LATVIJAS BANKA
EIROSISTĒMA

ISBN 978-9934-578-14-4

DISCUSSION PAPER

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GETTING OLD IS NO PICNIC? SECTOR-SPECIFIC RELATIONSHIP BETWEEN WORKERS AGE AND FIRM PRODUCTIVITY

3 · 2019

CONTENT

ABBREVIATIONS

AR – autoregression
CSB – Central Statistical Bureau of Latvia
EU – European Union
EU28 – 28 EU Member States
Eurostat – Statistical Office of the European Communities
ICT – information and communication technologies
IT – information technologies
GMM – generalised method of moments
NACE – nomenclature statistique des activités économiques dans la Communauté Européenne
OECD – Organisation for Economic Co-operation and Development
OLS – ordinary least squares

ABSTRACT

This study provides new evidence on sector-specific differences in the age-productivity profiles in a country that has witnessed substantial shifts in the economic structure and features flexible labour market and high labour force participation among the elderly. Using a matched employer–employee dataset of Latvian firms, the paper unveils a conventional hump-shaped or downward sloping relationship in manufacturing and trade, but almost no or very small negative effect of ageing workforce in knowledge-intensive service sectors that largely employ high-skilled white-collar employees. The results suggest that investing in human capital, in particular training of elderly employees as well as addressing severe skill shortages in the ICT services sector have to be considered to reduce the downward pressure of ageing on firm performance. It also highlights the importance of efforts made by public institutions in improving health care and promoting healthier lifestyles to increase the number of healthy life years.

Keywords: firm productivity, ageing population, age-productivity profile

JEL codes: C23, L25

The authors are grateful to Gundars Dāvidsons (Latvijas Banka) and Povilas Lastauskas (Lietuvos bankas; Vilnius University) as well as participants of the Baltic Economic Conference and research seminars held at Lietuvos bankas and Tartu University for the valuable comments.

The views expressed in this paper are those of the authors and do not necessarily reflect the stance of Latvijas Banka. The authors assume sole responsibility for any errors and omissions.

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1. INTRODUCTION

The average age of workers has been rising rapidly in most industrialised countries. People now live longer due to advances in health care, improving living standards and healthier lifestyles. The above improvements that lower mortality and drive population ageing have triggered researchers' interest in quantifying the relationship between employees' age and firm productivity.

From the theoretical point of view, this relationship is a complex phenomenon and is a combination of various physiological and psychological factors, such as physical capacity (strength and reaction), cognitive abilities (vocabulary size, verbal ability, memory) and experience. Physical capacity declines with age, while experience improves later on in life and may compensate for the decline in physical capacities. As regards cognitive abilities, their effect is not straightforward. Although research demonstrates a decline in certain cognitive abilities with age (Verhaeghen and Salthouse (1997)), particularly fluid abilities, such as reasoning and speed (Schwartzman et al. (1987)), the number of the so-called crystallised abilities (e.g. strategic thinking) improves with age (Ilmarinen (2012)). The total effect of ageing depends on the specific skills required at a particular workplace, on work organization as well as technology, and it might differ across occupations and economic sectors. Thus, the age-productivity relation in the services sector is presumably more stable due to the absence of physically demanding work (Göbel and Zwick (2012)). New technologies cause changes in the demand for specific skills by reducing the need for manual workers and increasing the importance of crystallised cognitive abilities (that are related to accumulated knowledge) and experience. Similarly, improvements in health care and education alongside increasing on-the-job training opportunities change personal abilities. Therefore, age-productivity profiles are not static and vary over time (Skirbekk (2008)).

There is neither straightforward definition of nor measure for productivity. Wages do not always follow productivity as seniority wage schemes are evident in some countries and sectors[1]. Most of the studies employ one of the four measures of productivity: i) managers' subjective assessment of their employees (a survey of managers, e.g. Medoff and Abraham (1980)); ii) data on errors made by employees (in manufacturing, e.g. Börsch-Supan and Weiss (2016)); iii) a direct measure of productivity (for certain activities and professions, such as publications in economic journals per researcher, e.g. Van Ours (2009) or F1 drivers, e.g. Castellucci et al. (2011)); iv) value added per employee calculated based on a matched employer–employee dataset.

A large body of literature on the age-productivity relationship considers industrialised countries with well-established economies. This paper contributes to the existing literature by studying the age-productivity relationship in Latvia, a country that is different in several respects. In the 1990s, it underwent transition from a command to market economy with substantial shifts in the economic structure, educational attainment and quality. Now, two decades after the transition, it features a flexible

[1] An extensive survey of studies examining the wage-age relationship is provided by De Hek and Van Vuuren (2010).

labour market[2] and high labour force participation among the elderly[3] on the one hand and low health care standards and one of the lowest healthy life expectancies in the OECD (the World Health Organisation[4]) on the other. This makes Latvia an interesting and appropriate case for extending investigation of sector-specific age-productivity relationships.

Over the last few decades, Latvia has experienced notable demographic shifts. Its population has both been shrinking and greying with the average age rising from 38 years in 2000 to 43 years in 2017. The share of people aged between 25 and 54 years has been declining and is expected to get as low as 34% in 2030. These developments have not only been caused by a downward sloping trend in mortality but they also result from emigration of mostly young individuals after Latvia joined the EU in 2004 (Hazans (2013)).

The detailed employer–employee dataset available for the time period between 2006 and 2015 has been used for the purpose of this study. The age-productivity relationship is estimated separately for aggregated macroeconomic sectors that may have different work and skill requirements. We account for the role of cohorts, tenure and firm size when estimating the age-productivity profile. In order to cope with the possible endogeneity of age structure of a firm to productivity shocks, we estimate the age-productivity relationship using the system GMM econometric approach, where employees' age structure at a firm is instrumented by its lagged values. Labour productivity is estimated per employee without accounting for the actual number of hours worked as the latter are only available from mid-2013. However, developments in value added per employee are only marginally driven by differences in hours per head, at least if the very recent data on hours worked is employed.

