Boosting the employment rate of older men and women

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An empirical assessment using Belgian firm-level data on productivity and labour costs*

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Abstract

European countries need to expand employment among older individuals. Many papers have examined this issue from different angles. However, very few seem to have considered its gender dimension properly, despite evidence that lifting the overall senior employment rate requires significantly raising that of women older than 50. The key issue examined by this paper is whether employers are willing to employ more older workers, in particular older women. The answer depends to a large extent on the ratio of older individuals' productivity to their cost to employers. To address this question we tap into a unique firm-level panel of Belgian data to produce robust evidence on the causal effect of age/gender on productivity and labour costs. We take advantage of the panel structure to identify age/gender-related differences from within-firm variation. Moreover, inspired by recent developments in the production function estimation literature, we address the problem of endogeneity of the age/gender mix, using a structural production function estimator (Olley & Pakes, 1996; Levinsohn & Petrin, 2003) alongside IV-GMM methods where lagged value of labour inputs are used as instruments. Our results indicate a small negative impact of larger shares of older men on the productivity-labour cost ratio. An increment of 10%-points of in their share causes a 0.17 to 0.69%-point contraction. However, the main result is that the equivalent handicap with older women is larger, ranging from 1.3 to 2.0%-points. This is not good news for older women's employability. And the vast services industry does not seem to offer working conditions that mitigate older women's disadvantage, on the contrary.

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JEL Classification: J24, C33, D24

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1. Introduction

In most EU countries, demographics (ageing populations[1]) and public policy[2] (reforms aimed at raising the employment rate of older individuals) will combine to increase the share of older workers in the labour force. Across the EU, there is also the fact that older women are clearly less present in employment than older men.[3] But this should change. The first point we raise in this paper is that a greying workforce will also become more female. Two elements combine in support of this prediction. The first one is the lagged effect[4] of the rising overall female participation in the labour force (Peracchi & Welch, 1994).[5] The second factor is labour policy. Policymakers will concentrate on promoting older women's employment because - conditional on a certain young- or prime-age participation record - women still leave the labour market earlier than men[6] (Fitzenberger *et al.*, 2004).

The second focal point of this paper is the idea that higher employment among the older segments of the EU population (male or female) will only materialise if firms are willing to employ these individuals. One cannot take for granted that older individuals who are willing to work - and are strongly enticed to do so because (early) retirement benefits are no longer accessible - do obtain employment. Anecdotal evidence abounds to suggest that firms "shed" older workers. Dorn & Sousa-Poza (2010)[7] 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.

The existing economic literature primarily covers the supply side of the old-age labour market. It examines the (pre)retirement behaviour of older individuals (Mitchell & Fields, 1983) 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

1 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 Belgium, 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).
2 The Lisbon Agenda suggested raising employment of individuals aged 55-64 to at least 50% by 2010.
3 See the European Labour Force Survey (EU-LFS) 2010.
4 Also referred to as a cohort effect.
5 Driven, inter alia, by a higher educational attainment of women and a lower fertility of the younger generations.
6 In other words, life-cycle participation/employment profiles vary by gender. And the female profiles have not changed markedly across cohorts.
7 The International Social Survey Program data (ISSP) allows them to identify individuals who i) were early retirees and ii) assessed their own status as being involuntary, using the item "I retired early - by choice" or "I retired early - not by choice" from the questionnaire.

evidence that easy access[8] and high replacement rates (Blondäl & Scarpetta, 1999; Lefèbvre, 2008; Jousten *et al.*, 2008) 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 poor health status precipitates retirement (Kalwij & Vermeulen, 2008) or the importance of non-economic factors (i.e. family considerations) in the decision of older women to retire (Pozzebon & Mitchell, 1989 ; Weaver, 1994).

The demand side of the labour market for older individuals has started to receive some attention from economists. Several authors have examined the relationship between age and productivity at the level where this matters most: firms. They estimate production functions expanded by the specification of a labour-quality index à la Hellerstein & Neumark (1999) (HN henceforth).[9] 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. Similarly, the analysis of German data by Göbel & Zwick (2009) produces little evidence of an age-related productivity decline. By contrast, Grund & Westergård-Nielsen (2008) find that both mean age and age dispersion in Danish firms are inversely U-shaped in relation to firms' productivity. Finally, Lallemand & Ryck (2009), using Belgian firm-level survey data,[10] show that older workers (>49) are significantly less productive than prime-aged workers, particularly in ICT firms.

But, to adequately assess the effect of age on labour demand, one needs to focus simultaneously on firm-level productivity and pay (or labour costs). Under proper assumptions (see Section 2), this amounts to analysing the sensitivity of the productivity-labour cost ratio 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). These authors estimated productivity and wages equations (using American firm-level data that included information on the age structure of the workforce) and found that both wages and productivity tend to increase with age. Aubert & Crépont (2004, 2007), in turn, observed 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 ratio is observed with rising shares of workers aged over 55. The majority of papers

[8] 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.

[9] 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 productivity.

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

based on firm-level 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 (Myck, 2010), with a negative impact on the productivity-labour cost ratio after 55 (Skirbekk, 2004, 2008). However, van Ours & Stoeldraijer (2010), in their recent analysis of Dutch manufacturing firm-level data, find little evidence of much age-related negative impact on the productivity-labour cost ratio.

Our point is that none of the existing papers has adequately considered the *gender* dimension of ageing, in a context where women are likely to form a growing part of the older labour force. This paper aims at filling that void. We try to assess the current willingness of employers to (re)employ older male and female workers. And we posit that the answer to this question largely depends on how larger shares of older (male or female) workers affect private firms' productivity-labour cost ratio. We assume in particular that a sizeable negative impact of older men/women on that ratio can adversely affect their respective chances of being employed.

In this paper we also use firm-level direct measures of productivity and labour cost. Our Belgian data[11] permit a direct estimation of age-gender/productivity-labour cost ratio profiles, where the parameter estimates associated with the shares of older workers (male and female) in the workforce can be directly interpreted as conducive to weak or strong labour demand or employability (more on this in Section 2). Our measure of firms' productivity (valued added) enhances comparability of data across industries, which vary in their degree of vertical integration (Hellerstein *et al.*, 1999). Moreover, 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. Our data also contain information on firms from the large and expanding services industry[12], where administrative and intellectual work is predominant, and where female employment is important. Many observers would probably posit that age and gender matters less for productivity in a service-based economy than in one where agriculture or industry dominates. Finally, it is worth stressing that our panel comprised a sizeable number of firms (9,000+) and covered a relatively long period running from 1998 to 2006.

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11 The raw firm-level data are retrieved from Belfirst. 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.

12 According 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 earlier. Similar figures and trends characterize other EU and OECD countries.

In this paper, we try to find evidence of a negative (or positive) effect on *i)* average productivity, *ii)* average labour costs and *iii)* the productivity-labour cost ratio[13] of larger shares of older (male and female) workers. We also employ the framework pioneered by HN, which consists of estimating production and/or labour cost functions that explicitly account for labour heterogeneity. Applied to firm-level data, this methodology presents two main advantages. First, it delivers productivity differences across age/gender groups that can immediately be compared to a measure of labour costs differences, thereby identifying the net contribution of an age/gender group to the productivity-labour cost ratio (which can be directly interpreted as conducive to weak or strong employability). Second, it measures and tests for the presence of market-wide impact on the productivity-labour cost ratio that can affect the overall labour demand for the category of workers considered.

The HN methodology is suitable for analysing a wide range of workers' characteristics, such as race, education, gender and marital status, e.g. Hellerstein & Neumark (1999), Hellerstein *et al*.(1999), Borowczyk, Martins & Vandenberghe (2010), and richer data sets regarding employees, *e.g.* Crépon, Deniau & Pérez-Duarte (2002). In this paper, we focus exclusively on gender and age.

From the econometric standpoint, recent developments of HN's methodology have tried to improve the estimation of the production function by the adoption of alternative techniques to deal with a potential heterogeneity bias (unobserved time-invariant determinants of firms' productivity that are correlated with labour inputs) and simultaneity bias (endogeneity in input choices in the short run that includes firm's age-gender mix). A standard solution to the heterogeneity bias is to resort to fixed-effect analysis (FE henceforth), be it via first-differencing or mean-centring of panel data. As to the endogeneity bias, the past 15 years has seen the introduction of new identification techniques.[14] One set of techniques follows the dynamic panel literature (Arellano & Bond, 1991; Aubert & Crépon, 2003; Blundell & Bond, 2000; Göbel & Zwick, 2009; or van Ours & Stoeldraijer, 2010), which basically consists of using lagged values of labour inputs as instrumental variables (IV henceforth). A second set of techniques, initially advocated by Olley & Pakes (1996) or more recently by Levinsohn & Petrin (2003) (LP henceforth), are somewhat more structural in nature. They consist of using observed intermediate input decisions (i.e. purchases of raw materials, services, electricity...) to "control" for (or proxy) unobserved short-term productivity shocks.

