Labour Economics xxx (2012) xxx–xxx

Contents lists available at SciVerse ScienceDirect

Labour Economics

journal homepage: www.elsevier.com/locate/labeco

Are firms willing to employ a greying and feminizing workforce?☆

V. Vandenberghe *

Université catholique de Louvain, IRES, 3 place Montesquieu, B-1348 Louvain-la-Neuve (Belgium)

HIGHLIGHTS

► Are firms willing to employ more older individuals, in particular older women?
► We focus on how larger shares of older workers affects gross profits.
► We find limited negative impact of rising shares of older men.
► But a large negative effect of larger shares of older women.
► Services industry does not mitigate older women's disadvantage.

ARTICLE INFO

Article history:
Received 10 December 2011
Received in revised form 13 July 2012
Accepted 18 July 2012
Available online xxxx

JEL classification:
J11
J14
J21

Keywords:
Ageing workforce
Gender
Productivity
Profitability
Linked employer–employee data
Endogeneity and simultaneity bias

ABSTRACT

Are employers willing to employ more older individuals, in particular older women? Higher employment among the older segments of the population will only materialize if firms are willing to employ them. Although several economists have started considering the demand side of the labour market for older individuals, few have considered its gender dimension properly; despite evidence that lifting the overall senior employment rate in the EU requires significantly raising that of women older than 50. In this paper, we posit that labour demand and employability depend to a large extent on how the age/gender composition of the workforce affects firm's profits. Using unique firm-level panel data we produce robust evidence on the causal effect of age/gender on productivity (value added per worker), total labour costs and gross profits. 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-gender mix choices in the short run) by combining first differences with *i)* the structural approach suggested by Ackerberg, Caves and Frazer (2006), *ii)* alongside more traditional IV-GMM methods (Blundell and Bond, 1998) where lagged values of labour inputs are used as instruments. Results suggest no negative impact of rising shares of older men on firm's gross profits, but a large negative effect of larger shares of older women. Another interesting result is that the vast and highly feminized services industry does not seem to offer working conditions that mitigate older women's productivity and employability disadvantage, on the contrary. This is not good news for older women's employability and calls for policy interventions in the Belgian private economy aimed at combating women's decline of productivity with age and/or better adapting labour costs to age-gender productivity profiles.

1. Introduction

Expanding the range of employment opportunities available to older workers will become increasingly important in most EU countries as demographics (ageing populations[1]) and public policy[2] will combine to increase the share of older individuals in the labour force. Across the EU, with the exception of some Nordic countries, there is also 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

☆ Funding for this research was provided by the Belgian Federal Government-SPP Politique scientifique, "Société et Avenir" programme, The Consequences of an Ageing Workforce on the Productivity of the Belgian Economy, research contract TA/10/031B. We would like to thank Mariann Rigo, Fabio Waltenberg, participants in the Ageing Workforces workshop held in Louvain-la-Neuve in Sept. 2010, and anonymous referees for their comments and suggestions on previous versions of this paper.

* Economics Department, IRES, Economics School of Louvain (ESL), Université catholique de Louvain (UCL), 3 place Montesquieu, B-1348 Belgium.
E-mail address: vincent.vandenberghe@uclouvain.be.

[1] 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.

0927-5371/$ – see front matter © 2012 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.labeco.2012.07.004

this prediction. The first one is the lagged effect[4] of the rising overall female participation in the labour force (Peracchi and 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 materialize 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 and 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.

In short, there is a need to understand better the capacity of EU labour markets to adapt to ageing and feminizing workforces.

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 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 to early retirement benefits[8] and old-age pension systems made it financially unattractive to work after the age of 55. The implicit tax on continued work has risen strongly since the 1960s and has played a significant role in the drop in the employment rate among older individuals (Blöndal and Scarpetta, 1999; Jousten et al., 2008). Other papers with a supply-side focus examine how poor 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).

The demand side of the labour market for older individuals has started to receive some attention from economists. Some have examined 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).[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. By contrast, Grund and Westergård-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 the German evidence by Göbel and Zwick (2009), using panel data 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[10], conclude that older workers (>49) are significantly less productive than prime-age workers, particularly in ICT firms.

Using panel data and coping with the simultaneity of production and the age structure of the workforce has become key in this literature (more in Section 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 difference between individuals' contribution to production and their cost to employers; in other words how their affect (gross) profits. This paper analyses the sensitivity of productivity, labour costs and profits to the workforce structure of firms. Under proper assumptions (see Section 2), this amounts to analyzing the sensitivity these firm-level outcomes to the age/gender shares forming the overall workforce.

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 profits after 55 (Grund and Westergård-Nielsen, 2008; Skirbekk, 2004, 2008).

Turning to authors using (*a priori* more trustworthy) panel data, the evidence is mixed. For Belgium, Cataldi et al. (2011)[11] 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 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. True enough, some existing papers consider gender within an HN framework, but they primarily aim at assessing the presence of gender wage discrimination (Vandenberghe, 2011b). Others consider the impact of age or gender (Pfeifer and Wagner, 2012) on firms' performance, but separately. None examines the role of gender in combination with age. Technically, for instance, the Pfeifer & Wagner paper analyses the impact of the overall share of older workers plus that of the overall share women (*vs*. men) on productivity and profits; whereas this paper assesses the impact of shares of women (and men) belonging to different age groups. This is apparently a small difference. But it is essential to get a chance to assess the (potentially variable) willingness of employers to (re)employ older male and female workers (…).

Throughout this paper, we posit that labour demand largely depends on how larger shares of older (male or female) workers affect private firms' gross profits, i.e. the difference between productivity (value added) and total labour cost.[12] More specifically, we try to find firm-level evidence of a negative (or positive) *short-run* effect of larger shares of older (male and female) workers on *i)* average productivity,

[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.

[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 marginal product.

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

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

[12] Strictly speaking, value added minus labour cost is equal to «*Gross operating surplus: the surplus generated by operating activities after the labour factor input has been recompensed*». It is the sum available to pay the share and debt holders, to pay [corporates] taxes and eventually to finance all or a part of investment. OECD on-line glossary (http://stats.oecd.org/glossary/detail.asp?ID=1178).

Please cite this article as: Vandenberghe, V., Are firms willing to employ a greying and feminizing workforce?, Labour Econ. (2012), http://dx.doi.org/10.1016/j.labeco.2012.07.004

ii) average labour costs and *iii)* the difference between these two i.e. gross profits. We assume in particular that a sizeable negative impact of older men/women on gross profits can adversely affect their respective chances of being employed. Such assumption may puzzle those thinking about a labour market in equilibrium. How can firms accept lower profits by employing less profitable workers; why don't they find ways to not employ them? It is true that if perfect equilibrium prevails, both in the short- and longer run, works like this one would always conclude that all types of workers equally contribute to profits and are equally employable. But short-term rigidities or labour market disequilibria probably exist in many countries; and certainly in the Belgium where labour regulations abound. What is more, they do not preclude that firms, in the medium to longer run, respond to short-term imbalances by laying off less profitable workers. In other words, short-term imbalances are probably the necessary, but plausible, condition to spot productivity and profitability differences between workers with firm-level data and gauge the intensity of the labour demand they face. [13]

As to the data, it is worth stressing that we use *direct* measures of use firm-level productivity (value added) and overall labour cost. The difference between these two delivers our measure of firms' profitability. Our Belgian data[14] thus permit a direct estimation of age-gender/ productivity and profitability 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,[15] 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 (9000+) and covered a relatively long period running from 1998 to 2006.

In this paper we 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 profits (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 profits 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 and Neumark (1995), Hellerstein et al. (1999), and richer data sets regarding employees, *e.g.* Crépon et al. (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, generally via first-differencing (FD) of panel data.

As to the simultaneity bias, the past 15 years has seen the introduction of new identification techniques.[16] One set of techniques follows the dynamic panel literature (Arellano and Bond, 1991; Aubert and Crépon, 2003; Blundell and Bond, 2000; or van Ours and Stoeldraijer, 2011), which basically consists of using lagged values of (first-differenced) labour inputs as instrumental variables (FD-IV-GMM henceforth). A second set of techniques, initially advocated by Olley and Pakes (1996), Levinsohn and Petrin (2003) (OP, LP henceforth), and more recently by Acherberg et al. (2006) (ACF 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.

In this paper we use these recent applications of the HN methodology that we apply to panel data that have been first differenced (FD), 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; Cataldi et al., 2011), we first estimate the relevant parameters of our model using FD “internal” instruments (i.e lagged values of endogenous labour inputs) (FD-IV-GMM henceforth). 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 Acherberg 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 (FD-ACF henceforth). From a methodological point of view, an interesting aspect of the paper is that it shows that the results delivered by FD-ACF are very similar to those delivered by FD-IV-GMM, and also that they are completely different than those stemming from ACF alone (i.e. without FD).

Belgium is known for its low employment rate among individuals aged 50+. A less publicized fact is that it is particularly low among older women. Their overall employment rate at 30% remains 11% below the EU15 average according to the EU Labour Force Survey of 2010, and 12%-points lower than that of old men. But these are data that include public employment. If we consider our own data (see Section 3), covering only the private economy, the male/female gap is even wider. Female workers aged 50–64 represent a mere 2 to 4% or the overall private-sector labour force: only a 1/4 of the male-equivalent percentage. Most economists would herald Belgium's easy access to (early) retirement benefits and the financial disincentives to continue to work at older ages imbedded these regimes as the key determinants of the country's low employment rate among individuals aged 50 and over. The problem with that argument is that it fails to account for the above-mentioned gender employment asymmetries. Social security benefits are as generous and as easily accessible for older men than it is for women.