The study suggests notable differences in the age-productivity profiles across sectors. It unveils a conventional hump-shaped or downward sloping relationship in manufacturing and trade, but almost no or very small negative effect of ageing workforce in knowledge-intensive service sectors that largely employ high-skilled white-collar employees. Hence, the productivity drop is particularly evident in the sectors requiring physical strength and speed in which employees without tertiary education are predominantly employed. On the whole, it seems that the demographic shifts in the age structure may be detrimental to overall productivity of the Latvian economy and reduce economic growth in the coming years. Nevertheless, when interpreting these results and their implication for future growth, one should keep in mind that the economic structure is shifting over time, with the role of traditional sectors shrinking. Moreover, the estimated profiles cannot be considered static. As firms improve technologies and work organization and invest more in training human capital, including elderly workers, the profile may get flatter.

The estimation results presented in the paper should be interpreted with caution because of several problems with econometric estimation. First, the magnitude of the obtained coefficients is large, resulting in improbable contributions of some age categories to firm productivity. Second, the uncertainty surrounding the coefficients is high, probably because of heterogeneity across individuals. Third, it proved

[2] See, e.g. Fadejeva and Opmane (2016) and Zasova (2011).
[3] The participation rate among 65–74 year olds in 2017 was 18%, the second highest in the EU (after Estonia) and almost twice as high as the EU28 average (Eurostat: *https://ec.europa.eu/eurostat/web/products-datasets/product?code=lfsq_epgais*).
[4] *http://apps.who.int/gho/data/node.imr.WHOSIS_000002?lang=en*.

impossible to satisfy the diagnostic tests of instrument validity in samples comprising both large and small firms.

The rest of the study is structured as follows. The next section provides a brief review of previous literature that explores the age-productivity relationship. Section 3 describes the construction of the dataset and the methodology used in the analysis with a particular focus on potential problems associated with the estimation of the age-productivity relationship. Section 4 presents the estimation results. Section 5 concludes.

2. LITERATURE REVIEW

The effects of ageing on productivity have been examined extensively. However, there is no consensus on the general age-productivity profile. Indeed, a large number of studies confirm the conventional finding of an inverted U-shaped relationship (with productivity rising until the prime age and then declining). Thus, Hellerstein and Neumark (1999; 2004), Haltiwanger et al. (1999), Aubert (2003) and Dostie (2011) among others show that productivity strongly declines after the age of 50–55, particularly for jobs where problem solving, learning and speed are important. Nevertheless, there is also evidence against the hump-shaped age-productivity profile and in favour of a flat or even positive relationship. Aubert and Crépon (2006) show that in France productivity peaks at the age of 40–45 and remains stable thereafter. Göbel and Zwick (2012) confirm a flat profile for Germany between 40 and 60 years of age. Börsch-Supan and Weiss (2016), using the data on errors from an assembly plant of a German car manufacturer, find that productivity keeps rising until the age of 60. Similarly, according to Malmberg et al. (2008), a higher share of older workers is not necessarily associated with lower productivity, particularly if firms are large and able to utilize older employees more efficiently.

In a nutshell, the productivity path after the age of 50 remains unclear. Göbel and Zwick (2009) as well as Van Ours and Stoeldraijer (2011) show that the shape of age-productivity profiles depends on the estimation strategy. More specifically, the relationship between the employees' age structure and firm productivity tends to be hump-shaped when cross-sectional data or pooled OLS are employed. Once unobserved heterogeneity of firms or possible endogeneity of age shares are taken into account, the evidence of a hump-shaped relationship is weaker.

The findings regarding the *sector-specific* age-productivity profiles, the main focus of this study, are also mixed. Crépon et al. (2003) for France and Göbel and Zwick (2012) for Germany, among others, do not find differences in the (nearly flat) shape of the age-productivity profile implied by sector affiliation. In contrast, Aubert and Crépon (2006), using French data, show that in manufacturing productivity peaks at the age of 35–39 and remains flat thereafter, whereas in the trade and services sectors productivity grows until a higher age. Mahlberg et al. (2013a) show that the revealed positive contribution of aged employees to firm productivity in Austria stems from services sectors, owing to specific work abilities required in the process of services provision. In manufacturing and construction, they document a flat relationship. Lallemand and Rycx (2009) illustrate that ICT intensive services sectors in Belgium are characterised by a larger loss of productivity as workers age, compared to other services sectors due to inability of elderly workers to cope with modern technologies. Mahlberg et al. (2013b) show that both sectoral and regional differences are sizeable.

While the number of studies exploring the age-productivity relationship in advanced economies is large, the evidence on Central and Eastern European countries having undergone economic transition is still rare. Roosaar et al. (2017), using a rich dataset of Estonian firms, confirm an inverse U-shaped curve for hired high-wage employees. The outflow of older employees is found to increase firm productivity, particularly in the group of low-wage earners. Lovász and Rigó (2013) examine Hungarian experience of economic transition. They find a large negative productivity gap for old skilled employees in foreign-owned companies at the beginning of the 1990s explained by economic skill obsolescence due to the transition from socialism. This interpretation is supported by the absence of productivity gap for unskilled employees.

To sum up, sector- and country-specific evidence on the age-productivity relationship differs notably across the previous studies. In addition, literature reveals low robustness of the estimation results to different estimation strategies, e.g. when accounting for cohorts, unobserved firm heterogeneity and endogeneity. Our paper is by no means redundant. It contributes to the existing literature by providing scarce evidence on sector-specific differences in the age-productivity pattern in a country that has undergone a very rapid (by historical standards) transition from a command to market economy.