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13 Strictly speaking the expression "productivity-labour cost ratio" used throughout this paper refers to the ratio of *i)* the difference between a firm's value added (*Y*) and its labour costs (*W*), and *ii)* to the firm's labour costs, i.e. (*Y-W)/W*.

14 See Ackerberg, Caves & Frazer (2006) for a recent review.

In this paper, we follow these most recent applications of HN's methodology. We combine and compare all the above-mentioned econometric techniques (FE, IV, OP-LP). Our main results are all based on within-firm variation that we derive from the use of FE (namely first differences). What is more, to control for the potential endogeneity of the share of old men and women employed by firms, in our preferred estimation methods we combine first differences with *i)* IV techniques and *ii)* the LP intermediate-goods proxy approach, which we implement using information on firms' varying level of intermediate consumption.[15]

The lax rules in terms of access and relatively high replacement rates characterizing the Belgian (pre)pension regimes are traditionally emphasized to explain the country's low employment rate among individuals aged 50 and over. This paper contains evidence that the latter could also be demand-driven. Firms based in Belgium face financial disincentives to employing older workers - particularly older women. Our most important results in this respect are those derived from the regression of the productivity-labour cost ratio on the share of older men and women. Using prime-age men as a reference, we show that a 10%-points rise in the share of older men causes a modest 0.16 to 0.69%-point reduction in the productivity-labour cost ratio. However, the situation is different for older women. Our preferred estimates suggest that a 10%-points expansion of their share in the firm's workforce causes a 1.3 to 2%-points reduction in the productivity-labour cost ratio; something that negatively affects their employability. Using prime-age women as a reference, we find that 10%-points expansion of old women's share causes a contraction of the productivity-labour cost ratio in the range of 1.1 to 1.24%-points. And these negative effects are even larger when we restrict the analysis to subsamples of firms (i.e. balanced panel, services industry). The ultimate point is that these results raise questions about the feasibility, in the current context, of a policy aimed at boosting the employment rate of older women.

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

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[15] It is calculated here as the differences between the firm's turnover (in nominal terms) and its net value added. It reflects the value of goods and services consumed or used up as inputs in production by enterprises, including raw materials and services bought on the market.

2. Methodology

In order to estimate age-gender productivity profiles, following most authors in this area, we consider a Cobb-Douglas production function (Hellerstein *et al.*, 1999; Aubert & Crépon, 2003, 2007; Dostie, 2006; van Ours & Stoeldraijer, 2010):

$$ln\,(Y_{it}/L_{it}) = lnA + \alpha\, ln\, QL_{it} + \beta\, lnK_{it} - lnL_{it} \qquad (1)$$

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 substitutable 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:

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

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 equation (2) becomes:

$$ln\, QL_{it} = ln\, \mu_0 + lnL_{it} + ln\,(1 + \sum_{k>0} (\lambda_k - 1)\, P_{ikt}) \qquad (3)$$

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 .

Since $ln(1+x) \approx x$, we can approximate (3) by:

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

And the production function becomes:

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

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

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

where:

$B=lnA+\alpha\ ln\ \mu_0$
$\lambda_k=\mu_k/\mu_0 \qquad k-=1...N$

$\eta_1 = \alpha\ (\lambda_1 - 1)$
….
$\eta_N = \alpha\ (\lambda_N - 1)$
$l_{it}=lnL_{it}$
$k_{it}=lnK_{it}$

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

[16] Does all this matter in practice? Our experience with firm-level data suggests values for β 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 valye). This means that λ_k are larger (in absolute value) than η_k.. If anything, estimates reported in the first column of Tables 2, 3 and Appendix 2 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 sectoral wage effects.

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

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 $P_{ik}= L_{ik}/L_{i0}$ 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:

$$ln\ (W_{it} /L_{it})= B^w + \eta^w{}_1\ P_{i1t} + \ldots\ \eta^w{}_N\ P_{iNt} \qquad (9)$$

where:

$$B^w = ln\ \pi_0$$
$$\eta^{\mathbf{w}}{}_1 = (\Phi_1 - 1)$$
$$\ldots.$$
$$\eta^{\mathbf{w}}{}_N = (\Phi_N - 1)$$

Like in the average productivity equation (6) coefficients $\eta^w{}_k$ 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 ratio for type k worker implies $\eta_k = \eta^w{}_k$. 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 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 equation (9). Considering three age groups (1=[20-29], 2=[30-49]; 3=[50-64[) and with prime-age (30-49) male workers forming the reference group, we get.

$ln(Y_{it}/L_{it})=B+(\alpha-1)l_{it}+$

$$\eta_{1m}P_{it}^{m18\text{-}29}+\eta_{3m}P_{it}^{m50\text{-}64}+\eta_{1f}P_{it}^{f18\text{-}29}+\eta_{2f}P_{it}^{f30\text{-}49}+\eta_{3f}P_{it}^{f50\text{-}64}+\beta k_{it}+\gamma F_{it}+\varepsilon_{it} \quad (10)$$

$ln\ (W_{it}/L_{it})=B^{W}+(\alpha^{W}-1)l_{it}+$

$$\eta^{W}{}_{1m}P_{it}^{m18\text{-}29}+\eta^{W}{}_{3m}P_{it}^{m50\text{-}64}+\eta^{W}{}_{1f}P_{it}^{f18\text{-}29}+\eta^{W}{}_{2f}P_{it}^{f30\text{-}49}+\eta^{W}{}_{3f}P_{it}^{f50\text{-}64}+\beta^{w}k_{it+}\ \gamma^{W}F_{it}+\varepsilon^{w}{}_{it} \quad (11)$$

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 ratio[19] as a linear function of its workforce determinants.

$Ratio_{it}\equiv ln\ (Y_{it}/L_{it})-ln\ (W_{it}/L_{it})=B^{G}+(\alpha^{G}-1)l_{it}+$

$$\eta^{G}{}_{1m}P_{it}^{m18\text{-}29}+\eta^{G}{}_{3m}P_{it}^{m50\_64}+\eta^{G}{}_{1f}P_{it}^{f18\text{-}29}+\eta^{G}{}_{2f}P_{it}^{f30\text{-}49}+\eta^{G}{}_{3f}P_{it}^{f50\text{-}64}+\beta^{G}k_{it}+\gamma^{G}F_{it}+\varepsilon^{G}{}_{it} \quad (12)$$

where: $B^{G}=B-B^{w}$; $\alpha^{G}=\alpha-\alpha^{W}$, $\eta^{G}{}_{1m}=\eta_{1m}-\eta^{w}{}_{1m}$; $\eta^{G}{}_{3m}=\eta_{3m}-\eta^{w}{}_{3m}$; $\eta^{G}{}_{1f}=\eta_{1f}-\eta^{w}{}_{1f}$; $\eta^{G}{}_{2f}=\eta_{2f}-\eta^{w}{}_{2f}$; $\eta^{G}{}_{3f}=\eta_{3f}-\eta^{w}{}_{3f}$; $\gamma^{G}=\gamma-\gamma^{w}$ and $\varepsilon^{G}{}_{it}=\varepsilon_{it}-\varepsilon^{w}{}_{it}$.

It is immediate to see that coefficients η^{G} of equation (12) provide a direct estimate of how the productivity-labour cost ratio 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} . The latter comprises total labour/firm size (*l*) and the amount of capital (*k*). In all the estimations presented hereafter F_{it} also contains region[20], year and 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 & Neumark, 1999). More importantly, since the data set we use do not

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[18] Labour costs used in this paper, which were measured independently of net-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.

contain sector price deflators, the introduction of these dummies can control for asymmetric variation in the price of firms' outputs at 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 there is proportional variation in wages by age/gender group along those dimensions (Hellerstein *et al.*, 1999).

It is also worth stressing the inclusion in F_{it} of firm-level information on 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). The resulting 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 reasonably to control for this likely source of bias when studying the causal relationship between age-gender and productivity, labour cost or the ratio between these two.

