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Are Older Workers Worthy of Their Pay? An Empirical Investigation of Age-Productivity and Age-Wage Nexuses

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Abstract Using longitudinal employer-employee data spanning over a 22-year period, we compare age-wage and age-productivity profiles and find that productivity increases until the age range of 50–54, whereas wages peak around the age 40–44. At younger ages, wages increase in line with productivity gains but as prime-age approaches, wage increases lag behind productivity gains. As a result, older workers are, in fact, worthy of their pay, in the sense that their contribution to firm-level productivity exceeds their contribution to the wage bill. On the methodological side, we note that failure to account for the endogenous nature of the regressors in the estimation of the wage and productivity equations biases the results towards a pattern consistent with underpayment followed by overpayment type of policies.

Keywords Aging · Productivity · Wages

JEL Classification J14 · J24 · J31

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1 Introduction

The increasingly larger share of total population accounted for by older individuals —aging— is a key component of world population trends since the mid-twentieth century. This aging process is now pervasive and accelerating.

Concerns over its economic consequences have focused on the growing burden on social security systems around the world arising from the persistent decline of the potential support ratio. A less researched but potentially equally important consequence of this aging process concerns labor productivity, as the labor force is also becoming older and that may further impact on growth prospects, depending on how labor productivity varies with the age of the worker.

Individual productivity depends on the workers' abilities (physical and cognitive), as well as on their education and experience. While experience tends to increase with age, workers' abilities are expected to decline as individuals get older. Avolio and Waldman (1994) place around 30 the age at which cognitive and physical abilities start to decline sharply, whereas Skirbekk (2004) sets at around 50 the age at which productivity starts to decline.[1] The decline in the productivity of labor with the age of the worker has been documented by a number of authors for specific occupations.[2] However, as noted by Galenson and Weinberg (2000), the threshold at which productivity starts to decline may itself be subject to change over time, due to the changing nature of output demand and technology, as well as to the observed trend in the amount of job-training provided and the rate of training obsolescence (Bartel and Sicherman 1993).

The fact that there is an important collective dimension to labor productivity (Aubert and Crépon 2003) opens the way to analyzing the age-productivity nexus at the firm level rather than at the worker individual level. Results obtained with firm level data indicate that a larger share of old workers has a detrimental effect on firm productivity (Haltiwanger et al. 1999; Lallemand and Rycx 2009), which is consistent with the findings obtained at the worker level.

All the studies referred so far, except Aubert and Crépon (2003), have concentrated only on the productivity side. None of them embraces a direct comparison of the productivity and wage profiles, to test whether the age-wage slope is steeper than the age-productivity slope. An early exception to this is offered by the work of Medoff and Abraham (1980), who document a positive association, within hierarchical grade level, between pay and experience, not related or even negatively related to individual performance on the job (as rated by the supervisors). Their results are interpreted as evidence against the human capital on-the-job training model and are consistent with Lazear's model of deferred compensation (Lazear 1979), which postulates that a pay scheme whereby workers are underpaid at the earliest stages of their careers within firms and overpaid later on is an admissible solution to the moral hazard problem the employer faces in a context of imperfect information on workers' actions.

[1] For a review of the literature on the evolution of cognitive skills over the life-cycle, see Skirbekk (2004).

[2] These include academia (McDowell 1982; Diamond 1986, and Oster and Hamermesh 1998) or track and field road racing (Fair 1994).

The first study to focus entirely on wage and productivity age profiles was Hellerstein and Neumark (1995). They have initiated a new track in the literature by proposing a simple but thoughtful method to test whether wage differentials traditionally captured by wage regressions are rooted in productivity differentials captured by production functions. The procedure relies on linked employer-employee data and consists essentially on estimating a production function and a wage function at the plant level, using a common specification, and then comparing the estimated coefficients across equations. Using firm level data from Israel, they estimate Cobb-Douglas production functions augmented with the inclusion of the shares of workers in the young, prime-age and older age brackets, finding that the upward sloping age-wage profile mirrors the upward sloping age-productivity profile. Similar results were obtained by Hellerstein et al. (1999), while Hægeland and Klette (1999) found that the wage premium for workers with higher experience (more than 15 years) exceeds their relative productivity, whereas the opposite is true for workers with 8–15 years of experience.

