Ageing and productivity: evidence from a matched employer-employee data set at the sector level[1]

Bernhard Mahlberg[#]
Institute for Industrial Research
Mittersteig 10, 1050 Vienna, Austria
(Mahlberg@iwi.ac.at)

Inga Freund
Vienna University of Technology
Institute of Mathematical Methods in Economics, Research Group Economics

Alexia Prskawetz
Vienna University of Technology
Institute of Mathematical Methods in Economics, Research Group Economics

and

Vienna Institute of Demography
Austrian Academy of Sciences

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Abstract

The workforce will age and shrink in most industrialized countries during the next decades. Whether these demographic developments might imply reduced productivity and lower economic growth will essentially depend on the productivity of an ageing workforce. So far research on the age-productivity profile has mainly been carried out at the individual, macro and firm level. In this paper we close a gap in the literature by analysing the link between the age structure of the labour force and average labour productivity at an inter-mediate level, i.e. within certain economic sectors. The analysis is based on a panel data set over six years (2002-2007) for the Austrian sectors of mining, manufacturing and market oriented services. Our results indicate a positive correlation of the share of older workers and productivity. The results for the share of younger workers are less clear-cut.

JEL Codes: J14, J24, J82
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[#] Corresponding author

1. Introduction

Low fertility levels, decreasing mortality and moderate levels of migration will lead to population ageing in most industrialized countries. While population shrinkage might not set in immediately, the age structure of the population and in particular the age structure of the workforce will grow older in the near future. Will an ageing and possibly shrinking workforce be able to maintain economic growth, social security systems and prosperity? An important pre-requisite for economic growth under conditions of population ageing will be the potential of increasing productivity. Research is therefore conducted on the interrelationship of ageing and productivity. Studies have been conducted at various levels of analysis; the individual (e.g. Skirbekk 2008), the firm (e.g. Aubert and Crépon 2006, Göbel and Zwick 2009) as well as country (e.g. Lindh and Malmberg 1999, Prskawetz et al. 2007) level. From our point of view it is the sector level, which seems to be under-explored up to now and offers some potential to gain new insights on ageing and productivity within a “special” economic aggregate. Hence, we aim at contributing to industry level research in order to close the literature gap with respect to a connection between ageing and labour productivity.

Based on a cross-section matched employer-employee data set in 2001 for Austrian firms our former study (Mahlberg et al. 2009) showed that there is a hump-shaped age-productivity pattern. Employees aged 15 to 29 years as well as employees aged 50 years and older negatively influence a firm's value added per worker as compared to the middle-aged (30 to 49 years) group of employees. In addition, OLS regression estimates yield, that training has a positive impact on average labour productivity at the firm level (with a lag of two years). However, the training effect vanishes as soon as we control for sector heterogeneity in terms of sector dummies. This fact lets us to conclude, that although value added is actually produced within firms, it is the industrial affiliation, which matters as well. Hence, our attention is drawn to the sector level itself.

Our aim in this paper is to figure out, whether a similar age-productivity pattern – as we observed at the firm level - may be found at the industry level as well. It is important to note, that the sector level presents an economic aggregate over firms. Hence, we deal with a kind of intermediate level between a firm and a country. It is therefore less intuitive in which way the age structure might be correlated to the productivity within an economic sector. At the firm level this correlation is more obvious since a firm's value added is produced – among various other input factors - with human capital of different age groups. At the aggregate, macro level it is the aggregate labour, consumption and savings (or investment) behaviour that will determine overall GDP.

Research results on a potential age-productivity link at the sector level may offer important insights for countries that undergo a fundamental transition in their economic structure. As we will explain, there are indeed some sectors, which are characterised by a rather young age structure of the employees, as well as other industries, for which the opposite is true. While we might capture changes in age structure across sectors, the short time span of our data will not allow capturing changes in the age structure within sectors.

Moreover, switching from the firm to the industry[2] level is accompanied by imprecision concerning the aggregation of the age structure as well as productivity. Firstly, as descriptive analysis indicates (cf. Freund et al., 2009), the average age distribution across firms within one economic sector does not necessarily coincide with the overall age distribution within the

[2] In this paper we consider the terms industry and sector as synonyms.

same industry, i.e. abstaining from averaging over firms. Secondly, as Levinsohn and Petrin (1999) point out, productivity increases at the industry level may not necessarily be traced back to "real" productivity increases at the firm level. It is rather the contrary: Their results show that decreases in "real" productivity at the firm level account for the largest part in productivity decreases at the industry level, whereas productivity increases at the industry level are mainly due to shifts of output shares from less to more productive firms. They emphasise the importance of firm heterogeneity. Thirdly, analysis on productivity effects of a firm's training activities provided to their employees (e.g. Dearden et al. 2005, Kuckulenz 2006), which are actually conducted at the industry level, point to the importance of externalities in terms of knowledge spill-overs among firms within one economic sector. Although we are not able to directly control for training (of different age groups) in this paper, these effects nevertheless might exist and drive the results through biased coefficients on the included variables. While the group of trained employees exists of younger employees as a rule, Bellmann and Leber (2008) show, that the elderly in small and medium sized firms run the risk of being "under-trained". Hence, age effects might also capture effects that actually emanate from training, but cannot separately be controlled for due to data restrictions.

Thus, we need to keep in mind that the level of analysis (sector vs. firm or macro level) might explain differences in the age-productivity profile. For instance, at the firm level, the negative correlation between the share of younger workers and productivity is rather stable, while the correlation between the share of older workers and productivity is rather small and might even vanish if one takes properly account for endogeneity and unobserved heterogeneity between firms. At the macro level however, it is rather the share of young workers that is less stable.