Other economists would argue that these gender employment discrepancies could be due to older women's intrinsically lower propensity to supply labour. This perhaps is the case. All we can say is that this paper contains strong econometric evidence that they low employment rate could also be demand-driven. Firms based in Belgium face financial disincentives to employing older women. Our most important results in

[13] The other condition is to adopt an econometric strategy that is good at capturing short-term relationships. But this is exactly what is done in this paper. The identification of the effect of age/gender on productivity and profits rests on panels; in particular on first-differenced data reflecting year-to-year changes (more on this below and in Section 2). By construction thus, what we highlight are short-term links between rising shares of older women/men and productivity, labour costs and profits.

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

[15] 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.

[16] See Acherberg et al. (2006) for a recent review.

this respect are those derived from the regression of profits on the share of older men and women. Using prime-age men as a reference, we show that a 10%-point rise in the share of older men causes no statistically significant reduction of either productivity (firms' value added per head) or gross profits (value added minus overall labour costs). However, the situation is different for older women. Our preferred estimates suggest that a 10%-point expansion of their share in the firm's workforce causes a 2.02 to 5.18% reduction in productivity and a 1.43 to 2.45% fall of profits; something that is likely to negatively affect their employability. The ultimate point is that these results raise questions about the feasibility, in the current Belgian 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 profit functions are unfolded. Section 3 is devoted to an exposition of the dataset. Section 4 contains the econometrics results. Our main conclusions are exposed in Section 5. That final section also contains a discussion of the various factors that may explain why older women (at least in Belgium) display a larger productivity and employability handicap than older men.

2. Methodology

2.1. Productivity, labour cost and profit equations with heterogeneous labour inputs

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 and Crépon, 2003, 2007; Dostie, 2011; van Ours and Stoeldraijer, 2011; Vandenberghe, 2011a,b):

$$ln\ (Y_{it}/L_{it}) = lnA + \alpha\ ln\ QL_{it} + ßlnK_{it} - lnL_{it} \quad (1)$$

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 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:

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

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:

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

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 .

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

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

And the production function becomes:

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

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

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

where:

$$B = lnA + \alpha\ ln\mu_0$$
$$\lambda_k = \mu_k/\mu_0 \qquad k- = 1\ldots N$$
$$\eta_1 = \alpha\ (\lambda_1 - 1)$$
$$\ldots.$$
$$\eta_N = \alpha\ (\lambda_N - 1)$$
$$l_{it} = lnL_{it}$$
$$k_{it} = lnK_{it}$$

Note first that Eq. (6), being loglinear in P, has coefficients that 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.[17]

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.[18] 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:

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

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

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

where:

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

Like in the average productivity Eq. (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 profits 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

[17] Does all this matter in practice? Our experience with firm-level data suggests values for $ß$ ranging from 0.6 to 0.8 (these values are in line with what most authors estimate for the share of labour in firms' output/added value). This means that λ_k is larger (in absolute value) than η_k. If anything, estimates reported in Tables 6–8 underestimate the true marginal productivity difference *vis-à-vis* prime-age workers.

[18] We will see, how, in practice via the inclusion of dummies, this assumption can be relaxed to account for sectoral wage effects.

Please cite this article as: Vandenberghe, V., Are firms willing to employ a greying and feminizing workforce?, Labour Econ. (2012), http://dx.doi.org/10.1016/j.labeco.2012.07.004

(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) male workers forming the reference group, we get.

$$ln(Y_{it}/L_{it}) = B + (\alpha - 1) l_{it} + \eta_{1m} P_{it}^{m18-29} + \eta_{3m} P_{it}^{m50-64} + \eta_{1f} P_{it}^{f18-29} + \eta_{2f} P_{it}^{f30-49} + \eta_{3f} P_{it}^{f50-64} + ß k_{it} + \gamma F_{it} + \varepsilon_{it} \quad (10)$$

$$ln\,(W_{it}/L_{it}) = B^W + \left(\alpha^W - 1\right) l_{it} + \eta^W{}_{1m} P_{it}^{m18-29} + \eta^W{}_{3m} P_{it}^{m50-64} + \eta^W{}_{1f} P_{it}^{f18-29} + \eta^W{}_{2f} P_{it}^{f30-49} + \eta^W{}_{3f} P_{it}^{f50-64} + ß^W k_{it} + \gamma^W F_{it} + \varepsilon^W{}_{it} \quad (11)$$

What is more, if we take the *difference* between the logarithms of average productivity (10) and labour costs[19] (11) we get a direct expression of gross profits[20] as a linear function of its workforce determinants.

$$\begin{aligned} Profits_{it} &\equiv ln\,(Y_{it}/L_{it}) - ln\,(W_{it}/L_{it}) = ln(Y_{it}/W_{it}) \quad (12)\\ &= ln(1 + (Y_{it} - W_{it})/W_{it}) \sim = (Y_{it} - W_{it})/W_{it}\\ &= B^P + \left(\alpha^P - 1\right) l_{it} + \eta^P{}_{1m} P_{it}^{m18-29} + \eta^P{}_{3m} P_{it}^{m50\_64}\\ &\quad + \eta^P{}_{1f} P_{it}^{f18-29} + \eta^P{}_{2f} P_{it}^{f30-49} + \eta^P{}_{3f} P_{it}^{f50-64}\\ &\quad + ß^P k_{it} + \gamma^P F_{it} + \varepsilon^P{}_{it} \end{aligned}$$

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

It is immediate to see that coefficients $\eta^P$of Eq. (12) provide a direct estimate of how profits is affected by changes in terms of percentages/shares of employed workers.

Note also the inclusion in Eq. (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 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., 1999). More importantly, since the data set we use do not 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). Detailed discussion of all firm-level controls included in F_{it} will be presented in the data section below.

2.2. Idenfication: heterogeneity and simultaneity bias

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 Eq. (10).[22] We assume that the latter has a structure that comprises three elements:

$$\varepsilon_{it} = \theta_i + \omega_{it} + \sigma_{it} \quad (13)$$

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 ω_{it} whose evolution corresponds to a first-order Markov chain, and is observed by the firm (but not by the econometrician) and (partially) anticipated by the firm, and, *iii)* a purely random shock σ_{it}.

Parameter θ_i in Eq. (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 fixed effects (using FD). FD are good at purging fixed effects and thus at coping with unobserved heterogeneity terms θ_i. The results from the FD estimation 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, an 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 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}. 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 (male/female) 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 (male/female) workers' productivity with OLS or FD.

To account for the presence of this simultaneity 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;

[19] 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.

[20] Value added minus labour cost is equal to the gross surplus:"the surplus generated by operating activities after the labour factor input has been recompensed. It allows to recompense the providers of capital (own funds and debt), to pay [corporate] taxes and eventually to finance all or a part of investment" (OECD, http://stats.oecd.org/glossary/detail.asp?ID=1178).

[21] NACE2 level.

[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 logistics companies 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.

Cataldi et al., 2011).[27] Our choice is to instrument the potentially endogenous first-differenced worker shares (ΔP_{it}^{k}) with their second differences ($\Delta P_{it}^{k} - \Delta P_{it-1}^{k}$) and lagged second differences ($\Delta P_{it-1}^{k} - \Delta P_{it-2}^{k}$) *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 FD-IV-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 Acherberg 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:

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

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 FD-IV-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:

$$int_{it} = f_t(\omega_{it},\ k_{it},\ ql_{it}) \tag{15}$$

By contrast, LP unrealistically assumes 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:

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

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

$$ln\ (Y_{it}/L_{it}) = B + \varphi\, ql_{it} + ßk_{it} + \gamma F_{it} + {f_t}^{-1}(int_{it},\ k_{it},\ ql_{it}) + \theta_{\mathbf{i}} + \sigma_{it} \tag{16b}$$

In a sense, we stick to what has traditionally been done in the dynamic-panel literature underpinning the FD-IV-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 $int_{it} = f_t(\omega_{it}, k_{it}, ql_{it})$, 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

$$ln\ (Y_{it}/L_{it}) = \Phi_t(int_{it},\ k_{it},\ ql_{it}, F_{it}) + \theta_{\mathbf{i}} + \sigma_{it} \tag{17}$$

Note that Φ_t encompasses $\omega_{it} = f_t^{-1}(.)$ displayed in Eq. (16b) and that φ, $ß$ 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 $\omega_{it} = f_t^{-1}(.)$ - 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 $\Phi_{it}^{hat} = (\upsilon_{a1})^{FD}\ int_{it} + (\upsilon_{a2})^{FD}\ \ int^2{}_{it} + \ldots + (\upsilon_{b1})^{FD}\ \ k_{it} + \ldots + (\upsilon_{c1})^{FD} ql_{it} + \ldots + (\upsilon_{d1})^{FD}\ int_{it}k_{it}\ \ldots$, where $(\upsilon_{a1})^{FD}$, $(\upsilon_{a2})^{FD}$… represent the first-differenced coefficient estimates on the polynomial terms.

Beyond, 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 $\boldsymbol{\omega}_{it}$ using first-stage estimates Φ_{it}^{hat} and candidate[32] values for the coefficients φ, $ß$, γ:

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

[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).

[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 in_{it}, a profit-maximizing (or cost-minimizing) optimal choice of int_{it} will generally directly depend on ql_{it} (Acherberg 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).

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

[32] OLS estimates for example.

