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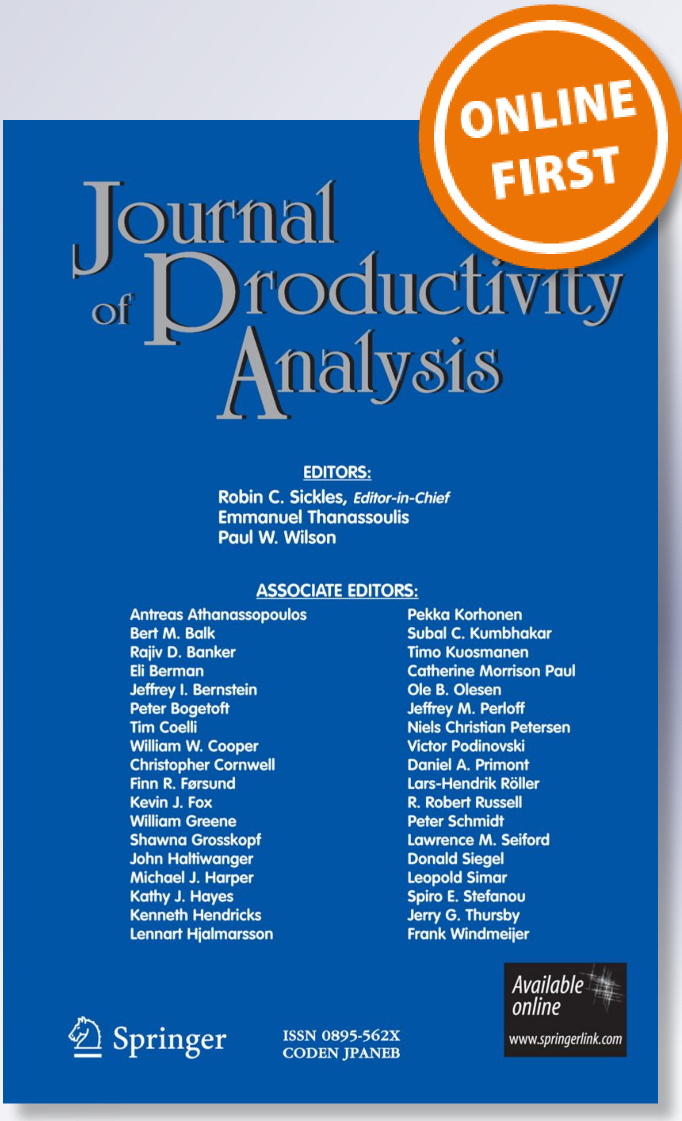

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Ageing and employability. Evidence from Belgian firm-level data

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Abstract The Belgian population is ageing due to demographic changes, so does the workforce of firms active in the country. Such a trend is likely to remain for the foreseeable future. And it will be reinforced by the willingness of public authorities to expand employment among individuals aged 50 or more. But are older workers employable? The answer depends to a large extent on the gap between older workers' productivity and their cost to employers. To address this question we use a production function that is modified to reflect the heterogeneity of labour with workers of different age potentially diverging in terms of marginal products. Using unique firm-level panel data we produce robust evidence on the causal effect of ageing on productivity (value added) and labour costs. We take advantage of the panel structure of data and resort to first-differences to deal with a potential time-invariant heterogeneity bias. Moreover, inspired by recent developments in the production function estimation literature, we also address the risk of simultaneity bias (endogeneity of firm's age-mix choices in the short run) using (1) the structural approach suggested by Ackerberg et al. Structural identification of production functions. Department of Economics, UCLA, (2006), (2) alongside more traditional system-GMM methods (Blundell and Bond in J Econom 87:115–143, 1998) where lagged values of labour inputs are used as instruments. Our results indicate a negative impact of larger shares of older workers on productivity that is not compensated by lower labour costs, resulting in a lower productivity-labour costs gap. An increment of 10 %-points of their share causes a 1.3–2.8 % contraction of this gap. We conduct several robustness checks that largely confirm this result. This is not good news for older individuals' employability and calls for interventions in the Belgian private economy aimed at combating the decline of productivity with age and/or better adapting labour costs to age-productivity profiles.

Keywords Ageing · Old labour productivity and employability · Panel data analysis

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1 Introduction

The Belgian population is ageing due to demographic changes,[1] so does the workforce of firms active in the country. Such a trend is likely to remain for the foreseeable

[1] Between 1999 and 2009, the share of individuals aged 50–65 in the total population aged 15–65 rose from 25.2 to 28.8 % (http://statbel.fgov.be).

future. In the coming years, in order to comply with EU recommendations[2] and to alleviate the rising cost of old-age publicly-funded pension schemes, the Belgian authorities will keep trying to expand (the currently very low) employment rate among those aged 50–64.[3] This will inevitably reinforce the demographic trends.

But ageing and policies aimed at maintaining older individuals in employment raise crucial issues that have received too little attention so far. Many existing studies look at the consequence of *ageing population* in terms of higher dependency rates and rising social security costs (Gruber and Wise 2004). Another strain of the literature on ageing examines the retirement behaviour of older individuals (Mitchell and Fields 1984) and its determinants; for example how the generosity of early-pension and other welfare regimes entices people to withdraw from the labour force (Saint-Paul 2009). In the Belgian case, there is strong evidence that easy access[4] and high replacement rates (Blöndal and Scarpetta 1999; Jousten et al. 2010) have played a significant role in the drop in the employment rate among older individuals since the mid 1970s. Other papers with a supply-side focus examine how bad health status precipitates retirement (Kalwij and Vermeulen 2008) or the importance of non-economic factors (i.e. family considerations) in the decision of older women to retire (Pozzebon and Mitchell 1989; Weaver 1994).

However, the consequences of *an ageing workforce* from the point of view of firms, forming the *demand side* of the labour market, have received much less attention, singularly in Belgium. EU-SILC data show a negative relationship between older individuals' employment rate and how much they cost to employ, suggesting the labour cost can be a barrier to old employment. There is also abundant evidence suggesting that firms "shed" older workers. Dorn and Sousa-Poza (2010)[5] show for instance that *involuntary* early retirement is the rule rather than the exception in several continental European countries. In Germany, Portugal, and Hungary, more than half of all early retirements are, reportedly, not by choice. These elements give to understand that one cannot take for granted that older individuals who are willing to work do get employed.

Some economists have started examining the relationship between age and productivity at the level where this matters most: firms. They have estimated production functions expanded by the specification of a labour-quality index à la Hellerstein and Neumark (1995) (HN henceforth).[6] According to Malmberg et al. (2008), an accumulation of high shares of older adults in Swedish manufacturing plants does not negatively impact plant-level productivity. By contrast, Grund and Westergaard-Nielsen (2008) find that both mean age and age dispersion in Danish firms are inversely U-shaped in relation to firms' productivity. But these authors use cross-sectional approaches. More recent analysis of German data by Göbel and Zwick (2009), using panel to control for the endogeneity of age structure, produces little evidence of an age-related productivity decline. By contrast, Lallemand and Rycx (2009), who use Belgian firm-level panel data,[7] conclude that older workers (>49) are significantly less productive than prime-age workers, particularly in ICT firms.

Using panel data and coping with the endogeneity of the age structure of the workforce has become key in this literature (more in Sect. 2). Another key distinction in terms of methodology is between studies which only examine productivity and those that simultaneously consider pay or labour costs. Economists with a focus on labour demand assess employability by examining the ratio of (or the gap between) individuals' productivity to (and) their cost to employers. This paper analyses the sensitivity of that gap to the workforce structure of firms. Under proper assumptions (see Sect. 2), this amounts to analysing the sensitivity of the productivity-labour cost gap to the age structure of firms.

One of the first papers that combined the productivity and labour cost dimensions was that of Hellerstein et al. (1999). In a recent replication of that seminal analysis using data covering the US manufacturing sector, the authors (Hellerstein and Neumark 2007) estimate relative productivity of workers aged 55+ is only 0.87 (ref. group $< 35 = 1$), whereas relative wages is 1.12. Most papers based on cross-sectional data conclude that firm productivity has an inverted U-shaped relationship with age, while labour costs are either rising with age or flat beyond a certain threshold with a negative impact on the

[2] The Lisbon Agenda suggested raising employment of individuals aged 55–64 to at least 50 % by 2010.

[3] According to Eurostat, that rate has risen a bit, from 30 % in 2007 to 37 % in 2010, but is still well below the EU average.

[4] While the age of 58 is a priori the minimum access age, a lower age of 55, 56 or 57 is possible in some sectors (steel, glass, textile, etc.), presumably reflecting more arduous working conditions. Similar exceptions exist for some workers in the building industry and those who worked shifts. Even more pronounced reductions in the minimum age are possible when the company is recognized as being in real trouble, under which circumstance the age can be brought down to 52 years, or even 50.

[5] Their survey data allow them to identify individuals who (1) were early retirees and who (2) assessed their own status as being involuntary using the item "I retired early—by choice" or "I retired early—not by choice" for the questionnaire.

[6] The key idea of HN is to estimate a production function (or a labour-cost function), with heterogeneous labour input, where different types (e.g. men/women, young/old) diverge in terms of marginal product.

[7] The Structure of Earnings Survey and the Structure of Business Survey conducted by Statistics Belgium.

productivity-labour cost gap after 55 (Skirbekk 2004, 2008).

Turning to authors using (a priori more trustworthy) panel data, the evidence is mixed. For Belgium, Cataldi et al. (2011)[8] find evidence of a negative effect of older workers on the productivity-labour cost gap. Aubert and Crépon (2003, 2007), observe that the productivity of French workers rises with age until around the age of 40, before stabilizing, a path which is very similar to that of wages. But a negative effect on the productivity-labour cost gap is observed with rising shares of workers aged 55+. On the contrary, the absence of such evidence seems to hold for manufacturing in the Netherlands, as explained by van Ours and Stoeldraijer (2011), and in Portugal for the whole economy, as shown by Cardoso et al. (2011).

Our Belgian firm-level data also allow for simultaneous estimation of age/productivity and age/labour costs equations.[9] This permits estimating productivity-labour cost gaps for different categories of workers (older, prime-age and younger). Our measure of firms' productivity (gross valued-added) enhances comparability of data across industries, which vary in their degree of vertical integration (Hellerstein et al. 1999). Moreover, given the availability of firm identifiers, we do not need to assign workers to firms using statistical matching methods like in Hellerstein et al. (1999). We have information on firms' capital stock, which is not the case in some works (e.g. Dostie 2011). We know with great accuracy how much firms spend on their employees. Some studies use individual information on gross wages, whereas we use firm-level information on annual gross wages plus social security contributions and other related costs. Moreover, our data contain information on firms from the large and expanding services sector,[10] where administrative and intellectual work is predominant.[11] Finally, it is worth stressing that our panel comprises a sizeable number of firms (9000+) and is relatively long, covering a period running from 1998 to 2006.

In this paper we test for the sensitivity of the productivity-labour cost gap to rising share of older workers (50–65) employing the framework pioneered by HN. The latter presents two main advantages. First, it provides a direct measure of relative productivity across age groups that can be immediately compared to a measure of relative labour cost, thereby identifying productivity-labour cost gaps. Second, it measures, and tests for the presence of, a concept of market-wide productivity-labour cost gap sensitivity that can impact on the overall labour demand for the category of workers considered. The HN methodology is suitable to analyse a large scope of worker characteristics, such as race and marital status, e.g. Hellerstein et al.(1999), Hellerstein and Neumark (2007), or gender (Vandenberghe 2011), and richer data sets regarding employees (e.g. Crépon et al. 2002). In this paper, we focus exclusively on age.

From the econometric standpoint, authors following the HN framework have tried to improve the quality of estimates by the adoption of alternative identification strategies to deal essentially with (1) potential heterogeneity bias (unobserved time-invariant determinants of firms' productivity that may be correlated to the age structure[12]) and (2) simultaneity bias (endogeneity in input choice, in the short-run that includes the age mix of the firm[13]). Aubert and Crépon (2003, 2007), Göbel and Zwick (2009) or van Ours and Stoeldraijer (2011) control for the heterogeneity bias using "within" or first-difference transformations, thereby analyzing the age-productivity-pay nexus solely from intra-firm variation, and deal with the simultaneity bias using lagged values of the age structures as instruments for the change in the age structure.[14] Dostie (2011) alternatively controls for the short-term endogeneity in input choice (including age mix) by applying the Levinsohn and Petrin's (2003) intermediate-good-proxy approach and takes into account both firm and workplace heterogeneity in the model of wage determination (more on this alternative approach below).

In this paper we use these recent applications of the HN methodology that we apply to panel data that have been first differenced (FD hereafter), in order to account for time-invariant unobserved heterogeneity. We also apply two strategies that are aimed at coping with endogeneity/simultaneity. Following many authors in this area (Aubert and Crépon 2003, 2007; van Ours and Stoeldraijer 2011;

[8] Extending the analysis *of Structure of Earnings Survey* and the *Structure of Business Survey* to examine age-wage-productivity nexus.