As for the current analysis a panel data set across sectors of mining, manufacturing and market oriented services over the period 2002 to 2007 is available, we will be able to apply some more sophisticated panel data estimation techniques. The econometric framework will be more closely related to applications at the firm level (cp. Aubert and Crépon 2006, Göbel and Zwick 2009) instead of common empiric economic growth models at the macro-level (cp. Lindh and Malmberg 1999, Prskawetz et al. 2007).

The paper is structured as follows: Section 2 reviews the relevant literature. In section 3 we introduce the theoretical model. A description of the data is presented in section 4. Results of the empirical application of the theoretical model are summarized in section 5. The last section (section 6) concludes.

2. State of the Art

Following Levinsohn and Petrin (1999) aggregate productivity changes at the industry level may be explained by different phenomena. Firstly, increases of real productivity at the firm level being based on learning processes, which take place within firms, lead to cumulated productivity growth at the sector level. Secondly, the pure redistribution of market shares, i.e. either the expansion of efficient firms or prevention of inefficient firms from failure, for instance, may also lead to changes in aggregate industry level productivity. Based on different estimation methods their empirical findings[3] are, that "real" productivity decreases at the firm

[3] Levinsohn and Petrin (1999) use an annual unbalanced panel data set for 6.665 Chilean plants ranging from 1979 to 1986 encompassing eight 3-digit level industries. Simultaneity is accounted for by proxying productivity shocks on the right hand-side of the equation. Moreover, the authors refer to selectivity regarding firm exit by anticipating next period's productivity biasing the capital stock, which is supposed to be lower for inefficient firms.

level are predominantly responsible for declining productivity, whereas shifting output shares from less to more productive firms mainly lead to a productivity increase at the sector level. Consequently, the observation of industries becoming more productive may not necessarily be traced back to an increase of real productivity at the firm level. Moreover, aggregate sector productivity might rise while it could be even the opposite development for firm level productivity. Thus, the authors emphasise the importance of firm heterogeneity (see Pöschl et al. 2009 for heterogeneity with regard to exports and size).

Assuming that efficient and inefficient or entering and exiting firms are characterised by a systematically different age structure of their employees, that may also be traced back to reverse causality of age and productivity, this may well lead to a divergent outcome with regard to the age-productivity pattern at the industry level compared to the firm level. Moreover, it challenges the econometric set-up.

Pöschl et al. (2009) analyse the "export premia" for Austrian firms, which turns out to be industry-dependent.[4] Based on descriptive statistics they find, that the "intensive margin" (= exports per firm) may matter more for overall exports than the "extensive margin" (= number of exporting firms). For the overall manufacturing sector a so-called bimodal distribution is found with a predominant number of firms, which are either not or highly engaged in exports. This distribution is traced back to comparative (dis-)advantages. On a more disaggregated level the prevalent pattern is, that most exporting firms (with exports > 0) have an export share above 50% of total sales, which mirrors the Austrian situation of a "small open economy" (Pöschl et al. 2009, p. 15) being geographically located in the centre of the European Union. The overall cumulative distribution shows, that a small share of firms accounts for the largest part of exports. Overall, although again characterised by heterogeneity among industries (as well as certain exceptions) exporting firms turn out to be larger than non-exporting Austrian firms in terms of sales, employment, their wage sum as well as investment. Moreover, "size" increases with export intensity implying small-scale non-exporters. An export premium is - albeit smaller, but - also found with respect to labour productivity defined as production value or wages per employee as well as investment intensity averaged over the period 2002-2006. Pöschl et al. (2009) show that export effects may play an important role in determining productivity, which apparently are industry-specific.[5] The emphasised heterogeneity of firms within one 2-/ 1-digit sector may lead to differing and compensatory effects on industry level as compared to firm level outcomes.

Based on a labour decomposition with respect to trained as well as untrained employees, Dearden et al. (2005) explore the causal relationship of training at the workplace and productivity (= "direct measure") on the one hand as well as wages (= "private return") and productivity on the other hand (p. 2).[6] While the training impact is significantly positive for both of the dependent variables, it is larger for productivity than for wages. Comparing their regression estimates for the latter with respective results at the individual level leads to the authors' conclusion of positive training externalities among firms, which are located within the same industrial sector (cp. Kuckulenz 2006).
This approach is followed by Kuckulenz (2006), who analyses potential sharing of training gains between the employer - in terms of higher productivity - and the employees - in terms of

[4] The authors consider 4.952 to 6.326 firms in the manufacturing sector (NACE D) on 23 2-digit level in the period 1997-2006 based on LSE data. They point to the methodological change in 2002 and construct two subsamples with regard to time intervals.
[5] The direction of causality between exports and productivity in the literature does not seem to be that clear-cut up to this point.
[6] They make use of 94 industries in the British economy excl. the service sector over the period 1983-1996.

higher wages.[7] Amongst others, high-skilled as well as young employees show a comparably high training participation. Based on her final regression outcome the author finds, that productivity is significantly and positively influenced by present and past training activities as well as the shares of employees in all age groups older than 17-20 years.[8] Kuckulenz (2006) draws two conclusions: Firstly, since the respective training coefficient from the productivity regression exceeds the one from the according regression on wages, the employer as well as the employees benefit from training activities. Secondly, there obviously exist "knowledge spill-overs" (p. 20) among firms within one sector, which is revealed by a comparison with results at the enterprise level (Zwick 2005).
Hence, although the above mentioned authors control for several further characteristics, particularly training, the overall age-productivity relation found does not follow a specific pattern at the sector level. Both papers find a negative impact emanating from the youngest age group as compared to the other age groups. Moreover, from our point of view externalities among enterprises, which are economically active in the same economic field, might also occur due to further kinds of knowledge spill-overs that are not necessarily based on training activities. Besides education, which we separately control for, these could arise from human capital in terms of experience, which may be proxied based on the age distribution of the labour force.