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 $t-1$ realization 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, $ß$ 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:

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

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

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

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

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

2.3. Identification: (positive) selection

The workers' sample used to estimate the above econometric models 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). And there is evidence (including in our data set as will appear in Section 3) that this low employment rate corresponds to early exit from the workforce of individuals that are intrinsically less educated, perhaps less motivated and thus less productive. 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; an that presumaly entice those of their older workers that are less productive to exit. 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. In short, this means that there is a risk of a positive (in employment) *selection bias*. To the extent that this selection bias is an issue we could *a priori* view estimated coefficients for older workers' relative productivity as lower-bounds (in absolute value).[33]

It is true that our analysis rests largely on first-differenced data (namely, FD, FD-IV-GMM, FD-ACF). But the (positive) selection argument remains, as the relatively small increments of older workers shares used to identify the effect of ageing on firm performance would be intrinsically larger in the absence of selection. Our first-difference estimates are driven by the addition to the 50–64 age category of individuals who are intrinsically more productive than those (more numerous) who would have inflated that age category in the absence of selection.

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 Bel-first 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.

Descriptive statistics are reported in Tables 1–4. In the upper part of Table 1, one sees that productivity (value-added per worker) is logically superior to labour costs (overall labour costs per worker). The third line of Table 3 shows the resulting gross profits (i.e. the difference between productivity and labour costs in logs) represent 37% of labour costs. Tables 1, 2 and 3 contain descriptive statistics about age/gender shares.[34] They suggest that firms based in Belgium have been largely affected by ageing over the period considered. Table 2 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 and Zwick (2009) show that between 1997 and 2007 the average age of the workforce in the EU25 has risen from 36.2 to 38.9.

Table 3 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%. While starting from a low level in 1998 (2.13%), the rise of the share of older women has been of more than 96% in cumulative terms. The corresponding figure for older men is only 48%.[35]

What may explain this gender asymmetry? We would formulate two (non-mutually exclusive) explanations. The first one, already mentioned above, is the "lagged effect" of surge of female participation in the labour market, itself explained by the lowering of the birth rate and a surge in the number of women accessing tertiary education. The second hypothesis is that of the impact of the pension reform that took place in Belgium in 1997. Before 1997, the legal age of retirement was 60 for women, but 65 for men. The European court of Justice considered this as a form of gender discrimination.

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

[34] For a comparison of how these age/gender shares compare with those obtained when using the working-age population, see Appendix 4.

[35] This gender asymmetry, at least regarding its dynamics, is confirmed by the examination of Belgian Labour Force Survey (LFS) data. In LFS, the share of women in total private-sector employment rises from 3.8% to 7.2% between 1999 and 2008, whereas that of men expanded only from 8.9% to 10.9% in 2008.

Please cite this article as: Vandenberghe, V., Are firms willing to employ a greying and feminizing workforce?, Labour Econ. (2012), http://dx.doi.org/10.1016/j.labeco.2012.07.004

Table 1
Bel-first-Carrefour panel. Main variables. Descriptive statistic.

Variable	Mean	Std. Dev.
Productivity (*i.e.* value added) per worker (th. €) [*log Y/L*]	4.077	0.566
Labour cost per worker (th. €) [*log W/L*]	3.705	0.381
Gross profit (as share of labour costs) [*log(Y/L))-log(W/L) = log(Y)-log(W) ≈ (Y-W)/W)*]	0.374	0.404
Capital (th. €) (th. €) [*log K*]	6.840	1.751
Number of workers (th. €) [*log L*]	3.936	0.994
Share of 18–29 (male)	0.287	0.163
Share of 30–49 (male) ref.	0.309	0.153
Share of 50–65 (male)	0.122	0.103
Share of 18–29 (female)	0.137	0.153
Share of 30–49 (female)	0.115	0.118
Share of 50–65 (female)	0.031	0.050
Use of intermediate inputs (th. €) (log)	8.938	1.574
Share of blue collar workers in total workforce [ref.white col.]	0.545	0.351
Share of manager in total workforce	0.010	0.042
Share of workers born in 1940 – <50	0.088	0.080
Share of workers born in 1950 – <60	0.224	0.114
Share of workers born in 1960 –<70 **ref**	0.326	0.106
Share of workers born in 1970 – <80	0.287	0.143
Share of workers born in 1980 – <90	0.068	0.090
Share of large firms (> = 50 workers)	7.374	0.217
Number of hours worked annually per employee (log)	0.565	0.496
Number of spells	8.714	0.976

Detailed definitions of variables are to be found in Appendix 3.
Source: Bel-first–Carrefour.

Table 2
Bel-first-Carrefour panel. Basic descriptive statistics. Evolution of shares of workers between 1998 and 2006.

Year	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.

The exact timing of gender alignment decided in 1997 is exposed in Table 4. The point is the coincidence between the calendar of the 1997 reform (first step towards alignment in 1997, full alignment in 2007) and that of our panel (1998–2006). Of course, there is no certainty that the increase in the share of older women in our data is primarily due to the reform. But one cannot exclude this hypothesis. What is more, it has some methodological interest as to the econometric identification of the consequences of ageing workforces.

If we assume that at least part of the increase in the share of elderly women can be ascribed to the 1997 reform, then we could argue that we are dealing with a "natural experiment". And the latter could help assess the impact of ageing on firm-level productivity. We will argue hereafter that there a chance that our estimates for older female workers are intrinsically less biased due to selectivity than those obtained for older men. We will elaborate on this in Section 5.2 at the end of the paper.

Intermediate inputs pay a key role in our analysis, as they are central to one of the two strategies we use to overcome the simultaneity 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 gross 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.

Fig. 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 gross profits.[36] These stylized facts suggests that, in the Belgian private economy, profits rises up to the (mean) age of 35–38 where it reaches 40%, but then declines steadily. It falls below 10% when mean age exceeds 55.

Fig. 2 is probably more directly echoing the main issue which is raised in this paper. It depicts the relationship between the share or older (50–64) men or women and profits. It suggests that firms employing shares of older men and women in excess of the 7–8% threshold make significantly less profits. It is also shows that firms employing a given share of older women systematically achieve lover profits than firms employing the same share of older men. At this stage, one should abstain from drawing any conclusion, as Figs. 1 & 2 are essentially stylized facts that do not control for the important difference in the way older men and women distribute across sectors and firms, that may dramatically differ in terms of productivity and profitability for reasons that are independent from the age structure of their workforces. Only adequate econometric analysis, with sector and firm fixed effects (see Section 4), will allow us to draw substantiated conclusions.

Remember that all our regressions contain a vector of control F_{it}. with region and year/sector interaction dummies. One should stress that our dataset does not contain the workers' educational attainment. But F_{it} 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). 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.

In truth, the correspondence blue-collar contract = manual work performed by individuals with little education *vs*. white-collar contracts = intellectual work performed by individuals more educated suffers more and more exceptions. Hence, many would rightly argue that 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. This said our data allow us to separate cohort from age effects. All our estimated models, F_{it} contains the share of workers by decade of birth (1940–50, 1950–60, 1970–80, 1980–90; 1960–70 being the reference decade). Of course, the latter shares do not perfectly reflect changes in educational attainment. What they capture is the contribution to firms' performance of all factors that are not explicitly accounted for in the model, and that are correlated with the decade of birth. That may, hopefully, comprise education, but also other things like women's changing preferences regarding work outside or the importance of a successful career in terms of personal achievement; *i.e.* elements that may indirectly influence women's productivity.

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 reasonably 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.

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

Table 3
Shares of male vs female old workers (50-64). Private sector economy. Belgium. 1998-2006.

	Share of old men	Share of old women	Evolution share of old men (1998 = 100)	Evolution share of old women (1998 = 100)
1998	9.92%	2.13%	100.00	100.00
1999	10.33%	2.30%	104.08	107.62
2000	10.73%	2.48%	108.13	116.25
2001	11.22%	2.72%	113.06	127.53
2002	11.69%	2.92%	117.76	136.82
2003	12.90%	3.31%	130.02	155.06
2004	13.47%	3.56%	135.75	166.73
2005	14.04%	3.83%	141.43	179.29
2006	14.72%	4.20%	148.31	196.86

Source: Bel-first, Carrefour.

Table 4
Pension reform of 1997. Calendar of the alignment of legal age of retirement for women on that of men.

	1996	1997	2000	2003	2006	**2009**
Male	65	65	65	65	65	65
Female	60	61	62	63	64	65

Source: www.socialsecurity.be.

Finally, echoing our discussion at the end of Section 2, we would like to present the evidence of positive selection emerging from our data. Table 5 displays the breakdown of workers forming our data set by age and white- *vs*. blue-collar status. Leaving aside the youngest group[37], it shows that the share of white-collar workers tends to decline with age (from 51.49% for the 30–35 group to 44.04% for the 45–50 group). This is perfectly logical as white-collar contracts are granted to better-educated workers. Wider access to tertiary education over the past decades logically explains why white-collar jobs are less prevalent among older workers. The key point, however, is that the trend is reversed beyond the age of 50, and even more beyond 55. The share of 55–65 workers with a white-collar position reaches 56.5%: significantly more that the 44.04% among the 45–50 group. This a strong indication that less-educated blue-collar workers leave earlier than their better-educated, and presumably more productive, white-collar peers.

This phenomenon could be linked to Belgium's early retirement regime. Early retirement is indeed very popular in Belgium (among both workers and employers), as it offers an alternative to unemployment benefits and ordinary layoffs. Early retirement benefits (ERB) are quite high (replacement rate can reach 80% *vs*. max. 60% for unemployment benefits). They are granted when firms need to downsize. 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 real trouble, under which circumstance the age can be brought down to 52 years, or even 50. In other words, firms who restructure have the possibility to keep most productive workers and entice/force the others to pre-retire.