[9] The raw firm-level data are retrieved from Bel-first. They are matched with data from Belgian's Social Security register containing detailed information about the characteristics of the employees in those firms, namely their age.

[10] According to the most recent statistics of the Belgian National Bank (http://www.nbb.be/belgostat), at the end of 2008 services (total employment—agriculture, industry and construction) accounted for 78 % of total employment, which is four percentage points more than 10 years before. Similar figures and trends characterize other EU and OECD countries.

[11] Many observers would probably posit that age matters less for productivity in a service-based economy than in one where agriculture or industry dominates.

[12] For instance, the age of the plant/establishment may affect productivity and simultaneously be correlated with the age of the workers; older workers being overrepresented in older ones.

[13] For instance, the simultaneity of a negative productivity shock (due to the loss of a major contract) and workforce ageing stemming from a recruitment freeze, causing reverse causality: from productivity to ageing.

[14] The authors use the Generalized Method of Moments (GMM) to estimate their parameters.

Cataldi et al. 2011), we first estimate the relevant parameters of our model using "internal" instruments (i.e. lagged values of endogenous labour inputs) using so-called System GMM (S-GMM here after). Second, we also implement the more structural approach initiated by Olley and Pakes (1996), further developed by Levinsohn and Petrin (2003) and more recently by Ackerberg et al. (2006) (ACF hereafter), which primarily consists of using intermediate inputs to control for short-term simultaneity bias. Note that we innovate within this stream, as we combine the ACF intermediate-good approach with FD, to better account for simultaneity and firm heterogeneity.

From a methodological point of view, an interesting aspect of the paper is that is shows that the results delivered by FD-ACF are very similar to those delivered by S-GMM, and also that they are completely different than those stemming from ACF alone (i.e. without FD).

Beyond, the paper essentially shows that an increase of 10 %-points in the share of older workers (50–64) in a typical Belgian firm depresses average productivity by 2–2.7 %. What is more, this productivity handicap is not totally (or not at all in some cases) compensated by lower relative labour costs for employers, resulting in a 1.3–2.8 % reduction of the productivity-labour cost gap. This is, in essence, bad news for the employment rate of older individuals, singularly for the reemployment prospects of those who become unemployed.

The rest of the paper is organized as follows. In Sect. 2, our methodological choices are unfolded, regarding the estimation of the production, labour cost and productivity-labour cost gap equations. Section 3 is devoted to an exposition of the dataset. Sections 4 and 5 contain the results and the main conclusions, respectively.

2 Methodology

In order to estimate age-productivity profiles, following most authors in this area, we consider a Cobb–Douglas production function (Hellerstein et al. 1999; Aubert and Crépon 2003, 2007; Dostie 2011; van Ours and Stoeldraijer 2011):

$$\ln(Y_{it}/L_{it}) = \ln A + \alpha \ln QL_{it} + \beta \ln K_{it} - \ln L_{it} \quad (1)$$

where: Y_{it}/L_{it} is the average value added per worker (average productivity hereafter) in firm i at time t, QL_{it} is an aggregation of different types of workers, and K_{it} is the stock of capital.

The variable that reflects the heterogeneity of the workforce is *the quality of labour index* QL_{it}. Let L_{ikt} be the number of workers of type k (e.g. young, prime-age, old/men, women) in firm i at time t, and μ_{ik} be their productivity. We assume that workers of various types are perfectly substitutable[15] with different marginal products. As each type of worker k is assumed to be an input in quality of labour aggregate, the latter can be specified as:

$$QL_{it} = \sum_k \mu_{ik} L_{ikt} = \mu_{i0} L_{it} + \sum_{k>0} (\mu_{ik} - \mu_{i0}) L_{ikt} \quad (2)$$

where: $L_{it} \equiv \sum_k L_{ikt}$ is the total number of workers in the firm, μ_{i0} the marginal productivity of the reference category of workers (e.g. prime-age men) and μ_{ik} that of the other types of workers.

If we further assume that a worker has the same marginal product across firms, we can drop subscript i from the marginal productivity coefficients. After taking logarithms and doing some rearrangements Eq. (2) becomes:

$$\ln QL_{it} = \ln \mu_0 + \ln L_{it} + \ln \left(1 + \sum_{k>0} (\lambda_k - 1) P_{ikt}\right) \quad (3)$$

where $\lambda_k \equiv \mu_k/\mu_0$ is the relative productivity of type k worker and $P_{ikt} \equiv L_{ikt}/L_{it}$ the proportion/share of type k workers over the total number of workers in firm i.

Using the approximation that $\ln(1 + x) \approx x$, (3) can be simplified as:

$$\ln QL_{it} = \ln \mu_0 + \ln L_{it} + \sum_{k>0} (\lambda_k - 1) P_{ikt} \quad (4)$$

And the production function becomes:

$$\ln(Y_{it}/L_{it}) = \ln A + \alpha \left[\ln \mu_0 + \ln L_{it} + \sum_{k>0} (\lambda_k - 1) P_{ikt}\right] + \beta \ln K_{it} - \ln L_{ik} \quad (5)$$

Or, equivalently, if $k = 0, 1, \ldots N$ with $k = 0$ being the reference group (e.g. prime-age male workers)

$$\ln(Y_{it}/L_{it}) = B + (\alpha - 1) l_{it} + \eta_1 P_{i1t} + \ldots \eta_N P_{iNt} + \beta k_{it} \quad (6)$$

where:

$$B = \ln A + \alpha \ln \mu_0$$
$$\lambda_k = \mu_k/\mu_0 \quad k = 1 \ldots N$$
$$\eta_1 = \alpha(\lambda_1 - 1)$$
$$\ldots$$
$$\eta_N = \alpha(\lambda_N - 1)$$
$$l_{it} = \ln L_{it}$$
$$k_{it} = \ln K_{it}$$

Note first that (6), being loglinear in P, has coefficients that can be directly interpreted as the percentage change in

[15] We will see, in Sect. 2, how this assumption can be relaxed, when we present the econometric models used to identify the key coefficients of this production function.

the firm's average labour productivity of a 1 unit (here 100 percentage points) change of the considered type of workers' share among the employees of the firm. Note also that, strictly speaking, in order to obtain a type k worker's relative marginal productivity, (i.e. λ_k), coefficients η_k have to be divided by α, and 1 needs to be added to the result.[16]

A similar approach can be applied to a firm's average labour cost. If we assume that firms operating in the same labour market pay the same wages to the same category of workers, we can drop subscript i from the remuneration coefficient π.[17] Let π_k stand for the remuneration of type k workers ($k = 0$ being reference type). Then the average labour cost per worker becomes:

$$W_{it}/L_{it} = \sum_{k} \pi_k L_{ikt}/L_{it} = \pi_0 + \sum_{k>0} (\pi_k - \pi_0) L_{ikt}/L_{it} \quad (7)$$

Taking the logarithm and using again $log(1 + x) \approx x$, we can approximate this by:

$$\ln(W_{it}/L_{it}) = \ln \pi_0 + \sum_{k>0} (\Phi_k - 1) P_{ikt} \quad (8)$$

where the Greek letter $\Phi_k \equiv \pi_k/\pi_0$ denotes the relative remuneration of type k workers ($k > 0$) with respect to the ($k = 0$) reference group, and $P_{ikt} = L_{ikt}/L_{it}$ is again the proportion/share of type k workers over the total number of workers in firm i.

The logarithm of the average labour cost finally becomes:

$$\ln(W_{it}/L_{it}) = B^w + \eta_1^w P_{i1t} + \cdots \eta_N^w P_{iNt} \quad (9)$$

where:

$$B^w = \ln \pi_0$$
$$\eta_1^w = (\Phi_1 - 1)$$
$$\ldots.$$
$$\eta_N^w = (\Phi_N - 1)$$

Like in the average productivity Eq. (6) coefficients η_k^w capture the sensitivity to changes of the age/gender structure (P_{ikt}).

The key hypothesis test of this paper can now be easily formulated. Assuming spot labour markets and cost-minimizing firms, the null hypothesis of no impact on the productivity-labour cost gap for type k worker implies $\eta_k = \eta_k^w$. Any negative (or positive) difference between these two coefficients can be interpreted as a quantitative measure of the disincentive (incentive) to employ the category of workers considered. This is a test that can be easily implemented, if we adopt strictly equivalent econometric specifications for the average productivity and average labour cost; in particular if we introduce firm size (l) and capital stock (k) in the labour cost Eq. (9). Considering three age groups (1 = [20–29], 2 = [30–49]; 3 = [50–64]) and with prime-age (30–49) workers forming the reference group, we get:

$$\ln(Y_{it}/L_{it}) = B + (\alpha - 1)l_{it} + \eta_1 P_{it}^{18-29} + \eta_3 P_{it}^{50-64} +_{+} \beta k_{it} + \gamma F_{it} + \varepsilon_{it} \quad (10)$$

$$\ln(W_{it}/L_{it}) = B^w + (\alpha^W - 1)l_{it} + \eta_1^W P_{it}^{18-29} + \eta_3^W P_{it}^{50-64} + \beta k_{it} + \gamma^W F_{it} + \varepsilon_{it}^w \quad (11)$$

What is more, if we take the *difference* between the logarithms of average productivity (10) and labour costs[18] (11) we get a direct expression of the productivity-labour cost gap[19] as a linear function of its workforce determinants.

$$Gap_{it} \equiv ln(Y_{it}/L_{it}) - ln(W_{it}/L_{it}) = B^G + (\alpha^G - 1)l_{it} + \eta_1^G P_{it}^{18-29} + \eta_3^G P_{it}^{50-64} + \beta^G k_{it} + \gamma^G F_{it} + \varepsilon_{it}^G \quad (12)$$

where: $B^G = B - B^w$; $\alpha^G = \alpha - \alpha^W$, $\eta_1^G = \eta_1 - \eta_1^w$; $\eta_3^G = \eta_3 - \eta_3^w$; $\gamma^G = \gamma - \gamma^w$ and $\varepsilon_{it}^G = \varepsilon_{it} - \varepsilon_{it}^w$.

It is immediate to see that coefficients η^G of Eq. (12) provide a direct estimate of how the productivity-labour cost gap is affected by changes in terms of percentages/shares of employed workers.

Note also the inclusion in (12) of the vector of controls F_{it}. In all the estimations presented hereafter it contains region,[20] year X sector[21] dummies. This allows for systematic and proportional productivity variation among firms along these dimensions. This assumption can be seen to expand the model by controlling for year and sector-specific productivity shocks or trends, labour quality and intensity of efficiency wages differentials across sectors and other sources of systematic productivity differentials (Hellerstein et al.

[16] Does all this matter in practice? Our experience with firm-level data suggests values for α ranging from 0.6 to 0.8 (these values are in line with what most authors estimates for the share of labour in firms' output/added value). This means that λ_k are larger (in absolute value) than η_k. If anything, estimates reported in the first column of Tables 3 and 4 underestimate the true marginal productivity difference vis-à-vis prime-age workers.

[17] We will see, how, in practice via the inclusion of dummies, this assumption can be relaxed to account for sector/industry wage effects, that must be important given Belgium's tradition of binding sector-level wage bargaining.

[18] Labour costs used in this paper, which were measured independently of value added, include the value of all monetary compensations paid to the total labour force (both full- and part-time, permanent and temporary), including social security contributions paid by the employers, throughout the year. The summary statistics of the variables in the data set are presented in Table 1.

[19] Measured in %. This is because the logarithms, used in conjunction with differencing, convert absolute differences into relative (i.e., percentage) differences: i.e. $(Y - W)/W$.

[20] NUTS1 Belgian regions : Wallonia, Flanders and Brussels.

[21] NACE2 level.

1999). More importantly, since the dataset we use does not contain sector price deflators, the introduction of these dummies can control for asymmetric year-to-year variation in the price of firms' outputs at the sector level. An extension along the same dimensions is made with respect to the labour cost equation. Of course, the assumption of segmented labour markets, implemented by adding linearly to the labour cost equation the set of year/sector dummies, is valid as long as there is proportional variation in wages by age group along those dimensions. Detailed discussion of all firm-level controls included in F_{it} will be presented in the data section below.

But, as to a proper identification of the causal links, the main challenge consists of dealing with the various constituents of the residual ε_{it} of Eq. (10).[22] We assume that the latter has a structure that comprises three elements:

$$\varepsilon_{it} = \omega_{it} + \theta_i + \sigma_{it} \tag{13}$$

where: $cov(\theta_i, P_{ik,t}) \neq 0$, $cov(\omega_{it}, P_{ik,t}) \neq 0$, $E(\sigma_{it}) = 0$

In words, the OLS sample-error term potentially consists of (1) an unobservable firm fixed effect θ_i; (2) a short-term shock ω_{it} (whose evolution may correspond to a first-order Markov chain), and is observed by the firm (but not by the econometrician) and (partially) anticipated by the firm, and, (3) a purely random shock σ_{it}.