To our knowledge further investigations with respect to productivity at an intermediate level rather refer to a geographical decomposition, i.e. regions (e.g.Tang and MacLeod 2006, Hirte and Brunow 2008) and/ or do not exactly refer to our main focus (e.g. Dietz and Bozemann 2005), which is the labour force's age structure. However, the main motivation for our analysis emanates from our own as well as further research at the firm level.[9] Various studies found a hump-shaped age pattern in connection with labour productivity, which seems to diminish particularly for older ages at the firm level, when applying more recent estimation techniques.

With the aim to disentangle age-productivity and age-earnings profiles for various worker types Hellerstein et al. (1999)[10] in particular differentiate employees based on age (<35 years, ≥35 and ≤54 years, ≥55 years), which mirrors their experience or tenure respectively. The authors find that higher wages of employees above the age of 35 years are justified by their higher productivity as compared to their youngest counterparts.

Basically following a very similar methodological approach Crépon et al. (2002)[11] find increasing wages over age (<25, 25-34, 35-49 and 50+ years), whereas productivity decreases again from a certain point onwards implicating an overpayment at higher and/ or under-payment at younger ages. The analysis is improved by Aubert and Crépon (2006), who take unobserved heterogeneity into account and control for "simultaneity" of the dependent (= labour productivity) and independent (= age structure, i.e. 5-year age groups from 25 to 60 plus, <25 and ≥60) variables based on more sophisticated methods of regression analysis. While the between effects (BE) estimation rather hints towards a U-shaped age-productivity profile with a minimum at the age of 40 to 44 years, the results yield a hump-shaped age-productivity pattern peaking at the age of 30 to 34 years in the within dimension over time

[7] She considers 58 German industries over a time interval of seven years (1996-2002).
[8] Age Share Dummies are a relatively crude way of measuring age, as probably in each sector nearly every age group may be found.
[9] In the following we will strongly focus on the relevant facts as highlighted in the recent literature with regard to the interest of our current study. For detailed justification see the respective paper.
[10] They make use of an employer-employee data set.
[11] They focus on French manufacturing firms.

(FE). The pattern nearly completely flattens for higher ages reaching the top for employees aged 40 to 44 years, while the impact of employees at lower ages remains comparatively negative, when applying a General Method of Moments (GMM) estimation. Furthermore, a positive selection effect of the most productive elderly staying in the labour market might lead to the positive productivity impact emanating from the oldest age group of employees.
Malmberg et al. (2008) find a hump-shaped age effect on value added per employee[12] as long as they do not consider unobserved fixed effects. The inclusion of all age groups - being possible due to the construction of logarithms - reveals a negative productivity impact of older employees, which is true for large as well as small firms. Having a closer look at the situation within an average firm over time shows a completely different picture: A negative productivity impact is detected for younger employees, while the coefficient for older employees even turns around its sign and prime-aged workers are of less importance.
Göbel and Zwick (2009) systematically lead through different estimation techniques in order to exclude potential biases in detecting the labour productivity impact of the workforce's age structure (= 5-year age group shares + merged tails of age distribution) on establishment level.[13] While POLS[14] estimation obviously still underestimates the influence on labour productivity emanating from old employees, the FE estimator takes unobserved heterogeneity into account. Moreover, the applied difference GMM as well as system GMM regression methods control for possibly existing simultaneity (= endogeneity) of the regressors and labour productivity. The authors finally conclude that labour productivity on the establishment level peaks in the age group of 50-55 years and decreases only slightly for higher ages.

Also macro-economic studies generally confirm a hump-shaped age impact at the country level, i.e. on GDP growth. Interestingly, it is the negative impact from the young age group, which seems to be less stable in this the macro context.

Switching to a neoclassical growth model, which takes technology convergence into consideration, Lindh and Malmberg (1999) focus on GDP per worker growth. Having a look at the age structure of the population (= 0 to 14 years (= reference group), 15 to 29, 30 to 49, 50 to 64 and 65+ years in cumulative Cobb Douglas term) the age group share of workers being 50 to 64 years old significantly positively affects economic growth. The influence of younger age groups is rather ambiguous, whereas the oldest age group share carries out a relatively negative growth impact.
Within their EU report Prskawetz et al. (2007) reproduce the Swedish study (cp. Lindh and Malmberg 1999) for EU 14 member countries in a first step. With regard to economic growth it is also the middle-aged population age group share (50 to 64 years), which performs best, while the effect emanating from the oldest age group (65 years and older) is lower. On the one hand, the impact on economic growth of younger age groups (15 to 29 and 30 to 49 years) is not that clear-cut and depends on further controls. On the other hand, a higher (lower) share of the youngest (middle and oldest) age group positively drives the catching-up process towards the technological frontier.

In explaining output per worker (growth) based on workforce age shares (in 10-year groups) Feyrer (2004) is able to show, that the age group share of 40 to 49 year old people exhibit the most positive impact. Thereupon, he regresses each of the input factors of a Cobb Douglas

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[12] They divide the labour force of Swedish firms into three age groups (<30 years, ≥30 and ≤50 years, >50 years).
[13] Their linked employer-employee panel data set encompasses the years 1997-2005 for approximately 8,500 German establishments with nearly 7 Mio. employees.
[14] POLS = Pooled Ordinary Least Squares

production function on the same set of age shares. The author finds a significant positive correlation of the share of 40 to 49 years and total factor productivity (TFP) in terms of the Solow residual, while the age impact on human as well as physical capital are of less importance. Younger (10 to 19, 20 to 29 and 30 to 39 years) as well as older (50 to 59 and 60+ years) age group show a lower correlation with TFP as compared to the reference group (40 to 49 years).