3. METHODOLOGY AND DATA

In order to estimate the age-productivity relationship, we start from the traditional Cobb–Douglas production function for firm *i* in period *t*:

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{*\beta} \tag{1}$$

where Y_{it} denotes value added by firm *i* at time *t*, K_{it} is the capital stock used and L^*_{it} denotes the effective number of workers employed. α and β are capital and labour shares respectively.

The effective labour input L^*_{it} is further decomposed into a weighted sum of various categories of employees (*j* referring to different age, gender, cohort or tenure), assuming their perfect substitution:

$$L_{it}^{*} = \sum_{j=0}^{J} \lambda_j L_{ijt} = \lambda_0 L_{i0t} + \sum_{j=1}^{J} \lambda_j L_{ijt} = \lambda_0 L_{it} \left(1 + \sum_{j=1}^{J} \left(\frac{\lambda_j}{\lambda_0} - 1\right) \frac{L_{ijt}}{L_{it}}\right) \tag{2}$$

where the weights are represented by a category's *j* marginal productivity parameter λ_j that is constant across firms and time periods. λ_0 is the marginal productivity of a reference category.

After the log transformation of (2), one obtains:

$$\ln(L_{it}^{*}) = \ln(\lambda_0) + \ln(L_{it}) + \ln\left(1 + \sum_{j=1}^{J} \gamma_j \frac{L_{ijt}}{L_{it}}\right) \approx \ln(\lambda_0) + \ln(L_{it}) + \sum_{j=1}^{J} \gamma_j \frac{L_{ijt}}{L_{it}} \tag{3}$$

where $\gamma_j = \frac{\lambda_j}{\lambda_0} - 1$ denotes the relative productivity of an employee from category *j* with respect to the reference group of employees.

Substituting (2) into the log of (1) gives the production function of the following form:

$$\ln(Y_{it}) = \ln(A_{it}) + \beta \ln(\lambda_0) + \alpha \ln(K_{it}) + \beta \ln(L_{it}) + \beta \sum_{j=1}^{J} \gamma_j \frac{L_{ijt}}{L_{it}} \qquad (4).$$

Finally, after controlling for additional enterprise characteristics (denoted X_{sit}), we end up estimating the following equation:

$$\ln(Y_{it}) = \ln(A_{it}) + \beta\ln(\lambda_0) + \alpha\ln(K_{it}) + \beta\ln(L_{it}) + \beta\sum_{j=1}^{J}\gamma_j\frac{L_{ijt}}{L_{it}} + \rho X_{sit} + v_i + \varepsilon_{it} \qquad (5).$$

The positive estimated coefficient γ_j implies that a firm with a higher share of employees that falls into the j category is more productive (i.e. creates higher value added per worker) than a reference firm.[5] In this study, by j we mean different age groups, each within (mostly) five-year brackets: below 24, 25–29, 30–34, 35–39, 40–44, 45–49, 50–54, 55–61, 62 and above.

Low productivity of elderly versus prime-age workers, revealed in many empirical studies, may merely reflect the fact that elderly employees come from a cohort with less educational attainment or there have been technological improvements favouring younger employees to a larger extent (see a discussion in Göbel and Zwick (2012)). To estimate relative productivities of workers attributable to natural ageing, a possible cohort effect should be controlled for, particularly in a country that has undergone a significant economic transition with changes in educational standards. Similarly, the length of employment or tenure should also be accounted for. Employees with a longer tenure may be less motivated or, on the contrary, they could have accrued firm-specific expertise and work more efficiently than entrants. One may confuse this effect with that of natural ageing. To avoid severe multicollinearity between age, cohort and tenure groups, we choose different widths of time windows.

To explain the chosen econometric estimation technique, the following considerations should be noted. First, it is necessary to account for unobserved time invariant firm heterogeneity by including the firm fixed effect. Second, OLS estimates of the production function are biased if changes in the age composition are not exogenous to changes in firm productivity. The problem occurs when, for example, firms hit by a positive productivity shock are encouraged to hire younger workers whose share in their workforce increases. In the case of a negative productivity shock younger employees may be the first ones a firm would want to lay off (the last in, first out principle) with a decline in their share. Hence, the age structure of a firm may be a consequence rather than a cause of firm productivity and should be instrumented. In this study, following Göbel and Zwick (2009), among others, we employ the system GMM estimation approach (Blundell and Bond (1998)) to address these problems.

Following De Loecker (2013), we acknowledge the role exports play for small and open economies and include the lagged exporter status (dummy) in the set of regressors. We treat the lagged exporter status as predetermined, while capital and labour inputs (including the age, cohort, gender and tenure shares) as endogeneous variables.[6] We acknowledge that the error term ε_{it} in (5) may follow the autoregressive process and add the first lag of both dependent and explanatory variables on the right-hand side of the equation. Finally, we account for the fact that our estimates are made on the firm level rather than at employee level, and we weight firms by the number of employees.

To verify the estimation results, several diagnostic tests are performed. First, instrument validity is tested by means of the Hansen J-test of overidentifying restrictions. The null of this test is that instruments are not correlated with the error

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[5] Even though γ_j coefficients imply elasticities of *value-added* to the relative share of workers in group j, these, by construction, could also be interpreted as elasticities of *labour productivity*.

[6] Thus, in the differenced equation two period lagged levels of endogenous variables are used. In the level equation, we use the first lag of the first difference as instruments. It is reasonable to assume that the recent lags have a higher correlation with the contemporary values of endogenous variables, including age shares.

term of the production function. The failure to reject the null hypothesis implies that instruments are valid. Second, we perform the AR(2) test for the absence of second order autocorrelation in the differenced error term.