Both the representativeness and the validity of these results are currently subject to intense debate. The need to ground the empirical work on longitudinal data so as to control more effectively for the relevant firm characteristics (including unobserved time-invariant characteristics) is now widely agreed upon (Hellerstein et al. 1999). Firm-productivity shocks (which are, by definition, time-varying and therefore not captured by firm fixed-effects or similar methods) might as well bias the results, because firms may have more difficulty adjusting some types of labor than others due, for example, to the adoption of inverse seniority rules. In such cases, the bias in the estimation of older workers' productivity would arise out of the fact that changes in input shares are endogenous. Attempts to overcome this problem include using the GMM estimators (Aubert and Crépon 2003; Göbel and Zwick 2009 and van Ours and Stoeldraijer 2011) and two-stage regression methods (Dostie 2011).[3]

In this article we also test the hypothesis that older workers are "overpaid", by comparing the contribution of different demographic groups to both the firm sales (which we take as a proxy for production) and its wage bill. The approach we adopt also provides evidence on the attractiveness of older workers for their employers, and thereby on their employability. Our work relies on administrative longitudinal data on workers and their firms of remarkable quality, which cover the entire workforce in the manufacturing and services private sector in Portugal. Problems commonly faced by panel datasets, such as panel attrition and over- or under-sampling of some groups of workers, are not present. Given its administrative nature and the fact that workers within each plant can have access to all the information reported, measurement problems are also reduced. Our analysis spans an unusually long period of more than 20 years.

[3] Aubert and Crépon (2003) estimate first-differenced production and labor cost functions, treating the input levels and input shares as endogenous and using lagged values of those variables as instruments. Göbel and Zwick (2009) and van Ours and Stoeldraijer (2011) also use an instrumental variable approach, estimating production and wage equations in first differences and using lagged values of the age structure as instrument for the change in the age structure. Dostie (2011) estimates productivity shocks in the first step and uses them as regressors to estimate the productivity equation in the second step.

Given the high quality of our database we believe that our results provide reliable estimates of the effects of aging on productivity and wages. Indeed, all previous research on this topic is based on cross-sectional data or on panel data shorter than the length of the age intervals considered in the analysis. Hence, identification of the effects of age on wages and productivity depends on either cross-sectional variation or, for panel data studies, mostly on turnover of workers. In this latter case the scope to observe existing workers aging is reduced over a short period of time during which relatively few workers “cross the border” of the age brackets. Identification is thus based on a smaller number of firms than would be the case with longer panels. Depending on the actual distribution of workers age inside each age bracket considered, this advantage may be more or less relevant. Because we have data spanning 22 years and use 5-year age brackets, we are in a better position to capture aging of the firms’ workforce and are thus able to obtain estimates of the parameters of interest based on within-firm variation largely due to the aging of each firm’s workforce. The precision of our estimates is enhanced by the fact that we are able to introduce detailed information on worker characteristics, particularly the education level. We also note that our results are obtained from data that span over different stages of the business cycle and cannot be attributed to the timing of observation.

The paper is organized as follows. Section 3 describes the data. Section 4 presents the models under estimation. Section 5 discusses the results and Sect. 6 concludes.

2 Background Information on the Portuguese Labor Market

A long standing feature of the Portuguese economy is that it is a low productivity-low wage economy. These features remained unchanged during the period analyzed in this article, which was essentially a period of low unemployment and relatively high employment rate.[4]

Alongside the rapid increase of the workforce average level of education, the aging of the Portuguese population is one of the most important changes observed in the last few years. Between 1991 and 2001, when the last two Censuses of the Population were held, the share of the population aged 65 or more rose from 13.6 percent to 16.4 percent. That share is expected to rise to 20.6 percent in 2020 and 32.0 percent in 2050 (Torres 2009).

Forcefully, the aging of the Portuguese population also implies the aging of the Portuguese workforce, whose size and age structure are expected to change very rapidly in the next years. By 2030, the European Union estimates that the size of the working age population in Portugal will be 6.3 percent below its 2005 level. Also in 2030, the share of people aged 55–64 in the working-age population is expected to

[4] From 1995 to 2009, the unemployment rate averaged 7.0 percent, two percentage points below the EU15 average in the same period. Labor productivity per person employed was 63.3 per cent of the EU15 average and average gross annual earnings (2000–2006) were 40.1 percent of the same average. In 2009, the overall employment rate was equal to 66.3 percent and the female employment rate was equal to 61.6 percent. These figures compare with an EU-15 average of 65.9 and 59.9 percent, respectively. All figures are from Eurostat—Labour Market Statistics.

increase from the 16.5 percent recorded in 2005 to 23.4 percent European Commission (2007).

Policy makers are increasingly aware of the need to delay the moment at which workers exit the labor market. Increasing the employment rate of older people and the age at which people stop working are now consensual targets of the employment policy in Europe, including Portugal. It should be noted however, that Portugal has a relatively high employment rate of older people (49.7 percent in 2009, for an European target of 50.0 percent in 2010) which is partly due to the fact that the average age at which workers exit the labor market is also high (62.6 years of age, 1.4 years above the European average). It has been noted before (Machado 2010) that the late departure out of employment may be attributed to low wages and subsequent lower retirement pensions, as some workers attempt to counter the decline of their earnings by combining the retirement pension with a post-retirement job.