Parameter θ_i in (13) represents firm-specific characteristics that are unobservable but driving average productivity. For example, the vintage of capital in use, or the overall stock of human capital,[23] firm-specific managerial skills, location-driven comparative advantages….[24] And these might be correlated with the age structure of the firm's workforce, biasing OLS results. Older workers for instance might be overrepresented among plants built a long time ago, that use older technology. However, the panel structure of our data allows for the estimation of FD models that eliminate fixed effects. The results from FD can be interpreted as follows: a group (e.g. young, prime-age or old) is estimated to be more (less) productive than another group if, within firms, a increase of that group's share in the overall workforce translates into productivity gains (loss).

This said, the greatest econometric challenge is to go around the simultaneity/endogeneity bias (Griliches and Mairesse 1995). The economics underlying that concern is intuitive. In the short run, firms could be confronted to productivity deviations, ω_{it}; say, a lower turnover, itself the consequence of a missed sales opportunity. Contrary to the econometrician, firms may know about ω_{it} (and similarly about it short-term dynamics). An anticipated downturn could translate into a recruitment freeze, or, alternatively, into a multiplication of "involuntary" (early) retirements.[25] A recruitment freeze affects youth predominantly, and translates into rising share of older workers during negative spells, creating a negative correlation between older workers' share and productivity, thereby leading to underestimated estimates of their productivity (when resorting to OLS or even FD estimates). By contrast, if firms primarily promote early retirements when confronted with adverse demand shocks,[26] we would expect the correlation to be positive, leading to an overestimation of older workers' productivity with OLS or FD.

To account for the presence of this endogeneity bias we first estimate the relevant parameters of our model using only "internal" instruments. The essence of this strategy is to use lagged values of endogenous labour inputs as instruments for the endogenous (first-differenced) labour inputs (Aubert and Crépon 2003, 2007; van Ours and Stoeldraijer 2011; Cataldi et al. 2011).[27] First differences are good at purging fixed effects and thus at coping with unobserved heterogeneity terms θ_i. But (lagged) variables in level, although they might be orthogonal to the short-term shock ω_{it}, tend to prove poor predictors of first differences (i.e. they are weak instruments). Blundell and Bond (1998) then proposed an improved estimator called system-GMM (S-GMM) that uses extra moment conditions. S-GMM consists of a system of two equations estimated simultaneously. One corresponds to the above-mentioned first-difference equation, where the instruments are the (lagged) labour inputs in level. The second equation consists of using regressors in level, with (lagged) first-differenced of the endogenous variables as instruments. S-GMM estimator has become the estimator of choice in many applied panel data settings. We use it here to cope with simultaneity/endogeneity of the labour inputs (i.e. both the overall level of labour and the share by age).

[22] And its equivalent in Eq. (12).

[23] At least the part of that stock that is not affected by short-term recruitments and separations.

[24] Motorway/airport in the vicinity of logistic firms for instance.

[25] Dorn and Sousa-Poza (2010) report that, in many Continental European countries, the proportion of involuntary retirement is significantly higher in years with increasing unemployment rates. One explanation for this finding is that firms promote early retirement when they are confronted with adverse demand shocks in an economic recession.

[26] In Belgium, while 58 is a priori the minimum access age for early retirement benefits, reductions in the minimum age are possible when the company is recognized [by the Ministry of Social Affairs] as being in deep trouble, under which circumstances the age can be brought down to 52 years, or even 50.

[27] The other key feature of these methods is that they are based on the Generalized Method of Moments (GMM), known for being more robust than 2SLS to the presence of heteroskedasticity (see "Appendix" in Arellano, 2003).

An alternative to S-GMM that seems promising and relevant is to adopt the structural approach initiated by Olley and Pakes (1996) (OP hereafter) and further developed by Levinsohn and Petrin (2003) (LP hereafter), and more recently by Ackerberg et al. (2006) (ACF, hereby). The essence of the OP approach is to use some function of a firm's investment to control for (proxy) time-varying unobserved productivity, ω_{it}. The drawback of this method is that only observations with positive investment levels can be used in the estimation. Many firms indeed report no investment in short panels. LP overcome this problem by using material inputs (raw materials, electricity,…) instead of investment in the estimation of unobserved productivity. They argue that firms can swiftly (and also at a relatively low cost) respond to productivity developments, ω_{it}, by adapting the volume of the intermediate inputs they buy on the market. ACF argue that there is some solid and intuitive identification idea in the LP paper, but they claim that their two-stage estimation procedure delivers poor estimates of the labour coefficients and propose an improved version of it.

Simplifying our notations to make them alike those used by ACF, average productivity equation becomes:

$$\ln(Y_{it}/L_{it}) = B + \varphi\, ql_{it} + \beta k_{it} + \gamma F_{it} + \varepsilon_{it} \tag{14a}$$

with the labour quality index (or vector of labour inputs) equal to:

$$\varphi ql_{it} \equiv (\alpha - 1)l_{it} + \eta_1 P_{it}^{18-29} + \eta_3 P_{it}^{50-64} \tag{14b}$$

and the ACF error term:

$$\varepsilon_{it} = \omega_{it} + \sigma_{it} \tag{14c}$$

Note that the latter does not contain a proper fixed effect θ_i, as we have assumed above, and as is traditionally assumed by the authors using S-GMM.

Like ACF, we assume that firms' (observable) demand for intermediate inputs (int_{it}) is a function of the time-varying unobserved term ω_{it} as well as (log of) capital, and the quality of labour index ql_{it} and its components:

$$\text{int}_{it} = f_t(\omega_{it}, k_{it}, ql_{it}) \tag{15}$$

By contrast, LP unrealistically assume that the demand of intermediate goods is not influenced by that of labour inputs.[28]

ACF further assume that this function f_t is monotonic in ω_{it} and its other determinants, meaning that it can be inverted to deliver an expression of ω_{it} as a function of int_{it}, k_{it}, ql_{it}, and introduced into the production function:

$$\ln(Y_{it}/L_{it}) = B + \varphi ql_{it} + \beta k_{it} + \gamma F_{it} + f_t^{-1}(\text{int}_{it}, k_{it}, ql_{it}) + \sigma_{it} \tag{16a}$$

We use this strategy here. However—unlike ACF—we do this in combination with first differences (FD) to properly account for firm fixed effects θ_i,meaning that our production function writes

$$\ln(Y_{it}/L_{it}) = B + \varphi ql_{it} + \beta k_{it} + \gamma F_{it} + f_t^{-1}(\text{int}_{it}, k_{it}, ql_{it}) + \boldsymbol{\theta}_i + \sigma_{it} \tag{16b}$$

In a sense, we stick to what has traditionally been done in the dynamic-panel literature underpinning the S-GMM strategy discussed above. We also believe that explicitly accounting for firm fixed effects increases the chance of verifying the key monotonicity assumption required by the ACF approach in order be able to invert out ω_{it}, and completely remove the endogeneity problem. In the ACF framework (similar in that respect to the LP or OP ones), the firm fixed effects are *de facto* part of ω_{it}. Allowing for a time-varying firm effect is a priori appealing. For instance, it preserves more identifying variation.[29] On the other hand, the evidence with firm panel data is that fixed effects capture a large proportion (>50 %) of the total productivity variation.[30] This tentatively means that, in the ACF intermediate goods function $\text{int}_{it} = f_t(\omega_{it}, k_{it}, ql_{it})$, the term ω_{it} can vary a lot when switching from one firm to another and, most importantly, in a way that is not related to the consumption of intermediate goods. In other words, firms with similar values of int_{it} (and k_{it} or ql_{it}) are characterized by very different values of ω_{it}. This is something that invalidates the ACF assumption of a one-to-one (monotonic) relationship, and the claim that the inclusion of intermediate goods in the regression adequately controls for endogeneity/simultaneity. This said, we still believe that intermediate goods can greatly contribute to identification, but conditional on properly accounting for firm fixed effects. In practice, how can this be achieved? The ACF algorithm consists of two stages. We argue that only stage one needs to be adapted.

In stage one, like ACF, we regress average productivity on a composite term Φ_t that comprises a constant, a 3rd order polynomial expansion in int_{it}, k_{it}, ql_{it}, and our vector of controls added linearly. This leads to

$$\ln(Y_{it}/L_{it}) = \Phi_t(\text{int}_{it}, k_{it}, ql_{it}, F_{it}) + \boldsymbol{\theta}_i + \sigma_{it} \tag{17}$$

[28] Consider the situation where ql_{it} is chosen at $t-b$ $(0 < b < 1)$ and int_{it} is chosen at t. Since ql_{it} is chosen before int_{it}, a profit-maximizing (or cost-minimizing) optimal choice of int_{it} will generally directly depend on ql_{it} (Ackerberg et al. 2006).

[29] Fixed effect estimators only exploit the within part of the total variation.

[30] Another illustration of the same idea is that published studies have documented, virtually without exception, enormous and persistent measured (but unexplained) productivity differences across firms, even within narrowly defined industries (Syverson 2011).

Note that Φ_t encompasses $\omega_{it} = f_t^{-1}(\cdot)$ displayed in (16b) and that φ, β and γ are clearly not identified yet.[31] The point made by ACF is that this first-stage regression delivers an unbiased estimate of the composite term Φ_{it}^{hat}; i.e. productivity net of the purely random term σ_{it}. We argue that this is valid only if there is no firm fixed effect θ_i or if the latter can be subsumed into $\omega_{it} = f_t^{-1}(\cdot)$—something we believe unrealistic and problematic for the reasons exposed above. Hence, we prefer assuming that fixed effects exist and explicitly account for them; which can easily be done by resorting to first differencing (FD) to estimate Eq. (17). The FD-estimated coefficients—provided they are applied to variables in levels—will deliver an unbiased prediction of Φ_{it}^{hat}. Specifically, Φ_{it}^{hat}, net of the noise term and firm-fixed effects, is calculated as $\Phi_{it}^{hat} = (\upsilon_{a1})^{FD}\text{int}_{it} + (\upsilon_{a2})^{FD}\text{int}_{it}^2 + \cdots + (\upsilon_{b1})^{FD}k_{it} + \cdots + (\upsilon_{c1})^{FD}ql_{it} + \cdots + (\upsilon_{d1})^{FD}\text{int}_{it}k_{it}\ldots$, where $(\upsilon_{a1})^{FD}$, $(\upsilon_{a2})^{FD}, \ldots$ represent the first-differenced coefficient estimates on the polynomial terms.

As an aside, note the presence in Φ_t of a 3rd order polynomial expansion in (inter alia) ql_{it}. and its components, namely l_{it}, P_{it}^{18-29}, P_{it}^{50-64}. To this point, the production function (a Cobb–Douglas) has been specified so that workers of different types have different marginal products but are perfectly substitutable. Because this specification may be too restrictive, we should also consider evidence from estimates of a production function in which workers are imperfect rather than perfect substitutes. Resorting to a translog specification is what Hellerstein et al. (1999) did in their seminal paper. But the first stage equation above (17) consists of regressing the log of productivity on a 3rd order polynomial that contains interaction terms between the various labour input variables. We have thus gone part-way toward doing what Hellerstein et al. (1999) do when estimating translog production function to allow for imperfect substitutability across age groups. We will mobilise this feature when presenting our results in Sect. 4.

Returning to the ACF procedure, we basically argue that their second stage is unaffected by the modifications discussed above. Key is the idea that one can generate implied values for ω_{it} using first-stage estimates Φ_{it}^{hat} and candidate[32] values for the coefficients φ, β, γ:

$$\omega_{it} = \Phi_{it}^{hat} - ql_{it}\varphi - \beta k_{it} - \gamma F_{it} \tag{18}$$

ACF assume further that the evolution of ω_{it} follows a first-order Markov process

$$\omega_{it} = E[\omega_{it|}\omega_{it-1}] - \xi_{it} \tag{19}$$

That assumption simply amounts to saying that the realization of ω_{it} depends on some function g(·) (known by the firm) of $t-1$ realisation and an (unknown) innovation term ξ_{it}.

$$\omega_{it} = g(\omega_{it-1}) + \xi_{it} \tag{20}$$

By regressing non-parametrically (implied) ω_{it} on (implied) ω_{it-1}, ω_{it-2}, one gets residuals that correspond to the (implied) ξ_{it} that can form a sample analogue to the orthogonality (or moment) conditions identifying φ, β, and γ. We would argue that residuals ξ_{it} are orthogonal to our controls F_{it}

$$\mathrm{E}\left[\xi_{it|}F_{it}\right] = 0 \tag{21a}$$

Analogous to ACF, we would also argue that capital in period t was determined at period $t-1$ (or earlier). The economics behind this is that it may take a full period for new capital to be ordered and put to use. Since k_{it} is actually decided upon $t-1$, $t-2,\ldots$, it must be uncorrelated with the implied innovation terms ξ_{it}:

$$\mathrm{E}\left[\xi_{it|}k_{it}\right] = 0 \tag{21b}$$

Labour inputs observed in t are probably also chosen sometime before, although after capital—say in $t-b$, with $0 < b < 1$. As a consequence, ql_{it} will be correlated with at least part of the productivity innovation ξ_{it}. On the other hand, assuming *lagged* labour inputs were chosen at time $t-b-1$ (or earlier), ql_{it-1}, $ql_{it-2}\ldots$ should be uncorrelated with the innovation terms ξ_{it}. This gives us the third (vector) of moment conditions needed for identification of φ:

$$\mathrm{E}[\xi_{it|}ql_{it-1}, ql_{it-2}, \ldots] = 0 \tag{22a}$$

or more explicitly, given the composite nature of ql_{it}, we have:

$$\mathrm{E}[\xi_{it|}l_{it-1}, l_{it-2}\ldots] = 0 \tag{22b}$$

$$\mathrm{E}\left[\xi_{it|}P_{it-1}^{18-29}, P_{it-2}^{18-29}\ldots\right] = 0 \tag{22c}$$

$$\mathrm{E}\left[\xi_{it|}P_{it-1}^{50-54}, P_{it-2}^{50-64}\ldots\right] = 0 \tag{22d}$$

3 Data

As stated above, we are in possession of a panel of around 9,000 firms with more than 20 employees, largely representative in terms of sector/industry (see Table 7, "Appendix"), location, size, capital used, labour cost levels, productivity. These observations come from the Belfirst database. Via the so-called Carrefour data warehouse, using firm identifiers, we have been able to inject information on the age of (all) workers employed by these firms,

[31] Note in particular that the non identification of vector φ (ie. labour input coefficients) in the first stage is one of the main differences between ACF and LP.