One issue that remains unaddressed in our study is the potential problem of self-selection of elderly employees. Workers aged above 61 have an option to retire early with the official retirement age in Latvia being somewhat above 63 at the moment of writing this paper. Over the sample period, the early retirement option was available at 60 years of age, while the official retirement age was 62. Thus, elderly workers staying in the labour market are likely to be those that a priori enjoy a good health condition, are motivated, better educated and have a higher position (e.g. managerial) at a firm. However, at the same time, the old-age pension level is quite low in Latvia, hence the share of elderly citizens remaining active beyond the retirement age is relatively high. In 2017, the participation rate among 65–74 year olds was 18%, the second highest in the EU (after Estonia) and almost twice as high as the EU28 average. Therefore, we reckon that the selection problem in Latvia can be less pronounced than in industrialised countries, and the estimation results for the oldest age group can still be interpreted, albeit with a degree of caution.

We use data from two datasets compiled by the CSB: the firm indicator dataset and employee data. These datasets are matched to construct an employer–employee database. The firm indicator dataset contains records from companies' balance sheets and profit and loss statements as well as provides data on value added, the number of employees, personnel costs, production value and the use of intermediate inputs. Employee data based on the State Revenue Service information from companies' social insurance tax declarations allows tracking employees. Both datasets contain an anonymous firm identifier that allows matching these two datasets. The matched database contains firms from all sectors of the Latvian economy, except for the financial services sector and government sectors, and covers the period 2006–2015, with the number of firms varying between 61 159 in 2006 and 88 265 in 2015.

After excluding outliers[7] and the establishments not reporting some of the variables, the matched employer–employee database contains data on 22–25 thousand firms per year. Unfortunately, we do not possess data on the number of hours employees actually work at the firm for the whole time period as this data is reported starting from mid-2013 only. This is one of the limitations of our study; however, the productivity profile is only marginally affected by differences in hours per head, at least if the very recent data on hours worked is employed.[8] Another weakness of the database is the lack of data on professions and the educational attainment of employees.

[7] We eliminate outlying observations following Lopez-Garcia et al. (2015) who apply a multi-step exclusion procedure based on the values of various ratios (capital, turnover, labour costs, intermediate inputs and value added to labour or capital) and their numerator and denominator. First, the given ratio is coded as missing one in case of an abnormal growth – more than two interquartile ranges above or below the median growth in the respective sector and year. Moreover, the procedure identifies the source of the extreme growth (the numerator or denominator) and codes it as missing. Second, the variable is coded as missing if its ratio, with respect to labour, falls into the top 1 and 99th percentiles of the distribution for the respective ratio. Thus, we remove 1%–2% of observations for value added, turnover, capital, wages, and intermediate inputs. More important data losses come from non-reporting of several variables (e.g. the number of employees or size of fixed assets), a problem that is more pronounced for small enterprises.

[8] Evidence is available upon request.

Tables A1 and A2 present summary of descriptive statistics of the indicators used in our regressions.

4. ESTIMATION RESULTS AND DISCUSSION

In this section, we present the estimation results (see Table A3) and age-productivity curves (see Figure 1) drawn based on age-category coefficient estimates for six aggregated macroeconomic sectors[9] with the largest number of firms. The dependent variable is log of a firm's value added, the parameter estimates are obtained using the system GMM econometric approach. We use employees aged between 40 and 44 years as the reference age category where all age group coefficients are estimated with respect to this category. The reference tenure is three and more years. The reference cohort represents those who were born before 1955. Only three cohorts are chosen so that the selected time windows of age and cohort groups do not overlap.[10] The complete (or even close to complete) overlap would lead to inaccurate estimates and exaggerated standard errors. The reference gender is male employees.

The estimation results suggest that in manufacturing an increase in the share of employees aged between 25 and 35 years raises firm productivity as the coefficients of two age categories (25–29 and 30–34) are positive and statistically significant. In turn, employing a larger number of elderly employees versus the reference group does not exert any significant impact on productivity. This means that for manufacturing the age-productivity profile balloons with the share of employees up to 35 years of age, then drops at the reference age and remains essentially flat thereafter. A similar pattern is observed in construction, but the differences between younger employees and the reference group workers are mostly statistically insignificant despite physical abilities requirements associated with work in this sector. In transport and particularly in trade employees older than the prime age contribute negatively to firm productivity. In trade, productivity declines with the share of employees older than 50 and remains significantly lower versus the reference group beyond the retirement age.

Turning to knowledge-intensive services, in the ICT services sector, the point estimate reaches its maximum around the age of 40. In contrast to most other sectors, young workers have a significantly lower productivity than the reference group of workers. It should be noted though that the cohort effect in this sector is large, positive and statistically significant for those born after 1975. This cohort of IT professionals has obtained more advanced education in IT and communication. Furthermore, recent advances in technical progress and IT may have particularly favoured younger generations of employees in this sector. In the ICT services sector, we also find a small statistically significant drop in productivity for 45–55 years old employees. Surprisingly, in the professional services sector (that includes sectors such as legal activities, accounting, research, etc.) the age-productivity profile is downward sloping, but, as will be shown later, the presence of a very large number of micro firms exhibiting a different pattern compromises this finding.