The legislation on retirement and retirement pensions was modified 4 times since year 1993. In 1993, the changes in the law aimed at gradually equalizing the legal age of retirement of men and women (currently set at the age of 65 for both), and increasing the minimum number of years in employment required to become eligible for receiving a retirement pension (currently 15 years). Also in 1993, the legal age of retirement was made more flexible. Until then, workers were allowed to retire before reaching the legal age only in case of disability. Since 1993, conditional on meeting the eligibility requirement, workers may retire as soon as they reach the age of 60 if they are long-term unemployed or they are in an occupation that is deemed physically too-demanding. However, conditions of access to an old-age pension before the legal retirement age were toughened in 1999 when the corresponding pensions were also reduced, initially by 4.5 percent per each year of retirement anticipation and, since 2007, by 0.5 percent per each month of anticipation. Individuals are allowed to remain in employment even after claiming an old-age pension. However, since 2007, the law excludes the possibility that the individuals that retire continue to work for their past employer for a 3-year period starting from the date when the old-age pension is first due.

3 Data Source and Descriptive Statistics

The data were gathered annually, between 1986 and 2008,[5] by the Ministry of Employment in Portugal, in an inquiry that every plant with wage earners is legally obliged to fill in (*Quadros de Pessoal*). Information on all the personnel working for the plant in a reference week is reported. Public administration and domestic service are not covered; the coverage of agriculture is low, given its low share of wage earners. For the remaining sectors, the mandatory nature of the survey leads to an extremely high response rate and in practice the population of firms with wage earners in manufacturing and the services private sector is covered.

Each firm entering the database is assigned a unique identification code and it can thus be followed over time. Reported data include the firm's location, industry, employment, sales, ownership of equity capital (national, foreign, or public), and the worker's

[5] Worker level data are not available for 1990 and 2001.

gender, age, schooling, occupation, seniority within the firm, monthly earnings (split into several components), and duration of work. Sales for year t are reported in year $t + 1$.

As in Haltiwanger et al. (1999) we measure productivity as total sales per labor unit. Although this is common in the literature,[6] we recognize that total output (or valued added) would be a more accurate measure of productivity. The choice of sales for the computation of productivity was dictated by data availability. We also lack information on capital stock. This may be of less concern given that Foster et al. (2001) showed that labor productivity and total factor productivity are closely associated. In the same line, Dostie (2011) found that the age-productivity differentials were virtually identical if the model was estimated with and without controlling for the capital stock.

The fact that sales are reported the following year requires dropping the data on 2008 (the final year). Also, for firms that run out of business, the final observation must be discarded and if a firm fails to report in one particular year, data on the previous year will not be considered in our analysis (a constraint that led to dropping 13% of the firm observations in the initial dataset). Sales outliers[7], a negligible share of the dataset (0.1%), have also been dropped.

Wage-earners tracked in the panel dataset with a valid identification number, aged 18–65 years, are considered in the analysis. Extensive checks have been performed to guarantee the accuracy of the data, using the variables gender, date of birth and highest schooling level achieved. Wage outliers have been dropped.[8]

Firms in manufacturing and services have been kept for analysis, thus dropping firms in agriculture, fishing, mining and construction industries (10% of the initial dataset). Only firms with more than 5 workers in the conditions specified above throughout the period under analysis have been kept. Given the small firm size structure in the Portuguese economy, this led to further dropping 42% of the observations firm-year in the original data set.

The final data set includes over 300,000 observations firm-year on 41,815 firms. Descriptive statistics are presented in the Appendix.

4 Empirical Model

Our empirical approach is based on the estimation of one firm-level wage equation and one firm-level productivity equation that share a common specification. The aim is to compare across equations the estimates obtained for the coefficients of the same regressors, our primary interest being the coefficients of the age-related covariates.

[6] Other examples are Aubert and Crépon (2003), and Hellerstein et al. (1999). Using sales as a proxy for productivity could be problematic if, as it is the case here, firms have different degrees of vertical integration. However, we note that using first-differences controls for all time-invariant firm characteristics and these should include vertical integration.

[7] Sales above 10 times the percentile 99 or below half the percentile 1. All models were estimated with and without the outliers. The results (available from the authors upon request) do not change because of that.