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

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

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

In other words, the OLS sample-error term potentially consists of *i)* an unobservable firm fixed effect θ_i; *ii)* a short-term shock that is anticipated by the firm (but not by the econometrician), ω_{it} , and, *iii)* 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, the overall stock of human capital[23], firm-specific managerial skills, location-driven comparative advantages.[24] And these might be correlated with the age-gender structure of the firm's workforce, biasing OLS results. Older workers for instance might be overrepresented among plants built a long time ago using older technology. However, the panel structure of our data allows for the estimation of models with firm

[22] And its equivalent in equation (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.

fixed effects (FE). The results from the FE estimation (using first differences in our case) can be interpreted as follows: a group (e.g. male or female) 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). Algebraically, the estimated FE model corresponds to

$$\Delta ln\ (Y_{it}/L_{it}) = \Delta B + (\alpha - l)\ \Delta l_{it} + \eta_{1m}\Delta P_{it}^{m18\text{-}29} + \eta_{3m}\Delta P_{it}^{m50\text{-}64} + \eta_{1f}\Delta P_{it}^{f18\text{-}29} + \eta_{2f}\Delta P_{it}^{f30\text{-}49} + \eta_{3f}\Delta P_{it}^{f50\text{-}64} + \beta^{w}\ \Delta k_{it} + \gamma \Delta F_{it} + \Delta \varepsilon_{it} \quad (14)$$

$$\Delta ln\ (W_{it}/L_{it}) = \Delta B^{W} + (\alpha^{w} - l)\ \Delta l_{it} + \eta_{1m}\Delta P_{it}^{m18\text{-}29} + \eta_{3m}\Delta P_{it}^{m50\text{-}64} + \eta_{1f}\Delta P_{it}^{f18\text{-}29} + \eta_{2f}\Delta P_{it}^{f30\text{-}49} + \eta_{3f}\Delta P_{it}^{f50\text{-}64} + \beta^{w}\ \Delta k_{it} + \gamma^{w}\Delta F_{it} + \Delta \varepsilon^{w}_{it} \quad (15)$$

$$\Delta Ratio_{it} = \Delta B^{G} + \alpha^{G}\Delta l_{it} + \eta_{1m}\Delta P_{it}^{m18\text{-}29} + \eta_{3m}\Delta P_{it}^{m50\text{-}64} + \eta_{1f}\Delta P_{it}^{f18\text{-}29} + \eta_{2f}\Delta P_{it}^{f30\text{-}49} + \eta_{3f}\Delta P_{it}^{f50\text{-}64} + \beta^{G}\ \Delta k_{it} + \gamma^{G}\Delta F_{it} + \Delta \varepsilon^{G}_{it} \quad (16)$$

where the Δ operator reflects first differences. With FE estimation the error term of the production equation becomes:

$$\Delta \varepsilon_{it} = \Delta \omega_{it} + \Delta \sigma_{it} \quad (17)$$

where $cov(\Delta\omega_{it}, \Delta P_{it}^{k}) \neq 0$ and $E(\Delta\sigma_{it}) = 0$

This said, the greatest econometric challenge is to go around the simultaneity/endogeneity bias (Griliches & 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 $\Delta\omega_{it}$). An anticipated downturn can translate into a recruitment freeze. Since the latter predominantly affects youth, we should expect that the share of older (male/female) workers to increase during negative spells, and decrease during positive ones. This would generate negative correlation between the share of older (male/female) workers and the productivity of firms, thereby leading to underestimated estimates of the their relative productivity when resorting to OLS or even FE estimates.

To account for the presence of this endogeneity bias we first estimate the relevant parameters of our model using IV techniques. This is a strategy regularly used in the production function literature with labour heterogeneity (Aubert & Crépon, 2003, 2007; van Ours & Stoeldraijer, 2010). Our choice is to instrument the potentially endogenous first-differenced worker shares (ΔP_{it}^{k}) with their second differences (ΔP_{it}^{k} - ΔP_{it-1}^{k}) and lagged second differences (ΔP_{it-1}^{k}- ΔP_{it-2}^{k}) *i.e.* past changes of the annual variations of the worker age/gender mix. The key assumptions are that these past changes are *i)* uncorrelated with current year-to-year changes of the productivity term $\Delta\omega_{it}$, but *ii)* still reasonably correlated with those of the workers' shares ΔP_{it}^{k}.

An alternative to IV that seems promising and relevant it to adopt the more structural approach initiated by Olley & Pakes (1998) (OP hereafter) and further developed by Levinsohn & Petrin (2003), and used recently by Dostie (2006). The essence of the OP approach is to use some function of a firm's investment to control for 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. Whenever information of intermediate inputs is available in a data set — which happens to be the case with ours — it can be used to proxy short-term productivity deviations.

Following OP, LP assume that the demand for intermediate inputs (int_{it}) is a function of the time-varying unobserved productivity level ω_{it} as well as the current level of capital:

$$int_{it} = f(\omega_{it}, k_{it}) \tag{18}$$

LP further assume that this function is monotonic in ω_{it} and k_{it}, meaning that it can be inverted to deliver an expression of ω_{it} as a function of int_{it} and k_{it}. In the LP framework, the residual (13) becomes:

$$\varepsilon_{it} = \theta_i + f^{1}(int_{it}, k_{it}) + \sigma_{it} \tag{19}$$

And LP argue that $\omega_{it}=f^{1}(int_{it}, k_{it})$ that can be approximated by a 3rd order polynomial expansion in int_{it} and k_{it}.. We replicate this strategy here. However, unlike LP or OP, we do this in combination with first differences to account for firm fixed effects θ_i. In a sense, we stick to what has traditionally been done in the dynamic panel literature underpinning the IV 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 LP approach in order to invert out ω_{it}, and completely remove the endogeneity problem.

Algebraically, our strategy simply consists of implementing LP to variables (the initial ones + those generated to form the LP polynomial expansion term[25]) that have been first-differenced. Justification is straightforward. First-differencing means that one deals with an expression of the residuals equals to

$$\Delta\varepsilon_{it} = \Delta\big(f^{1}(int_{it}, k_{it})\big) + \Delta\sigma_{it} \quad (20)$$

If one assumes, like LP, that the inverse demand function f^{1} *(.)* can be proxied by a 3rd order polynomial expansion in int_{it} and $k_{it,}$, that expression becomes

$$\Delta\varepsilon_{it} = \Delta\big(\chi + \upsilon_1\, int_{it} + \ldots + \upsilon_3\, int^3_{it} + \upsilon_4\, k_{it} + \ldots + \upsilon_5\, k^3_{it} + \upsilon_6\, int^2_{it}k_{it} + \upsilon_7\, int_{it}k^2_{it} + \ldots\big) + \Delta\sigma_{it} \quad (21)$$

As the first-difference operator applies to a *linear* expression, the above notation is thus equivalent to

$$\Delta\varepsilon_{it} = \upsilon_1\, \Delta int_{it} + \ldots + \upsilon_3\, \Delta(int^3_{it}) + \upsilon_4\, \Delta k_{it} + \ldots + \upsilon_5\, \Delta(k^3_{it}) + \upsilon_6 \Delta(int^2_{it}k_{it}) + \upsilon_7\, \Delta(int_{it}k^2_{it}) + \ldots + \Delta\sigma_{it} \quad (22)$$

3. Data description

As already stated, we are in possession of a panel of around 9,000 firms with more than 20 employees, largely documented in terms of sector, location, size, capital used, labour cost levels and productivity (value added). 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/gender of (all) workers employed by these firms, and this for a period running from 1998 to 2006.

A weakness of our dataset is that is does not contain the workers' educational attainment. The point is that younger cohorts are better-educated and, for that reason, potentially more productive than older ones. As we do not control for educational attainment, how much is this likely to bias our productivity-by-age (and gender) estimates? Not so much, we think, for two reasons. First, although we do not observe education, our vector of controls F_{it} comprises good firm-level proxies for education (i.e. the share or blue-collar workers and the share of managers). Second, as stated above, we identify the effect of age on productivity from within-firm variation of age/gender shares over (panel/observation) time. With first differences, identification comes from the comparison

[25] $int_{it}, int^2_{it}, int^3_{it}, k_{it}, k^2_{it}, k^3_{it}, int^2_{it}k_{it}, int_{it}k^2_{it}\ldots$

between *i)* productivity gains achieved by firms with rising shares of old (50-64) workers *ii)* and those obtained by firms with no (or less of) such rises. How do the two types of firms compare in terms of cohort changes between *t* and *t+1*? By definition, the average year of birth rose in both types of firms. In a panel, cohort/year-of-birth and time of observation are monotonically related: individuals belonging to a particular age band in *t+1* are more likely to belong to younger cohorts than those observed in *t* in the same age band. Still, the workers' average year of birth has probably risen more in the second type of firms, due to a more pronounced propensity to replace older workers by younger ones. But even so, we would argue that the resulting asymmetries in terms human capital dynamics (not captured by the firm-level proxies mentioned above) are unlikely to correlate with short-term productivity differences across the two types of firms. This is because it probably takes time for firms to mobilise the extra (general) human capital younger cohorts bring along.

Descriptive statistics are reported in Table 1. They suggest that firms based in Belgium have been largely affected by ageing over the period considered. Table 1 shows that between 1998 and 2006, the mean age of workers active in private firms located in Belgium rose by almost 3 years: from 36.2 to 39.1. This is very similar what has occurred Europe-wide. For instance Göbel & 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. Table 1 also shows that, in the Belgian private economy, between 1998 and 2006, the percentage of old male workers (50-65) has risen steadily from 10% to almost 15%. And the proportion of older women has risen even more dramatically, from 2% to 4.1%.