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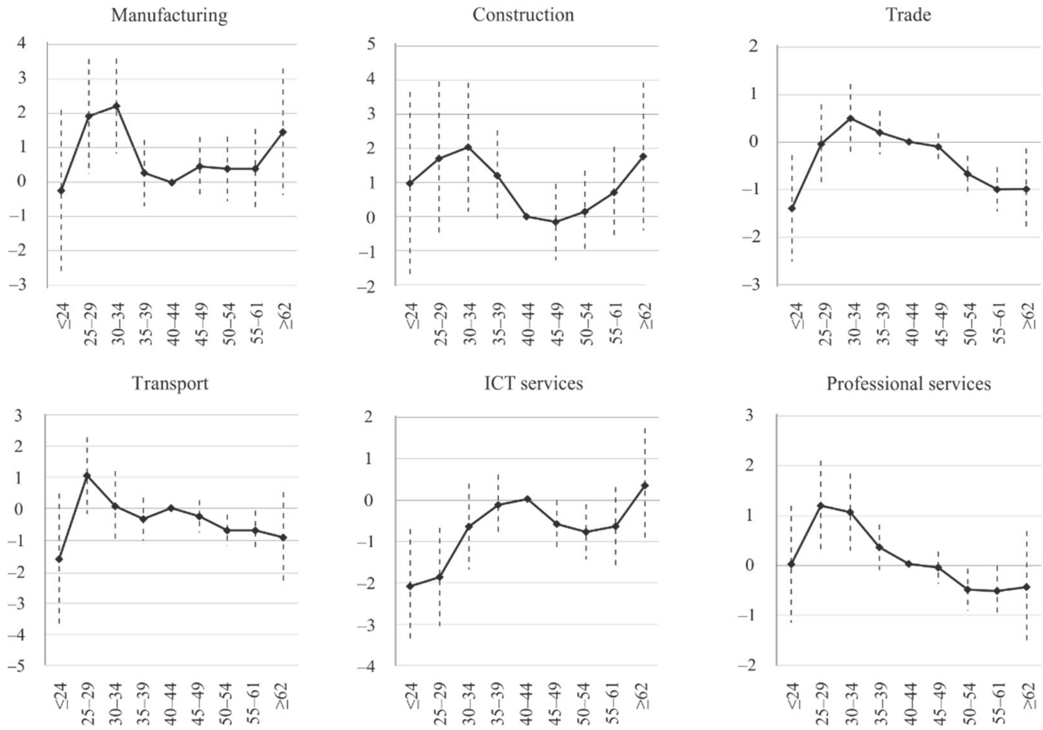
[9] In this study, we aggregate NACE sectors as follows: manufacturing (NACE 10–33), construction (NACE 41–43), trade (NACE 45–47), transport (NACE 49–53), ICT services (NACE 58–63), professional services (NACE 69–75). ICT services are considered by Eurostat high-tech knowledge-intensive services, professional services are knowledge-intensive market services.

[10] For example, Göbel and Zwick (2012) use five-year time windows for age groups and 10-year windows for cohorts. We also tried different window sizes of cohorts; however, the key results of this study remain broadly unaltered.

Figure 1
Age-productivity profile by aggregated macroeconomic sectors, controlling for the cohort effect



Sources: CSB and authors' calculations.
Note. The figure is based on age-category coefficient estimates in Table A3.

As regards the effect of the included control variables, the results reveal that incumbent workers are more productive than entrants in trade and transport and appear less productive in the professional services sector. A high share of female workers is associated with lower firm productivity in manufacturing. This finding might be related to the fact that a large number of female employees in manufacturing work part-time.[11] The estimates of capital and labour shares imply increasing returns to scale in several sectors which is counter-intuitive. However, a number of other studies employing firm-level data were also unable to document constant returns to scale. This is related to a low explanatory power of the instruments used in the estimation (see, e.g. a discussion in Aubert and Crépon (2006)).

The magnitude of the estimated age group coefficients appears very large, particularly when compared to the previous literature. The latter, however, mostly examines larger countries with more developed economies (e.g. Germany in Göbel and Zwick (2012), Belgium in Lallemand and Rycx (2009), Austria in Mahlberg et al. (2013a) and France in Aubert and Crépon (2006)). In contrast, the coefficients obtained by Roosaar et al. (2017) for neighbouring Estonia and by Lovász and Rigó (2013) for Hungary, the countries which, similar to Latvia, witnessed significant shifts in the economic structure, also appear unusually large. An additional concern (also documented previously) is related to large variances of estimators that suggests heterogeneity among employees belonging to the same age group and, possibly, differences between the sectors grouped into a single macroeconomic sector.

[11] In 2015, 3% of men and 11% of women had part-time contracts in manufacturing (Eurostat: *https://ec.europa.eu/eurostat/web/products-datasets/product?code=lfsq_epgais*).

We also suspect that very small firms are intrinsically different from the larger ones, and their inclusion may bias the estimation results. In small firms, even minor labour flows may result in a significant variation in the employees age structure, shaping average age-productivity profiles across sectors. In larger companies, the age structure is more stable with respect to the departure of incumbent and hiring new employees.

Severe heterogeneity (across employees, firms and sectors) inherent in the sample is probably responsible for very poor results of the diagnostic tests. More specifically, the validity of the instruments is overwhelmingly rejected by the Hansen J-test across all sectors but the ICT services sector. Moreover, we observe the presence of second-order serial correlation in the residuals in a few sectors.[12] This compromises our estimation results.