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

The estimated firm-level average wage equation is:

$$\ln(w_{it}) = \alpha^w + \beta^w \ln(L_{it}) + \sum_j \gamma_j^w l_{j,it} + \delta^w X_{it} + \varepsilon_{it}^w, \tag{1}$$

where subscript i denotes the firm, subscript t stands for time and subscript j denotes labor types. w_{it} denotes the firm-level average hourly wage,[9] L_{it} is total labor (as measured by the total number of employees at the firm), $l_{j,it}$ is the share of labor input j (e.g., workers with age j) and X_{it} is a vector of firm specific characteristics.

The firm-level productivity equation is:

$$\ln(q_{it}) = \alpha^q + \beta^q \ln(L_{it}) + \sum_j \gamma_j^q l_{j,it} + \delta^q X_{it} + \varepsilon_{it}^q, \tag{2}$$

where q_{it} is a measure of productivity (i.e., sales per yearly worker-hour[10]), and all other variables carry the exact same meaning as in the wage equation. All monetary variables were deflated using the GDP deflator, base 2008.

As noted by Hægeland and Klette (1999) and Haltiwanger et al. (1999), these two equations can be interpreted as simple descriptive equations with no behavioral content. Both simply relate average wage and productivity levels to firm characteristics and the composition of its workforce. However, as also noted by Hægeland and Klette (1999), the wage equation is the firm-level equivalent of the standard wage equation commonly estimated with worker data. Worker characteristics usually controlled for in worker-level regressions show up as the share of the corresponding type of labor at the firm level and firm-specific characteristics, such as size and age, show up untransformed.

Similarly, van Ours and Stoeldraijer (2011) show that the productivity equation can be derived from a standard Cobb-Douglas production function augmented to include controls for firm-specific characteristics. Structural interpretation of the productivity equation is possible under the assumption that workers of different age groups are substitutes for each other, although their marginal productivity is allowed to differ (for details, see van Ours and Stoeldraijer 2011). Under these assumptions, α^q may be interpreted as the average productivity of labor of the age-reference worker type, β^q as the total labor elasticity of output, and γ_j^p the contribution of labor type j relatively to the baseline category for the firm's productivity. From the wage equation, parameters γ_j^w also measure the differential contribution of labor type j to the firm's average hourly wage.

The two equations share the same set of regressors. Vector $l_{j,it}$ includes the share of the total number of worker-hours that is accounted for by each type of labor considered. We defined labor types according to gender (females), highest level of education

[9] The monthly wage bill was computed for firm j at time t as $W_{jt} = \sum_i (bw + reg)_{ijt}$, where i refers to the worker, bw stands for base-wage, and reg are other regularly paid components of the worker's pay, all evaluated in gross terms. Similarly, total hours refers to the sum of monthly hours reported for all workers in the firm.

[10] The yearly worker-hours were computed as 12 times the reported monthly hours.

achieved (university degree, high school degree, 9, 6 or 4 years of education), and age (nine categories, defined on a 5-year basis, from 18 to 65 years of age, with the category 35–39 omitted). Vector X_{it} includes controls for the firm age (years since the firm was created), firm size (log of the total number of workers), origin of capital (foreign or public, with private as the omitted category), industry (20 dummy variables), location (one dummy variable equal to 1 if the firm is located in the Lisbon area), and time (19 years dummies).

We start by estimating Eqs. (1) and (2) by pooled OLS. Yet, for OLS estimators to remain unbiased it is essential that all the regressors in the two equations are uncorrelated with the corresponding error term. This is unlikely the case in the event that firm-level productivity/wages and the age-structure of its workforce are jointly determined by an unobserved third factor.[11]

To address this difficulty, we also estimate Eqs. (1) and (2) using a specification with firm fixed-effects (FE). In doing so, we are assuming that the error terms (ε_{it}) in the two equations may be decomposed into a time-invariant unobserved effect (a_i) and an idiosyncratic error term (u_{it}):

$$\varepsilon_{it} = a_i + u_{it} \tag{3}$$

Although fixed-effects estimation appropriately solves the heterogeneity bias (assuming that the omitted regressors are constant over time), it does not handle the endogeneity bias that will be present if the dependent variables in the two equations and the age-structure of its workforce are jointly determined such that shocks affecting productivity and wages also translate into changes in the composition of the workforce. 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. Therefore, the shares of older workers are likely to be negatively correlated with productivity shocks, thereby leading to biased estimates of the corresponding parameters in both OLS and fixed-effects estimation. Furthermore, an omitted variables bias will also persist after fixed-effect estimation if some of the omitted variables are not constant over time.

To account for both sources of endogeneity we also estimate Eqs. (1) and (2) in first-differences by the generalized method of moments (GMM). All age shares are instrumented with the corresponding levels lagged two and three periods (years). The implicit assumption is that productivity shocks in one period, although possibly correlated with the contemporaneous variations in labor shares, are uncorrelated with their levels two and three years before.

