers with younger ones. As a consequence, the average wage of the firm is likely to change immediately if the firm operates pay rules based on tenure. However, the effect on the firm's value added may not be visible until the new personnel has learned to adapt to specificities of the firm. Typically, employers will retain part of the older workers during a transition period so as to ensure knowledge transfers from older to younger workers.

To investigate the incidence of this phenomenon on our results, we estimated an alternative specification of the baseline model that allows for a delayed impact of changes in age shares on productivity, in particular by using longer differences instead of the year-to-year changes in our baseline model. Columns 5–7 in Appendix C are based on differences over 3 years (i.e. between t and $t-3$). In this regression the wage coefficients remain almost unchanged, although the coefficient of determination of the model decreases somewhat compared to the first-differenced specification. The productivity coefficient of older workers in the model with longer differences remains significant and increases in absolute value. As a consequence, the positive (negative) productivity-wage gaps for younger (older) workers are wider in the specification with longer differences (see column 7). Older workers therefore appear to be even less productive and overpaid with respect to their relative productivity once we allow for the productivity impact of changes in a firm's age composition to occur after a transition period of several years.[11]

[11] Our baseline specification controls for the composition of the firm's labour force (see Sect. 5.1.) An alternative perspective on our question can be obtained by regressing our dependent variables on age shares without workers control variables in the model. In this case, an age group composition in terms of education or occupation is viewed as a constituent element of its impact on productivity, wages and productivity-wage gaps instead of isolating the age coefficients from these characteristics. We have computed the first differences estimator (both static and dynamic) excluding worker controls and find our conclusions unaltered.

6 Impact of ICT Intensity on Productivity and Wages of Age Groups

The relationship between age and productivity is likely to differ across firms: the studies reviewed in Sect. 2 suggest that certain characteristics of the work environment such as computerization or the use of innovative technologies play an asymmetric role for younger and older workers. Given the scarce empirical evidence on the link between age-productivity profiles and ICT, this section presents estimates of our model for two distinct types of firms: those belonging to sectors intensively using or producing ICT goods and services and those that do not. The subdivision of firms is based on the ICT taxonomy developed by O'Mahoney and van Ark (2003).[12]

Applied to our sample, this ICT taxonomy classifies 666 firms as ICT and 1,096 as non-ICT firms.[13] These two types differ along several dimensions (see Table 1). Both the average hourly value added and wage are higher in ICT compared to non-ICT firms (for the period 1999–2006 the ICT values were 12 and 13% higher, respectively), confirming the intuition that ICT firms are in general more productive. Differences in the educational and occupational composition also exist: the workforce of ICT firms is on average much more educated and more concentrated in white collar occupations compared to non-ICT firms. Interestingly, ICT firms are also characterised by a more feminine labour force and sign more part- and medium-time work contracts. Moreover, it is noteworthy that non-ICT employment is predominantly concentrated in the manufacturing sector (around 68%), while a large fraction of workers employed in ICT firms is also found in wholesale and retail trade (around 26%) and real estate, renting and business activities (around 17%). By contrast, the age composition of the two sectors hardly differs: although ICT firms have a somewhat younger labour force, the respective proportions of our three age groups are relatively close.