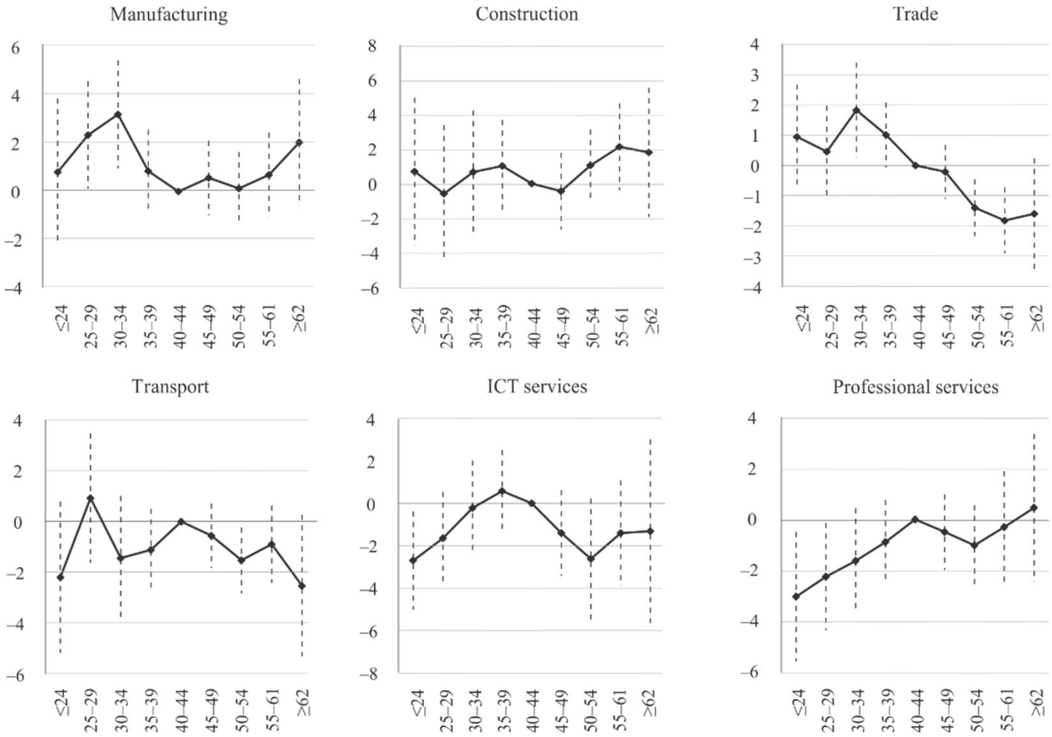
When the production function is estimated separately for each sector (i.e. not their aggregates) the diagnostic test results appear satisfactory, implying that, probably, the sector-specific heterogeneity is indeed high, and it is very difficult to achieve instrument validity when aggregating diverse sectors. We also reveal that the results for large macroeconomic sector aggregates are in some instances driven by individual sectors. Thus, the above decline in productivity beyond the prime age in transport arises from the land transport sector and in professional services from the management consultancy and architectural and engineering activity sectors, whereas a downward sloping pattern in trade is observed in both wholesale and retail trade as well as in trade of motor vehicles, i.e. qualitatively there is no difference between sectors.

We also estimate (5) separately for large firms, i.e. the ones whose number of employees exceeds nine. This brings about notable improvements in instrument validity as the null hypothesis of both the Hansen J-test and AR(2) test is not rejected at any conventional significance level in all macroeconomic sectors with the exception of the trade sector. Dropping small firms also induces changes in the age-productivity profiles in some sectors (see Table A4 and Figure 2). The changes are most obvious in the professional services sector. Hiring younger employees now lowers firm productivity, while the point estimate peaks at the oldest age category. This radical change in the profile might be explained by the presence of a very large number of microenterprises in this sector.[13] A special tax regime for microfirms provides incentives for many companies to split into a number of smaller ones. As a result, the object of examination is not a single firm but a number of small related firms. In the ICT services sector, all previously reported differences between age categories disappear, implying that the age structure of workforce in large firms does not affect their productivity.

Less pronounced changes are obtained for more traditional sectors. In manufacturing, labour productivity of 25–35 aged employees is consistently higher relative to the rest of the categories. In construction, we still do not find significant effects of the age structure on firm productivity. In trade, dropping small firms changes the pattern slightly; however, we still confirm lower productivity of employees beyond their prime age.

[12] We applied several methods to improve the results of the diagnostic tests, including changing the set of instruments and lags and employing the difference GMM instead of the system GMM, but this did not bring significant improvements.
[13] The number of observations in the professional services sector falls from 22 202 to 2577 when only large firms are examined.

Figure 2
Age-productivity profile by aggregated macroeconomic sectors, controlling for the cohort effect (firms ≥10 employees)



Sources: CSB and authors' calculations.
Note. The figure is based on age-category coefficient estimates in Table A4.

Overall, it is not surprising that in the areas where accumulating expert competence and crystalised cognitive abilities are particularly important, such as high-tech and market knowledge-intensive service sectors, there is no robust evidence of a hump-shaped or downward sloping age-productivity pattern. In the traditional sectors, e.g. manufacturing, it is probably the case that physical strength is still required that helps to explain high productivity associated with younger age. In trade, reaction and speed as well as the ability to use modern technologies play an important role. These abilities diminish when a person gets older.

Indeed, when looking at the occupational distribution within sectors (see Table A5), manufacturing and trade are the sectors with the largest share of manual workers representing elementary occupations (19.4% in manufacturing) and sales personnel (48% in trade) with monotonous and rigid duties. By contrast, in the knowledge-intensive service sectors, i.e. the ICT and professional services sectors, the share of managers, professionals and technicians considered to be high-skilled white-collar occupations with a higher degree of flexibility and the smallest frequency of hard physical work (see Handel (2012)), exceeds 80%.

Similarly, there is considerable heterogeneity in educational attainment across sectors (see Table A6). The proportion of workers with primary or secondary education (i.e. without any specific skills) is highest in manufacturing, construction, transport and trade (above 50%), while it is merely 30% in the ICT services sector and 19% in the professional services sector. By contrast, in the latter two sectors the proportion of employees with tertiary education is around 30%. Tertiary-educated employees presumably possess stronger learning abilities, also in their older age.

There are also some differences in employees' participation in informal education and training across sectors. Employees in the ICT and professional services sectors take part in training more often than those employed in any other macroeconomic sector, also in their older age (see Table A7). Participation in adult training enables workers to boost motivation and skills as they age. However, these differences are not sizeable and should not be overemphasised.