Hence, our final step is to estimate by GMM the two equations:

$$\Delta \ln(w_{it}) = \beta^w \Delta \ln(L_{it}) + \sum \gamma_j^w \Delta l_{j,it} + \delta^w \Delta X_{it} + \Delta\varepsilon_{it}^w, \tag{4}$$

[11] This is specially a concern in our case because, due to data limitations, we do not control for the capital stock, even though the problem may be mitigated as we include among the regressors the age and size of the firm and the industry it belongs to.

and

$$\Delta \ln(q_{it}) = \beta^q \Delta \ln (L_{it}) + \sum \gamma_j^q \Delta l_{j,it} + \delta^q \Delta X_{it} + \Delta\varepsilon_{it}^q, \tag{5}$$

using $l_{j,i(t-s)}$ with $s = 2, 3$ as instruments for $\Delta l_{j,it}$, with j being equal to all the age-shares considered.[12] The estimated equations account for clustering at the firm level and thus all reported statistics are robust in the presence of arbitrary heteroskedasticity and clustering. As commonly done we report a battery of tests to help assess the validity of the GMM approach.

5 Wage and Productivity Age Profiles

The first panel in Fig. 1 and the first and fourth columns in Table 1 report the results of our basic specification, the OLS model. Although obtained from firm-level data, the inverted u-shaped wage-earnings profile is rather similar to the one usually detected in worker-level wage regressions. Up to the interval between 50 and 54 years of age, an increase of one percentage point in the share of workers in each age bracket has an increasingly large impact on the firm's average hourly wage. Only for the top two age brackets (above the age of 55) does that effect decline. The age-productivity profile also has an inverted u-shaped pattern and reaches its peak at the 40-44 age range. After that, there is a marked decline, with older workers experiencing an increasingly smaller contribution to the firm's productivity.

Both results are consistent with an human capital interpretation, as they indicate that, up to a certain age, older (more experienced) workers become more productive and get paid higher wages.

However, if we compare the two profiles, we see that the changes in wages associated with increasing age are consistently larger than the changes in productivity.

Such a pattern lends support to the existence of a mechanism of deferred compensation over the life-cycle, with worker wages always growing faster than productivity. For example, with everything else constant, replacing workers aged 35–39 (the reference category) by workers aged 50–54 would lead to a decline in average productivity of 0.061% per percentage point change, but an increase in average wages of 0.175%.[13]

Estimation of the productivity and wage equations by firm fixed-effects conveys a fundamentally similar result—see the second panel in Fig. 1 and columns 2 and 5 in Table 1—, even if the wage profile is slightly different in the OLS and FE regressions. Once we control for firm unobserved time-invariant characteristics, we find that larger shares of older workers are monotonically associated with higher average wages. The productivity profile indicates declining productivity starting now at age 30. Compared to the OLS estimates, these results indicate that the share of oldest workers is indeed larger in low-pay workplaces.

[12] Given the fact that we do not have other instruments available but lagged values of the endogenous variables (in levels), we chose to use the minimum number of lags that pass the Hansen test, so as to maximize the number of observations used in the estimation.

[13] One percentage point equals 0.01 in the scale of measurement of the shares.