[32] OLS estimates for example.

and this for a period running from 1998 to 2006, which is a long panel as compared to what is usually found in the literature.

Descriptive statistics are reported in Tables 1 and 2. Table 2 in particular suggests that firms based in Belgium have been largely affected by ageing over the period considered. It shows that between 1998 and 2006, the average age of workers active in private firms located in Belgium rose by almost 3 years: from 36.15 to 39.10. This is very similar what has occurred Europe-wide. For instance Göbel and Zwick (2009) show that between 1987 and 2007 the average age of the workforce in the EU25 has risen from 36.2 to 38.9. In the Belgian private economy (Table 2), between 1998 and 2006, the percentage of old workers (50–65) has risen steadily from 12 to 19 %. But the proportion of prime-age workers has also risen from 39 % to almost 45 %.

Intermediate inputs play a key role in our analysis, as they are central to one of our strategies to overcome the simultaneity/endogeneity bias. Our measure (Table 1, line 8) is a direct one, and reflects the value of goods and services consumed or used up as inputs in production by

Table 1 Bel-first/Carrefour panel—main variables—descriptive statistic

Variable	No. obs.	Mean	SD
Value added per worker (log)	77417	4.08	0.56
Labour cost per worker (log)	77845	3.71	0.38
Number of workers (log)	77856	3.94	1.00
Capital (th. €) (log)	77906	6.16	1.99
Workers aged 18–29/total workforce	79215	0.423	0.18
Workers aged 30–49/total workforce	79215	0.424	0.13
Workers aged 50–65/total workforce	79215	0.153	0.11
Use of intermediate input (th. €)	62152	8.97	1.56
Blue-collar workers/total workforce	77739	0.547	0.35
White-collar workers/total workforce	77739	0.435	0.35
Managers/total workforce	77739	0.010	0.04
Number of hours worked annually per employee (log)	77593	7.38	0.16
Training costs/total labour costs (annual basis, %)	42608	0.38	1.11
Training hours/total worked hours (annual basis, %)	42654	0.34	0.92
Share of firms in 10–90th perc. Size[a] bracket (spells)	79215	0.90	0.30
Number of spells	79194	8.73	0.94

[a] Size is defined as the firms' overall labour force

Detailed definitions of variables are available in Table 14, in "Appendix"

Source: Bel-first-Carrefour

Table 2 Bel-first/Carrefour panel, basic descriptive statistics—evolution of shares of workers between 1998 and 2006

Years	Mean age (year)	Share of 18–29 (%)	Share of 30–49 (%)	Share of 50–65 (%)
1998	36.15	48.58	39.35	12.08
1999	36.43	46.98	40.37	12.67
2000	36.64	45.84	40.90	13.26
2001	37.00	44.24	41.77	14.00
2002	37.37	42.61	42.76	14.64
2003	37.96	40.64	43.12	16.24
2004	38.33	39.17	43.77	17.06
2005	38.72	37.66	44.43	17.91
2006	39.10	36.33	44.66	19.00

Source: Bel-first-Carrefour

enterprises, including raw materials, services and various other operating expenses.

Figure 1 (left panel) displays how the (log of) average productivity and the (log of) average labour costs evolve with mean age, for the year 2006 subsample. The right panel of Fig. 1 corresponds to the difference between these two curves which is equal to the productivity-labour cost gap expressed in percent.[33] These stylised facts suggests that, in the Belgian private economy, the productivity-labour cost gap in percent rises up to the (mean) age of 35–38 where it reaches 40 %, but then declines steadily. It falls below the 10 % threshold when mean age exceeds 55.

Figure 2 is probably more directly echoing the main issue raised in this paper. It depicts the relationship between the share of older (50–64) workers and the average productivity and the average labour costs. It also suggests that firms employing larger shares of older workers in excess of the 10 % threshold have a significantly smaller productivity-labour cost gap.

Remember that all our regressions contain a vector of control F_{it} with region and year/sector interaction dummies. Additionally, F_{it} also contains the share of blue-collar workers (55 %) and those with a managerial status (1 %) (the reference being the white-collar category with 44 %) (Table 1). This distinction cuts across major categories of employment contracts in Belgium: the blue-collar contracts (applicable mostly to manual/low-level functions), white-collars contracts (applicable to intellectual/middle management functions) and managerial ones (used for those occupying intellectual/strategic-decisional positions). In truth, the correspondence blue-collar contract = manual work performed by individuals with little education versus white-collar contracts = intellectual work

[33] For small values, the log-first-difference transformation delivers *a* good approximation of the relative difference in percent: ie. $\log(Y) - log(LC) \approx (Y - LC)/LC$.

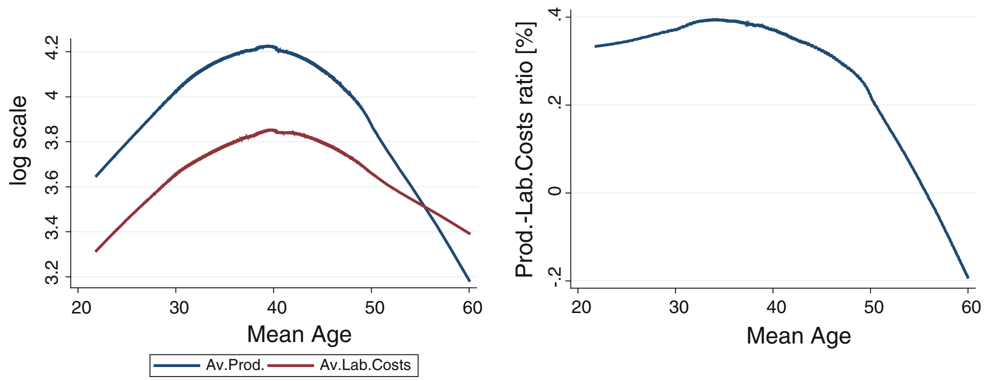

Fig. 1 *Left panel* Average productivity and average labour costs. *Right panel* Productivity-labour cost gap (%) according to mean age, year 2006. *Curves* on display correspond to locally weighted regression of y [i.e. log of average productivity, log of average labour cost (*left panel*) and productivity-labour cost gap in % (*right panel*)] on x (i.e. mean age). OLS estimates of y are fitted for each subsets of x. This method does not require specifying a global function of any form to fit a model to the data, only to fit segments of the data. It is thus semi-parametric

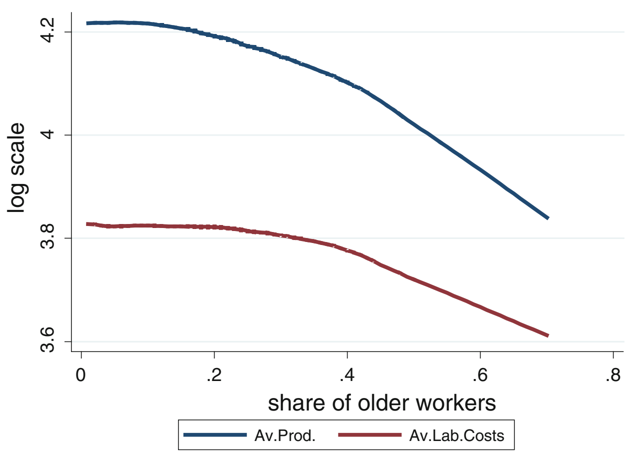

Fig. 2 Average productivity and average labour cost (in log) according to share of old (50–64) workers, year 2006. *Curves* on display correspond to locally weighted regression of y (i.e. log of average productivity, log of average labour cost on x (i.e. share of workers age 50–64). OLS estimates of y are fitted for each subsets of x. This method does not require specifying a global function of any form to fit a model to the data, only to fit segments of the data. It is thus semi-parametric

performed by individuals more educated suffers more and more exceptions. We propose to use it here as a proxy for education and skills, that we do not observe in our data, but which may correlate both with productivity and age, causing bias. We will see in Sect. 4 how the use of decade-of-birth cohorts can usefully complement this strategy.

F_{it} also comprises the (log of) average number of hours worked annually per employee obtained by dividing the total number of hours reportedly worked annually by the number of employees (full-time or part-time ones indistinctively). That variable is strongly correlated with the intensity of part-time work. Although there is little evidence that older workers more systematically resort to part-time work in Belgium, it seems reasonable to control for this likely source of bias when studying the causal relationship between age–gender and productivity, labour costs or the gap between these two.

4 Econometric results

Table 3 presents the parameter estimates of the average productivity (i.e. value added per worker) (see Eq. 10, Sect. 2), labour costs (Eq. 11) and productivity-labour cost gap Eq. (12), under five alternative econometric specifications. Note that, Eq. (12) being the difference between Eqs. (10) and (11), it is logical to verify that $\eta - \eta^W \approx \eta^G$ for each age category. Standard errors on display have been computed in a way that accounts for firm-level clustering of observations. To get the results on display in Table 3 we use all available observations forming our (unbalanced) panel.

4.1 Main results

The first set of parameter estimates comes from OLS, using total variation [1]. The next strategy [2] consists of using intermediate inputs à-la-ACF. Then comes first differences (FD), where parameters are estimated using only within-firm variation [3]. Next are our preferred models, i.e. those presenting the enviable characteristic of dealing with heterogeneity and simultaneity, in an integrated way. Models [4] and [5] implement the Blundell-Bond strategy relying on a system of equations using internal lagged[34] labour

[34] Our Stata xtabond2 command uses lags of the specified variables in levels dated $t-2$ as instruments for the FD equation and uses the $t-1$ first-differences as instruments in the levels equation. Full details are reported below the results tables in "Appendix".

Table 3 Parameter estimates (SE)—older (50–64) workers productivity (η_3), average labour costs (η_3^{w}) and productivity-labour cost gap (η_3^{G})—overall, unbalanced panel sample

	[1] OLS	[2] First differences	[3] Intermediate inputs ACF[a]	[4] System GMM (all available data)	[5] System GMM (same sample as for [6])	[6] First differences + intermediate inputs ACF[a]
Productivity (η_3)	−0.277***	−0.112***	−0.284***	−0.194***	−0.274***	−0.220***
SE	(0.021)	(0.025)	(0.052)	(0.034)	(0.044)	(0.054)
Labour costs (η_3^{w})	−0.191***	−0.052***	−0.141***	0.024	0.012	−0.090***
SE	(0.012)	(0.013)	(0.010)	(0.015)	(0.018)	(0.007)
Prod.-lab. costs gap (η_3^{w})	−0.094***	−0.059**	−0.099**	−0.230***	−0.289***	−0.127***
SE	(0.018)	(0.023)	(0.045)	(0.032)	(0.043)	(0.021)
No. obs.	79,187	68,991	38,944	77,069	38,944	
Controls	All data are deviations from region + year interacted with NACE2 industry means. See "Appendix" for NACE2 classification of industries					
	Capital, number of employees, hours worked per employee[b], share of blue-collar workers, share of managers	Capital, number of employees, hours worked per employee[b], share of blue-collar workers, share of managers + firm fixed effects	Capital, number of employees, hours worked per employee[b], share of blue-collar workers, share of managers	Capital, number of employees, hours worked per employee[b], share of blue-collar workers, share of managers + firm fixed effects[b]		
Orthogonality conditions/ instruments used to identify endog. labour inputs			Innovation in $\omega_{it} \perp\!\!\!\perp L_{1/3}$ labour inputs	L_2.(Log of labour, share of workers aged 18–29, share of workers aged 50–64)		Innovation in $\omega_{it} \perp\!\!\!\perp L_{1/3}$ labour inputs