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[12] ICT firms are found in the following sectors: Clothing (NACE 18); Printing and publishing (NACE 22); Mechanical engineering (NACE 29); Other electrical machinery and apparatus, except insulated wire (NACE 31); Other instruments, except scientific instruments (NACE 33); Building and repairing of ships and boats (NACE 351); Aircraft and spacecraft (NACE 353); Furniture, miscellaneous manufacturing; recycling (NACE 36–37); Wholesale trade and commission trade, except of motor vehicles and motorcycles (NACE 51); Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods (NACE 52); Financial activities, except insurance and pension funding (NACE 65); Activities auxiliary to financial intermediation (NACE 67); Renting of machinery and equipment (NACE 71); Legal, technical and advertising (NACE 741–743); Office machinery (NACE 30); Insulated wire (NACE 313); Electronic valves and tubes (NACE 321); Telecommunication equipment (NACE 322); Radio and television receivers (NACE 323); Scientific instruments (NACE 331); Communications (NACE 64); Computer and related activities (NACE 72). Non-ICT firms are found in the following sectors: Quarrying (NACE 14); Food, drink and tobacco (NACE 15–16); Textiles (NACE 17); Leather and footwear (NACE 19); Wood and products of of wood and cork (NACE 20); Pulp, paper and paper products (NACE 21); Mineral oil refining, coke and nuclear fuel (NACE 23); Chemicals (NACE 24); Rubbers and plastics (NACE 25); Non-metallic mineral products (NACE 26); Basic metals (NACE 27); Fabricated metal products (NACE 28); Motor vehicles (NACE 34); Construction (NACE 45); Sale, maintenance and repair of motor vehicles and motorcycles ; retail sale of automotive fuel (NACE 50); Hotels and restaurants (NACE 55); Inland transport (NACE 60); Water transport (NACE 61); Air transport (NACE 62); Supporting and auxiliary transport activities; activities of travel agencies (NACE 63); Real estate activities (NACE 70); Other business activities (NACE 749).

[13] The sum of ICT and non-ICT firms (1,762) is greater than the total number of firms in the baseline model (1,735). This is due to a small number of firms that changed NACE codes during the period 1999–2006. Supression of these firms does not affect our conclusions.

To test formally for differences between ICT and non-ICT firms, we add to our baseline model: a) a dummy variable that equals 1 if the firm is classified as being ICT intensive and b) interactions between this ICT dummy and all other explanatory variables. We focus here on the specification with dynamic first differences. The conclusions drawn from the baseline regressions and the robustness tests—i.e. heterogeneity bias in pooled OLS and absence of endogeneity—also apply to specifications with interaction variables but are not repeated here due to space constraints.

The coefficients for dynamic first-differences are presented in Table 3. Looking at the wage coefficients (column 3), the estimates suggest that age has a stronger impact on remuneration in ICT than in non-ICT environments: younger workers in ICT firms are paid significantly less (with respect to prime age workers) than in non-ICT firms. By contrast, the relationship between the share of older workers and the firms' average wage is not significantly different in ICT and non-ICT environments. This suggests that some of the wider wage dispersion in ICT firms (see Table 1) is due to a more prominent role of the age dimension in the wage setting of ICT compared to non-ICT firms. We performed a formal Wald test (i.e. a Chow test with the robust variance estimates) to see whether the interaction coefficients for younger and older workers are jointly different from zero. The F statistic for the wage equation is 2.98, implying that the age-wage relationship is significantly different in ICT firms.

As for the productivity coefficients (column 2 in Table 3), the results suggest that the lower productivity of older workers relative to the prime age group that we found in our baseline regression appears in both ICT and non-ICT firms: a one percentage point increase of the share of older workers decreases firm productivity by 0.11% for both types of firms. The interaction variables for ICT firms are individually and jointly insignificantly different from zero. This suggests that relative productivities across age groups do not depend on the ICT environment of firms.[14]

The resulting productivity-wage gaps are also similar in both sectors (column 4 in Table 3): older workers appear to be significantly over- and younger workers underpaid compared to their relative contributions to the firm value added in both ICT and non-ICT firms. Again, we cannot reject the hypothesis that the ICT interaction coefficients for younger and older workers are individually and jointly equal to zero. Although the impact of the share of young workers on wages is found to be smaller in non-ICT firms, the magnitude of the productivity-wage gaps appear to be similar in both types of work environment.