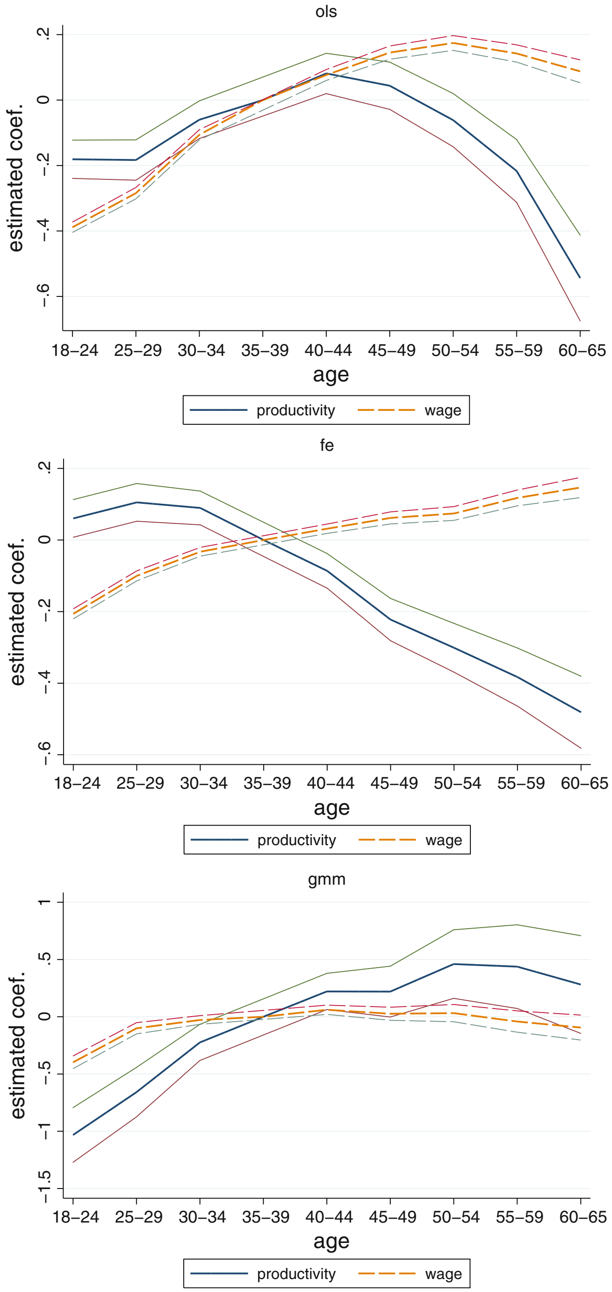

Fig. 1 Production and wage cost functions: Ordinary Least Squares, Fixed Effects, and General Method of Moments estimation. *Source*: Computations based on Portugal (1986–2008)

Table 1 Wage and sales regressions (ordinary least squares, fixed effects, and general method of moments)

	Wages			Sales		
	OLS	FE	GMM	OLS	FE	GMM
	(1)	(2)	(3)	(4)	(5)	(6)
Employment (log)	0.050 (0.001)***	0.015 (0.002)***	−0.004 (0.003)	0.001 (0.005)	−0.292 (0.008)***	−0.641 (0.014)***
Age of the firm	0.0009 (0.00008)***			0.004 (0.0003)***		
Public ownership	0.079 (0.012)***			−0.218 (0.057)***		
Foreign ownership	0.165 (0.006)***			0.224 (0.021)***		
Lisbon	0.064 (0.003)***			0.098 (0.010)***		
Share workers aged 18–24	−0.389 (0.008)***	−0.206 (0.007)***	−0.398 (0.028)***	−0.181 (0.030)***	0.060 (0.027)**	−1.032 (0.122)***
Share workers aged 25–29	−0.284 (0.009)***	−0.100 (0.007)***	−0.101 (0.025)***	−0.183 (0.031)***	0.105 (0.027)***	−0.658 (0.110)***
Share workers aged 30–34	−0.106 (0.008)***	−0.033 (0.006)***	−0.028 (0.019)	−0.060 (0.029)**	0.090 (0.024)***	−0.224 (0.081)***
Share workers aged 40–44	0.077 (0.008)***	0.032 (0.007)***	0.061 (0.021)***	0.081 (0.031)***	−0.086 (0.025)***	0.221 (0.081)***
Share workers aged 45–49	0.145 (0.010)***	0.062 (0.009)***	0.026 (0.029)	0.044 (0.037)	−0.222 (0.030)***	0.220 (0.113)**
Share workers aged 50–54	0.175 (0.012)***	0.074 (0.010)***	0.032 (0.038)	−0.061 (0.041)	−0.301 (0.035)***	0.460 (0.153)***
Share workers aged 55–59	0.142 (0.013)***	0.118 (0.011)***	−0.042 (0.047)	−0.217 (0.049)***	−0.383 (0.041)***	0.438 (0.186)***
Share workers aged 60–65	0.088 (0.018)***	0.147 (0.014)***	−0.094 (0.056)*	−0.544 (0.067)***	−0.481 (0.051)***	0.281 (0.218)
Share workers university	1.943 (0.019)***	1.049 (0.025)***	0.875 (0.056)***	2.060 (0.076)***	0.373 (0.084)***	0.505 (0.151)***
Share workers high-school	0.996 (0.017)***	0.465 (0.020)***	0.371 (0.052)***	1.546 (0.071)***	0.173 (0.070)**	0.587 (0.142)***
Share workers 9 years school	0.711 (0.016)***	0.332 (0.019)***	0.283 (0.050)***	1.065 (0.069)***	0.094 (0.065)	0.487 (0.129)***
Share workers 6 years school	0.454 (0.015)***	0.205 (0.017)***	0.191 (0.048)***	0.401 (0.066)***	−0.125 (0.061)**	0.388 (0.121)***
Share workers 4 years school	0.230 (0.014)***	0.125 (0.016)***	0.081 (0.044)*	0.219 (0.064)***	−0.138 (0.057)**	0.017 (0.092)
Share female workers	−0.243 (0.004)***	−0.203 (0.008)***	−0.198 (0.011)***	−0.689 (0.017)***	−0.181 (0.030)***	0.050 (0.041)