As former research has shown there are various potential factors, which are supposed to be correlated with labour productivity at the industry level motivating our analysis. It turns out, that the formerly found hump-shaped age-productivity pattern strongly depends on the estimation method applied, availability of control variables, respective data source as well as the analytical level. While OLS estimation on panel data relies on the possibility of reasonable pooling the information for various individuals, a FE model takes unobserved heterogeneity into account, whereas IV, e.g. GMM, methods additionally control for endogeneity. Moreover, sector heterogeneity may be caused through firm entry and exit, export shares as well as certain types of knowledge spill-overs. In the end, dealing with different economic levels opens some space for different compensatory as well as aggregation effects being at work.

3. Theoretical Model

We start with a Cobb Douglas production function and focus on the input factor labour and its decomposition. Labour in our model is basically represented by age shares, which are augmented by several further labour force characteristics in the following.

In the basic model capital K_i and labour L_i^* within a certain sector i are combined with a technology parameter A (= Solow residual) and result in a certain output Y_i[15]:

$$Y_i = K_i^{\alpha} L_i^{*\beta} A \qquad (1)$$

As the age structure of the workforce is a central element of our analysis we particularly focus on the definition of labour L_i^*, which may be modelled in different ways. Initially following Crépon et al. (2002)[16] we decompose total labour input L_i^* within a sector into a weighted sum according to certain types of workers k, which are perfectly substitutable and implemented by an additive sum[17]. The weights are represented by an individual productivity parameter λ_{ik}.

$$\begin{aligned} L_i^* &= \textstyle\sum_{k=0}^{m} \lambda_{ik} L_{ik} \\ &= \lambda_{i0} L_{i0} + \sum_{k=1}^{m} \lambda_{ik} L_{ik} \\ &= \lambda_{i0}\, L_i \left(1 + \sum_{k=1}^{m} \left(\frac{\lambda_{ik}}{\lambda_{i0}} - 1\right) \frac{L_{ik}}{L_i}\right) \end{aligned}$$

$$\ln(L_i^*) = \ln(\lambda_{i0}) + \ln(L_i) + \ln\left(1 + \textstyle\sum_{k=1}^{m} \gamma_{ik} \frac{L_{ik}}{L_i}\right) \qquad (2)$$

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[15] For simplifying reasons we abstain from time subscripts here.
[16] Crépon et al. (2002) make use of the aggregate production function within their theoretical model.
[17] An alternative way in order to abstain from the assumption of perfect substitutability would be to implement a Cobb Douglas type aggregate of labour.

where λ_{i0} is the productivity of the reference group of workers, which analogously holds for workers of type k (λ_{ik}) and $\gamma_{ik} = \frac{\lambda_{ik}}{\lambda_{i0}} - 1$ [18]. The latter is assumed to be constant across sectors, i.e. $\gamma_{ik} \equiv \gamma_k$.

We now assume constant returns to scale, i.e. $\alpha + \beta = 1$, and go back to equation (1). Taking logs and inserting the term for L_i^* emanating from equation (2) yields:

$$\ln(Y_i) = \alpha \ln(K_i) + (1-\alpha)\ln(\lambda_{i0}) + (1-\alpha)\ln(L_i) + (1-\alpha)\ln\left(1 + \sum_{k=1}^{m} \gamma_{ik} \frac{L_{ik}}{L_i}\right) + \ln(A) \tag{3}$$

Considering, that the expression for $\ln(\lambda_{i0})$ is captured within the constant c, subtracting $\ln(L_i)$ from both sides and implementing the approximation $ln(1+x) \approx x$, which in fact holds for $x \ll 1$, leads to the basic equation in per worker terms being estimated in section 5:

$$\ln\left(\frac{Y_i}{L_i}\right) = c + \alpha \ln\left(\frac{K_i}{L_i}\right) + (1-\alpha) \sum_{k=1}^{m} \gamma_k \frac{L_{ik}}{L_i} + \delta \ln(X_i) + u_i \tag{4}$$

where u_i represents the error term being the remaining part of A that cannot be explained with the help of further explanatory variables X_i [19] serving as a sector-specific control[20]. Now we are consistent with our empirical approach in dividing output and capital through L_i instead of L_i^*. Furthermore, the term on the absolute number of employees $\ln(L_i)$ drops out. The estimated (age) share coefficients are composed of the Cobb Douglas parameter α as well as γ_{ik}.[21]

4. Data

Composition of the data set

The newly created panel data set contains yearly employer-employee data for the years 2002-2007. The data set emerged from matching industry level data from the structural business statistics of Statistics Austria with data from the Main Association of Austrian Social Security Institutions ("Hauptverband der Sozialversicherungsträger"), national account of Statistics Austria, and micro census of Statistics Austria.

Our sector characteristics are collected from the structural business statistics of Statistics Austria. The underlying survey is conducted yearly and provides data concerning the structure

[18] See Crépon et al. (2002), footnote 3. This term also corresponds to the "relative (marginal) productivity differential" of a trained worker compared to an untrained worker" $\frac{MP_T - MP_U}{MP_U}$ in Konings and Varnomelingen (2009), p. 5.

[19] In fact, X_i may encompass several sector specific characteristics m, so that actually $\sum_1^m \delta_m \ln(X_{im})$. Although we start numbering with *1* instead of *0*, this does not necessarily mean, that any shares or reference groups respectively are included here.

[20] Hence, A becomes sector-specific in retrospect (A_i).

[21] Since we introduce several labour shares in addition to the age variables (see Chapter 5), the estimated coefficients, i.e. the respective overall productivity effects, actually consist of a third component, namely the proportion to which the respective labour force characteristic contributes to total ("quality weighted") labour input L_i^*.