Yet, it should be noted that our results do not allow to make any definite statement about the causality of the observed correlations. The point is that "being ICT intensive" may not be considered as an exogenous treatment that can be assimilated to a natural experiment. As a result, what we interpret as the direct impact of the ICT environment

[14] Interestingly, our results corroborate other empirical findings according to which age-productivity profiles are relatively similar between different sectors. For instance, in one of the few studies that exist on Belgium, Vandenberghe and Waltenberg (2010) argue that the lower relative productivity of older workers is not mitigated by the working conditions of the service sector. In contrast, our results do not support Lallemand and Rycx (2009)'s conclusion for the Belgian private sector according to which age structure effects on productivity would be stronger in ICT than in non-ICT firms. Yet, differences in results can probably be explained by the fact that Lallemand and Rycx (2009) had only access to cross-sectional data.

Table 3 Estimation results (dynamic first differences) for different ICT environments

Dependent variable	Value added per hour worked (ln)	Mean wage per hour worked (ln)	Value added-wage gap (ln)
One year lagged dependent variable	−0.36***	−0.32***	−0.37***
	(0.10)	(0.03)	(0.09)
Share (Age <30)	0.07	−0.10***	0.16***
	(0.06)	(0.02)	(0.06)
Share (Age >50)	−0.11*	0.11***	−0.22***
	(0.06)	(0.02)	(0.07)
Share (Age <30)*ICT [a]	−0.11	−0.08**	−0.03
	(0.08)	(0.04)	(0.09)
Share (Age >50)*ICT [a]	0.07	0.05	0.02
	(0.09)	(0.05)	(0.10)
ICT [a]	0.00	−0.00	0.01
	(0.01)	(0.00)	(0.01)
F statistic	2.00	39.04	11.71
Adjusted *R* squared	0.12	0.42	0.18
Number of observations	5,459	5,459	5,459
Number of firms	1,735	1,735	1,735

***,**,* significant at the 1, 5 and 10% level. Robust standard errors are reported between brackets

We control for worker characteristics that include the educational and occupational composition of the firm's workforce (6 and 8 categories, respectively), share of female employees, working time (3 categories) and share of non-standard work contracts. We control for firm characteristics that include size (5 dummies), firm vintage age (3 dummies) and industry (8 dummies), but they are dropped since they are time invariant. We also control for year dummies (5)

[a] ICT is a dummy variable that is equal to one if a firm belongs to a sector intensively producing or using ICT goods and services (classification based on O'Mahoney and van Ark 2003, for more details see footnote 12)

on the productivity and remuneration of workers in different age groups is only one of many mechanisms that may affect the productivity and wage profiles of ICT and non-ICT firms. For instance, it is possible that a negative impact of ICT on old-age productivity is offset by the fact that the workforce in ICT firms is on average more educated (see Table 1) and potentially more motivated. This being said, our model accounts for some of such indirect factors by controlling for a number of firm-level workforce characteristics (see Sect. 5.1). Moreover, as highlighted by an anonymous referee, "this issue may be less of a problem when using the productivity-wage gap as a dependent variable, as one could assume that the remaining bias (after first differencing and instrumenting of age shares) could be present in both productivity and pay measurements". Finally, it should be noted that the approach presented in this paper addresses a range of measurement issues that improve considerably the reliability of estimation results compared to existing research. For instance, the consequential issue of time-invariant unobserved firm heterogeneity could not be addressed with the data used by Lallemand and Rycx (2009).

7 Conclusion

The ageing of the labour force in Europe and elsewhere creates the need to disentangle the relationship between age, wage and productivity. In this paper, we examine how changes in the proportion of young (16–29 years), middle-aged (30–49 years) and older (more than 49 years) workers affect the productivity and remuneration of firms. We further investigate the presence of productivity-wage gaps for these age groups in different ICT environments. To do so, we use longitudinal matched employer-employee data covering the Belgian private sector over the period 1999–2006. Our data allows to tackle a range of measurement issues that have hampered the existing literature in this area of research: the panel data provides accurate information on average productivity and wages within firms; controls for a wide range of worker and firm characteristics; includes age variables in terms of hours worked rather than on a per capita basis; and permits to deal with time-invariant unobserved firm heterogeneity, the endogeneity of age shares and state dependence of firm productivity and wages.