As already mentioned above, the magnitude of the age category coefficients is unusually large, making their economic interpretation risky. Another thing that should be kept in mind when considering economic interpretation of the estimated coefficients is that the share of one age category cannot change independently of other age categories as an increase in the share of one category of workers is accompanied by a decline in the share of one or more other categories. To mention a single example, our coefficient estimates for the trade sector imply that a 10 percentage point drop in the share of 30–34 year olds in a larger firm accompanied by a rise in the share of 50–54 year olds decreases firm productivity by around 60% on average. We hardly believe this estimate is completely reliable. It also implies that if the current structure of the Latvian economy persists into the future, current long-term demographic projections[14] together with estimated coefficients imply a 12% drop in labour productivity of Latvian firms by 2030, i.e. by 1.0% per year. However, the eventual impact of ageing will depend on potential changes in the structure of the Latvian economy. The absence of a robust evidence of a negative productivity premium in knowledge-intensive services sectors suggests that it is possible to compensate the effect of ageing population on productivity in more traditional sectors, such as trade and manufacturing, by increasing the importance of high-tech sectors that demand high-skilled workers. However, it does not seem an easy task to get done. Skill shortages in the ICT sector (OECD (2017)), among other problems, are likely to prevent this sector from expanding in the near term. In addition, inadequate spending on research and development, low innovation activity and insufficient human resources measures prevent elderly employees in other sectors from catching up in terms of productivity. Addressing these issues requires prompt action by Latvian authorities and should be placed high ranked on the policy agenda.

5. CONCLUSIONS

This study casts light on the relation between firm workforce age composition and productivity in a sample of Latvian firms. The analysis is based on the detailed employer–employee dataset spanning the period 2006–2015 and covering up to 25 000 firms annually. Possible endogeneity, simultaneity and unobserved firm heterogeneity are addressed by employing the system GMM estimation approach and accounting for tenure and cohort effects. We split our sample into several sector aggregates and find a certain degree of heterogeneity in the relationship across sectors. In particular, the negative effect of the share of older employees seems to emanate from establishments operating in manufacturing and trade. These sectors are characterised by a higher share of low-skilled blue-collar employees. The relationship gets more complicated in more knowledge-intensive services sectors with a large share of high-skilled white-collars, i.e. the ICT services and professional services

[14] Eurostat: *http://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=proj_15npms&lang=en*.

sectors where we find almost no or minor negative effect of ageing workforce or a very unstable pattern.

As more data become available, this research should be extended to investigate how age-productivity profiles change over time and what is the role of investment in human capital, such as on-the-job training for this relationship.

APPENDIX

Table A1
Descriptive statistics

Variable	Mean	Median	Standard deviation
Ln (size of firm)	1.65	1.49	1.29
Ln (capital stock)	3.14	3.08	2.48
Female employees	0.43	0.39	0.33
Entrants	0.16	0.08	0.23
Tenure 1–2 years	0.28	0.21	0.30
Tenure 3 and more years	0.56	0.61	0.35
Cohort before 1955	0.13	0.01	0.20
Cohort between 1955 and 1975	0.53	0.52	0.30
Cohort after 1975	0.34	0.30	0.31
Aged under 25	0.06	0.00	0.12
Aged 25 to 29	0.10	0.00	0.16
Aged 30 to 34	0.12	0.03	0.19
Aged 35 to 39	0.13	0.05	0.20
Aged 40 to 44	0.14	0.06	0.21
Aged 45 to 49	0.14	0.06	0.20
Aged 50 to 54	0.13	0.04	0.19
Aged 55 to 61	0.13	0.02	0.20
Aged above 61	0.06	0.00	0.13

Sources: CSB and authors' calculations.
Note. Number of observations = 184 780.

Table A2
Mean values of the variables used by sector

Variable	Manufacturing	Construction	Trade	Transport	ICT services	Professional services
Ln (size of firm)	2.24	1.94	1.65	1.77	1.41	1.04
Ln (capital stock)	3.78	3.21	2.56	3.84	2.48	2.10
Female employees	0.37	0.20	0.52	0.27	0.39	0.54
Entrants	0.17	0.24	0.14	0.17	0.14	0.14
Tenure 1–2 years	0.29	0.30	0.26	0.30	0.29	0.27
Tenure 3 and more years	0.54	0.46	0.60	0.53	0.57	0.59
Cohort before 1955	0.15	0.13	0.12	0.12	0.08	0.11
Cohort between 1955 and 1975	0.52	0.49	0.54	0.61	0.40	0.48
Cohort after 1975	0.33	0.38	0.34	0.27	0.52	0.41
Aged under 25	0.06	0.07	0.06	0.04	0.08	0.06
Aged 25 to 29	0.09	0.11	0.10	0.08	0.17	0.12
Aged 30 to 34	0.11	0.13	0.12	0.10	0.18	0.15
Aged 35 to 39	0.13	0.13	0.13	0.12	0.16	0.15
Aged 40 to 44	0.13	0.13	0.15	0.16	0.12	0.14
Aged 45 to 49	0.14	0.12	0.14	0.16	0.09	0.12
Aged 50 to 54	0.14	0.12	0.13	0.15	0.08	0.10
Aged 55 to 61	0.14	0.13	0.12	0.14	0.08	0.11
Aged above 61	0.06	0.06	0.05	0.05	0.04	0.05
Number of observations	22 658	15 640	60 298	16 468	7 567	22 202

Sources: CSB and authors' calculations.