Detailed results (coefficients for all explanatory variables plus test results) for models [4] [5] and [6] are presented in Tables 8, 9 in "Appendix"

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[a] Ackerberg, Caves and Frazer

[b] Average number of hours worked by employee on an annual basis, which is strongly correlated to the incidence of part-time work

Table 4 Robustness analysis parameter estimates (SE), older (50–64) workers productivity (η_3) and productivity-labour cost gap (η_3^G)

	Overall, unbalanced panel (ref.)	Balanced panel	Controlling for cohort effects	Excluding financial, real estate, utilities and non-profit activities[a]	Firms in 10–90th perc. size[b] bracket
[4] System GMM					
Productivity (η_3)	−0.194***	−0.182***	−0.394***	−0.176***	−0.245***
SE	(0.034)	(0.033)	(0.035)	(0.034)	(0.034)
Prod.-lab. costs gap (η_3^G)	−0.230***	−0.212***	−0.218***	−0.318***	−0.251**
SE	(0.032)	(0.032)	(0.033)	(0.032)	(0.033)
No. obs.	77,069	73,580	77,069	75,360	69,801
Controls	All data are deviations from region + year interacted with NACE2 industry means. See "Appendix" for NACE2 classification of industries				
	Capital, number of employees, hours worked per employee[c], share of blue-collar workers, share of managers + firm fixed effect				
Instr. indentifying endog. labour inputs	L_2.(Log of labour, share of workers aged 18–29, Share of workers aged 50–64)				
[6] First differences + intermediate inputs ACF[d]					
Productivity (η_3)	−0.220***	−0.376***	−0.207***	−0.285***	−0.351***
SE	(0.054)	(0.000)	(0.064)	(0.053)	(0.045)
Prod.-lab. costs gap (η_3^G)	−0.127***	−0.146***	−0.100**	−0.164***	−0.132**
SE	(0.021)	(0.023)	(0.057)	(0.023)	(0.031)
No. obs.	38,944	37,968	38,944	37,251	31,445
Controls	All data are deviations from region + year interacted with NACE2 industry means. See "Appendix" for NACE2 classification of industries				
	Capital, number of employees, hours worked per employee[e], share of blue-collar workers, share of managers + firm fixed effects				
Orthog. conditions identifying endog. labour inputs			Innovation in $\omega_{it} \perp\!\!\!\perp$ $L_{1/3}$ labour inputs		

Detailed results (coefficients for all explanatory variables plus test results) for all models are presented in Tables 10, 11 in "Appendix"

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[a] Electricity, gas, steam and air-conditioning supply,water supply, sewerage, waste management and remediation financial and insurance activities; activities of households as employers; undifferentiated goods activities of extra-territorial organisations and bodies real estate activities

[b] Size is defined as the firms' overall labour force

[c] Average number of hours worked by employee on an annual basis, which is strongly correlated to the incidence of part-time work

[d] Ackerberg et al. (2006)

inputs as instruments (S-GMM). Model [4] provides estimates using all available observations, while model [5], being similar in all other respects to model [4], uses the (smaller) sample of firms reporting their use of intermediate inputs.[35] The last model [6] combines FD and the ACF intermediate-goods proxy idea (FD-ACF).[36] Thus, the S-GMM estimates of model [5] and the FD-ACF estimates of model [6] are directly comparable. Estimated coefficients for the older workers variable (η_3, η_3^w, η_3^G) are summarized by Table 3. All corresponding tables, with the full set of coefficients[37] and test statistics, are available in the "Appendix". In all of our S-GMM estimates, summarized in Table 3 (and also Tables 4, 5), our instruments pass the Hansen test of overidentification restriction at the 5 % level. In may cases instruments also pass the Sargan test[38] and Arellano–Bond test for AR(1) or AR(2). These test statistics are available in "Appendix".

In Table 3, parameter estimates (η) for the average productivity equation support the evidence that older workers (50–65) are less productive than prime-age

[35] Note that intermediate inputs are a crucial element of ACF's modelling strategy.

[36] As suggested in Sect. 2 (Eqs. 21a, 21b, 22a, 22b, 22c, 22d), identification is provided by a set of moment conditions imposing orthogonality between implied innovation terms ξ_{it} and k_{it}; ξ_{it} and lags 1–3 of the labour inputs.

[37] Except for region, year/nace2 dummies.

[38] Note that the Sargan test is theoretically dominated by the Hansen test in case of non-sphericity of the error terms (Roodman, 2006).

Table 5 Parameter estimates (SE), older (50–64) workers productivity (η_3) and productivity-labour cost gap (η_3^G), training costs

	All available data Overall unbalanced panel	Firms reporting positive training *spending* (ref.) (A)	Firms reporting training *spending* equal or above 2 % of the overall annual payroll cost (B)
[4] System GMM			
Productivity per head. (η_3)	−0.194***	−0.238***	−0.252***
SE	(0.034)	(0.043)	(0.049)
Productivity-labour cost gap (η_3^G)	−0.230***	−0.255***	−0.254***
SE	(0.032)	(0.044)	(0.049)
No. obs.	77,069	49,230	37,590
[6] First differences + intermediate goods ACF[a]			
Productivity per head. (η_3)	−0.220***	−0.496***	−0.515***
SE	(−0.054)	(0.043)	(0.054)
Productivity-labour cost gap (η_3^G)	−0.127***	−0.263***	−0.306***
SE	(−0.021)	(0.031)	(0.056)
No. obs.	38,944	23,217	17,882

Detailed results (coefficients for all explanatory variables plus test results) for all models are presented in Tables 12,13 in "Appendix"

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[a] Ackerberg, Caves and Frazer

(30–49) workers (our reference category). Sizeable (and statistically significant) negative coefficients are found across the range of models estimated. OLS results [1] suggest that an increase of 10 %-points in the share of old workers depresses productivity by 2.7 %. But this is compensated by a sizeable and statistically significant reduction of the average labour cost. A 10 %-points rise in the share of old workers depresses labour costs by 1.9 %. In all this translate into a .9 % reduction of the productivity-labour cost gap, synonymous with lower employability.

But OLS results suffer from unobserved heterogeneity bias. Even the inclusion of controls in F_{it}, mostly a large set of dummies,[39] is probably insufficient to account for firm-level singularities that may affect simultaneously firms' productivity and age structure. First-differencing as done in [2] is still the most powerful way out of this problem. Results from this model point at a much lower productivity handicap for older workers: an increase of 10 %-points of their share in the workforce depresses productivity by 1.12 %. Similarly, the labour cost coefficient appears smaller (in absolute value): a 10 %-points increment in the share of older workers leads to a .52 % reduction of the average cost for employers. Both results are supportive of the idea that older workers are overrepresented (within NACE2 industries) in firms that are intrinsically less productive and remunerative. But the productivity effect still dominates the labour cost one, with the implication that a 10 %-points surge of the share of older workers translates into a .59 % reduction of the productivity-labour cost gap.

OLS also potentially suffers from endogeneity bias. This justifies considering ACF i.e. using intermediates goods to proxy for a plant's unobservable productivity shocks. ACF has the advantage over the more typical FD panel data approach of allowing for time-varying plant effects and allowing for more identifying variation in the other inputs. It is not, however, a complete panacea. We have explained above that it is difficult to believe in the existence of a one-to-one relationship between a firm's consumption of intermediates goods and a term ω_{it} that would systematically comprise all the firms' unobservables. Results [3] in Table 3 somehow comfort us in our a priori scepticism. ACF fails to take us significantly away from OLS, as point estimates are essentially identical. A 10 %-points rise in the share of older workers depressed productivity by 2.8 % (2.7 % with OLS), reduces labour costs by 1.4 % (1.9 % with OLS); that eventually translates into a depreciation of the productivity-labour cost gap of .99 % (.94 % with OLS).

Remember also that ACF—due to the inclusion of interaction terms between the various age share variables—is a way to allow for imperfect substitutability across labour age groups (Hellerstein et al. 1999). We interpret the great similarity between our ACF results [3] and those of the OLS-estimated Cobb–Douglas production function [1] as an indication that the assumption of perfect substitutability across age groups may not be abusive or a major source of distortion of our key estimates.

We now turn to our preferred models. If FD [2] probably dominates ACF [3], FD alone is not sufficient. The endogeneity in labour input[40] choice is a well-documented

[39] All our models, including OLS, use data in deviations from region (Wallonia, Flanders, Brussels) plus year interacted with NACE2 industry means. See Table 7 in the "Appendix" for a detailed presentation of the NACE2 classification.

[40] Remember that one specificity of our analysis is to assume endogeneity for both (1) the choice of the overall level of labour and (2) the age structure of the workforce.

problem in the production function estimation literature (e.g. Griliches and Mairesse 1995). In short, heterogeneity and endogeneity deserved to be simultaneously treated. And this is precisely what we attempt to do in [4],[5] by estimating S-GMM, and in [6] by combining FD with ACF (see Sect. 2 for the algebra). Estimations [4, 5] and [6] in Table 3 are a priori the best insofar as the parameters of interest are identified from within-firm variation to control for firm unobserved heterogeneity, and that they control for short-term endogeneity biases either via the use of ACF's intermediate input proxy, or internal instruments.

Comparing the estimates provided by model [4] and [5], one can see that the results obtained with the smaller sample using S-GMM qualitatively do not differ from those obtained with the larger sample. Thus, when interpreting S-GMM estimates, we will use all available data, and refer to the results in [4].

Model [4], based on S-GMM, shows that a 10 %-points rise in the share of older workers depresses productivity by .1.94 % (vs. 1.1 % with FD), increases labour costs by a mere .24 % (−.52 % with FD); which eventually turns into a depreciation of the productivity-labour cost gap of 2.3 % (.59 % with FD). Those from the FD-ACF model [6] are very similar: a 10 %-points rise in the share of older workers causes a drop of productivity of 2.2 %, of labour costs of .9 % and productivity-labour cost gap of 1.27 %. Both series of estimates are significant at the 1 % threshold.

As to the labour demand for older workers, the most important parameters are those of the productivity-labour cost gap equation (η_3^G). Negative signs basically tell us that older workers (50–64) display lower productivities ($\eta_3 < 0$) that are not fully compensated by lower labour costs; implying that they could be less employable than the reference category.

It is also worth stressing that our preferred models [4],[5] and [6] deliver estimates of older workers' productivity that are *lower* than those obtained with FD [2]. This is supportive of the idea that private firms based in Belgium primarily resort to early retirements—rather than recruitment freezes—to cope with negative demand shocks. Remember that, in that case, we have predicted in Sect. 2 that models that do not control for endogeneity (OLS or FD) overestimate older workers' productivity.

4.2 Robustness analysis

We have undertaken four further steps in our analysis to assess the robustness of results reported in Table 4. For each of these extensions, the focus will be on the results of our preferred models [4] and [6].

First, we test whether we reach similar conclusions, with regards to those coming from the unbalanced panel used so far, when we restrict the analysis to the (only slightly smaller) *balanced* panel[41] sample. The rationale for doing is at least twofold. First, data quality is likely to be lower with the unbalanced panel. Poor respondents are likely to be overrepresented among short-lived firms forming the unbalanced part of the panel. Second, and more importantly, entering and exiting firms probably have a-typical, not so meaningful, productivity-age profiles. Entering firms (that tend also to be those exiting the sample due to a high mortality rate among entrants) are usually less productive and employ a younger workforce than incumbents. More to the point, the short-term dynamic of their productivity performance (which matters a lot in an analysis that rests heavily on FD estimates) is much less predictable and inadequately captured by the identification strategies mobilised in this paper. Bartelmans and Doms (2000) reviewing the US evidence, explain that a few years after entry a disproportionate number of entrants have moved both to the highest and the lowest percentiles of the productivity distribution.

Parameter estimates are exposed on the right-hand side of Table 4, alongside those of Table 3 (preferred models [4], [6] only) for comparison purposes. If anything, the old worker employability handicap (η_3^G) highlighted with the unbalanced panel is confirmed. In terms of average productivity, S-GMM [4] shows that a 10 %-points expansion of older workers' share in the firm's workforce causes a 1.82 % reduction (vs. 1.9 % with the unbalanced panel), whereas FD-ACF model [6] points at 3.7 % fall (2.2 % with the unbalanced data). In terms of productivity-labour cost gap (i.e. employability), S-GMM suggests that a 10 %-points expansion causes a 2.12 %-points decline (vs. 2.3 % with unbalanced panel), while FD-ACF points at a 1.46 % contraction of the gap (1.27 % with unbalanced data).

Second, we explicitly control for the potential bias caused by cohort effects. A weakness of our dataset is indeed that it does not contain a direct measure of the workers' educational attainment. The share of blue-collar workers which we include as a control may, in the Belgian context, act as a proxy for low educational attainment. Still, many would rightly argue this is insufficient to properly control for the fact that younger cohorts are better-educated, or use more recent vintages of capital, and, therefore, they are potentially more productive than older ones. How large is the risk that our estimates confound age and cohort effects, and consequently exaggerate the age-related productivity handicap? Not so much it seems.