(single-plant vs. multi-plant firm), sector affiliation, employment, investment activities and performance of enterprises at the national and regional level in a breakdown by economic branches in accordance with OeNACE[22]. It encompasses the economic branches of production (C "Mining and quarrying", D "Manufacturing", E "Electricity, gas and water supply", F "Construction") and selected sections of the service sector (G "Wholesale and retail trade; repair of motor vehicles and motorcycles, personal and household goods", H "Hotels and restaurants", I "Transport, storage and communication", J "Financial intermediation", K "Real estate, renting and business services"). Not included in the survey are the sectors "Agriculture, hunting and forestry" and "Fishing" (NACE A and B) as well as "Public administration and defence; compulsory social security", "Education", "Health and social work", "Other community, social and personal service activities", "Activities of households" and "Extra-territorial organizations and bodies" (NACE L to Q). The structural business survey includes economic indicators of 29,371 enterprises in 2002, 31,966 enterprises in 2003, 32,891 enterprises in 2004, 34,312 enterprises in 2005, approx. 37,500 enterprises in 2006, and approx. 37,000 enterprises in 2007, respectively. The values are extrapolated to the data of the whole firm population in the investigated sectors and yield the final statistics. It contains the following indicators: value added, no. of workers, revenue, personal expenditures, inter-mediate inputs, investments, sum of wages, no. of self-employed, no. of white-collar workers, no. of blue-collar workers, no. of apprentices, no. of home workers, no. of part time workers.[23] All variables (except for employment) are deflated to constant prices of 2005 by the harmonized consumer price index taken from Statistics Austria. In addition, data on net fixed capital are taken from national accounts of Statistics Austria.[24] The data serve as a measure of capital stock and are valued at replacement cost of 2005.

The workforce characteristics emerge from social security data. These are collected from the Main Association of Austrian Social Security Institutions and provide information on age, gender, and social status (white-collar worker vs. blue-collar worker) of individuals employed in firms of the sectors considered.[25] In principal these data contain all employees (white-collar and blue-collar workers, home workers, apprentices, full-time and part-time workers) and some self-employed persons. Data on educational attainment are taken from micro census of Statistics Austria and added to the data set.

Hofstätter et al. (2009) emphasise two decisive characteristics of "HV" data: Firstly, these are based on employment relationships incl. the possibility of several of these being attributed to one person. Secondly, every single employment period regardless of its length is recorded without any kind of smoothing. Based on the year 2008, OeNACE 2008 and employed persons ("unselbständig beschäftigt") they focus on employment possibilities, i.e. new registrations, for older persons on an industry perspective. The authors state, that

[22] NACE (Nomenclature of economic activities) is a code that represents the classification of economic activities within the European Union, while OeNACE accords to the Austrian version. While all other levels of OeNACE are identical with the corresponding levels of NACE an additional hierarchical level - the national sub-classes - was added to represent the Austrian economy in a more detailed and specific way. For details see European Commission (2002) and Statistics Austria (2003). Based on the classification of our data we use the OeNACE version of 2003.

[23] These data are directly taken from the publications on the structural business statistics of Statistics Austria. For further details on sample selection, methods of extrapolation etc. in structural business statistics see e.g. Statistics Austria (2009b).

[24] These data were provided by Statistics Austria. For details on the computation procedure of net fixed capital see Schwarz (2002) and Statistics Austria (2009a, p. 154).

[25] The Main Association of Austrian Social Security Institutions provided us with these data aggregated to NACE sections for this particular research purpose. Data for the manufacturing sector (NACE D) are less aggregated to NACE subsections. Data on section "Manufacture of coke, refined petroleum products and nuclear fuel" (NACE DF) are not available from Statistics Austria due to secrecy reasons.

approximately 20% of the employees have been at least 50 years old. Moreover, people in this age group have superiorly benefited from the increase of new registrations (= "Neuanmeldung") as compared to 2007. The Austrian economy is characterised by a remarkable dynamic with respect to overall registration (="Anmeldung") as well as deregistration, which is particularly traced back to seasonal sectors. Roughly one third of recruiting firms also hired older persons. With regard to those industries, which are relevant for our analysis, a relatively high share (20%-30%) of persons aged 50 years and older are employed in "Mining", "Energy" and "Water supply" as well as "Financial intermediation" and "Real estate business".[26]

Structural business statistics as well as the national accounts data, the social security data and micro census data contain a sector identifier which allows linking these four data sets. Data of social security contains only white-collar workers, blue-collar workers, and apprentices differentiated with regard to gender. Self-employed persons and public servants are a priori excluded.[27] Temporary agency workers ("Zeitarbeiter") are assigned to temporary employment companies and not to the firms they actually work for. All persons with other atypical employment relationships like service contract ("Werkvertrag") are also not linked to their employer. The matched data set is aggregated to 21 sectors[28,29] and covers all firms of the Austrian firm population as well as all employees working in the investigated sectors. The data represent approximately 276 thousand firms and 2.5 million employees per year on average. With regard to the industry level our panel data set is constructed to be balanced.

While the structural business statistics is based on yearly averages (with regard to the number of employees)[30], social security data and micro census count every single employee, who has ever been working in one of the included firms. This issue is of special importance, when these two data sets are related to one another for analytical purposes. As already stated, all variables have been accumulated across firms per sector.

Descriptive Statistics

Descriptive statistics (mean values, standard deviations, minima and maxima for selected characteristics) for all four samples are presented in Table 1. From this table it can be seen that in terms of *value added per worker* and net fixed assets per worker the sectors are substantially different from each other. A closer look at the data with respect to value added per employee the sectors C (Mining and quarrying), E (Electricity, gas and water supply) and J (Financial intermediation) present the most productive industries. In terms of *capital stock* sector E (Electricity, gas and water supply) and also sector K (Real estate, renting and business activities) are of extraordinary size, which is highlighted when concentrating on per capita figures. Clearly, both of these industries are particularly capital intensive.