Intermediate inputs pay a key role in our analysis, as they are central to one of the two strategies we use overcome the simultaneity or endogeneity bias (see Section 2). The level of intermediate inputs used by a firm is calculated here as the difference between its turnover (in nominal terms) and net value-added. It reflects the value of goods and services consumed or used up as inputs in production by that firm, including raw materials, services and various other operating expenses (see 4th column from the right in Table 1 for descriptive statistics).

Table 1: Belfirst-Carrefour unbalanced panel. Basic descriptive statistics: mean (Standard deviation)

								Shares (male)			Shares (female)						
Year	**Firms**	**Productivity (i.e. value-added) per worker (in th. €)**	**Labour cost per worker (in th. €)**	**Product.-Lab. cost ratio (%)**	**Firm size (# workers)**	**Capital (in th. €)**	**Mean age**	**18-29**	**30-49**	**50-64**	**18-29**	**30-49**	**50-64**	**Intermediate goods cons. (in th. €)**	**Share of blue-collar workers**	**Share of managers**	**Hours worked annual per worker**
1998	8265	66.03	39.01	0.40	107.86	6402	36.16	0.338	0.298	0.100	0.147	0.095	0.021	27991	0.57	0.01	1661.07
		(106.59)	(26.81)	(0.40)	(474.31)	(95642)	(4.29)	(0.18)	(0.16)	(0.09)	(0.17)	(0.11)	(0.04)	(158639)	(0.35)	(0.05)	(270.46)
1999	8431	69.10	40.29	0.40	111.05	6561	36.44	0.326	0.303	0.105	0.144	0.100	0.022	28466	0.57	0.01	1659.24
		(182.35)	(23.94)	(0.42)	(474.76)	(99485)	(4.24)	(0.17)	(0.15)	(0.09)	(0.16)	(0.11)	(0.04)	(162346)	(0.35)	(0.04)	(272.37)
2000	8624	69.46	41.26	0.39	113.75	6843	36.65	0.315	0.305	0.109	0.143	0.104	0.024	34447	0.56	0.01	1639.33
		(110.10)	(22.91)	(0.42)	(471.75)	(107777)	(4.21)	(0.17)	(0.15)	(0.09)	(0.16)	(0.11)	(0.04)	(222657)	(0.35)	(0.05)	(252.62)
2001	8825	69.47	42.73	0.37	121.06	7424	37.01	0.303	0.310	0.114	0.139	0.109	0.026	35869	0.55	0.01	1623.49
		(99.05)	(23.95)	(0.40)	(511.26)	(114725)	(4.19)	(0.16)	(0.15)	(0.10)	(0.15)	(0.11)	(0.05)	(256231)	(0.35)	(0.04)	(257.45)
2002	8966	71.96	44.67	0.35	127.59	7960	37.39	0.291	0.315	0.118	0.134	0.113	0.028	37472	0.54	0.01	1611.62
		(189.14)	(34.31)	(0.39)	(689.97)	(125480)	(4.16)	(0.16)	(0.15)	(0.10)	(0.15)	(0.11)	(0.05)	(271372)	(0.35)	(0.04)	(253.42)
2003	9051	73.19	45.47	0.35	127.35	8390	37.99	0.277	0.316	0.131	0.128	0.115	0.032	38153	0.54	0.01	1597.14
		(101.82)	(23.95)	(0.39)	(643.51)	(133174)	(4.26)	(0.15)	(0.15)	(0.10)	(0.14)	(0.11)	(0.05)	(254540)	(0.35)	(0.04)	(228.56)
2004	9060	76.49	46.95	0.37	129.36	8725	38.35	0.267	0.320	0.137	0.123	0.119	0.034	42160	0.54	0.01	1611.07
		(91.16)	(26.27)	(0.38)	(644.25)	(141718)	(4.28)	(0.15)	(0.15)	(0.11)	(0.14)	(0.12)	(0.05)	(296393.55)	(0.35)	(0.03)	(226.40)
2005	9036	78.86	48.26	0.36	131.55	7976	38.73	0.258	0.323	0.142	0.117	0.122	0.037	47597	0.53	0.01	1594.23
		(101.11)	(28.32)	(0.40)	(644.64)	(60537)	(4.24)	(0.15)	(0.15)	(0.11)	(0.13)	(0.12)	(0.05)	(416162)	(0.35)	(0.04)	(228.21)
2006	8936	81.10	49.31	0.37	133.41	8155	39.11	0.249	0.322	0.149	0.113	0.125	0.041	52837	0.52	0.01	1572.85
		(96.90)	(30.24)	(0.41)	(638.59)	(59825)	(4.25)	(0.14)	(0.14)	(0.11)	(0.13)	(0.12)	(0.06)	(510248)	(0.35)	(0.04)	(211.68)

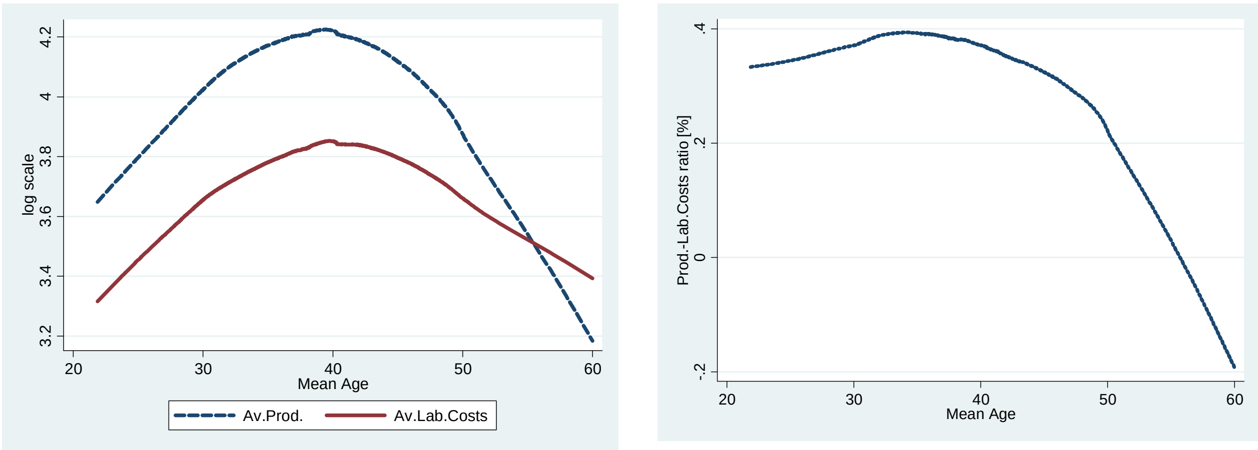
Source: Belfirst-Carrefour panel, our calculus

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 Figure 1 corresponds to the difference between these two curves which is equal to the productivity-labour cost ratio.[26] These stylised facts suggests that, in the Belgian private economy, the productivity-labour cost ratio 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 or older (50-64) men or women and the productivity-labour cost ratio. It suggests that firms employing shares of older men and women in excess of the 7-8% threshold have a significantly smaller productivity-labour cost ratio. It is also shows that firms employing a given share of older women systematically achieve a lower ratio than firms employing the same share of older men.

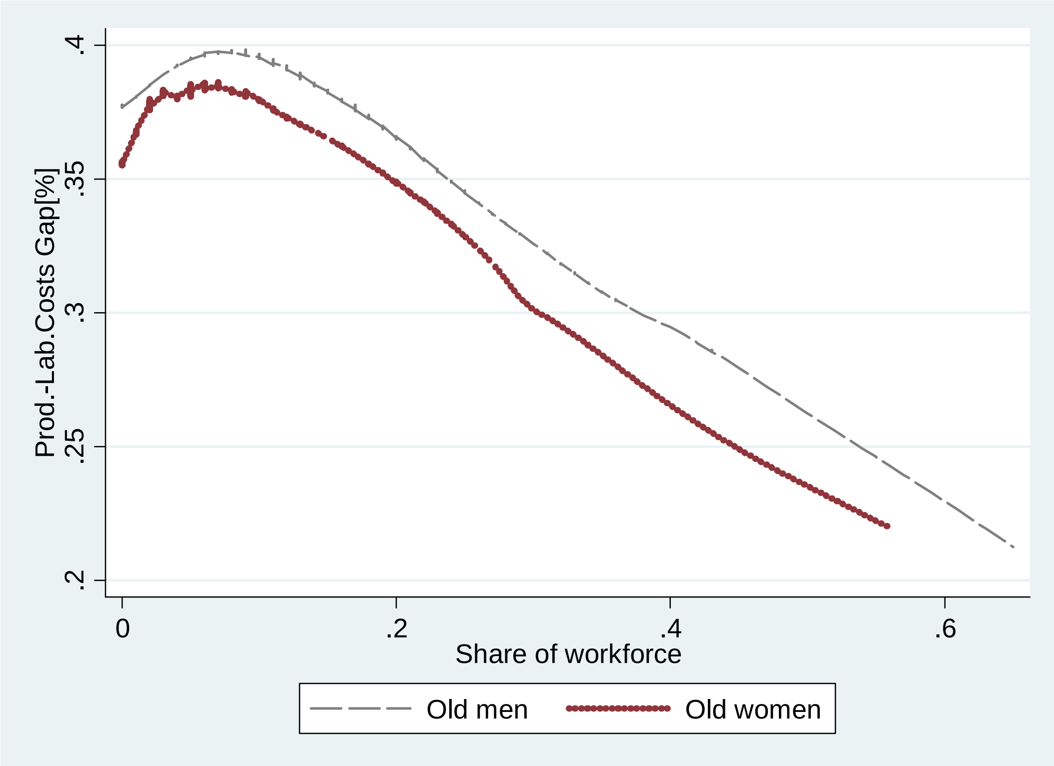
[26] Logarithms, used in conjunction with differencing, convert absolute differences (*Y-W)* into relative differences: i.e. (*Y-W)/W*.