Table 1 continued

	Wages			Sales		
	OLS	FE	GMM	OLS	FE	GMM
	(1)	(2)	(3)	(4)	(5)	(6)
Const	0.604	0.901	0.009	3.660	4.558	−0.014
	(0.152)***	(0.177)***	(0.001)***	(0.684)***	(0.635)***	(0.004)***
Obs.	301,328	301,328	112,861	301,328	301,328	112,861
$R2$	0.744	0.918	0.04	0.406	0.776	0.041
F statistic	2,906.4***	1,838.1***	89.6***	607.933***	102.971***	207.7***
Hansen-J Statistic			8.936			14.353*
Endogeneity Test			142.007***			83.222***
Kleinberger-Paap kr LM			1,268.2***			1,268.2***
Kleinberger-Paap kr Wald			106.4***			106.4***

Education refers to the highest level achieved. The OLS regression includes controls for the industry (20 dummy variables) and time (19 dummy variables); the FE regression includes controls for time (19 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. Firm-clustered robust standard-errors in parenthesis. *p* value in *brackets*. Significance levels: * 10%; ** 5%; *** 1%. *Source*: Computations based on Portugal, MTSS (1986–2008)

Our preferred specification accounts for the possible endogeneity of changes in the composition of the workforce, via GMM estimation. The statistical tests that we implement (see Table 1) seem to corroborate the validity of our approach. In the wages equation, the Hansen-J statistic fails to reject the null hypothesis at any conventional level of significance (p value equals 0.34), pointing to the validity of the instruments. In the sales equation, at the five percent level, the Hansen-J statistic fails to reject the null hypothesis, suggesting that the instruments are uncorrelated with the error term (p value equals 0.07). In either case, the highly significant values for the endogeneity test suggest that our endogenous variables should be treated as such. The detected patterns of the coefficients change slightly (see the third panel in Fig. 1 and columns 3 and 6 in Table 1) and, as expected, the estimated standard errors are now larger, specially in the case of the productivity equation. Now, the age-productivity curve is upward sloping throughout most age ranges and peaks at the 50–54 age bracket. The age-wage profile shows an inverted-u shaped as in the OLS case.[14] However, given the large confidence intervals, we cannot discard the possibility of a basically flat age-wage profile starting at age 35.

A steep age-productivity profile indicates considerable on-the-job training in the early years of participation in employment, a fact also noted by Hægeland and Klette (1999). However, the fact that the age-wage profile becomes less steep than the age-productivity profile around age 30–34, and essentially flat in the prime-age range, also indicates that the returns to training are appropriated by workers earlier on and by employers only subsequently.

[14] Note that the more compressed scale in the third panel in Fig. 1 shows an apparently flatter wage profile.

We note that our productivity profiles are broadly consistent with previous findings. Our final estimates indicate that workers reach their maximum contribution to productivity at the age 50–54, a result that confirms Skirbekk (2004) estimate of around 50. This result is also similar to that obtained by Göbel and Zwick (2009).

As in previous studies based on cross-section data and broad age intervals (Hellerstein and Neumark 1995; Hellerstein et al. 1999) or short panels (Aubert and Crépon 2003; Dostie 2011; van Ours and Stoeldraijer 2011), our results on wages also indicate that workers are paid according to their relative contribution to output, though not over their entire working-life. Productivity increases are passed on to young workers under the form of higher wages, but not to prime-age or old workers.

Finally, as a robustness check we re-estimate all our models separately for manufacturing and for services. The results[15] indicate that the age-wage and age-productivity profiles are very similar in the two sub-samples.

The use of a more adequate estimation method (GMM) highlights that the decline in workers' productivity as they grow older is not as marked as more naive estimation methods would lead us to believe. Overall, the evidence collected shows that early in the lifecycle both productivity and wages increase at a fast pace. Productivity goes on increasing steadily into old age, to reach a plateau between ages 50 and 59, declining afterwards. Note that at the ages 50–59, productivity is larger than at much younger ages, namely at the reference group 35–39. After age 60, the point estimate still suggests a high productivity, even though we cannot preclude the possibility that it goes back to the levels of the reference group (see the very wide confidence intervals). On their side, wages reach a plateau earlier than productivity and even decline at older ages.

Although we cannot extrapolate our results beyond the age of 65, taken at face value, they would not substantiate concerns over the impact of aging on productivity or profitability. The same would also apply to the consequences of extending the compulsory age of retirement that many governments around the developed world are considering as a means to ease the pressure on their increasingly burdened retirement pension plans. But, as we said, these implications would hold only to the extent that productivity does not decrease severely around the age of 70, which is not what other studies indicate, and would also depend on which workers (if any) would be left out of employment due to older workers remaining in employment for longer periods, not to mention that other issues (such as health status or workers' well-being) could not be ignored if such a policy change were to be considered.