Modernity of capital stock is defined as ratio of net to gross fixed asset. Data on net as well as on gross fixed asset are taken from national accounts. This measure expresses the percentage

[26] Due to a more up to date categorisation being in place, these just approximately accord to the NACE categories C, E, J and K in the version, which we use.
[27] Since labour productivity is calculated based on the structural business statistics, while age shares emanate from social security data, this imbalance might theoretically lead to a bias of the results. For instance, self-employed persons contribute to value added, whereas they are not counted for the age distribution.
[28] Because we received information on workforce characteristics from the social security data aggregated to NACE sections we had to transform the data on firm characteristics to the same aggregation level.
[29] Data are aggregated to NACE sections. Only the NACE section D (manufacturing) has been disaggregated more strongly to NACE subsections.
[30] This proceeding changed at the beginning of 2002.

of the assets which are not depreciated and thereby provides information about the ageing process of the fixed assets. The higher these values the less capital stock is depreciated. Thus, high values of this indicator indicate that a sector uses relatively recent equipments. On average, modernity amounts to 0.60. The disparities between sectors are quite small. The least modern (0.54) sector is DL (Manufacture of electrical and optical equipment), while the most modern (0.71) industry is industry K (Real estate, renting and business activities).

Intangible assets contain the stocks of software as well as the value of concessions, industrial and similar rights and assets and licenses in such rights and assets. The proportion of these types of assets amounts to around 2 percent of whole capital stock on average. In most of the sectors this share is at most 5 percent. The sector J (financial institutions) juts out with a share of 12 percent.

The category of *micro, small and medium-sized enterprises* (SME) is made up of enterprises employing fewer than 250 persons.[31] All firms employing 250 workers and more are referred to as large enterprises. With respect to the share of SME the discrepancy between sectors are minor. In most of sectors more than 90 percent of enterprises belong to the category of SME. Sector DF (Manufacture of coke, refined petroleum products and nuclear fuel) is the only sector which is less dominated by SME.

The *age composition of workforce* at the industry level is captured by three age shares: young (15 to 29 years), middle-aged (30 to 49 years) and old (50+ years). In terms of this indicator the differences between sectors are remarkable as well. While for instance the sectors H (Hotels and restaurants) and K (Real estate, renting and business activities) are rather young, the opposite holds for sectors C (Mining and quarrying) and E (Electricity, gas and water supply). An inter-temporal comparison shows that the Austrian workforce went through slight ageing with an increase of age of nearly one year on average during our observation period. Although part of the ageing process is identical for all industries due to a common demographic trend as well as Austria-specific pension policies, we additionally observe a an ageing trend that varies across sectors, which might be due to industry- and age-specific workplace requirements, for instance.

Educational levels are grouped by attainment into (a) basic education (up to nine years), (b) upper secondary education with medium skill attainment, which includes apprenticeships and short cycle vocational education (ten to twelve years of schooling), (c) upper secondary education with higher skill attainment, which encompasses the Austrian gymnasium and its equivalents, such as vocational colleges (twelve to thirteen years of schooling) and (d) tertiary education including postgraduate studies, teacher training colleges, etc. The medium skill upper secondary education (referred to as 'lower secondary education' in the tables) is the most prevalent category with a share of 59 percent, on average. The differences between sectors are remarkable. A closer look at the distribution of education shares across sectors reveals the following: The sector with the highest share of basic education is DC (Manufacture of leather and leather products) and with the lowest is E (Electricity, gas and water supply). Sector C has the highest share of lower secondary educated employees, while it is the lowest share in industry K. Sector J (financial institutions) reaches the highest share of upper secondary educations and sector DC (Manufacture of leather and leather products) the lowest. The highest educated workforce can be found in sector K (Real estate, renting and business activities). In this sector the share of tertiary educated workforce is the highest. The

[31] This definition is similar to that of the European Commission (2003). The Commission's definition not only contains limits of staff headcount but also financial ceilings (annual turnover and annual balance sheet total). Because we do not have access to these financial indicators we adopt only the staff headcount limit.

sector employing the lowest share of academics is sector DD (Manufacture of wood and wood products).

Within the employee distribution based on the s*ocial security status* (= type of "occupations") we find huge difference between sectors as well. White-collar and blue-collar workers constitute the largest parts. While white-collar workers dominate in sectors DG (Manufacture of chemicals, chemical products and man-made fibres), DL (Manufacture of electrical and optical equipment), E (Electricity, gas and water supply), G (Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods), J (Financial intermediation) and K (Real estate, renting and business activities), blue-collar workers constitute the largest share in sector C (Mining and quarrying), the major divisions of sector D (Manufacturing) and sector H (Hotels and restaurants). The highest share of apprenticeships is found in sector F (construction industry), which should be highly correlated with the share of young employees.

Tab. 1: List of variables.

Variable	Mean	Std. Dev.	Min	Max
Sector Characteristics				
Value added per worker (in TEUR)	71.06	33.80	25.68	184.31
Net fixed assets per worker (in TEUR)	210.43	264.04	57.54	1171.76
Modernity of fixed assets	0.60	0.04	0.54	0.71
proportion of				
Tangible assets	0.98	0.02	0.88	1.00
Intangible assets	0.02	0.02	0.00	0.12
proportion of				
small and medium sized enterprises	0.98	0.04	0.75	1.00
large enterprises	0.02	0.04	0.00	0.25
Employee-characteristics				
Proportion of employees				
Aged under 30 ('young')	0.28	0.05	0.16	0.43
Aged 30 to 49 ('prime-aged')	0.55	0.03	0.46	0.62
Aged over 49 ('old')	0.17	0.04	0.10	0.30
Proportion of				
Basic education	0.19	0.07	0.05	0.46
Lower secondary education	0.59	0.09	0.32	0.77
Upper secondary education	0.15	0.07	0.04	0.40
Tertiary education	0.07	0.05	0.01	0.24
Proportion in occupation				
Self-employed	0.06	0.05	0.00	0.21
White collar	0.39	0.19	0.10	0.90
Blue collar	0.51	0.18	0.05	0.73
Apprenticeship	0.04	0.02	0.01	0.09
Home worker	0.00	0.00	0	0.01
Proportion of				
Male employees	0.69	0.16	0.41	0.88
Female employees	0.31	0.16	0.12	0.59
Proportion of				
Part-time	0.11	0.06	0.02	0.28
Full-time	0.89	0.06	0.72	0.98

Moreover Table 1 shows that the differences in terms of *share of female workers* are also noticeable. A closer look at the data reveals that sector H (hotel and restaurant) business is clearly dominated by women. This is also the case for sector DB (manufacture of textiles and textile products) as well as sector DC (leather and leather products). Industries with a rather balanced gender structure (over age groups) are sectors G (Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods), J (Financial intermediation) and K (Real estate, renting and business activities).