Figure 1: (Left panel) Average productivity and average labour costs. (Right panel) Productivity-Labour cost ratio (%) 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 labour costs ratio [right panel]) on *x* (i.e. mean age). OLS estimates of *y* are fitted for each subsets of *x*. This method does not required to specify 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.

Figure 2: Productivity-Labour cost ratio (in %) according to share of older men or women



Curves on display correspond to locally weighted regression of *y (productivity-labour cost ratio)* on *x (shares)*. It does this by fitting an OLS estimate of *y* for each subsets of *x*. This method does not require to specify 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.

4. Econometric results

Table 2 presents the parameter estimates of the average productivity (see equation 10, Section 2), labour costs (equation 11) and productivity-labour cost ratio equations (12), under four alternative econometric specifications. Note that, with equation (12) being the difference between equation (10) and equation (11), it is logical to verify that $\eta\text{-}\eta^{W}\approx\eta^{G}$ for each age/gender 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 2 we use all available observations forming of our (unbalanced) panel.

The first set of parameter estimates come from OLS, using total variation [1]. Then come first differences (FD), where parameters are estimated using only within-firm variation [2]. The next strategy [3] consists of using first-differenced variables and instrumenting the workforce share first differences with second differences and lagged second differences. The last model [4] combines first differences and the LP intermediate-goods proxy idea.

Although they come at the cost of reduced sample sizes, estimations [3] [4] in Table 2 are *a priori* the best insofar as *i)* the parameters of interest are identified from within-firm variation to control for firm unobserved heterogeneity, and *ii)* that they control for short-term endogeneity biases either via the use of LP's intermediate input proxy, or internal instruments (second differences, lagged second differences). In the latter case, note that we estimate the relevant parameters of our model using the General Method of Moments (GMM), known for being more robust to the presence of heteroskedasticity.[27]

Heterogeneity bias might be present since our sample covers all sectors of the Belgian private economy and the list of controls included in our models is limited. Even if the introduction of the set of dummies (namely year, sector and region) in F_{it} can account for part of this heterogeneity bias, first-differencing as done in [2], [3] or [4] is still the most powerful way out. But first differences alone [2] are not sufficient. The endogeneity in labour input choices is well documented problem in the production function estimation literature (*e.g*. Griliches & Mairesse, 1995) and also deserved to be properly and simultaneously treated. And this is precisely what we have attempted to do in [3] and [4] by combining first differences with techniques like IV-GMM or LP.

To assess the credibility of our IV-GMM approach [3] we performed a range of diagnostic tests. First, an Anderson correlation relevance test. If the correlation between the instrumental variables and the endogenous variable is poor (*i.e.* if we have "weak" instruments) our parameter estimate may be biased. The null hypothesis is that the instruments are weak (correlation in nil). Rejection of the null hypothesis (low p-values) implies that the instruments pass the weak instruments test, i.e. they are highly correlated with the endogenous variables. In all our GMM estimates reported in Table 2 our instruments pass the Anderson correlation relevance test. Second, to further assess the validity of our instrument we use the Hansen-Sargan test. – also called Hansen's J test – of overidentifying restrictions. The null hypothesis is that the instruments are valid instruments (i.e., uncorrelated with the error term), and that the instruments are correctly "excluded" from the estimated equation. Under the null, the test statistic is distributed as chi-square in the number of overidentifying restrictions. A failure to reject the null hypothesis (high p-values) implies that the instruments are exogenous. In all our IV-GMM estimates we cannot reject the null hypothesis that these restrictions are valid.

[27] Our estimates are based on Stata's "ivreg2" suite, with the "gmm" option

In Table 2, parameter estimates (η) for the average productivity equation support the evidence that older worker (50-65) - both men and women - are less productive than prime-age (30-49) male workers (our reference category). Sizeable (and statistically significant) negative coefficients are found across the range of models estimated. Those from the LP model [4] suggest that an increase of 10%-points in the share of old male workers depresses productivity by 1.15%-points. Model [3], based on IV-GMM, points at a smaller (not statistically significant) drop by only 0.39%-point.

As to old women both IV-GMM [3] and the LP model [4] deliver large negative estimates of the impact of larger shares of old women on productivity. An increase of 10%-points in the share of older female workers reduces productivity by 2.52%-points [3] to 2.5% -points [4].

Turning to the average labour cost coefficients (η^W), we see that those for older men and women are very similar once we control for firm heterogeneity and/or simultaneity [3][4]. They are negative but of small magnitude, although often statistically significant at the 10% level. Estimates for model [4] show that a 10%-points rise of the share of older male (female) workers reduces average labour cost by 0.46%-point (1.2%-point respectively). In short, particularly for men we do not find strong evidence of age-related decline of average labour costs in the Belgian private sector economy; something that accords relatively well with the country well-established tradition of seniority-based wage progression.

However, regarding the labour demand for older men and women, the most important parameters are those of the productivity-labour cost ratio equation (η^G). Their sign informs as to whether a lower productivity is fully compensated by lower labour costs. Remember that we posit that a negative (and statistically significant) coefficient is a indication that the category of workers is less employable than the reference category. Results for old men are mixed. Model [3] delivers negative but not statistically significant results. Model [4] suggests that a 10%-points rise of their share causes a modest 0.69%-point reduction of the productivity-labour cost ratio. Those for model [3] are not statistically significant.

The situation is completely different for old women. Model [3] suggests that a 10%-points expansion of their share in the total workforce causes a 2%-points reduction of the productivity-labour cost ratio. And model [4] points to a 1.3%-points drop of that ratio.

Table 2 - Parameter estimates (*standard errors*[£]). Older (50-64) male/female and prime-age (30-49) female workers productivity (η), average labour costs(η^w) and productivity-labour cost ratio (η^G). Overall, unbalanced panel sample.

	[1]-OLS	**[2]-First Differences**	**[3]-First Differences+ IV-GMM**	**[4]- First Differences + intermediate inputs LP[$$]**
		Share of 50-64 (Men)		
Productivity (η_{3m})	-0.233***	-0.095***	-0.039	-0.115***
std error	*(0.023)*	*(0.028)*	*(0.038)*	*(0.035)*
Labour Costs (η^w_{3m})	-0.176***	-0.023*	-0.020	-0.046***
std error	*(0.013)*	*(0.012)*	*(0.016)*	*(0.014)*
Prod.-Lab. Costs ratio (η^G_{3m})	-0.063***	-0.071***	-0.016	-0.069**
std error	*(0.020)*	*(0.027)*	*(0.037)*	*(0.034)*
		Share of 30-49 (Women)		
Productivity (η_{2f})	-0.293***	-0.035	-0.114**	-0.034
std error	*(0.021)*	*(0.033)*	*(0.046)*	*(0.040)*
Labour Costs (η^w_{2f})	-0.351***	-0.042***	-0.033*	-0.027*
std error	*(0.012)*	*(0.014)*	(0.019)	*(0.016)*
Prod.-Lab. Costs ratio (η^G_{2f})	0.053***	0.005	-0.081*	-0.006
std error	*(0.018)*	*(0.032)*	*(0.045)*	*(0.040)*
		Share of 50-64 (Women)		
Productivity (η_{3f})	-0.610***	-0.229***	-0.252***	-0.250***
std error	*(0.039)*	*(0.053)*	*(0.071)*	*(0.063)*
Labour Costs (η^w_{3f})	-0.643***	-0.060***	-0.052*	-0.120***
std error	*(0.022)*	*(0.023)*	*(0.029)*	*(0.025)*
Prod.-Lab. Costs ratio (η^G_{3f})	0.022	-0.169***	-0.201**	-0.130**
std error	*(0.033)*	*(0.052)*	*(0.070)*	*(0.061)*
Controls	capital, number of employees,hours worked per employee[a], share of blue-collar workers, share of managers + fixed effects: year, nace2, region	capital, number of employees, hours worked per employee[a], share of blue-collar workers, share of managers + fixed effects: year, **firm**	capital, number of employees, hours worked per employee[a], share of blue-collar workers, share of managers + fixed effects: year, **firm**	capital, number of employees, hours worked per employee[a], share of blue-collar workers, share of managers + fixed effects: year, **firm**
Test			Instruments: second differences and lagged second differences. **IV relevance**: Anderson canon. corr. LR statistic√ **Overidentifying restriction**: Hansen J statistic √	
Nobs.	76,341	66,383	49,207	52,160

a: Average number of hours worked by employee on an annual basis, which is strongly correlated to the incidence of part-time work.
£:Standard errors estimates are robust to firm-level clustering
*p < 0.05, **p < 0.01, *** p < 0.001
[$] Levinsohn and Petrin