Results based on our preferred specification indicate that workers above 49 years are significantly less productive than their younger colleagues. Moreover, while relative productivities across age groups are not found to differ significantly between ICT and non ICT firms, the upward sloping age-wage profile appears to be somewhat steeper in ICT firms. Yet, whatever the ICT environment, findings show that young workers are paid below and older workers above their marginal productivity.

Our results may have important policy implications. Firstly, the fact that older workers are found to be less productive than their younger colleagues suggests that policies aiming to improve the employment rate of older people (e.g. abolishing early retirement schemes or lifting the legal retirement age) may be detrimental for firm productivity. This result also suggests that more effort should be devoted to: a) the improvement of working conditions so as to reduce the impact of ageing on workers' physical and mental health (and productivity) and b) the implementation of high-quality training programmes for the elderly.

Secondly, the fact that age-productivity profiles do not appear to depend on the ICT environment of firms suggests that one should be cautious with oversimplifications according to which technological change would be intrinsically positive for technologically literate youngsters and necessarily bad for veterans who started their career in the pre-internet area. New technologies are likely to perform more diversified roles than simply rendering accumulated skills obsolete as suggested by parts of the theoretical literature. Some technologies, including ICT, might also help older workers to maintain constant levels of productivity by assisting them in a wide range of cognitive and physically demanding tasks. By contrast, older workers employed in areas in which the pace of technological change in production processes is slow (like, for instance, in the construction sector) might face more difficulties to keep up with younger workers' higher physical and cognitive abilities.

Finally, our conclusion that young workers are paid below their marginal productivity while older workers appear to be "overpaid" is in line with the deferred payment model developed by Lazear (1979). This compensation scheme may be beneficial to both employers and employees in internal labour markets and raise the present value of career compensation. Indeed, the adoption of such scheme would improve employees' productivity (because it stimulates workers' effort, reduces monitoring costs and enables firms to hire and retain the best employees) and hence allow firms to pay higher present value career compensation than otherwise (Ehrenberg and Smith 2003). As a consequence, the observed under- and over-payment of respectively young and older workers in the Belgian private sector should not be harmful to employers with internal labour markets, except if the present value of career compensation exceeds that of marginal productivities. The same should be true for their employees unless: (i) career compensation falls short of marginal product value, (ii) the firm goes bankrupt before they retire, (iii) they are fired before they reach an age at which they benefit from potential end-of-career overpayment. The latter reason should not be neglected because deferred compensation schemes may incite firms to dismiss workers before they get older so as to maximise their profits (at least in the short run). An important caveat of this interpretation is that a significant fraction of firms operate on external labour markets where workers and firms are more concerned with the immediate relation between pay and productivity (Lazear and Oyer 2003). The optimality of a deferred compensation scheme on that portion of the labour market is therefore less straightforward. Given that age-productivity profiles appear to be similar in ICT and non-ICT firms, the higher wage penalty we observe for young workers (relative to prime age workers) in ICT firms suggests that deferred payment may be positively related to ICT-capital intensity.

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Appendix A: Further Description of the Data

The 'Structure of Earnings Survey' (SES) is a stratified sample. The stratification criteria refer respectively to the region (NUTS-groups), the principal economic activity (NACE-groups) and the size of the firm. The sample size in each stratum depends on the size of the firm. Sampling percentages of firms are respectively equal to 10, 50 and 100% when the number of workers is lower than 50, between 50 and 99, and above 100. Within a firm, sampling percentages of employees also depend on size. Sampling percentages of employees reach respectively 100, 50, 25, 14.3 and 10% when the number of workers is lower than 20, between 20 and 50, between 50 and 99, between 100 and 199, and between 200 and 299. Firms employing 300 workers or more have to report information for an absolute number of employees. This number ranges between 30 (for firms with between 300 and 349 workers) and 200 (for firms with 12,000 workers or more). To guarantee that firms report information on a representative sample of their workers, they are asked to follow a specific procedure. First, they have to rank their employees in alphabetical order. Next, Statistics Belgium gives them a random letter (e.g. the letter O) from which they have to start when reporting information on their employees (following the alphabetical order of workers' names in their list). If they reach the letter Z and still have to provide information on some of their employees, they have to continue from the letter A in their list. Moreover, firms that employ different categories of workers, namely managers, blue- and/or white-collar workers, have to set up a separate alphabetical list for each of these categories and to report information on a number of workers in these different groups that is proportional to their share in total firm employment. For example, a firm with 300 employees (namely, 60 managers, 180 white-collar workers and 60 blue-collar workers) will have to report information on 30 workers (namely, 6 managers, 18 white-collar workers and 6 blue-collar workers). For more details see Demunter (2000).