4. Econometric results

Table 6 presents the parameter estimates of the average productivity (see Eq. (10), Section 2), labour costs (Eq. (11)) and profit Eq. (12), under four alternative econometric specifications. Note that, with the profit Eq. (12) being the difference between Eqs. (10) and (11), it is logical to verify that $\eta - \eta^W \approx \eta^P$ 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 6 we use all available observations forming of our (unbalanced) panel.

The first set of parameter estimates comes from OLS, using total variation [1]. Then comes first differences (FD), where parameters are estimated using only within-firm variation [2]. Model [3] combines FD and the IV-GMM approach using internal lagged labour inputs as instruments (FD-IV-GMM). The last model [4] combines FD and the ACF intermediate-goods proxy idea (FD-ACF).[38]

Estimations [3] [4] in Table 6 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 simultaneity biases either via the use of ACF's intermediate input proxy, or internal instruments.

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. 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) 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 and 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 ACF.

To assess the credibility of our FD-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 FD-IV-GMM estimates reported in Table 5 and beyond 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 FD-IV-GMM estimates we cannot reject the null hypothesis that these restrictions are valid (p-values > 0.1).

In Table 5, parameter estimates (η) for the productivity equation delivered by our preferred models [3],[4] suggest that older men (50–64) are as productive and employable as prime-age (30–49) male workers (our reference category). OLS [1] results suggest that 10%-point rise in the share of old male workers depresses firms' overall labour productivity by 1.92%. FD [2] results deliver a very similar estimate of −1.57% which suggest that older workers are not

[37] In that youngest age group less-educated employees, holding blue-collar positions, should be over-represented because it is quite improbable that all university-educated individuals younger than 24 or 25 have already entered the labour force.

[38] As suggested in Section 2 (Eqs.(21), (22a)–(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 to 3 of the labour inputs.

[39] All our models, including OLS, use data in deviations from year interacted with NACE2 industry means. See Appendix 2 for a detailed presentation of the NACE2 classification.

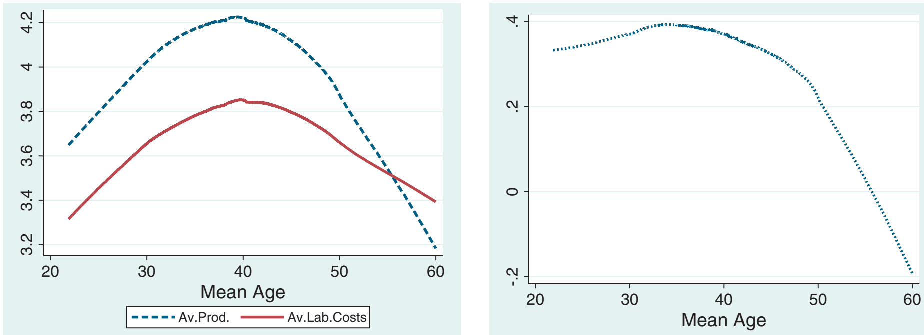

Fig. 1. (Left panel) productivity (value added per worker) and overall labour costs per worker. (Right panel) Profits (% of labour costs) according to mean age. Year 2006. Curves on display correspond to locally weighted regression of y (*i.e.* log of average productivity, log of average labour cost [left panel] and profits [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.

particularly concentrated in intrinsically less productive firms. What is interesting is that their productivity handicap completely disappears when account is taken of the selectivity bias. Both FD-IV-GMM [3] and FD-GMM [4] show that a 10%-point rise in the share of old male worker has no statistically significant impact on productivity. This is supportive of the recruitment-freeze story exposed in Section 2. Firms that stop recruiting youth during downturns (synonymous with lower production) experience a rise in their share of older workers. This means that there is a short-term negative correlation between older workers' share and productivity, thereby leading to OLS or FD parameters that underestimate the true ones.

The story is significantly different regarding older women's productivity. OLS [1] estimates point at a large handicap relative to prime-age men. 10%-point rise in the share of old female workers depresses productivity by 4.59%. Resorting to FD [2] - which is a way to control for the propensity of older women to concentrate in intrinsically less productive firms and sectors - reduces that handicap by half, as 10%-point rise in the share of old female appears to lead only to a 2.36% reduction of firms' overall labour productivity. But unlike for older men, further controlling for selectivity does make their productivity handicap vanish, on the contrary. Both FD-IV-GMM [3] and the FD-ACF model [4] deliver large negative estimates of the impact of larger shares of old women. An increase of 10%-points in their share reduces productivity by 2.02% [3] to 5.81% [4].

Turning to the average labour cost coefficients (η^W), we find some evidence of lower labour cost for older men and women. Estimates for model [3] show that a 10%-point rise of the share of older male (female) workers reduces average labour cost by 0.32% (0.58% respectively), but these coefficients are not statistically significant. Evidence from model [4] is supportive of more statistically significant (at the 10% threshold) wage declines of 1.32% for men, and 2.45% for women. The slightly lower labour costs for older women could reflect the fact that they have accumulated lower tenure in firms; something that, ceteris paribus, may reduce their cost to employ in a country where seniority plays an important role in wage formation.

However, regarding the labour demand for older men and women, the most important parameters are those of the profit equation (η^P). Their sign informs as to whether a lower productivity is fully compensated by lower labour costs and thus has no negative impact on gross profits. Remember that we posit that a negative (and statistically significant) coefficient is an indication that the category of workers is less employable than the reference category. Results for old men are clear Both model [3] and model [4] delivers a coefficient that is not statistically different from 0, which tentatively means that older men are not less employable from the point of view of firms than their prime-age colleagues.

The situation is very different for old women. Model [3] suggests that a 10%-point expansion of their share in the total workforce causes a 1.43% statistically significant reduction of profits. And model [4] points to a 2.45%, also statistically significant, drop of profits.

4.1. Robustness analysis

We have undertaken three further steps in order to assess the robustness of our results. The outcomes are reported in Table 7. Only the sensitivity of the parameter estimates for preferred models [3], [4] are considered. We also privilege the productivity and the profit equations.

4.1.1. Balanced panel

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[40] 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 (i.e. plant closing) 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 mobilized 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.

Thus, by way of sensitivity analysis we now present the parameter estimates (for models [3][4] and only for the productivity and profit equations[41]) based on balanced panel data, consisting only of firms surveyed in each of the 9 years between 1998 and 2006. This subset comprises 7933 firms (*vs.* approx. 9000 in the unbalanced sample). The small difference between the two datasets suggests that right-hand attrition (i.e. plant closing) should not *a priori* play a key role in the analysis. On average (see Appendix 1 for the details) they are remarkably 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

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

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

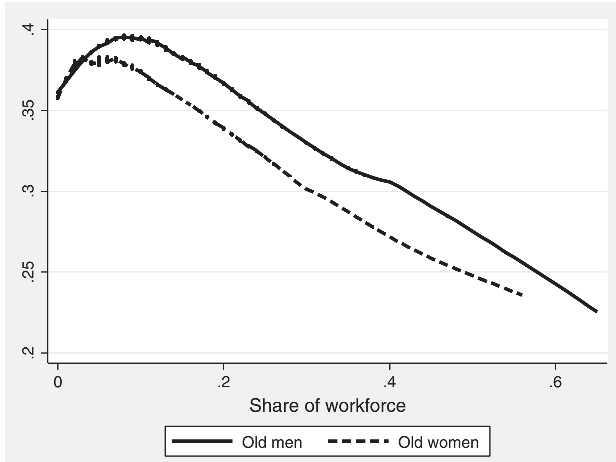

Fig. 2. Gross profits (% of overall labour costs) according to share of older men or women. Curves on display correspond to locally weighted regression of profits (y) on age shares (x). It does this by fitting an OLS estimate of y for each subsets of x. This method does not require to specify a global function of any form to fit a model to the data, only to fit segments of the data. It is thus semi-parametric.

exposed on the right-hand side of Table 7, alongside those of Table 6 for comparison purposes. For old men, productivity and employability/profit parameter estimates (η^P) delivered by both model [3] and model [4] are consistently not statistically different from zero. By contrast, for older women, both models deliver coefficients that are systematically larger in magnitude than with the unbalanced panel. FD-IV-GMM [3] shows that a 10%-point expansion of their share in the firm's workforce causes a 2.51% reduction of productivity (*vs.* 2.02% with the unbalanced panel), while FD-ACF model [4] points at a 6.43% fall (*vs.* 5.18% with the unbalanced panel). A similar amplification of older women's handicap is observed when considering the employability/profit equation. Model [3] shows that a 10%-point expansion of their share in the total workforce causes a 1.80% statistically significant reduction of profits (*vs.* 1.43% with the unbal. panel). And model [4] now points to a 4.5% drop of profits (v. 2.45% with the unbal. panel).

4.1.2. Service industry

Second, we examine whether we reach substantially different conclusions, as to productivity/profit gender asymmetry, when we further restrict the sample to the *services industry*. Remember that observers posit that age and gender differences probably 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 also reported on the right-hand side of Table 7. The key result is that the important gender asymmetry emerging from the analysis that pools all sectors is reinforced when using services-only data. For older women, both model [3] and model [4] deliver productivity (η) and employability/profit coefficients (η^P) that are of larger magnitude than those obtain with the overall data set. FD-IV-GMM [3] shows that a 10%-point expansion of their share in the firm's workforce causes a 3.3% reduction of firms' overall labour productivity (*vs.* 2.02% with overall sample), whereas FD-ACF model [4] points at a 6.44% reduction (*vs.* 5.18% with the bal. & all sectors pooled data).

As to employability, according to model [3] the old women's employability handicap reaches 2.76% (*vs.* 1.43% with the overall sample). Model [4] delivers a similar picture: the handicap rises to 6.44% (*vs.* 5.18% with the overall sample). 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.