Table 3 contains a series of important results that can be derived from a further analysis of those displayed in Table 2. The first column simply reproduces the estimates for the average productivity and productivity-labour cost ratio equations, using our preferred estimation strategies [3] [4]. The following columns contain the results of three *hypothesis tests* aimed at answering key questions about age and gender. First, are old women (50-64) less productive [and less employable, due to a lower productivity-labour cost ratio] than old men? The question amounts to verifying that $\eta_{3m} > \eta_{3f}$ [$\eta^G_{3m} > \eta^G_{3f}$] in absolute value and testing H0: $\eta_{3m} = \eta_{3f}$ for productivity [H0: $\eta^G_{3m} = \eta^G_{3f}$ for employability]. Results for IV-GMM model [3] point to a 21.3%-points productivity handicap for old women relative to old men. In terms of employability their handicap is of 18.4%-points. Both estimates are highly statistically significant.

The second question that can be addressed is whether old women's productivity[employability] handicap relative to old men is driven by more pronounced effects of age on women than on men's productivity[employability]. To that purpose we can first check whether age negatively affects the productivity[employability] of men and women separately. As already stated above, the evidence for old vis-à-vis prime-age male workers (ie. estimated η_{3m} [η^G_{3m}]) is mixed. Results for the IV model [3] suggest an absence of significant deterioration of productivity[employability], whereas LP model [4] is supportive of such a deterioration: -11%-points in terms of productivity and -6.9% in terms of employability. Assessing the situation of older women is less immediate and requires hypothesis testing (ie. rejecting H0: $\eta_{2f} = \eta_{3f}$ [H0: $\eta^G_{2f} = \eta^G_{3f}$]). Results for IV model [3] point to a 13.8%-points statistically-significant productivity handicap for old women relative to prime-age women. In terms of employability, the handicap is of 11.9%-points. Similar results are obtained with LP model [4], namely a productivity handicap of 21.7%-points, and an employability handicap of 12%-points. Furthermore, we can test whether age affects more women's than men's productivity[employability] by testing H0: $\eta^G_{3f} - \eta^G_{2f} = \eta^G_{3m}$ [H0: $\eta_{3f} - \eta_{2f} = \eta_{3m}$]. Results point to a 9 to 10%-points handicap of women vis-à-vis men in terms of age-related productivity decline, and a 5.4 to 10%-points handicap in terms of employability decline. But none of these estimates appear statistically significant.

Table 3 – Parameter estimates (*standard errors*[£]) and hypothesis testing. Older (50-64) male/female and prime-age (30-49) female workers productivity (η), average labour costs(η^{w}) and productivity-labour cost ratio (η^{G}). Overall, unbalanced panel sample.

	Coefficient	Hyp Test $\eta_{3f}=\eta_{3m}$			Hyp Test $\eta_{3f}=\eta_{2f}$			Hyp Test $\eta_{3f}-\eta_{2f}=\eta_{3m}$		
		$\eta_{3f}-\eta_{3m}$	**F**	**Prob >F**	$\eta_{3f}-\eta_{2f}$	**F**	**Prob >F**	$(\eta_{3f}-\eta_{2f})-\eta_{3m}$	**F**	**Prob >F**
[3] - First Differences+ IV-GMM[$]										
Productivity										
Men 50-64 (η_{3m})	-0.039 *(0.038)*									
Women 30-49 (η_{2f})	-0.114** *(0.046)*	-0.213***	7.75	0.0054	-0.138*	3.75	0.059	-0.099	1.47	0.2256
Women 50-64 (η_{3f})	-0.252*** *(0.071)*									
Prod.-Lab. Costs ratio										
Men 50-64 (η^{G}_{3m})	-0.016 *(0.037)*									
Women 30-49 (η^{G}_{2f})	*-0.081** *(0.045)*	-0.184**	6.11	0.0135	-0.119*	2.94	0.0863	-0.103	1.68	0.1955
Women 50-64 (η^{G}_{3f})	-0.201** *(0.070)*									
[4]- First-Differences + intermediate inputs LP[$$]										
Productivity										
Men 50-64 (η_{3m})	-0.115*** *(0.035)*									
Women 30-49 (η_{2f})	-0.034 *(0.040)*	-0.135*	3.78	0.0518	-0.217***	11.72	0.0006	-0.101	1.91	0.1668
Women 50-64 (η_{3f})	-0.250*** *(0.063)*									
Prod.-Lab. Costs ratio										
Men 50-64 (η^{G}_{3m})	-0.069** *(0.034)*									
Women 30-49 (η^{G}_{2f})	-0.006 *(0.040)*	-0.061	0.80	0.3698	-0.124**	4.01	0.045	-0.054	0.58	0.4470
Women 50-64 (η^{G}_{3f})	-0.130** *(0.061)*									

£:Standard errors estimates are robust to firm-level clustering

*p < 0.05, **p < 0.01, *** p < 0.001

$:IV-GMM: Instruments: second differences and lagged second differences. Tests: IV relevance: Anderson canon. corr. LR statistic √ Overidentifying restriction: Hansen J statistic √

$$: Levinsohn &. Petrin

We have undertaken two further steps in our analysis:

i) 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 (smaller) *balanced* panel[28] 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 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 first-difference estimates) is much less predictable and inadequately captured by the identification strategies mobilised in this paper. Bartelmans & 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.

ii) Second, we examine whether we reach substantially different conclusions, as to the productivity-labour cost ratio gender asymmetry, when we further restrict the sample to the *services industry*. We do this because observers *a priori* posit that age and gender should matter less for productivity in a services-based economy than in one where agriculture or industry dominates.

4.1. Balanced vs. unbalanced panel

Our main analysis so far has been based on unbalanced panel data that comprise all firms available in our sample. By way of sensitivity analysis we now present the parameter estimates (for models [3][4] and only for the productivity and productivity-labour cost ratio equations[29]) based on balanced panel data, consisting only of firms surveyed in each of the 9 years between 1998 and 2006. This subset comprises 7,933 firms (vs. approx. 9,000 in the unbalanced sample). On average

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[28] The sample of firms that are observed observed *every* year between 1998 and 2006.

[29] Those from the labour cost equation (η^W) can be easily inferred from the relationship $\eta + \eta^W \approx \eta^G$

(see Appendix 1 for the details) they are quite similar to those of the unbalanced set, be it in terms of average value-added, labour cost or size...

If anything, the old worker gender asymmetry highlighted with the unbalanced panel now appears stronger. Parameter estimates are exposed on the right-hand side of Table 4, alongside those of Table 3 for comparison purposes. For old men, productivity-labour cost parameter estimates (η^G) are consistently not statistically different from zero: a 10%-points rise of their share causes a 0%-point (IV-GMM [3]) to 0.038%-point drop (LP [4]). By contrast, for older women, both models deliver coefficients that are larger in magnitude than with the unbalanced panel. IV-GMM [3] shows that a 10%-points expansion of their share in the firm's workforce causes a 2.5%-points reduction (vs. 2%-points with the unbalanced panel), whereas LP model [4] points at 1.6%-point fall (vs. 1.3%-point using the unbalanced panel).

Table 4 also contains the results of three cross-gender tests of equality. In short, these tend to reinforce the conclusions obtained with the unbalanced panel. First, old women (50-64) appear significantly less productive and less employable than old men. Results for IV-GMM [3] point to a 25.7%-points productivity handicap (vs. 21.3%-points with the unbalanced panel) of old women relative to old men. In terms of employability the old women's handicap is of 25%-point (vs. 18.4%-points in Table 3). And both estimates are highly statistically significant. The other results on display in Table 4 confirm that age negatively affects the productivity[employability] of women Results for IV-GMM [3] point to a 19.6%-points (vs. 13.8%-points with unbal. data) statistically-significant productivity handicap for old women relative to prime-age women. In terms of employability the handicap rises from 11.9 (unbal.) to 18.3%-points with the balanced panel. Similar results are obtained with LP model [4], namely a productivity handicap rising from 21.7%-points (unbal.) to 24.2%-points. And an employability handicap jumping from 12.4 (unbal.) to 14.7%-points. There is also stronger evidence that age affects more women's than men's productivity[employability]. Results, in the last column of Table 4 show female productivity[employability] handicaps that are systematically above the 10%-points threshold. And most of them are now statistically significant.