Appendix B

See Table 4.

Table 4 First differences with IV (GMM)

Dependent variable	Value added per hour worked (ln)	Mean wage per hour worked (ln)	Value added-wage gap (ln)
Share (Age <30)	0.00	−0.16***	0.16
	(0.10)	(0.04)	(0.11)
Share (Age >50)	−0.03	0.13***	−0.16
	(0.14)	(0.05)	(0.14)
F statistic	1.17	36.78	12.90
R squared	0.00	0.32	0.06
Under-identification[a]	0.00	0.00	0.00
Weak identification[b]	259	259	259
Endogeneity[c]	0.78	0.87	0.74
Number of observations	5,459	5,459	5,459
Number of firms	1,735	1,735	1,735

***,**,* significant at the 1, 5 and 10% level. Robust standard errors are reported between brackets

We control for worker characteristics that include the educational and occupational composition of the firm's workforce (6 and 8 categories, respectively), share of female employees, working time (3 categories) and share of non-standard work contracts

We control for firm characteristics that include size (5 dummies), firm vintage age (3 dummies) and industry (8 dummies), but they are dropped since they are time invariant. We also control for year dummies (7)

[a] *p*-value associated to Kleibergen-Paap rk LM statistic. The null hypothesis is that the equation is under-identified

[b] Kleibergen-Paap rk Wald *F* statistic. The null hypothesis is that identification is weak

[c] *p*-value associated to difference of Sargan–Hansen statistics. The null hypothesis is that age share variables are exogenous (i.e. that no instrumentation is required)

Appendix C

See Table 5.

Table 5 First differences with lagged dependent variable

Dependent variable	First differences[a]			Long differences[b]		
	Value added per hour worked (ln)	Mean wage per hour worked (ln)	Value added-wage gap (ln)	Value added per hour worked (ln)	Mean wage per hour worked (ln)	Value added-wage gap (ln)
Share (Age <30)	0.02	−0.13***	0.15***	0.09	−0.16***	0.24**
	(0.04)	(0.02)	(0.05)	(0.10)	(0.02)	(0.11)
Share (Age > 50)	−0.09**	0.13***	−0.21***	−0.19*	0.10***	−0.28***
	(0.05)	(0.02)	(0.05)	(0.10)	(0.03)	(0.10)
One year lagged dependent variable	−0.34***	−0.32***	−0.36***	0.24***	0.10***	0.21***
	(0.08)	(0.02)	(0.07)	(0.05)	(0.02)	(0.04)
F statistic	2.36	65.03	20.25	2.70	27.18	7.27
R squared	0.13	0.41	0.19	0.08	0.33	0.09
Number of observations	5,459	5,459	5,459	2,870	2,870	2,870
Number of firms	1,735	1,735	1,735	1,230	1,230	1,230

***,**,* significant at the 1, 5 and 10% level. Robust standard errors are reported between brackets

We control for worker characteristics that include the educational and occupational composition of the firm's workforce (6 and 8 categories, respectively), share of female employees, working time (3 categories) and share of non-standard work contracts

We control for firm characteristics that include size (5 dummies), firm vintage age (3 dummies) and industry (8 dummies), but they are dropped since they are time invariant. We also control for year dummies

[a] Differences based on year-to-year changes

[b] Differences based on changes between t and $t-3$

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