Table 5
Share of workers according to age and blue- *vs.* white-collar status.

	Blue-collar	White collar
0_18 − <30	51.84	48.16
1_30 − <35	48.51	51.49
2_35 − <40	51.23	48.77
3_40 − <45	53.89	46.11
4_45 − <50	55.96	44.04
5_50 − <55	54.19	45.81
6_55 − <65	43.50	56.50

Source: Bel-first, Carrefour.

4.1.3. Larger firms

Third, we check whether firm size (*i.e.* overall number of workers) matters. In particular, we exclude the firms with less than 50 workers. Mechanically, for very small firms, even very small changes in the number of workers (+1 or −1) – that are potentially insignificant for productivity - are likely to translate into large variations of *shares* by age and gender. This could *a priori* complicated identification. This is why we have decided to redo the analysis after excluding smaller firms with 50 workers or less. Parameter estimates from models [3] [4] appear in the last column of Table 7. In short, they comfort the overall picture highlighted so far which is that unlike old men older women suffer from a significant productivity and employability handicap. FD-IV-GMM [3] shows that a 10%-point expansion of their share in the firm's workforce causes a 3.65% reduction of firms' overall labour productivity (*vs.* 2.02% with overall sample), whereas FD-ACF model [4] points at a 4% reduction (*vs.* 5.18% with overall sample). In terms of employability, model [3] estimates older women's handicap to be 3.96% (*vs.* 1.43% with the overall sample). Model [4] estimates it at 4% (*vs.* 5.18% with the overall sample).

4.2. Important cross-gender tests of equality

Another interesting aspect of the H-N methodology applied to age/gender shares is that is allows running three *hypothesis tests* which point at key economic and policy questions regarding age and gender.

Table 6
Parameter estimates (standard errors[£]). Older (50–64) male/female and prime-age (30–49) female workers productivity (η), average labour costs (η^w) and profits (η^P). Overall, unbalanced panel sample.

	[1]-OLS	[2]-First differences (FD)	[3]-FD-IV-GMM	[4]-FD + intermediate inputs ACF[$]
Share of 50–64 (men)				
Productivity (η_{3m})	−0.192***	−0.157**	0.047	−0.043
std error	*(0.032)*	*(0.035)*	*(−0.026)*	*(0.081)*
Labour costs (η^{w}_{3m})	−0.162***	−0.095***	−0.032	−0.132*
std error	*(0.019)*	*(0.018)*	*(0.024)*	*(0.074)*
Profits (P^{R}_{3m})	−0.030	−0.065**	0.011	0.045
std error	*(0.026)*	*(0.027)*	*(0.049)*	*(0.066)*
Share of 30–49 (women)				
Productivity (η_{2f})	−0.232***	−0.017	−0.121***	−0.331***
std error	*(0.021)*	*(0.033)*	*(0.046)*	*(0.092)*
Labour COSTS (η^{w}_{2f})	−0.246***	−0.051***	−0.050***	−0.073
std error	*(0.013)*	*(0.017)*	*(0.022)*	*(0.070)*
Profits(η^{P}_{2f})	0.014	0.032	−0.070	−0.195***
std error	*(0.017)*	*(0.031)*	*(0.044)*	*(0.071)*
Share of 50–64 (women)				
Productivity (η_{3f})	−0.459***	−0.236***	−0.202***	−0.518***
std error	*(0.043)*	*(0.057)*	*(0.077)*	*(0.148)*
Labour costs (η^{w}_{3f})	−0.468***	−0.113***	−0.058	−0.245*
std error	*(0.025)*	*(0.028)*	*(0.036)*	*(0.130)*
Profits(η^{P}_{3f})	0.002	−0.134***	−0.143**	−0.245**
std error	*(0.034)*	*(0.050)*	*(0.073)*	*(0.118)*
#Obs.	78,477	68,287	49,439	38,624
Controls	All data are deviations from region + year interacted with NACE2 industry means. See Appendix 2 for NACE2 classification of industries			
	Capital, number of employees, hours worked per employee[a], share of blue-collar workers, share of managers, share of workers by **decade of birth**	Capital, number of employees, hours worked per employee[a], share of blue-collar workers, share of managers, share of workers by **decade of birth** + fixed effects: **firm**	Capital, number of employees, hours worked per employee[a], share of blue-collar workers, share of managers, share of workers by **decade of birth** + fixed effects: **firm**	Capital, number of employees, hours worked per employee[a], share of blue-collar workers, share of managers, share of workers **by decade of birth** + fixed effects: **firm**
Orthogonality conditions/ instruments used to identify endog. labour shares			Second differences and lagged second differences	Innovation in ω_{it} *lag*1–3 labour shares Innovation in ωit *lag*1–3 labour shares
Identification tests			IV relevance: Anderson canon. corr. LR statistic√ Overidentifying restriction: Hansen J statistic √	

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.
$ Ackerberg, Caves and Frazer.

We report and comment the results obtained using the unbalanced overall sample and the balance one. As in the previous section, we focus on our preferred models [3],[4] and on the productivity and profit equations.

First, are old women (50–64) less productive [and less employable, due to lower profits] than old men? The question amounts to verifying that $\eta_{3m} > \eta_{3f}$ [$\eta^{P}_{3m} > \eta^{P}_{3f}$] in absolute value and testing H0: $\eta_{3m} = \eta_{3f}$ for productivity [H0: $\eta^{P}_{3m} = \eta^{P}_{3f}$ for employability]. Results with the overall unbalanced data appear in Table 8. The first column contains the same parameter estimates as those reported in Table 6 and first column of Table 7. The FD-IV-GMM model [3] points to a 2.49% productivity handicap for old women relative to old men, and an employability handicap of 1.45%. In other words, using older men as a reference, a 10%-point rise of their share in the labour force causes a 2.39% contraction of firms' productivity and a 1.45% reduction of profits. Both estimates are highly statistically significant. Similar, also highly statistically significant are obtained with model [4].

The second question is - for each gender separately - how age affects productivity [employability] using the prime-age category as a reference. In other words, are older women less productive [employable] than prime-age women, and are older men less productive [employable] than prime-age men? The answer for older men has already been given, as our choice so far has been to use prime-age men as a reference group. In short, estimated η_{3m} [η^{P}_{3m}]) already reported in Table 5 point at an absence of any significant handicap. Assessing the situation of older women relative to prime-age women is less immediate and requires hypothesis testing (ie. rejecting H0: $\eta_{2f} = \eta_{3f}$ [H0: $\eta^{P}_{2f} = \eta^{P}_{3f}$]). Results for FD-IV-GMM model [3] point to a 0.81% productivity handicap (not statistically significant at the level of 5%) for old women relative to prime-age women. In terms of employability, the handicap is of 0.073% (also not statistically significant). Results with FD-ACF model [4] are similar in magnitude and also not statistically significant, namely a productivity handicap of 1.87%, and an employability handicap of 0.05%.

The third question is whether age affects men and women's productivity [employability] differently. It implies computing the within gender differences (older *vs.* prime-age women and older *vs.* prime age men)[42] and then to test whether these differences diverge significantly across gender. This amounts to testing H0: $\eta_{3f} - \eta_{2f} = \eta_{3m}$ [H0: $\eta^{P}_{3f} - \eta^{P}_{2f} = \eta^{P}_{3m}$]. Models [3],[4] point to (respectively) a 1.28% to 1.44% productivity handicap of women *vis-à-vis* men in terms of age-related productivity decline, and a 0.84% to 0.96% handicap in terms of employability decline. But none of these estimates are statistically significant at the level of 5%.

Turning to the balanced panel (Table 9), we get results that are very much in line with those obtained with the unbalanced panel (Table 8) regarding question 1. Older women, clearly appear less productive [employable] than older men (column 1, Table 9). The novelty is that we now get negative and statistically significant results for question 2 and question 3 (column 2 and 3, Table 9) which strengthen the idea that age is particularly harmful to women's productivity [employability].

Model [3] points to a 1.72% (*vs.* 0.81% with the unbal. data) statistically-significant productivity handicap for old women relative to prime-age ones (question 2). In terms of employability, the handicap is now of 1.42% (*vs.* 0.73%), and is statistically-significant. ACF model [4] even delivers estimates that are both of larger magnitude and more statistically significant.

Model [3] points to a 1.55% (*vs.* 1.28% with the unbal. data) now statistically-significant handicap of women vis-à-vis men in terms of age-related productivity decline (question 3). In terms of age-related employability decline, the handicap is now of 1.71% (*vs.* 0.84%), and is

[42] What we did to answer question 2.

Please cite this article as: Vandenberghe, V., Are firms willing to employ a greying and feminizing workforce?, Labour Econ. (2012), http://dx.doi.org/10.1016/j.labeco.2012.07.004

Table 7
Parameter estimates (standard errors[£]). Older (50–64) male/female and prime-age (30–49) female workers productivity (η), average labour costs(η^w) and profits (η^P). Robustness analysis.