[41] The sample of firms that are observed *every* year between 1998 and 2006. By and large, descriptive statistics are quite similar to those of the unbalanced set (Table 2), be it in terms of average value-added, labour cost or firm size…

The third column of Table 4 contains the estimates of a model where the shares of workers for each *decade-of-birth cohort* (namely: 1940–50, 1950–60, 1960–70 (ref.), 1970–80, 1980–90) have been included as additional explanatory variables. S-GMM [4] shows that a 10 %-points expansion of older workers' share in the firm's workforce causes a 3.9 % reduction (vs. 1.9 % with the unbalanced panel), whereas FD-ACF model [6] points at 2.07 % fall (2.2 % with the unbalanced data). In terms of productivity-labour cost gap (i.e. employability), S-GMM suggests that a 10 %-points expansion causes a 2.18 %-points decline (vs. 2.3 % with unbalanced panel), while FD-ACF points at a 1 % contraction of the gap (1.27 % with unbalanced data). In all, these suggest that cohort (and the confounding factors that they capture) only play a minor role in determining the relative productivity and employability of older workers.

Third, we examine whether we reach substantially different conclusions when we exclude observations from the financial/insurance industry, real estate, utilities and a few other activities that can be associated with the non-profit sector.[42] We do this because many argue that the productivity and capital of firms in these industries are hard to measure. Results, in the fourth column of Table 4, productivity handicap (η_3) for older workers very similar to one estimated using the unbalanced panel. In terms of employability (i.e. productivity-labour cost gap) their handicap appears even larger. S-GMM suggests that a 10 %-points expansion of their share causes a 3.18 % decline (vs. 2.3 % with unbalanced panel), whereas FD-ACF points at a 1.64 % contraction of the gap (1.27 % with unbalanced data).

Fourth, we check whether firm size (i.e. overall number of workers) matters. We exclude the firms that systematically (i.e. during the 9 years of the panel) stay below the 10th percentile[43] and above the 90th percentile of the overall (annual) sample distribution. The main reason for doing this is to somehow reconnect with that important stream of the empirical literature that has assumed (and convincingly shown) that worker outcomes are primarily associated with (or caused by) firm characteristics, notably their size.[44] So far in this paper, we have assumed that firms' outcomes are caused by the characteristics of their employees, in particular their age. But contrary to some authors in this stream of research (Hellerstein et al. 1999), we have not included firm size class dummies in our vector of control F_{it}. Results (Table 4, last column) regarding productivity performances are mixed. Both S-GMM and FD-ACF point at a slightly larger productivity handicap than when using the overall sample of firms. Estimates of the employability handicap obtained with the "trimmed" data are almost equal to those obtained with the overall sample of firms. Although this analysis is very limited in scope, it is supportive of the idea that the relationship between age, productivity and labour costs that we have highlighted in this paper is orthogonal to the one relating firm size to the last two dimensions.

4.3 Company-based training

In a final extension, we try to analyze the role of company-based training. At this stage we have established that an aging workforce means lower productivity performance for firms, that is not compensated by lower labour costs. And this may adversely affect the demand for older individuals. A policy to support old labour demand—aimed at preserving or increasing the employment rate of senior individuals could require either (1) to reform the Belgian wage formation mechanism, in particular seniority-based wage rules, or (2) to introduce labour cost subsidies targeted at senior workers. However, an increased company-based training effort could also combat—at the source—the problem of age-related declining productivity.

There is evidence, in Belgium of a (positive) causal relationship between the intensity of firm-based training and labour productivity. Konings and Vanormelingen (2010), using Belgian firm-level data find evidence of a positive causal effect of company-based training on the overall labour productivity of large firms (which is not to be confounded with the relative productivity of older workers à-la-HN as estimated here). On the other hand, international and Belgian evidence rather supports the view that older employees get relatively less training (or less effective training) than younger employees (D'Addio et al. 2010). *Ceteris paribus*, this could rather increase older workers' employability handicap vis-à-vis younger groups.

Our empirical strategy to examine this question is to use information about company-based (and -financed) training gathered in the Social Report (available in Bel-first). Bel-first contains (1) the annual number of hours during which

[42] Electricity, gas, steam and air-conditioning supply, water supply, sewerage, waste management and remediation financial and insurance activities; activities of households as employers; undifferentiated goods activities of extra-territorial organisations and bodies real estate activities. See "Appendix", Table 7 for more details.

[43] Remember that our overall sample already excludes firms with less than 20 employees.

[44] The relationship between firm size and labour productivity is well documented. Van Ark and Monnikhof (1996) document this relationship for France, Germany, Japan, the United Kingdom and the United States. For example, they show that in 1987, the gross output per employee in US manufacturing plants with 0–9 employees was 62 per cent of that of all manufacturing plants, while the gross output per employee in plants with 500 or more employees was 126 per cent of that of all manufacturing plants.

workers were trained and (2) the cost of training to the employers. Both can be expressed as shares of the total payroll or total number of hours worked annually. Descriptive statistics reported in Table 1 (Sect. 3) suggest that the average firm in our sample spends the equivalent 0.38 % of its total labour/payroll cost on company-based training. And, on average, the time dedicated to training represents 0.34 % of the total number of hours worked annually. Unfortunately, Bel-first does not inform us about how this training effort is distributed across age groups inside firms. The only thing we can reasonably do is try to assess how estimates of productivity and employability handicap (namely η_3, η_3^G) are affected by firm's (variable) propensity to dedicate time and money to training.

Key results are reported in Tables 5, 6. The first column reproduces the results for the overall sample that includes many non-respondents and firms reporting zero training effort. The ones obtained with the sub-sample of firms that report strictly positive training spending or training hours in Bel-first are displayed in the two columns to the right. We distinguish those that just report positive training effort (A) and those, less numerous, that report training effort at least equal to the 2 % threshold (B) [either the overall labour costs (Table 5) or of the total number of hours worked (Table 6)]. Firms belonging to (B) can be considered as training-intensive firms: 2 % may appear as small number but it is more than 5 times the average (Table 1).

The main result is that our two preferred econometric methods point at a larger productivity handicap of older workers inside firms training more (A and B). Estimates delivered by the S-GMM[4] strategy using training cost data (Table 5) show that a 10 %-points rise of the share of older workers causes a fall of firm's overall labour productivity per head of 2.52 % among training-intensive firms [B] (vs. 2.37 % in [A] group and 1.94 % in general). The FD-ACF method [6] even highlights a significantly larger productivity handicap inside training-intensive firms (B): a 10 %-point rise of the share of older workers goes along with a 5.15 % fall of labour productivity (vs. 4.96 % for group [A] and −2.2 % in general). These results are largely confirmed by the analysis based on hours of training instead of training costs (Table 6). In short, these results constitute evidence that current forms of training, inside Belgian firms, although they may be good for the overall labour productivity of the firm as shown by Konings and Vanormelingen (2010), do not mechanically compensate for age-related productivity handicaps, on the contrary.

5 Conclusions

As a socio-economic phenomenon, population ageing in Europe will affect more than the welfare system as it will also affect the age structure of the *workforce*. In particular, the share of older workers (aged 50 plus) will rise significantly due to the demographics. And this trend will be reinforced by policies aimed at maintaining more of those older individuals in employment. Optimists may believe that an ageing workforce will have only a minimal impact on firms' performance and labour markets. This paper contains evidence, based on the analysis of private

Table 6 Parameter estimates (SE), older (50–64) workers productivity (η_3) and productivity-labour cost gap (η_3^G), training hours

	All available data Overall unbalanced panel	Firms reporting positive training *hours* (ref.) (A)	Firms reporting *hours* of training equal or above 2 % of the total number of worked hours (B)
[4] system GMM			
Productivity per head (η_3)	−0.194***	−0.254***	−0.272***
SE	(0.034)	(0.043)	(0.049)
Productivity-labour cost gap (η_3^G)	−0.230***	−0.254***	−0.254***
SE	(0.032)	(0.044)	(0.049)
No. obs.	77,069	49,647	37,161
[5] First differences + intermediate goods ACF[a]			
Productivity per head (η_3)	−0.220***	−0.470***	−0.533***
SE	(−0.054)	(0.042)	(0.131)
Productivity-labour cost gap (η_3^G)	−0.127***	−0.225***	−0.319***
SE	(−0.021)	(0.030)	(0.058)
No. obs.	38,944	23,416	17,782

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[a] Ackerberg, Caves and Frazer

Detailed results (coefficients for all explanatory variables plus test results) for all models are presented in Tables 12,13 in "Appendix" economy firm-level panel data, suggesting the opposite. We show that the age structure of firms located in Belgium is a key determinant of their productivity. Rising shares of workers aged 50–65 could translate into lower productivity *ceteris paribus*. An increase of 10 %-points in the share of older workers (50–65) depresses value-added per worker by 2–2.7 %, depending on the estimation method chosen.

Our paper also investigates the consequences of an ageing workforce for the demand for older workers. We ask in particular whether firms based in Belgium are a priori willing to employ more older workers. The answer is no, as we find robust evidence of a negative impact of older workers on the productivity-labour cost gap: an increment of 10 %-points of their share in the firms' workforce causes a 1.3–2.8 % contraction. The reason for this is that lower productivity of older workers is not compensated by lower labour costs, on the contrary in some cases. We posit that is likely to depress the labour demand for older workers, in particular to compromise their chances of re-employment in case of job loss.

This key result is reproduced, and even reinforced, when we turn to several variants of our main analysis (i.e. elimination of firms that are not observed during the 9 consecutive years forming our panel, control for cohort effects, exclusion of firms belonging to sectors where productivity is difficult to measure).

Further, we consider the potential role of job training, in particular the question of whether firms that consistently spend money to train their workers have a particular configuration (more favourable) of the productivity by age profile. Enthusiasts would argue that increased training effort could compensate the problem of age-related declining productivity. But sceptics would point at the abundant international evidence that older employees get relatively less training (or less effective training) than younger employees (D'Addio et al. 2010). Our results are rather supportive of the sceptical view. Our preferred econometric methods point at a larger productivity handicap of older workers inside firms that spend significantly more than average on training. Combating age-related productivity declines via training can still probably be achieved. But, certainly in the Belgium context, it calls for a large range of far-reaching initiatives. These include more training targeted at individuals aged 40+. Efforts are needed to persuade workers and their employers of the need to keep (re)training beyond 50. This probably requires mentality changes as well as a marked reallocation of existing resources. The extension of the career horizon, imposed by the gradual postponement of the end of the carrier, provided it is adequately factored in, should help the stakeholders make the necessary steps into that direction. If this does not suffice, providing training subsidy to older workers may become a relevant policy.

We finish by briefly mentioning some limits and considerations that should be held in mind when interpreting our results. First, only "average firm profiles" are calculated, which may imply that we overlook the (in)capacity or some firms to neutralize the effect of ageing on productivity (by implementing or not *ad hoc* actions that compensate for the age-related loss of performance). Second, and most importantly, the workers' sample that we use in this paper might not be representative of the entire population of older individuals aged 50–65. Belgium, alongside a few other EU countries, is known for its very low employment rate among individuals aged 50 or more (37 % in 2010 according to Eurostat). This means that there is a risk of a positive *selection bias*, in particular if this low employment rate corresponds to early ejection from the workforce of individuals that are intrinsically less productive or less motivated.[45] To the extent that this selection bias is an issue, we could view our estimated coefficients for older workers' relative productivity as lower-bounds (in absolute value).[46]

Third, the econometric strategies underpinning this literature are still developing. This could soon deliver improvements and eliminate some of the divergence in terms of the impact of ageing observed between this paper and a few others (van Ours and Stoeldraijer 2011 for the Netherlands; Cardoso et al. 2011 for Portugal). An open question is whether "natural experiments" (now commonly used in empirical labour economics in order to identify causal relationships) could help assess the impact of ageing on firm-level productivity. To our knowledge, such a strategy has never been used to disentangle the age-productivity-pay nexus.

Finally, the important cross-country differences (Belgium vs. Portugal or the Netherlands) with regard to how age, productivity and labour costs are related could be due to data specificities or to econometric issues. But one cannot reject the hypothesis that they point to country effects. It could be, for instance, that the way age affects productivity is partially dependant on the set of labour-

[45] Early retirement is very popular in Belgium (among both workers and employers), as it offers a much preferable alternative to ordinary layoffs. Early retirement benefits are relatively generous (replacement rate can reach 80 % vs. max. 60 % for unemployment benefits). They are regularly used by firms that need to downsize. While 58 is a priori the minimum access age for early retirement benefits, reductions in the minimum age are possible when the company is recognized [by the Ministry of Social Affairs] as being in real trouble, under which circumstance the age can be brought down to 52 years, or even 50.

[46] In other works, the estimated coefficients could be **less** negative than the actual ones.

market institutions present in one country. Some of these institutions may be conducive to greater investment (from both employers and employees), combating or compensating age-related productivity declines, whereas others may have the opposite effect. The issue remains open for discussion and calls for more research.