In terms of the *share of part time workers* the differences are again considerable. Its distribution over the sectors coincides with that of female employees which obviously confirms that part time work is female in Austria.

5. Results

This section concentrates on the implementation of our theoretical model. The dependent variable measures (the natural logarithm of) labour productivity at the sector level. It is based on the aggregate value added for each industrial sector divided by the overall number of employees within the respective industry. Labour productivity is regressed on three age-share variables, four education shares, the share of gender, sector-specific variables such as the modernity of capital stock (the ratio of gross to net fixed assets per worker measured by a continuous variable), the proportion of intangible assets (measured by a continuous variable), and the share of large firms (measured by a continuous variable). A further set of variables includes the share of workers in various occupations as well as the share of part-time workers and six time dummy variables. As reference categories we choose the shares of prime-aged workers, basic educated workers, male employees, tangible assets, small and medium sized enterprises as well as the shares of blue-collar workers and full-time workers, and the time dummy variable for 2002. These variables are excluded to keep us from perfect multi-collinearity. Our cross-section comprises 21 industrial sectors, which are sectors C (mining and quarrying) to K (real estate, renting and business activities) on one-digit level. Sector D (manufacturing) is broken down on two-digit level.[32] The longitudinal dimension ranges from 2002 to 2007. Moreover, data restrictions only allow controlling for a limited number of independent variables.

In the following analysis we apply ordinary least squares estimates (POLS) as well as classical panel data estimation techniques such as fixed effects (FE), random effects (RE) and between effects (BE) estimates, which allow to control for time-invariant individual fixed or random effects. In the process of POLS estimations we test for heteroscedasticity by applying the Breusch-Pagan / Cook-Weisberg and the Szroeter's tests. Both tests clearly confirm heteroscedasticity. Furthermore by using the Wooldridge test for autocorrelation in panel data (cf. Wooldridge, 2002)[33], the model is positively tested for serial correlation, i.e. first-order autocorrelation of residuals is detected. Both problems are solved by taking into account heteroscedasticity and autocorrelation in feasible generalized least squares (FGLS) estimation.

The results of the estimates are presented in Table 2. It includes regression results of POLS (column 2), as well as of FGLS (column 3) and of three panel regression estimations FE, RE and BE (columns 4, 5 and 6). The regression coefficients on the age categories presented in the subsequent tables indicate the marginal effect of an increase in the respective share, assuming that the omitted share adjusts.

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[32] As already mentioned above, NACE subsection DF (Manufacture of coke, refined petroleum products and nuclear fuel) is excluded, since data are not available.
[33] implemented in Stata by Drukker (2003) and called xtserial

Tab. 2: Panel estimation on extended model.

Variable	POLS	FGLS	FE	RE	BE
Proportion of employees					
Aged under 30	-3.602**	0.086	1.765†	0.994	-2.910
Aged 30 to 49 (r.c.)	-	-	-	-	-
Aged over 49	2.628*	2.339*	1.628	2.863*	3.785
Proportion of					
Basic education (r.c.)	-	-	-	-	-
Lower secondary education	0.357	0.238*	0.008	0.016	2.464
Upper secondary education	0.465	0.060	0.348	0.263	-0.277
Tertiary education	0.196	0.173	-0.061	-0.045	3.840
Proportion of					
Male employees (r.c.)	-	-	-	-	-
Female employees	-0.759**	-0.563**	-0.933	-0.377	-0.042
Net fixed assets per worker	0.155**	0.209**	0.050	0.208**	0.107
Modernity of fixed assets	-1.638**	-0.854	1.981	0.759	-1.686
proportion of					
Tangible assets (r.c.)	-		-	-	-
Intangible assets	5.159**	3.797**	-0.727	0.612	7.546
proportion of					
small and medium sized enterprises (r.c.)	-	-	-	-	-
large enterprises	5.359**	1.881*	-0.868	-0.926	3.782
Proportion in occupation					
Self-employed	2.328**	-1.472*	-0.417	-3.030**	3.465
White collar	0.107	0.503**	1.135*	0.877**	0.012
Blue collar (r.c.)	-		-	-	-
Apprenticeship	-1.962	-0.446	8.594**	1.724	-5.455
Home worker	-44.838**	-15.803**	-14.201*	-8.859	-60.632†
Proportion of					
Part-time	-0.556	-0.523†	-1.318†	-1.654**	-2.164
Full-time (r.c.)	-	-	-	-	-
Constant	5.871**	4.018**	1.919†	3.347**	4.04
Number of observations	126	126	126	126	126
Adjusted R^2	0.933		0.616		0.976

Significance levels: †: 10%, *: 5%, **: 1%
Dummy variables account for time-fixed effects.
POLS … Pooled Ordinary Least Squares, FGLS … Feasible Generalized Least Squares, FE … Fixed Effects, RE … Random Effects, BE … Between Effects
FGLS takes into account heteroscedasticity and autocorrelation in residuals.