	Overall, unbalanced panel sample	Balanced sample	Service industry only	Large firms only (>50)
[3]-FD-IV-GMM				
Productivity				
Men 50–64 (η_{3m})	0.047	−0.018	−0.098	−0.017
	(−0.026)	*(0.052)*	*(0.076)*	*(0.073)*
Women 30–49 (η_{2f})	−0.121***	−0.079*	−0.169*	−0.073
	(0.046)	*(0.047)*	*(0.061)*	*(0.069)*
Women 50–64 (η_{3f})	−0.202***	−0.251***	−0.330***	−0.365***
	(0.077)	*(0.080)*	*(0.102)*	*(0.108)*
Profits				
Men 50–64 ($\eta^R{}_{3m}$)	0.011	0.029	−0.035	0.009
	(0.049)	*(0.050)*	*(0.072)*	*(0.070)*
Women 30–49 ($\eta^R{}_{2f}$)	−0.070	−0.039	−0.128	−0.109*
	(0.044)	*(0.045)*	*(0.058)*	*(0.065)*
Women 50–64 ($\eta^R{}_{3f}$)	−0.143**	−0.180**	−0.276**	−0.396**
	(0.073)	*(0.076)*	*(0.097)*	*(0.103)*
#obs	49,439	46,397	24,947	29,208
[4]-FD + ACF intermediate inputs LP[$]				
Productivity				
Men 50–64 (η_{3m})	−0.043	0.011	0.045	0.126
	(0.081)	*(0.083)*	*(0.045)*	*(0.126)*
Women 30–49 (η_{2f})	−0.331***	−0.164**	−0.254**	−0.227**
	(0.092)	*(0.073)*	*(−0.254)*	*(−0.227)*
Women 50–64 (η_{3f})	−0.518***	−0.634***	−0.644***	−0.377***
	(0.148)	*(0.132)*	*(−0.644)*	*(−0.377)*
Profits				
Men 50–64 ($\eta^P{}_{3m}$)	0.045	0.111	0.129	0.147
	(0.066)	*(0.067)*	*(0.129)*	*(0.147)*
Women 30–49 ($\eta^P{}_{2f}$)	−0.195***	−0.110*	−0.240**	−0.156**
	(0.071)	*(0.064)*	*(−0.240)*	*(−0.156)*
Women 50–64 ($\eta^P{}_{3f}$)	−0.245**	−0.450**	−0.678**	−0.400**
	(0.118)	*(0.111)*	*(−0.678)*	*(−0.400)*
#obs	38,296	36,073	19,841	29,927

Controls: capital, number of employees, hours worked per employee, share of blue-collar workers, share of managers, share of workers by decade of birth + firm fixed effects. FD-IV-GMM: Instruments = second differences and lagged second differences. Tests: IV relevance: Anderson canon. corr. LR statistic √ Overidentifying restriction: Hansen J statistic √. FD-ACF: Innovation in ω_{it} *lag*1–3 labour share, innovation in ω_{it} *lag*1–3 labour shares. £: Standard errors estimates are robust to firm-level clustering; *p<0.1, **p<0.05, *** p<0.01.
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.
[$]Ackerberg, Caves and Frazer.

statistically-significant. ACF model [4], again, deliver estimates that are of larger magnitude and more statistically significant.

5. Conclusions

5.1. Main results

Our results, using our preferred models 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 (value adder per worker) by 2.02 to 5.18% and gross profits by 1.43 to 2.45%. The employability handicap of old female workers is driven by a lower productivity that is not compensated for by lower labour costs. The equivalent results for older men suggest an absence of any statistically significant impact of their presence of productivity and profits. If anything, the older worker gender asymmetry obtained with our overall panel appears stronger when restricting the analysis to *i)* the balanced part of the panel (elimination of closing firms), *ii)* the services industry or *iii)* larger firms. This is not good news for older women's employability.

This said, 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.

Also, this paper focuses on gross profits (i.e. the difference between value added and overall labour costs) which is, presumably, an important metric for labour demand. What we show here is that firms employing older women record a lower level of (gross) profits. But how does this ultimately translate in terms of return on capital? The answer depends on the amount of capital in use per capita in firms with larger shares of older female workers. If it is the same as in firms employing a younger or more masculine workforce, then returns will be lower, and this will further entice firms to reduce their demand of older female workers. Alternatively, these firms could operate with a lower capital base, in order to maintain returns. That could somehow preserve labour demand, but implies than an older and more feminized workforce will lead to the expansion of activities than are intrinsically less capital-intensive. This raises important issues (*e.g.* the degree of complementarity between young/old labour and capital) that go beyond the scope of this paper, but certainly call for more research by economists with an interest in ageing.

5.2. Why would older women be less productive then older men?

Although this somehow exceeds the agenda of this paper, there is a need to elaborate on some of the reasons that could explain the old female (relative) handicap highlighted in this paper, particularly the factors driving older women's productivity handicap.

The positive selectivity bias (i.e. the propensity of our coefficients to underestimate the productivity handicap mentioned above) could be less pronounced for older women. Our data show that in Belgium, between 1996 and 2006, there has been a more pronounced rise of employment among older women than older men. If only a fraction of

Table 8
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 profits (η^P). Unbalanced panel sample.

	Overall sample	Hyp test $\eta_{3f}=\eta_{3m}$ (old women *vs.* old men)			Hyp test $\eta_{3f}=\eta_{2f}$ (old women *vs.* prime-age women)			Hyp test $\eta_{3f}-\eta_{2f}=\eta_{3m}$ (within gender ageing differences)		
		$\eta_{3f}-\eta_{3m}$	Chi^2	Prob > F	$\eta_{3f}-\eta_{2f}$	Chi^2	Prob > F	$(\eta_{3f}-\eta_{2f})-\eta_{3m}$	Chi^2	Prob > F
[3]-FD-IV-GMM										
Productivity										
Men 50–64 (η_{3m})	0.047									
	(−0.026)									
Women 30–49 (η_{2f})	−0.121***	−0.249**	5.18	0.0229	−0.081	1.11	0.2923	−0.128	0.46	0.4965
	(0.046)									
Women 50–64 (η_{3f})	−0.202***									
	(0.077)									
Profits										
Men 50–64 ($\eta^P{}_{3m}$)	0.011									
	(0.049)									
Women 30–49 ($\eta^P{}_{2f}$)	−0.070	−0.153**	4.38	0.0364	−0.073	1.01	0.3153	−0.084	1.19	0.2761
	(0.044)									
Women 50–64 ($\eta^P{}_{3f}$)	−0.143**									
	(0.073)									
#obs	49,439									
[4]-FD + *ACF intermediate inputs LP*[$]										
Productivity										
Men 50–64 (η_{3m})	−0.043									
	(0.081)									
Women 30–49 (η_{2f})	−0.331***	−0.475**	17.86	0.0000	−0.187	0.90	0.3437	−0.144	0.64	0.4233
	(0.092)									
Women 50–64 (η_{3f})	−0.518***									
	(0.148)									
Profits										
Men 50–64 ($\eta^P{}_{3m}$)	0.045									
	(0.066)									
Women 30–49 ($\eta^P{}_{2f}$)	−0.195***	−0.290***	10.40	0.0013	−0.050	0.10	0.748	−0.096	0.45	0.5045
	(0.071)									
Women 50–64 ($\eta^P{}_{3f}$)	−0.245**									
	(0.118)									
#obs	38,296									

Controls: capital, number of employees, hours worked per employee, share of blue-collar workers, share of managers, share of workers by decade of birth + firm fixed effects. FD-IV-GMM: Instruments = second differences and lagged second differences. Tests: IV relevance: Anderson canon. corr. LR statistic √ Overidentifying restriction: Hansen J statistic √. FD-ACF: Innovation in $\omega_{it\perp}$ *lag*1–3 labour share, innovation in $\omega_{it\perp}$ *lag*1–3 labour shares. £:Standard errors estimates are robust to firm-level clustering; *p<0.1, **p<0.05, *** p<0.01.

that extra rise can be ascribed to the 1997 reform, then part of their productivity handicap, as identified it in this paper, could be the consequence of a exogeneous "natural experiment". Consequently, the tendency of our coefficients to underestimate the productivity handicap caused by the presence of more older workers inside firms could be **less** pronounced for women than men. Simply said, our estimates of the firm-level performance caused by the addition of older female workers could better reflect the actual productivity impact of ageing than the estimates we get from the observation of increment in the share older male workers.

Gender health gap could also be an issue (van Oyen et al., 2010; Case and Paxson, 2004). Women in Belgium – as in the US and many other advanced economies - have worse self-rated health, visit GPs more often, and have more hospitalization episodes than men, from early adolescence to late middle age.[43] This said, the existing evidence rather suggests that this health gender gap tends to shrink when individuals turn 50 and more.

Lastly, in Belgium, like throughout much of the OECD, more and more people aged 50–64 need to provide informal care to their old parents aged 70 +[44] while, perhaps, they are still intensively supporting their children who, for example, need baby-sit help. The point is that informal carers are predominantly female aged 50–64 (OECD, 2011). Caring responsibilities may cause burnout and stress, and lead to a lower attachment to the labour force, that is not properly captured by our data. All this could ultimately translate in to lower firm-level productivity.

5.3. Policy implications

Finally how do our main results translate into policy-relevant considerations and recommendations? Most economists believe that the main obstacle to raising the employment rate among individuals aged 50 + is supply-side driven.[45] We argue that our research delivers robust evidence that the latter could also be demand-driven. Firms based in Belgium could face financial disincentives to employing older workers - particularly older women. We show that the age/

[43] But they are less likely to die at each age.

[44] Which is, incidentally, another clear manifestation of ageing.

[45] There is indeed no doubt that welfare institutions played a role in lowering the country' supply of old labour, and have contributed to its low employment rate, singularly amongst women. According to Eurostat, in the first quarter of 2010, only 36% of individuals aged 55–64 were employed; which is 11.1%-points lower than the European average (EU 15). What is more, old women's employment rate (barely 30%) lags behind that of men (44%). In Belgium, qualifying for early retirement benefits was, at least until early 2012, relatively easy by international standards. The age of 58 was a priori the minimum access age, but a lower age of 55, 56 or 57 was possible in some sectors (steel, glass, textile, etc.). Even more pronounced reductions in the minimum age were applicable when the company was recognized as being in financial trouble, under which circumstance the age could be brought down to 52 years, or even 50.