6 Conclusion

Based on the analysis of the establishment-level determinants of productivity and wages, we conclude that older workers are, indeed, worthy of their pay in the sense that their contribution to production is above their contribution to total payroll.

Our preferred specification indicates that the age-productivity profile is upward sloping up to the 50–54 age interval and that it stays constant from that point onwards.

[15] Available from the authors upon request.

Similar age-productivity profiles were previously reported for other labor markets (Hellerstein and Neumark 1995; Hellerstein et al. 1999; van Ours and Stoeldraijer 2011, e.g.). The estimated age-wage profile has a different shape—it slopes upward up to 25–29 age interval at which point it becomes essentially flat.

Notwithstanding, the age-productivity and age-wage profiles are virtually indistinguishable from one another for all age intervals above the age of 39 interval, and that is a direct consequence of the imprecise nature of the age-productivity estimates as in Hellerstein and Neumark (1995). Despite this fact, our results indicate that the contribution of older workers to productivity is similar or higher than their contribution to the wage bill. They are thus consistent with theoretical models that postulate that wages are attached to productivity, such as the human capital model. We do not find any evidence that could corroborate deferred compensation-type models.

Our results do not validate concerns over the potential negative impact of the aging of the working population on labor productivity or employer's profitability. We conclude that policies aimed at postponing the age of retirement, such as the ones recently implemented in Portugal, are not likely to produce adverse economic effects. For the extra-period that they remain in the labor market, the employability of older workers is not reduced, at least not if the matches they are involved in do not dissolve for reasons outside their control, such as firms' shutting down. Notice, however, that these conclusions are valid for retirement ages within the range that have been discussed throughout most developed countries (between 65 and 70), but cannot be generalized for ages above that.

Finally, the comparison between the results of OLS and fixed-effects estimation, on one hand, and GMM estimation, on the other hand, also indicates that failure to account for unobserved firm heterogeneity and endogeneity of changes in factor shares biases the results towards finding evidence of underpayment followed by overpayment policies. Non-random distribution of workers of different ages across firms coupled with selective firing policies, if not properly accounted for, can be mistaken for older workers being overpaid.

Appendix: Descriptive Statistics

See Table 2

Table 2 Descriptive statistics

Variable	Mean or %	SD
Av. sales per labor hour (euro)	72.754	243.776
Av. hourly wage (euro)	4.483	2.822
Employment (log)	3.192	0.981
Age of the firm	25.163	16.469
Industry (food, bev. omitted)		
Textiles, clothing, leather	0.186	

Table 3 continued

Variable	Mean or %	SD
Wood, cork, furniture	0.063	
Paper, printing	0.028	
Chemicals, rubber, plastic	0.030	
Other non-metallic mineral prod.	0.040	
Metals, machinery	0.102	
Other manuf.	0.007	
Trade, repairs	0.228	
Hotels, restaurants	0.070	
Transport, communication	0.037	
Financial intermediation	0.011	
Real estate, renting and business activities	0.054	
Education	0.023	
Health, social serv.	0.043	
Sewage, refuse disposal	0.003	
Membership orgs.	0.007	
Recreational, cultural, sports activ.	0.008	
Other household, personal serv.	0.005	
Ownership of capital (private omitted)		
Public	0.007	
Foreign	0.051	
Lisbon	0.329	
Share of workers aged 18–24	0.162	0.161
Share of workers aged 25–29	0.171	0.121
Share of workers aged 30–34	0.162	0.106
Share of workers aged 35–39	0.141	0.097
Share of workers aged 40–44	0.120	0.093
Share of workers aged 45–49	0.096	0.089
Share of workers aged 50–54	0.073	0.081
Share of workers aged 55–59	0.048	0.066
Share of workers aged 60–65	0.027	0.049
Share of workers w/ highest level university degree	0.057	0.128
Share of workers w/ highest level high-school degree	0.129	0.165
Share of workers w/ highest level 9 years education	0.145	0.147
Share of workers w/ highest level 6 years education	0.223	0.196
Share of workers w/ highest level 4 years education	0.421	0.279
Share of female workers	0.453	0.323
Year		
1987	0.040	
1988	0.042	
1989	0.041	

Table 2 continued

Variable	Mean or %	SD
1991	0.044	
1992	0.044	
1993	0.043	
1994	0.045	
1995	0.044	
1996	0.044	
1997	0.047	
1998	0.048	
1999	0.050	
2000	0.051	
2002	0.056	
2003	0.058	
2004	0.061	
2005	0.064	
2006	0.067	
2007	0.069	
N	301,328	

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