Table 4 – Parameter estimates (*standard errors*£) and hypothesis testing. Older (50-64) male/female and prime-age (30-49) female workers productivity (η), average labour costs(η^{w}) and productivity-labour cost ratio (η^{G}). Balanced panel sample.

	Coef. (unbal.)	Coef. (bal.)	Hyp Test $\eta_{3f}=\eta_{3m}$: $\eta_{3f}-\eta_{3m}$	F	Prob >F	Hyp Test $\eta_{3f}=\eta_{2f}$: $\eta_{3f}-\eta_{2f}$	F	Prob >F	Hyp Test $\eta_{3f}-\eta_{2f}=\eta_{3m}$: $(\eta_{3f}-\eta_{2f})-\eta_{3m}$	F	Prob >F
[3] - First Differences+ lagged IV-GMM$											
Productivity											
Men 50-64 (η_{3m})	-0.039	-0.036									
	(0.038)	*(0.039)*									
Women 30-49 (η_{2f})	-0.114**	-0.098**	-0.257***	10.75	0.001	-0.196***	7.21	0.0079	-0.159*	3.69	0.0549
	(0.046)	*(0.048)*									
Women 50-64 (η_{3f})	-0.252***	-0.293***									
	(0.071)	*(0.073)*									
Prod.-Lab. Costs ratio											
Men 50-64 (η^{G}_{3m})	-0.016	0.000									
	(0.037)	*(0.038)*									
Women 30-49 (η^{G}_{2f})	*-0.081**	-0.067	-0.250***	10.71	0.0011	-0.183**	6.62	0.0101	-0.183**	5.11	0.0238
	(0.045)	*(0.046)*									
Women 50-64 (η^{G}_{3f})	-0.201**	-0.250***									
	(0.070)	*(0.072)*									
#obs	49,211	46,006									
[4]- First-Differences + intermediate inputs LP$$											
Productivity											
Men 50-64 (η_{3m})	-0.115***	-0.093***									
	(0.035)	*(0.035)*									
Women 30-49 (η_{2f})	-0.034	-0.035	-0.183***	6.78	0.0092	-0.242**	14.11	0.0002	-0.148**	4.03	0.0488
	(0.040)	*(0.042)*									
Women 50-64 (η_{3f})	-0.250***	-0.276***									
	(0.063)	*(0.064)*									
Prod.-Lab. Costs ratio											
Men 50-64 (η^{G}_{3m})	-0.069**	-0.038									
	(0.034)	*(0.034)*									
Women 30-49 (η^{G}_{2f})	-0.006	-0.013	-0.122*	3.16	0.0755	-0.147**	5.46	0.0195	-0.110	2.28	0.1307
	(0.040)	*(0.041)*									
Women 50-64 (η^{G}_{3f})	-0.130**	-0.160**									
	(0.061)	*(0.063)*									
#obs	52,162	47,658									

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

£:Standard errors estimates are robust to firm-level clustering

*p < 0.05, **p < 0.01, *** p < 0.001

$:IV-GMM: Instruments: second differences and lagged second differences. Tests: IV relevance: Anderson canon. corr. LR statistic √ Overidentifying restriction: Hansen J statistic √

$$: Levinsohn &. Petrin.

4.2. Balanced panel restricted to the services industry

Secondly, we have re-estimated the average productivity and productivity-labour cost ratio equations (using the unbalanced panel data), but now isolating the services industry.[30] Remember that we do so because many observers posit that age and gender differences matter less for productivity in a service-based economy than in one where industry dominates. Another good reason for focusing on services is that women are overrepresented in that industry, in comparison with construction or manufacturing.

Parameter estimates from models [3] [4] are reported on the right-hand side of Table 5, alongside those presented in Table 3 and Table 4; again to facilitate comparison. The key result is that the important gender asymmetry emerging from the analysis of the panel pooling all sectors is reinforced when using services-only data. For older women, both model [3] and model [4] deliver employability coefficients (η^G) that are of larger magnitude than those displayed in Table 4 (all sectors pooled). IV-GMM [3] shows that a 10%-points expansion of their share in the firm's workforce causes a 3.5%-points reduction (vs. 2.5%-points with all sectors pooled), whereas LP model [4] points at a 1.77% reduction (vs. 1.6% when all sectors are pooled).

Table 5 also contains the results of the three important cross-gender tests of equality. And once again, the previous conclusions get reinforced. First, old women (50-64) appear much less productive and less employable than old men. Results for IV-GMM [3] point to a 28.9%-points productivity handicap (vs. 25.7%-points when all sectors are pooled) for old women with respect to their male peers. As to employability, the old women's handicap reaches 35.6%-points (vs. 25%-points in Table 4). The other results displayed in Table 5 also strengthen the idea that age is particularly harmful to women's productivity[employability]. Results for IV-GMM [3] point to a 25%-points (vs. 19.6%-points when all sectors are pooled) statistically-significant productivity handicap for old women relative to prime-age ones. In terms of employability, the handicap rises from 18.3 to 26.5%-points. Similar results are obtained with LP model [4]. There is also stronger evidence that age is more of an issue for women's than men's productivity[employability] in the services industry than in the overall private economy.

The tentative conclusion is that the (now dominant and highly feminized) services industry does not seem to offers working conditions to older women, mitigating their productivity or employability disadvantage vis-à-vis other categories of workers.

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[30] A detailed definition of these two large sectors in terms of NACE 2 categories is to be found in Appendix 2.

Table 5 - Parameter estimates (*standard errors*[£]) and hypothesis testing. Older (50-64) male/female and prime-age (30-49) female workers productivity (η), average labour costs(η^{w}) and productivity-labour cost ratio (η^{G}). Balanced panel sample, services industry.

	Coefficient (unbal.)	Coefficient (bal.)	Coefficient (bal. SERVICES)	Hyp Test $\eta_{3f}=\eta_{3m}$			Hyp Test $\eta_{3f}=\eta_{2f}$			Hyp Test $\eta_{3f}-\eta_{2f}=\eta_{3m}$		
				$\eta_{3f}-\eta_{3m}$	**F**	**Prob >F**	$\eta_{3f}-\eta_{2f}$	**F**	**Prob >F**	$(\eta_{3f}-\eta_{2f})-\eta_{3m}$	**F**	**Prob >F**
[3] - First Differences+ IV-GMM[$]												
Productivity												
Men 50-64 (η_{3m})	-0.039	-0.036	-0.067									
	(0.038)	*(0.039)*	*(0.055)*									
Women 30-49 (η_{2f})	-0.114**	-0.098**	-0.116*	-0.298***	9.03	0.0027	-0.250***	7.43	0.0064	-0.183*	2.91	0.0881
	(0.046)	*(0.048)*	*(0.061)*									
Women 50-64 (η_{3f})	-0.252***	-0.293***	-0.365***									
	(0.071)	*(0.073)*	*(0.092)*									
Prod.-Lab. Costs ratio												
Men 50-64 (η^{G}_{3m})	-0.016	0.000	-0.004									
	(0.037)	*(0.038)*	*(0.053)*									
Women 30-49 (η^{G}_{2f})	*-0.081**	-0.067	-0.095	-0.356***	13.57	0.0002	-0.265***	8.84	0.0029	-0.261*	6.26	0.0123
	(0.045)	*(0.046)*	*(0.059)*									
Women 50-64 (η^{G}_{3f})	-0.201**	-0.250***	-0.360***									
	(0.070)	*(0.072)*	*(0.089)*									
#obs	49,211	46,006	24,330									
[4]- First-Differences + intermediate inputs LP[$$]												
Productivity												
Men 50-64 (η_{3m})	-0.115***	-0.093***	-0.089*									
	(0.035)	*(0.035)*	*(0.050)*									
Women 30-49 (η_{2f})	-0.034	-0.035	-0.026	-0.232**	6.62	0.0101	-0.294***	13.46	0.0002	-0.206*	4.68	0.0305
	(0.040)	*(0.042)*	*(0.053)*									
Women 50-64 (η_{3f})	-0.250***	-0.276***	-0.320***									
	(0.063)	*(0.064)*	*(0.080)*									
Prod.-Lab. Costs ratio												
Men 50-64 (η^{G}_{3m})	-0.069**	-0.038	-0.010									
	(0.034)	*(0.034)*	*(0.049)*									
Women 30-49 (η^{G}_{2f})	-0.006	-0.013	0.015	-0.167*	3.60	0.0576	-0.192**	5.98	0.015	-0.182*	3.82	0.0505
	(0.040)	*(0.041)*	*(0.052)*									
Women 50-64 (η^{G}_{3f})	-0.130**	-0.160**	-0.177**									
	(0.061)	*(0.063)*	*(0.079)*									
#obs	52,162	47,658	25,506									

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

Standard errors were computed in a way that accounts for firm-level clustering of observations.

*p < 0.05, **p < 0.01, *** p < 0.001

$:IV-GMM: Instruments: second differences and lagged second differences. Tests: IV relevance: Anderson canon. corr. LR statistic √ Overidentifying restriction: Hansen J statistic √

$$: Levinsohn &. Petrin.