Table 9
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 profits (η^P). Balanced panel sample.

	Balanced panel	Hyp test $\eta_{3f}=\eta_{3m}$ (old women *vs.* old men)			Hyp test $\eta_{3f}=\eta_{2f}$ (old women *vs.* prime-age women)			Hyp test $\eta_{3f}-\eta_{2f}=\eta_{3m}$ (within gender ageing differences)		
		$\eta_{3f}-\eta_{3m}$	Chi^2	Prob>F	$\eta_{3f}-\eta_{2f}$	Chi^2	Prob>F	$(\eta_{3f}-\eta_{2f})-\eta_{3m}$	Chi^2	Prob>F
[3]-FD-IV-GMM										
Productivity										
Men 50–64 (η_{3m})	−0.018									
	(0.052)									
Women 30–49 (η_{2f})	−0.079*	−0.233***	8.59	0.0034	−0.172**	4.69	0.0304	−0.155*	3.45	0.0634
	(−0.079)									
Women 50–64 (η_{3f})	−0.251***									
	(0.080)									
Profits										
Men 50–64 ($\eta^R{}_{3m}$)	0.029									
	(0.050)									
Women 30–49 ($\eta^R{}_{2f}$)	−0.039	−0.209***	7.70	0.0055	−0.142*	3.52	0.0607	−0.171**	4.67	0.0307
	(0.045)									
Women 50–64 ($\eta^R{}_{3f}$)	−0.180**									
	(0.076)									
#obs	46,397									
[4]-FD + ACF intermediate inputs LP[$]										
Productivity										
Men 50–64 (η_{3m})	0.011									
	(0.083)									
Women 30–49 (η_{2f})	−0.164**	−0.646***	43.42	0.0000	−0.471***	9.67	0.0019	−0.482***	12.22	0.0005
	(0.073)									
Women 50–64 (η_{3f})	−0.634***									
	(0.132)									
Profits										
Men 50–64 ($^{\eta^P}{}_{3m}$)	0.111									
	(0.067)									
Women 30–49 ($^{\eta^P}{}_{2f}$)	−0.110*	−0.561***	45.46	0.0000	−0.340***	6.89	0.009	−0.451***	14.38	0.0001
	(0.064)									
Women 50–64 ($^{\eta^P}{}_{3f}$)	−0.450**									
	(0.111)									
#obs	36,073									

Controls: capital, number of employees, hours worked per employee, share of blue-collar workers, share of managers, share of workers by decade of birth + firm fixed effects. FD-IV-GMM: Instruments = second differences and lagged second differences. Tests: IV relevance: Anderson canon. corr. LR statistic √ Overidentifying restriction: Hansen J statistic √. FD-ACF: Innovation in ω_{it} *lag*1–3 labour share, innovation in ω_{it} *lag*1–3 labour shares. £:Standard errors estimates are robust to firm-level clustering; *p<0.1, **p<0.05, *** p<0.01.

gender structure of firms located in Belgium is a key determinant of their productivity and, what is more of their gross profits.

We show that the employability of older women is currently low, due primarily by to a negative effect of age on productivity that is not compensated by lower labour costs. Boosting older women's employability can thus be achieved by *i)* raising the numerator (productivity), or *ii)* reducing the denominator (labour cost) or *iii)* a combination of both.

Raising productivity – or more purposely given the evidence accumulated in this report, combating women's age-related productivity declines – probably calls for a large range of far-reaching initiatives. These perhaps include more training targeted at women aged 40+, although the existing evidence in Belgium is that, if the bulk of training opportunities and resources are concentrated on young and prime-age workers, there is no significant gender gap in terms of access to company based training of livelong learning opportunities. What is more, the scientific evidence about the relationship between training and productivity remains mixed (Dostie and Léger, 2011).

Better ergonomics could also play a key role. There is evidence (although somewhat too anecdotal for an economist to be thoroughly convincing, and not particularly gender-based) that small changes to the work environment can make a difference. In a recent experiment, BMW decided to staff one of its production lines with workers of and an age likely to be typical at the firm in 2030. At first “the pensioners' assembly line” was less productive. But the firm brought it up to the level of the rest of the factory by introducing 70 relatively small changes, such as new chairs, comfier shoes, magnifying lenses and adjustable tables (The Economist, 2010).

Lower labour costs for older women can be achieved in several ways. One is to revise centrally- defined seniority-based wage ladders. These systems are rather common across sectors and industries in Belgium, and probably need to be revisited given the perspective of longer carriers for categories productivity displaying diverging rates of age-related productivity declines. There is some evidence that seniority-based wage setting is indeed on the wane internationally. In Sweden, for example, seniority clauses pay arrangements have been replaced by merit- or performance-based clauses in the early 1990s. Similarly in Japan (one of the OECD countries most affected by ageing) there is increasing emphasis in the private sector on decentralized performance-related pay.

Another option is to selectively lower taxes and social security contributions on older categories of workers. It should ideally be combined with significant productivity-enhancing efforts and a commitment to revised wage ladders by social partners (see above). This is to limit the risk of them free riding the Treasury in order to boost old labour demand. Another point worth considering is that the tax wedge is particularly important in Belgium. It could probably be selectively reduced to stimulate the demand of categories older workers who turn out to be less employable. The direct foregone taxes and contributions entailed by these subsidies could be compensated by much lower (early)pensions payments and longer periods of activity and contributions (albeit at la lower rate during workers' final years of activity).

A number of countries, including Belgium to a moderate extent (Vandenberghe, 2011c), have taken direct action to reduce the cost of employing older workers through wage subsidies or a reduction in social security contributions. The question raised by our results (i.e. gender asymmetry as to how age affects productivity and employability) is whether such a policy could possibly better target older women. If differentiating social contributions by age or education level is largely perceived as logical and legitimate, differences of treatment across gender could prove more problematic. Gender discrimination is prohibited by European law (Gender Discrimination Act).

Appendix 1. Bel-first–Carrefour balanced panel. Main variables. Descriptive statistics.

Variable	Mean	Std. Dev.
Productivity (*i.e.* value added) per worker (th. €) [*log Y/L*]	4.079	0.546
Labour cost per worker (th. €) [*log W/L*]	3.698	0.366
Gross profit (as share of labour costs) [*log(Y/L))-log(W/L) = log(Y)-log(W) ≈ (Y-W)/W)*]	0.382	0.393
Capital (th. €) (th. €) [*log K*]	6.880	1.707
Number of workers (th. €) [*log L*]	3.948	0.981
Share of 18–29 (Male)	0.286	0.160
Share of 30–49 (Male) **ref.**	0.312	0.150
Share of 50–65 (Male)	0.124	0.102
Share of 18–29 (Female)	0.133	0.149
Share of 30–49 (Female)	0.114	0.116
Share of 50–65 (Female)	0.031	0.050
Use of intermediate inputs (th. €) (log)	8.972	1.540
Share of blue collar workers in total workforce [ref.white col.]	0.556	0.345
Share of Manager in total workforce	0.010	0.042
Share of workers born in 1940 — <50	0.091	0.079
Share of workers born in 1950 — <60	0.227	0.110
Share of workers born in 1960 — <70 ref.	0.327	0.103
Share of workers born in 1970 — <80	0.283	0.138
Share of workers born in 1980 — <90	0.065	0.085
Share of large firms (>= 50 workers)	0.589	0.492
Number of hours worked annually per employee (log)	7.377	0.196
Number of spells	9.000	0.000

Detailed definitions of variables are to be found in Appendix 3. Source: Bel-first-Carrefour.

Appendix 2. Sectors/industries and NACE2 codes/definitions

NACE2 code		Industry
10 to 12	Manufacturing	Manufacture of food products, beverages and tobacco products
13 to 15	Manufacturing	Manufacture of textiles, apparel, leather and related products
16 to 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 to 33	Manufacturing	Other manufacturing, and repair and installation of machinery and e
35	Utilities	Electricity, gas, steam and air-conditioning supply
36 to 39	Utilities	Water supply, sewerage, waste management and remediation
41 to 43	Construction	Construction
45 to 47	Services	Wholesale and retail trade, repair of motor vehicles and motorcycles
49 to 53	Services	Transportation and storage
55 + 56	Services	Accommodation and food service activities
58 to 60	Services	Publishing, audiovisual and broadcasting activities
61	Services	Telecommunications
62 + 63	Services	IT and other information services
64 to 66	Finance/ insurance	Financial and insurance activities
68	Services	Real estate activities
69 to 71	Services	Legal, accounting, management, architecture, engineering, technical
72	Services	Scientific research and development
73 to 75	Services	Other professional, scientific and technical activities
77 to 82	Services	Administrative and support service activities
90 to 93	Services	Arts, entertainment and recreation
94 to 96	Services	Other services
97 to 98	Non-profit	Activities of households as employers; undifferentiated goods
99	Non-profit	Activities of extra-territorial organizations and bodies

Appendix 3. (Detailing Table 1) — Bel-first/Carrefour panel. Main variables. Definition.