Table A3
Regression estimation results by macroeconomic sector

Variable	Manufacturing	Construction	Trade	Transport	ICT services	Professional services
Ln (size of firm)	0.568***	1.002***	1.195***	0.841***	1.554***	0.964***
Ln (capital stock)	0.444***	0.158**	0.073	0.215***	0.158***	0.162***
Female employees	–1.080**	1.045	–0.082	0.917**	–0.320	0.089
Entrants	–0.744	–0.571	–0.458	–0.571***	0.659	1.821**
Tenure 1–2 years	–0.013	–0.113	–0.320***	–0.072	0.044	–0.003
Tenure 3 and more years	ref	ref	ref	ref	ref	ref
Cohort before 1955	ref	ref	ref	ref	ref	ref
Cohort between 1955 and 1975	0.549	0.618	–0.571	–0.336	0.647	0.193
Cohort after 1975	0.201	0.835	–0.059	0.597	2.034*	–0.483
Aged under 25	–0.226	0.960	–1.380**	–1.618	–2.095**	–0.006
Aged 25 to 29	1.885*	1.671	–0.048	1.037	–1.873***	1.163**
Aged 30 to 34	2.175***	2.002*	0.482	0.057	–0.663	1.033**
Aged 35 to 39	0.274	1.179	0.190	–0.345	–0.140	0.331
Aged 40 to 44	ref	ref	ref	ref	ref	ref
Aged 45 to 49	0.464	–0.156	–0.102	–0.263	–0.600*	–0.073
Aged 50 to 54	0.393	0.144	–0.664***	–0.708**	–0.789*	–0.515**
Aged 55 to 61	0.393	0.692	–0.987***	–0.712*	–0.654	–0.543*
Aged above 61	1.439	1.734	–0.983*	–0.935	0.323	–0.464
Number of observations	22 658	15 640	60 298	16 468	7 567	22 202
Hansen J-stat	0.000	0.014	0.000	0.004	0.479	0.000
AR(2)	0.991	0.104	0.045	0.123	0.088	0.130

Sources: CSB and authors' calculations.
Notes. *ref* denotes the reference group for the age category and tenure effect. *(**)[***] denotes significance at 0.1(0.05)[0.01] level. Hansen J-stat is a p-value for the Hansen test of over-identifying restrictions whose null implies that the chosen instruments are valid. AR (2) is a p-value for a test for the absence of second order autocorrelation in the differenced error term.

Table A4
Regression estimation results by macroeconomic sector (firms ≥ 10 employees)

Variable	Manufacturing	Construction	Trade	Transport	ICT services	Professional services
Ln (size of firm)	0.877***	1.521***	1.337***	0.773***	1.102***	1.060***
Ln (capital stock)	0.354***	0.094	–0.023	0.255***	0.180***	0.201***
Female employees	–0.860*	0.743	–0.528	0.951	–0.464	0.576
Entrants	–0.745	–0.951	–1.194*	–0.196	0.657	0.504
Tenure 1–2 years	–0.081	–0.057	–0.529***	–0.030	0.194	0.091
Tenure 3 and more years	ref	ref	ref	ref	ref	ref
Cohort before 1955	ref	ref	ref	ref	ref	ref
Cohort between 1955 and 1975	1.272	0.414	–0.696	–1.597	–0.634	1.029
Cohort after 1975	0.214	3.288	–1.033	0.015	–0.740	3.272
Aged under 25	0.811	0.698	0.942	–2.197	–2.707*	–3.017**
Aged 25 to 29	2.349*	–0.581	0.455	–0.918	–1.654	–2.238*
Aged 30 to 34	3.207**	0.674	1.819*	–1.434	–0.271	–1.614
Aged 35 to 39	0.852	1.015	1.005	–1.118	0.582	–0.879
Aged 40 to 44	ref	ref	ref	ref	ref	ref
Aged 45 to 49	0.562	–0.431	–0.209	–0.558	–1.398	–0.491
Aged 50 to 54	0.127	1.047	–1.387**	–1.527*	–2.632	–1.014
Aged 55 to 61	0.696	2.125	–1.807***	–0.895	–1.407	–0.295
Aged above 61	2.046	1.809	–1.586	–2.524	–1.314	0.455
Number of observations	10 151	5 725	13 940	4 525	1 646	2 577
Hansen J-stat	0.115	0.222	0.000	0.717	0.711	0.790
AR(2)	0.251	0.168	0.037	0.933	0.163	0.142

Sources: CSB and authors' calculations.
Notes. *ref* denotes the reference group for the age category and tenure effect. *(**)[***] denotes significance at 0.1(0.05)[0.01] level. Hansen J-stat is a p-value for the Hansen test of over-identifying restrictions whose null implies that the chosen instruments are valid. AR (2) is a p-value for a test for the absence of second order autocorrelation in the differenced error term.

Table A5
Occupation of employees by sector (% of total)

Sector	Managers	Professionals	Technicians	Clerical support workers	Services and sales workers	Craft workers	Machine operators	Elementary occupations
Manufacturing	7.7	6.0	7.7	3.3	1.3	37.4	16.5	19.4
Construction	12.0	5.7	5.2	1.8	0.5	48.2	11.3	15.1
Trade	10.3	4.7	11.5	7.4	47.8	8.9	2.4	7.0
Transport	8.2	3.5	9.5	12.3	4.0	8.1	46.0	8.2
ICT services	13.9	45.9	21.2	10.4	1.4	4.0	1.2	1.9
Professional services	18.3	41.0	27.3	7.1	1.0	1.8	1.6	1.7
Other services	7.1	4.7	6.1	4.8	25.6	2.3	3.2	44.6

Sources: CSB Labour Force Survey (2011–2015) and authors' calculations.

Table A6
Level of educational attainment of employees by sector (% of total)

Sector	Primary and lower secondary education	General secondary education	Vocational education	Tertiary education
Manufacturing	29.9	30.7	32.7	6.7
Construction	26.4	30.3	35.2	8.1
Trade	25.6	30.1	34.9	9.5
Transport	22.8	33.4	35.6	8.1
ICT services	15.2	15.2	41.2	28.4
Professional services	8.5	10.4	46.7	34.3
Other services	31.3	31.0	29.0	8.7

Sources: CSB Labour Force Survey (2011–2015) and authors' calculations.

Table A7
Participation in education and training (% of employees)

Sector	Total sample	Age: from 50 years
Manufacturing	2.2	1.5
Construction	2.1	1.9
Trade	3.4	2.4
Transport	3.3	2.6
ICT services	5.4	2.9
Professional services	6.1	4.5
Other services	3.4	2.1

Sources: CSB Labour Force Survey (2011–2015) and authors' calculations.
Note. The share of employees having participated in adult training (seminars, courses, etc.) that is not part of formal education.

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