5. Conclusions

As a socio-economic phenomenon, population ageing in Europe will affect more than its welfare systems, as it will also affect the age structure of the *workforce*. In particular, the share of older workers (aged 50+) will rise significantly due to demographics. And this trend will be reinforced by policies aimed at maintaining more of those older individuals in employment. Another point we highlight in this paper is that a greying European workforce should also become more female. There is indeed robust evidence that older women are still under-represented in employment in comparison with older men. But this should change due to the combined effect of two elements. First, participation rates in the 50-60 age range will partially align with those currently observed in some Nordic countries (Sweden, Iceland), because successive cohorts of women with an increasing history of youth and prime-age participation are reaching older ages. Second, labour policy will try to close the gender participation gap that persists beyond 50, independently of the above-mentioned trend.

Optimists may believe that an ageing and feminized workforce will have only a minimal impact on firms' performance and on labour markets. This paper contains evidence, based on the analysis of private-economy firm-level panel data, that suggests the opposite. We show that the age/gender structure of firms located in Belgium is a key determinant of their productivity-labour cost ratio. Employing a larger share of female workers aged 50-64 could translate into lower profitability *ceteris paribus*. Our results show that, using prime-age men as a reference, an increase of 10%-points in the share of older female workers (50-64) depresses firms' productivity-labour cost ratio by 1.3 to 3.6%-points, depending on the estimation method and the sample chosen. The equivalent results for old men range from 0 to 0.69%. A closer look at the results reveals three important things. First, the handicap of old female workers vis-à-vis old male workers is driven by a lower productivity that is not compensated for by lower average labour costs. Second, older women are less productive and employable than prime-age women. Third, some of our results – obtained when focussing on balanced panel data and the service industry data - also support the idea that age affects women's productivity[employability] more than men's. In short, older women's employability handicap vis-à-vis older men stems from a productivity handicap that is *i)* not compensated for by lower labour costs, and *ii)* caused by a more pronounced effect of age.

We finish by briefly mentioning some limits that should be held in mind when interpreting our results. First of all, we lack further information about the composition of the workforce (education skills, previous training etc). Although we include proxies (share of blue-collar workers) and apply within transformations to controls for most of the firms' heterogeneity (including in terms of stock of human capital), there could still be problems with unobserved short-term changes in human capital levels that are related to the age/gender structure. Secondly, only "average firm profiles" are calculated, which may imply that we overlook the capacity of some firms to neutralize the effect of age and gender on productivity (by implementing *ad hoc* measures that compensate for the age/gender-related loss of performance). Thirdly, the worker sample that we use might not be representative of the entire population of older individuals aged 50-64. This means that there is a risk of a *selection bias*, in particular due to early ejection from the workforce of less productive/motivated older (male or female) workers. To the extent that this selection bias is an issue, we could view our estimated coefficients for older workers' productivity as lower boundaries (in absolute value).

Appendix

Appendix 1: Belfirst-Carrefour balanced panel. Basic descriptive statistics: mean (standard deviation)

Year	Firms	Productivity (i.e. value-added) per worker (in th. €)	Labour cost per worker (in th. €)	Productivity-Labour cost ratio(%)	Firm size (# workers)	Capital (in th. €)	Mean age	Shares (male) 18-29	Shares (male) 30-49	Shares (male) 50-64	Shares (female) 18-29	Shares (female) 30-49	Shares (female) 50-64	Intermediate goods cons. (in th. €)	Share of blue-collar workers	Share of managers	Hours worked annual per worker
1998	7933	66.51	39.13	0.41	109.61	6547	36.15	0.34	0.30	0.10	0.15	0.09	0.02	28707	0.57	0.01	1661.91
		(108.09)	(27.12)	(0.40)	(479.79)	(97403)	(4.24)	(0.18)	(0.16)	(0.09)	(0.17)	(0.10)	(0.04)	(161390)	(0.35)	(0.05)	(266.63)
1999	7933	69.65	40.22	0.40	112.35	6742	36.46	0.33	0.30	0.11	0.14	0.10	0.02	29226	0.57	0.01	1662.30
		(186.13)	(22.32)	(0.41)	(477.58)	(101966)	(4.19)	(0.17)	(0.15)	(0.09)	(0.16)	(0.11)	(0.04)	(165727)	(0.35)	(0.04)	(262.37)
2000	7933	69.47	41.00	0.40	115.24	7094	36.73	0.31	0.31	0.11	0.14	0.10	0.02	35342	0.56	0.01	1640.49
		(108.54)	(21.85)	(0.42)	(472.12)	(111802)	(4.12)	(0.16)	(0.15)	(0.09)	(0.15)	(0.11)	(0.04)	(228431)	(0.35)	(0.04)	(240.04)
2001	7933	69.59	42.28	0.38	123.16	7580	37.14	0.30	0.31	0.12	0.14	0.11	0.03	36819	0.56	0.01	1623.52
		(100.36)	(22.31)	(0.38)	(512.72)	(118939)	(4.07)	(0.16)	(0.15)	(0.09)	(0.15)	(0.11)	(0.04)	(264425)	(0.35)	(0.04)	(240.39)
2002	7933	69.65	43.79	0.36	123.74	7803	37.54	0.29	0.32	0.12	0.13	0.11	0.03	37868	0.56	0.01	1609.17
		(78.13)	(22.76)	(0.37)	(517.76)	(128983)	(4.04)	(0.15)	(0.15)	(0.10)	(0.14)	(0.11)	(0.05)	(278567)	(0.35)	(0.04)	(238.51)
2003	7933	71.84	44.80	0.36	121.63	8164	38.18	0.27	0.32	0.13	0.12	0.12	0.03	38155	0.55	0.01	1596.44
		(96.52)	(22.71)	(0.37)	(464.28)	(137848)	(4.09)	(0.15)	(0.14)	(0.10)	(0.14)	(0.11)	(0.05)	(260458)	(0.34)	(0.03)	(218.95)
2004	7933	75.28	46.28	0.38	124.12	8488	38.56	0.26	0.32	0.14	0.12	0.12	0.03	41973	0.55	0.01	1611.12
		(85.84)	(25.91)	(0.37)	(494.39)	(147582)	(4.10)	(0.14)	(0.14)	(0.11)	(0.13)	(0.12)	(0.05)	(307199)	(0.34)	(0.03)	(217.12)
2005	7933	77.32	47.35	0.37	125.81	7382	38.96	0.26	0.33	0.15	0.11	0.12	0.04	47382	0.55	0.01	1591.85
		(98.98)	(27.29)	(0.39)	(512.86)	(53878)	(4.08)	(0.14)	(0.14)	(0.11)	(0.13)	(0.12)	(0.05)	(435990)	(0.34)	(0.04)	(223.20)
2006	7933	78.97	48.37	0.37	127.03	7484	39.33	0.25	0.33	0.15	0.11	0.12	0.04	52163	0.54	0.01	1571.02
		(89.13)	(28.98)	(0.40)	(506.13)	(52265)	(4.14)	(0.14)	(0.14)	(0.11)	(0.13)	(0.12)	(0.06)	(533189)	(0.34)	(0.04)	(211.34)

Appendix 2 : Sectors (Industry vs Services) and NACE2 codes/definitions

Nac2 code	Industry
10 to 12	Manufacture of food products, beverages and tobacco products
13 to 15	Manufacture of textiles, apparel, leather and related products
16 to 18	Manufacture of wood and paper products, and printing
19	Manufacture of coke, and refined petroleum products
20	Manufacture of chemicals and chemical products
21	Manufacture of pharmaceuticals, medicinal chemical and botanical pro
22 + 23	Manufacture of rubber and plastics products, and other non-metallic
24 + 25	Manufacture of basic metals and fabricated metal products
26	Manufacture of computer, electronic and optical products
27	Manufacture of electrical equipment
28	Manufacture of machinery and equipment n.e.c.
29 + 30	Manufacture of transport equipment
31 to 33	Other manufacturing, and repair and installation of machinery and e
35	Electricity, gas, steam and air-conditioning supply
36 to 39	Water supply, sewerage, waste management and remediation
41 to 43	Construction
45 to 47	Wholesale and retail trade, repair of motor vehicles and motorcycles
	Services
49 to 53	Transportation and storage
55 + 56	Accommodation and food service activities
58 to 60	Publishing, audiovisual and broadcasting activities
61	Telecommunications
62 +63	IT and other information services
64 to 66	Financial and insurance activities
68	Real estate activities
69 to 71	Legal, accounting, management, architecture, engineering, technical
72	Scientific research and development
73 to 75	Other professional, scientific and technical activities
77 to 82	Administrative and support service activities
90 to 93	Arts, entertainment and recreation
94 to 96	Other services
97 to 98	Activities of households as employers; undifferentiated goods
99	Activities of extra-territorial organisations and bodies

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