Variable	Definition (by default, source is Bel-first
[1] Productivity (ie.value added) per worker (th. €) (*log Y/L*)	Value added, in th. euros, divided by the overall number of worker [3]
[2] Labour cost per worker (th. €) (*log W/L*)	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] Capital (th. €) (th. €) (*log K*)	Capital, in th. euros (includes intangible assets)
[4] Number of workers (th. €) (*log L*)	Total number of workers employed in the firm (averaged over the year). NB : our overall sample excludes firms with less than 20 employees.
[5] Male workers aged 18–29/total workforce	The age of (all) workers employed by the firm [4] is retrieved from the Belgium's Social Security register (the so-called Carrefour database), using firms' unique identifying code.
[6] Male workers aged 30–49/ total workforce **(ref. cat)**	
[7] Male workers aged 50–65/total workforce	
[8] Female workers aged 18–29/total workforce	
[9] Female workers aged 30–49/total workforce	
[10] Female workers aged 50–65/total workforce	
[11] 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.
[12] Blue-collar workers/ total workforce	Breakdown of the total number of employees [4] into three categories. *i)* blue-collar workers (55%), *ii)* those with a managerial status (1%) and *iii)* 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).
[13] White-collar workers/ total workforce **(ref. cat)**	
[14] Managers/total workforce	
[15] Number of hours worked annually per employee (log)	Obtained by dividing the total number of hours reportedly worked annually by the number of employees [4]. That variable is strongly correlated with the intensity of part-time work
[16] Share of workers born in 1940 — <50	Breakdown of the total number of employees [4] according to the decade of birth

Please cite this article as: Vandenberghe, V., Are firms willing to employ a greying and feminizing workforce?, Labour Econ. (2012), http://dx.doi.org/10.1016/j.labeco.2012.07.004

Appendix 3 (*continued*)

Variable	Definition (by default, source is Bel-first
[17] Share of workers born in 1950 − <60	
[18] Share of workers born in 1960 − <70 (ref. cat.)	
[19] Share of workers born in 1970 − <80	
[20] Share of workers born in 1980 − <90	
[21] Share of large firms (>=50 workers)	Share of spells (i.e. firm by year observations) corresponding to firms who employed more than 50 workers in 1998 (first year of the panel)
[22] Number of spells	Average number of times (i.e. years) firms are observed in the panel

Source: Bel-first–Carrefour.

Appendix 4

Age/gender shares related.

[A] to the working age population (20–64)				[B] the total workforce (18–64), private firms located in Belgium			
Age group	Femmes	Hommes	Total	Age group	Femmes	Hommes	Total
20–29	0.105	0.106	0.211	18–29	0.137	0.287	0.424
30–49	0.241	0.247	0.488	30–49	0.115	0.309	0.424
50–64	0.152	0.150	0.301	50–64	0.031	0.122	0.153
20–64	0.497	0.503	1.000	18–64	0.283	0.718	1.000

Source: EU-LFS, year 1999–2008.
Source: Belfirst–Carrefour, year 1998–2006.

References

Acherberg, D.A., Caves, K., Frazer, G., 2006. Structural identification of production functions. Department of Economics, Working Paper, UCLA.

Arellano, M., Bond, S., 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies 58, 277–297.

Aubert, P., Crépon, B., 2003. La productivité des salariés âgés: une tentative d'estimation. Economie et Statistique 368, 95–119.

Aubert, P., Crépon, B., 2007. Are older workers less productive. Firm-level evidence on age-productivity and age-wage profiles, *mimeo*, (French version published in *Economie et Statistique*).

Bartelmans, E.J., Doms, M., 2000. Understanding productivity: lessons from longitudinal microdata. Journal of Economic Literature 38 (3), 569–594.

Blöndal, S., Scarpetta, S., 1999. The retirement decision in OECD countries. OECD Economics Department Working Papers, No 202, OECD. Economics Department, Paris.

Blundell, R., Bond, S., 2000. GMM estimation with persistent panel data: an application to production functions. Econometric Reviews 19 (3), 321–340.

Cardoso, A., Guimarães, P., Varejão, J., 2011. Are older workers worthy of their pay? An empirical investigation of age–productivity and age–wage nexuses. De Economist 159 (2), 95–111.

Case, A.C., Paxson, Ch., 2004. Sex differences in morbidity and mortality. NBER Working Papers, No 10653. National Bureau of Economic Research, Ma.

Cataldi, A., Kampelmann, S., Rycx, F., 2011. Productivity-wage gaps among age groups: does the ICT environment matter? De Economist 159 (2), 193–221.

Crépon, B., Deniau, N., Pérez-Duarte, S., 2002. Wages, productivity, and worker characteristics: a french perspective. Série des Documents de Travail du CREST. Institut National de la Statistique et des Etudes Economiques.

Dorn, D., Sousa-Poza, A., 2010. Voluntary and involuntary early retirement: an international analysis. Applied Economics 42 (4), 427–438.

Dostie, B., 2011. Wages, productivity and aging. De Economist 159 (2), 139–158.

Dostie, B., Léger, P.Th., 2011. Firm-sponsored classroom training: is it worth it for older workers? IZA Discussion Papers, No 6123, IZA, Bonn.

Fitzenberger, B., Schnabel, R., Wunderlich, G., 2004. The gender gap in labour market participation and employment: a cohort analysis for West Germany. Journal of Population Economics 17 (1), 83–116.

Göbel, Ch, Zwick, Th., 2009. Age and productivity: evidence from linked employer–employee data. ZEW Discussion Papers, No 09-020. ZEW, Mannheim.

Griliches, Z., Mairesse, J., 1995. Production functions: the search for identification, *NBER working paper*, No 5067. NBER, Ma.

Grund, Ch., Westergård-Nielsen, N., 2008. Age structure of the workforce and firm performance. International Journal of Manpower 29 (5), 410–422.

Hellerstein, J.K., Neumark, D., 1995. Are earning profiles steeper than productivity profiles: evidence from israeli firm-level data. The Journal of Human Resources 30 (1), 89–112.

Hellerstein, J., Neumark, D., 2007. Production function and wage equation estimation with heterogeneous labor: evidence from a new matched employer–employee data set. In: Berndt, Ernst R., Hulten, Charles R. (Eds.), Hard-to-Measure Goods and Services: Essays in Honor of Zvi Griliches.

Hellerstein, J.K., Neumar, D., Troske, K., 1999. Wages, productivity, and worker characteristics: evidence from plant-level production functions and wage equations. Journal of Labour Economics 17 (3), 409–446.

Jousten, A., Lefèbvre, M., Perelman, S., Pestieau, P., 2008. The effects of early retirement on youth unemployment: the case of Belgium. IMF Working Paper, 08/30. IMF, Washington.

Kalwij, A., Vermeulen, F., 2008. Health and labour force participation of older people in Europe: what do objective health indicators add to the analysis? Health Economics 17 (5), 619–638.

Lallemand, T., Rycx, F., 2009. Are young and old workers harmful for firm productivity? De Economist 157, 273–292.

Levinsohn, J., Petrin, A., 2003. Estimating production functions using inputs to control for unobservables. Review of Economic Studies 70 (2), 317–341.

Malmberg, B., Lindh, T., Halvarsson, M., 2008. Productivity consequences of workforce ageing: stagnation or Horndal effect? In: Prskawetz, A., Bloom, D., Lutz, W. (Eds.), Population aging, human capital accumulation and productivity growth: Population and Development Review, Supplement to, vol. 34, pp. 238–256.

Mitchell, O.S., Fields, G.S., 1984. The economics of retirement behavior. Journal of Labour Economics 2 (1), 84–105.

OECD, 2011. Help wanted? Providing and Paying for Long-Term Care. OECD, Paris.

Olley, G.S., Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64 (6), 1263–1297.

Peracchi, F., Welch, F., 1994. Trends in labour force transitions of older men and women. Journal of Labour Economics 12 (2), 210–242.

Pfeifer, Ch, Wagner, J., 2012. Age and gender composition of the workforce. Productivity and profits: evidence from a new type of data for German enterprises, *IZA WP*, No 6341.

Pozzebon, S., Mitchell, O.S., 1989. Married women's retirement behavior. Journal of Population Economics 2 (1), 39–53.

Saint-Paul, G., 2009. Does welfare state make older workers unemployable. CEPR Discussion Paper, No. 7490, London.

Skirbekk, V., 2004. Age and individual productivity: a literature survey. In: Feichtinger, G. (Ed.), Vienna yearbook of population research 2004. Austrian Academy of Sciences Press, Vienna, pp. 133–153.

Skirbekk, V., 2008. Age and productivity capacity: descriptions, causes and policy options. Ageing Horizons 8, 4–12.

Syverson, C., 2011. What determines productivity? Journal of Economic Literature 49 (2), 326–365.

The Economist, 2010. The silver tsunami. Business will have to learn how to manage an ageing workforce. De Economist (Schumpeter column, Feb. 6th).

van Ours, J.C., Stoeldraijer, L., 2011. Age, wage and productivity in Dutch manufacturing. De Economist 159 (2), 113–137.

van Oyen, H., Deboosere, P., Lorant, V., Charafeddine, R., 2010. Les inégalités socials de santé en Belgique. BELSPO, Bruxelles.

Vandenberghe, V., 2011a. Boosting the employment rate of older men and women. An empirical assessment using Belgian firm-level data on productivity and labour costs. De Economist 159 (2), 159–191.

Vandenberghe, V., 2011b. Firm-level evidence on gender wage discrimination in the Belgian private economy. Labour: Review of Labour Economics and Industrial Relations 25 (3), 330–349.

Vandenberghe, V., 2011c. Peut-on se passer des préretraites? Reflets & Perspectives de la vie économique 0 (4), 107–124 (De Boeck Université).

Weaver, D., 1994. The work and retirement decision of older women: a literature review. Socil Security Bulletin 57 (1), 1–24.

Please cite this article as: Vandenberghe, V., Are firms willing to employ a greying and feminizing workforce?, Labour Econ. (2012), http://dx.doi.org/10.1016/j.labeco.2012.07.004