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Appendix

See Tables 7, 8, 9, 10, 11, 12, 13, 14.

Table 7 Sectors/industries and NACE2 codes/definitions

NACE2 code		Industry
10–12	Manufacturing	Manufacture of food products, beverages and tobacco products
13–15	Manufacturing	Manufacture of textiles, apparel, leather and related products
16–18	Manufacturing	Manufacture of wood and paper products, and printing
19	Manufacturing	Manufacture of coke, and refined petroleum products
20	Manufacturing	Manufacture of chemicals and chemical products
21	Manufacturing	Manufacture of pharmaceuticals, medicinal chemical and botanical pro
22 + 23	Manufacturing	Manufacture of rubber and plastics products, and other non-metallic
24 + 25	Manufacturing	Manufacture of basic metals and fabricated metal products
26	Manufacturing	Manufacture of computer, electronic and optical products
27	Manufacturing	Manufacture of electrical equipment
28	Manufacturing	Manufacture of machinery and equipment n.e.c.
29 + 30	Manufacturing	Manufacture of transport equipment
31–33	Manufacturing	Other manufacturing, and repair and installation of machinery and e
35	Utilities	Electricity, gas, steam and air-conditioning supply
36–39	Utilities	Water supply, sewerage, waste management and remediation
41–43	Construction	Construction
45–47	Services	Wholesale and retail trade, repair of motor vehicles and motorcycles
49–53	Services	Transportation and storage
55 + 56	Services	Accommodation and food service activities
58–60	Services	Publishing, audiovisual and broadcasting activities
61	Services	Telecommunications
62 +63	Services	IT and other information services
64–66	Finance/insurance	Financial and insurance activities
68	Services	Real estate activities
69–71	Services	Legal, accounting, management, architecture, engineering, technical
72	Services	Scientific research and development
73–75	Services	Other professional, scientific and technical activities
77–82	Services	Administrative and support service activities
90–93	Services	Arts, entertainment and recreation
94–96	Services	Other services
97–98	Non-profit	Activities of households as employers; undifferentiated goods
99	Non-profit	Activities of extra-territorial organisations and bodies

Table 8 (Detailing Table 3)—Parameter estimates (SE)—productivity, labour costs, and productivity-labour cost gap equations—models [4], [5] system GMM estimations

	[4] System GMM (all available data)			[5] System GMM (intermediate inputs sample)		
	Productivity	Labour cost	Productivity labour cost gap	Productivity	Labour cost	Productivity labour cost gap
Log of capital	0.062***	0.068***	−0.006**	0.062***	0.072***	−0.011***
	(0.003)	(0.001)	(0.003)	(0.004)	(0.002)	(0.004)
Log of labour	−0.047***	−0.104***	0.057***	−0.060***	−0.138***	0.080***
	(0.011)	(0.005)	(0.010)	(0.014)	(0.006)	(0.014)
Share of workers aged 18–29 [ref :30–49]	−0.201***	−0.199***	−0.017	0.016	−0.116***	0.126***
	(0.024)	(0.011)	(0.023)	(0.039)	(0.016)	(0.038)
Share of workers aged 50–64	−0.194***	0.024	−0.230***	−0.274***	0.012	−0.289***
	(0.034)	(0.015)	(0.032)	(0.044)	(0.018)	(0.043)
Share of blue-collar workers [ref: white coll.]	−0.121***	−0.125***	0.005	−0.123***	−0.134***	0.012**
	(0.003)	(0.002)	(0.003)	(0.006)	(0.003)	(0.006)
Share of managers	0.264***	0.252***	0.002	0.451***	0.347***	0.101***
	(0.018)	(0.008)	(0.017)	(0.024)	(0.010)	(0.023)
Log of hours worked per employee[a]	0.743***	0.634***	0.110***	0.719***	0.546***	0.173***
	(0.007)	(0.003)	(0.007)	(0.013)	(0.005)	(0.012)
_cons	−5.501***	−4.541***	−0.959***	−5.311***	−3.788***	−1.532***
	(0.076)	(0.034)	(0.072)	(0.120)	(0.050)	(0.117)
No. observations	77,069	77,069	77,069	38,944	38,944	38,944
No. firms	9,277	9,277	9,277	7,704.000	7,704.000	7,704.000
Av.number of spell per firm	8.31	8.31	8.31	4.940	4.940	4.940
Chi^2	73,419.64	305,334.497	1,347.035	40,878.443	180,532.303	1,196.739
Chi^2 p value	0.000	0.000	0.000	0.000	0.000	0.000
No. Instruments	11	11	11	11	11	11
Sargan	3.927	14.538	4.720	9.320	72.346	8.361
Sargan *df*	3	3	3	3	3.000	3.000
Sargan p value	0.269	0.002	0.193	0.025	0.000	0.039
Hansen	0.602	2.377	0.658	1.043	7.075	0.993
Hansen *df*	3	3	3	3	3.000	3.000
Hansen p value	0.896	0.498	0.883	0.791	0.070	0.803
AR(1)	−5.237	−3.819	−4.900	−3.177	−2.391	−3.065
AR(1) p value	0.000	0.000	0.000	0.001	0.017	0.002
AR(2)	−0.686	−0.096	−0.822	0.100	0.363	0.576
AR(2) p value	0.493	0.924	0.411	0.921	0.717	0.565

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[a] Average number of hours worked by employee on an annual basis, which is strongly correlated to the incidence of part-time work

All data are deviations from region + year interacted with NACE2 industry means. See Table 7, "Appendix" for NACE2 classification of industries

Instruments for first differences equation: *Standard*: D.(Log of capital, Share of blue-collar workers, Share of managers, Log of hours worked per employee); *GMM-type*: L_2.(Log of labour, Share of workers aged 18–29, Share of workers aged 50–64) collapsed

Instruments for levels equation: *Standard*: _cons, Log of capital, Share of blue-collar workers, Share of managers, Log of hours worked per employee; *GMM-type*: DL.(Log of labour, Share of workers aged 18–29, Share of workers aged 50–64) collapsed

Table 9 (Detailing Table 3)—Parameter estimates (SE)—productivity, labour costs, and productivity-labour cost gap equations—model [6] first differences + intermediate inputs ACF estimation

	[6] First differences + intermediate inputs ACF[$]		
	Productivity	Labour cost	Productivity labour cost gap
Log of capital	0.027***	0.017***	0.011***
	(0.005)	(0.003)	(0.002)
Log of labour	−0.172***	−0.140***	−0.062***
	(0.024)	(0.010)	(0.021)
Share of workers aged 18–29 [ref :30–49]	−0.028	−0.041***	0.085
	(0.063)	(0.006)	(0.059)
Share of workers aged 50–64	−0.220***	−0.090***	−0.127***
	(0.054)	(0.007)	(0.021)
Share of blue-collar workers [ref:white coll.]	−0.027	−0.074***	0.037***
	(0.020)	(0.007)	(0.020)
Share of managers	0.056*	−0.019	0.016***
	(0.031)	(0.012)	(0.016)
Log of hours worked per employee[a]	0.290***	0.294***	−0.000
	(0.014)	(0.014)	(0.004)
No. obs.	38,944		

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[a] Average number of hours worked by employee on an annual basis, which is strongly correlated to the incidence of part-time work

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List of instruments: log of capital, share of blue-collars, share of managers, log of hours worked per employee, lag 1/3(log of labour, share of 18–29, share of 50, 64), _cons

All data are deviations from region + year interacted with NACE2 industry means. See Table 7, "Appendix" for NACE2 classification of industries

Orthogonality conditions used to identify endog. Labour inputs: Innovation in $\omega_{it} \perp\!\!\!\perp L_{1/3}$ labour inputs

Table 10 (Detailing Table 4)—Parameter estimates (SE)—productivity and productivity-labour cost gap equations—robustness analysis—model [4] system GMM estimations

	Balanced panel		Controlling for cohort effects		Excluding financial, real estate, utilities and non-profit activities[a]		Firms in 10–90th perc. size[b] bracket	
	Productivity	Productivity labour cost gap	Productivity	Productivity labour cost gap	Productivity	Productivity labour cost gap	Productivity	Productivity labour cost gap
Log of capital	0.065***	−0.002	0.071***	0.010***	0.064***	0.021***	0.055***	0.003
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
Log of labour	−0.058***	0.037***	−0.083***	−0.001	−0.048***	−0.004	−0.037***	0.047***
	(0.010)	(0.010)	(0.015)	(0.014)	(0.011)	(0.010)	(0.009)	(0.009)
Share of workers aged 18–29 [ref :30–49]	−0.172***	−0.001	−0.505***	−0.116***	−0.172***	0.003	−0.212***	−0.021
	(0.024)	(0.023)	(0.024)	(0.023)	(0.025)	(0.023)	(0.024)	(0.024)
Share of workers aged 50–64	−0.182***	−0.212***	−0.394***	−0.218***	−0.176***	−0.318***	−0.245***	−0.251***
	(0.033)	(0.032)	(0.035)	(0.033)	(0.034)	(0.032)	(0.034)	(0.033)
Share of blue-collar workers [ref:white coll.]	−0.115***	0.006*	−0.103***	0.038***	−0.125***	0.015***	−0.121***	0.018***
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Share of managers	0.237***	−0.035**	0.256***	0.013	0.277***	−0.004	0.256***	−0.017
	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)	(0.018)

Table 10 continued

	Balanced panel		Controlling for cohort effects		Excluding financial, real estate, utilities and non-profit activities[a]		Firms in 10–90th perc. size[b] bracket	
	Productivity	Productivity labour cost gap	Productivity	Productivity labour cost gap	Productivity	Productivity labour cost gap	Productivity	Productivity labour cost gap
Log of hours worked per employee[c]	0.731***	0.099***	0.724***	0.082***	0.742***	0.126***	−5.581***	−0.921***
	(0.007)	(0.007)	(0.009)	(0.008)	(0.007)	(0.007)	(0.068)	(0.065)
Cohort 1940– < 50 [ref = 1960– < 70]			−0.040	−0.064				
			(0.096)	(0.071)				
Cohort 1950– < 60			−0.137*	−0.092*				
			(0.079)	(0.055)				
Cohort 1970– < 80			0.386***	0.238***				
			(0.099)	(0.083)				
Cohort 1980– < 90			0.410***	0.383**				
			(0.105)	(0.091)				
_cons	−5.397***	−0.832***	−5.145***	−0.622***	−5.513***	−0.640***	−5.581***	−0.921***
	(0.078)	(0.075)	(0.094)	(0.090)	(0.076)	(0.072)	(0.068)	(0.065)
No. observations	73,580		77,069		75,360		69,801	
No. firms	8,440		9,277		9,065		8,404	
Av.number of spell per firm	9		8.31		8.31		8.31	
Chi^2	68,283	1,132	76,663	4,437	4,857	4,857	1,293	1,132
Chi^2 p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
No. Instruments	11		15		11		11	
Sargan	3.486	9.823	4.153	11.804	3.987	5.329	5.944	7.910
Sargan *df*	3	3	3	3	3	3	3	3
Sargan p value	0.323	0.020	0.245	0.008	0.263	0.149	0.114	0.048
Hansen	0.385	1.530	0.850	2.138	0.662	0.743	0.805	1.138
Hansen *df*	3	3	3	3	3	3	3	3
Hansen p value	0.943	0.675	0.837	0.544	0.882	0.863	0.848	0.768
AR(1)	−5.091	−4.779	−5.321	−4.910	−5.231	−4.825	−5.243	−4.539
AR(1) p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	−0.625	−0.816	−0.707	−0.804	−0.676	−0.880	−0.396	−0.271
AR(2) p value	0.532	0.415	0.480	0.422	0.499	0.379	0.692	0.786

All data are deviations from region + year interacted with NACE2 industry means. See Table 7, "Appendix" for NACE2 classification of industries

List of control comprises: capital, number of employees, hours worked per employee, share of blue-collar workers, share of managers + firm fixed effects

Instruments for first differences equation: *Standard*: D.(Log of capital, Share of blue-collar workers, Share of managers, Log of hours worked per employee); *GMM-type*: L_2.(Log of labour, Share of workers aged 18–29, Share of workers aged 50–64) collapsed

Instruments for levels equation: *Standard*: _cons, Log of capital, Share of blue-collar workers, Share of managers, Log of hours worked per employee; *GMM-type*: DL.(Log of labour, Share of workers aged 18–29, Share of workers aged 50–64) collapsed

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[a] Electricity, gas, steam and air-conditioning supply,water supply, sewerage, waste management and remediation financial and insurance activities; activities of households as employers; undifferentiated goods activities of extra-territorial organisations and bodies real estate activities

[b] Size is defined as the firms' overall labour force

[c] Average number of hours worked by employee on an annual basis, which is strongly correlated to the incidence of part-time work

Table 11 (Detailing Table 4)—Parameter estimates (SE)—productivity and productivity-labour cost gap equations—robustness analysis model [6] IV—first differences + intermediate inputs ACF estimation