The POLS estimation yields a significantly negative correlation between the share of young employees and labour productivity on industry level and a significantly positive relationship of the share of old-aged employees as compared to the middle-aged ones. This means, sectors where the share of young workers increases (or the share of old workers decreases) - and the share of prime-age workers adjusts - by 1 percentage point, exhibit on average 3.6% (2.6%) lower productivity. To calculate the effect of an increase in the share of old workers, assuming that the share of young workers adjusts, one can take the difference between the two coefficients. Postestimation tests show that the POLS estimation suffers from heteroscedasticity and autocorrelation of residuals. Therefore the estimation results might be biased and the t-tests not reliable. Consequently, we conduct FGLS and taking into account heteroscedasticity and autocorrelation of residuals in order to check the robustness of the results.

Thus, the FGLS results differ from that of POLS. The significance of the coefficient of the share of young workers disappears whereas the significantly positive coefficient of the share of old workers remains approximately the same. The differences in the results could at least partly reflect the influence of heteroscedasticity and autocorrelation. The diminishing correlation of the youngest age group is also apparent in the RE estimations, where the coefficient decreases (0.086) and becomes positive but insignificant. The coefficient for the oldest age group is of the same size. According to the FE results the coefficient of youngest age group is positive and significant only on the 10%-level. The significance of the oldest age group disappears. The BE estimates yield insignificant coefficients for both age groups. The results of FE and BE estimates should be interpreted with caution because the observation period is relatively short, the variation over time in the data are minor and the number of observations per year is rather small.

All in all our results indicate a positive correlation between labour productivity and the share of old workers. This outcome might be traced back to a positive selection effect of employees at higher ages. In general the Austrian labour market is characterised by a rather low effective retirement age, so that those employees older than 50 years, who are still in the labour market, may be the productive ones.

With regard to education we find that in almost all estimations none of the three considered categories of education is significant. The only exception is the upper secondary education with medium skill attainment (which refers to as “lower secondary education” in Table 2). Probably, potential effects emanating from education may be better detected at the firm level, since firm heterogeneity within a certain sector is high and the respective education-occupation fit more adequate.

Compared to the share of males, an increasing share of women is associated with decreasing labour productivity throughout, which might be due to the fact that females often tend to work part-time. Unfortunately, we are not able to control for hours worked, but include the shares of part-time workers which are significantly negative for all samples as well. The coefficient is significant only in the POLS and FGLS estimations.

Regarding sector-specific characteristics we can observe that the modernity of capital stock plays a role only in the POLS estimation. Sectors where a smaller part of capital stock is depreciated indicating quite young fixed assets are less productive. This result seems to be counter intuitive because one may expect the modern equipments represents newest technology and influence productivity positively. Fortunately, in the other estimations the modernity turns out to be insignificant. Therefore this indicator is of minor importance. The proportion of intangible assets on total net fixed assets has a positive coefficient in all estimates except for FE. It is significant only in POLS and FGLS. A sector seems to be more productive if it has a bigger stock of software and concessions, industrial and similar rights. For the proportion of large enterprises the coefficient is significantly positive in POLS and FGLS estimations and insignificant in the other estimations. This result indicates that sectors with many large enterprises are better off and might hint towards economies of scale.

While a rising share of self-employed persons leads to decreasing productivity, an increase in white-collar workers compared to blue-collar workers is positively associated with productivity at the sector level according to almost all estimations. The only exceptions are POLS and BE, where the coefficients for the proportion of being self-employed is positive.

As already mentioned, the share of part-time employees has a significantly negative correlation with productivity in almost all estimations as compared to full-time employees. Due to individual fixed costs part-time workers are relatively more expensive for firms than full-time workers. Moreover, a higher number of part-time employees by definition reduces output per worker as compared to a smaller number of full-time employees producing a value added of identical size.

6. Conclusions

In this paper we present results from our analysis on the link between labour force ageing and labour productivity at the industry level. Based on different panel data estimation methods we find varying outcomes for mining, manufacturing, electricity, gas and water supply, construction and market oriented service sectors (NACE categories C to K) in the Austrian economy over the period 2002 to 2007. Data are aggregated to NACE sections. Only the NACE section D (manufacturing) has been disaggregated in more detail to NACE subsections.

Summing up the results of our analysis, we find a positive productivity effect of the share of old workers (50 years and older) on labour productivity. This outcome might be traced back to a positive selection effect of employees at higher ages. In general the Austrian labour market is characterised by a rather low effective retirement age, so that those employees older than 50 years, who are still in the labour market, may be the productive ones. Furthermore we find no evidence for a significant impact of the share of young workers (29 years and younger). Our results differ from our previous studies and many other studies in the literature which yield a negative correlation between the share of young workers and labour productivity as well as a negative or insignificant influence of the share of old workers.

The shape of the resulting age-productivity pattern depends on the estimation method applied. The positive productivity effect of the share of old workers can be found in all kinds of estimations although not significant in any case. A significant (negative) effect of the share of young workers can be found only from ordinary least squares. But we do not trust this result because the estimation suffers from heteroscedasticity and autocorrelation of residuals.

One drawback of our study is the scarcity regarding data diversity compared to firm level data. The industry level, which we analytically focus on, seems to be not as tangible as the firm or the country level, for instance. Further research might address the identification of determinants influencing the employment of older workers in Austria, since also a sector's workforce is not exogenously given, but determined endogenously by the firm of a sector itself – or its competitive environment respectively. More disaggregated data (e.g. to the NACE divisions) would be more suitable for our analysis. Implementing constant returns to scale may be rather strict as well. On the one hand, it allows for consistency in the transformation of the production function. On the other hand, it contradicts the regression outcome for the net fixed assets (i.e. capital) coefficient. Moreover, further research is needed in order to verify robustness of our preliminary results with respect to the exact model specification. And, as we have pointed out at the beginning of our discussion, some more understanding of the quite abstract inter-mediate economic level, where several (multiplicative or compensatory) phenomena may occur in parallel, is needed.

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