	Balanced sample		Controlling for cohort effects		Excluding financial, real estate, utilities and non-profit activities[a]		Firms in 10–90th perc. size[b] bracket	
	Productivity	Productivity labour cost gap	Productivity	Productivity labour cost gap	Productivity	Productivity labour cost gap	Productivity	Productivity labour cost gap
Log of capital	0.029***	0.011***	0.028***	0.012***	0.031***	0.012***	0.025***	0.009***
	(0.005)	(0.002)	(0.002)	(0.002)	(0.005)	(0.002)	(0.004)	(0.002)
Log of labour	−0.243***	−0.089***	−0.223***	−0.101***	−0.191***	−0.065***	−0.208***	−0.069***
	(0.024)	(0.008)	(0.008)	(0.006)	(0.023)	(0.007)	(0.017)	(0.008)
Share of workers aged 18–29 [ref :30–49]	−0.012	0.081	−0.068	0.091	−0.057	0.044	0.063	0.106*
	(0.079)	(0.061)	(0.074)	(0.073)	(0.073)	(0.062)	(0.081)	(0.063)
Share of workers aged 50–64	−0.376***	−0.146***	−0.207***	−0.100**	−0.285***	−0.164**	−0.351***	−0.132**
	(0.052)	(0.023)	(0.064)	(0.057)	(0.053)	(0.023)	(0.045)	(0.031)
Share of blue-collar workers [ref:white coll.]	−0.045***	0.032***	0.003	0.043***	−0.036*	0.030***	−0.032**	0.043***
	(0.016)	(0.009)	(0.010)	(0.006)	(0.020)	(0.009)	(0.016)	(0.008)
Share of managers	0.065**	0.046**	0.050***	0.058***	0.037	0.060***	0.057*	0.092***
	(0.032)	(0.022)	(0.015)	(0.010)	(0.039)	(0.020)	(0.033)	(0.019)
Log of hours worked per employee[c]	0.272***	−0.011**	0.654***	−0.024***	0.304***	0.002	0.278***	−0.000
	(0.014)	(0.004)	(0.014)	(0.004)	(0.015)	(0.005)	(0.015)	(0.004)
Cohort 1940– < 50 [ref = 1960– < 70]			0.047	0.037				
			(0.066)	(0.062)				
Cohort 1950– < 60			−0.098**	−0.026				
			(0.040)	(0.038)				
Cohort 1970– < 80			0.119**	0.070				
			(0.046)	(0.044)				
Cohort 1980– < 90			0.229***	0.187***				
			(0.050)	(0.047)				
No. obs.	37,968		38,944		37,251		31,445	

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*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. List of instruments: log of capital, share of blue-collars, share of managers, log of hours worked per employee, lag 1/3(log of labour, share of 18–29, share of 50, 64), _cons. Orthogonality conditions used to identify endog. Labour inputs: Innovation in $\omega_{it} \perp\!\!\!\perp L_{1/3}$ labour inputs. All data are deviations from region + year interacted with NACE2 industry means. See Table 7, "Appendix" for NACE2 classification of industries

[a] Electricity, gas, steam and air-conditioning supply,water supply, sewerage, waste management and remediation financial and insurance activities; activities of households as employers; undifferentiated goods activities of extra-territorial organisations and bodies real estate activities

[b] Size is defined as the firms' overall labour force

[c] Average number of hours worked by employee on an annual basis, which is strongly correlated to the incidence of part-time work

Table 12 (Detailing Tables 5, 6)—Parameter estimates (SE), productivity and productivity-labour cost gap equations—training costs and hours, model [4] system GMM estimations

	Firms reporting positive training *spending* (A)		Firms reporting company-based training *spending* equal or above 2 % of the overall annual payroll cost (B)		Firms reporting positive training *hours* (A)		Firms reporting *hours* of training equal or above 2 % of the total number of worked hours (B)	
	Productivity	Productivity labour cost gap	Productivity	Productivity labour cost gap	Productivity	Productivity labour cost gap	Productivity	Productivity labour cost gap
Log of capital	0.067***	−0.002	0.067***	−0.003	0.069***	−0.001	0.064***	−0.004
	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)
Log of labour	−0.057***	0.038**	−0.058***	0.038**	−0.065***	0.035**	−0.053***	0.037**
	(0.013)	(0.016)	(0.013)	(0.016)	(0.013)	(0.016)	(0.013)	(0.016)
Share of workers aged 18–29 [ref :30–49]	−0.279***	−0.045	−0.268***	−0.058	−0.286***	−0.042	−0.290***	−0.086**
	(0.030)	(0.031)	(0.034)	(0.036)	(0.030)	(0.031)	(0.034)	(0.036)
Share of workers aged 50–64	−0.238***	−0.255***	−0.252***	−0.254***	−0.254***	−0.254***	−0.272***	−0.279***
	(0.043)	(0.044)	(0.049)	(0.050)	(0.043)	(0.044)	(0.049)	(0.050)
Share of blue-collar workers [ref:white coll.]	−0.140***	0.006	−0.117***	0.021***	−0.137***	0.008	−0.118***	0.020***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Share of managers	0.261***	−0.042*	0.320***	−0.059**	0.260***	−0.039*	0.302***	−0.102***
	(0.022)	(0.022)	(0.026)	(0.025)	(0.022)	(0.022)	(0.026)	(0.026)
Log of hours worked per employee	0.755***	0.117***	0.768***	0.118***	0.751***	0.116***	−5.630***	0.119***
	(0.009)	(0.011)	(0.009)	(0.010)	(0.009)	(0.011)	(0.093)	(0.010)
_cons	−5.510***	−0.959***	−5.635***	−0.958***	−5.462***	−0.943***	−5.630***	−0.937***
	(0.094)	(0.113)	(0.093)	(0.106)	(0.095)	(0.112)	(0.093)	(0.106)
No. observations	49,230		37,590		49,647		37,161	
No. firms	6,991		5,079		7,036		4,970	
Av. number of spell per firm	7.04		7.40		7.06		7.48	
Chi^2	50,828	1,132	35,974	4,437	51,156	4,857	34,260	536
Chi^2 *p* value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
No. instruments	11		11		11		11	
Sargan	3.486	5.699	16.713	12.597	11.712	5.739	18.623	12.386
Sargan *df*	3	3	3	3	3	3	3	3
Sargan *p* value	0.008	0.127	0.001	0.006	0.008	0.125	0.000	0.006
Hansen	1.142	2.004	2.793	3.812	1.142	1.950	2.897	3.709
Hansen *df*	3	3	3	3	3	3	3	3
Hansen *p* value	0.767	0.572	0.425	0.283	0.767	0.583	0.408	0.295
AR(1)	−4.696	−4.186	−4.273	−4.085	−4.696	−4.188	−4.278	−4.007
AR(1) *p* value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2)	−0.625	−2.860	−3.028	−2.882	−3.063	−2.810	−2.968	−2.826
AR(2) *p* value	0.002	0.004	0.002	0.004	0.002	0.005	0.003	0.005

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

All data are deviations from region + year interacted with NACE2 industry means. See Table 7, "Appendix" for NACE2 classification of industries

Instruments for first differences equation: *Standard*: D.(Log of capital, Share of blue-collar workers, Share of managers, Log of hours worked per employee); *GMM-type*: L_2.(Log of labour, Share of workers aged 18–29, Share of workers aged 50–64) collapsed

Instruments for levels equation: *Standard*: _cons, Log of capital, Share of blue-collar workers, Share of managers, Log of hours worked per employee; *GMM-type*: DL (Log of labour, Share of workers aged 18–29, Share of workers aged 50–64) collapsed

Table 13 (Detailing Tables 5, 6)—Parameter estimates (SE), productivity, average labour costs, and equations—training costs and hours, model [6] first differences + intermediate inputs ACF estimation

	Firms reporting positive training spending (ref.) (A)		Firms reporting company-based training equal or above 2 % of the overall annual payroll cost (B)		Firms reporting positive training hours (ref.) (A)		Firms reporting company-based hours of training equal or above 2 % of the total number of worked hours (B)	
	Productivity	Productivity labour cost gap	Productivity	Productivity labour cost gap	Productivity	Productivity labour cost gap	Productivity	Productivity labour cost gap
Log of capital	0.026***	0.010***	0.024***	0.006	0.027***	0.011***	0.025***	0.007*
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
Log of labour	−0.215***	−0.089***	−0.225***	−0.084***	−0.215***	−0.089***	−0.224***	−0.085***
	(0.010)	(0.008)	(0.012)	(0.011)	(0.010)	(0.007)	(0.012)	(0.011)
Share of workers aged 18–29 [ref: 30–49]	−0.077	0.125	0.089	0.231**	−0.068	0.147*	0.120	0.254**
	(0.117)	(0.082)	(0.129)	(0.105)	(0.116)	(0.086)	(0.131)	(0.106)
Share of workers aged 50–64	−0.496***	−0.263***	−0.515***	−0.306***	−0.470***	−0.225***	−0.533***	−0.319***
	(0.043)	(0.031)	(0.054)	(0.056)	(0.042)	(0.030)	(0.056)	(0.058)
Share of blue-collar workers [ref:white coll.]	−0.088***	−0.004	−0.106	−0.056***	−0.083***	0.005	−0.099***	−0.046**
	(0.020)	(0.015)	(0.023)	(0.022)	(0.019)	(0.014)	(0.023)	(0.022)
Share of managers	0.106*	0.116***	0.090**	0.093**	0.112***	0.120***	0.126***	0.128***
	(0.035)	(0.029)	(0.042)	(0.042)	(0.034)	(0.028)	(0.044)	(0.045)
Log of hours worked per employee	0.682***	0.008	0.661***	−0.005	0.681***	0.005	0.656***	−0.009
	(0.010)	(0.011)	(0.012)	(0.013)	(0.010)	(0.011)	(0.013)	(0.013)
No. obs.	23,217		17,882		23,416		17,782	

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List of instruments: log of capital, share of blue-collars, share of managers, log of hours worked per employee, lag1/3(log of labour, share of 18–29, share of 50,64), _cons. Orthogonality conditions used to identify endog. Labour inputs: Innovation in $\omega_{it} \perp\!\!\!\perp L_{1/3}$ labour inputs. All data are deviations from region + year interacted with NACE2 industry means. See Table 7, "Appendix" for NACE2 classification of industries

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 14 (Detailing Table 1)—Bel-first/Carrefour panel, main variables, definition

Variable	Definition (by default, source is Bel-first)
[1] Value added per worker (log)	Value added, in th. euros, divided by the overall number of worker [3]
[2] Labour cost per worker (log)	Labour cost, which is measured independently of value added, includes the value of all monetary compensations paid to the total labour force (both full- and part-time, permanent and temporary), including social security contributions paid by the employers, throughout the year
[3] Number of workers (log)	Total number of workers employed in the firm (averaged over the year). NB: our overall sample excludes firms with less than 20 employees
[4] Capital (th. €) (log)	Capital, in th. euros (includes intangible assets)
[5] Workers aged 18–29/total workforce [6] Workers aged 30–49/total workforce [7] Workers aged 50–65/total workforce	The age of (all) workers employed by the firm [3] is retrieved from the Belgium's Social Security register (the so-called Carrefour database), using firms' unique identifying code
[8] Use of intermediate input (th. €)	Measured directly. It corresponds to the value of goods and services consumed or used up as inputs in production by enterprises, including raw materials, services and other operating expenses
[9] Blue-collar workers/total workforce [10] White-collar workers/total workforce [11] Managers/total workforce	Breakdown of the total number of employees [3] into three categories. (1) blue-collar workers (55 %), (2) those with a managerial status (1 %) and (3) the white-collar category with 44 %) (see Table 1). This distinction cuts across major categories of employment contracts in Belgium: the blue-collar contracts (applicable mostly to manual/low-level functions), white-collars contracts (applicable to intellectual/middle management functions) and managerial ones (use for those occupying intellectual/strategic-decisional positions)

Table 14 continued

Variable	Definition (by default, source is Bel-first)
[12] Number of hours worked annually per employee (log)	Obtained by dividing the total number of hours reportedly worked annually by the number of employees [3]. That variable is strongly correlated with the intensity of part-time work
[13] Training costs/total labour costs (annual basis, %)	Data basis contains (1) the annual number of hours during which workers were trained and (2) the cost of training to the employers. Both are expressed as shares (%) of the total labour cost (also used to compute [2]) or total number of hours worked annually [also used to compute [12])
[14] Training hours/total worked hours (annual basis, %)	
[15] Share of firms in 10–90th perc. size[a] bracket (spells)	Share of spells (i.e. firm by year observations) corresponding to firms that systematically (i.e. during the 9 years of the panel) stay below the 10th percentile and above the 90th percentile of the overall (annual) size distribution; size being defined as the firms' overall labour force [3]
[16] Number of spells	Average number of times (i.e. years) firms are observed in the panel

[a] Average number of hours worked by employee on an annual basis, which is strongly correlated to the incidence of part-time work

Source: Bel-first-Carrefour

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