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Nontechnical Summary

In most industrialised countries, the average age of the workforce has been growing rapidly during the recent years. If ageing workforces affect economic sectors differently, then the total impact of ageing depends on the industrial structure of an economy. It is therefore crucial to know how different sectors are affected by ageing workforces in order to assess the impact of ageing for the competitiveness of a country. This paper measures the impact of changes in the age structure of establishments on its productivity. Specifically, we estimate the productivity impact of different age groups separately for the services, manufacturing and metal manufacturing sectors.

We use German representative linked employer-employee panel data, in order to control for the characteristics of the establishments as well as the characteristics of the employees. In theory, the age-productivity profiles for different sectors should differ. For example, the importance of physical strength or the possibilities to compensate deficits in skills are likely to differ between age and sectors. However, controlling for several potential sources of estimation biases, we find no significant differences in the age-productivity profiles between sectors. Differences between sectors in the application of specific human resource measures for old employees could provide a possible explanation for our findings. These specific measures could help to compensate sector specific deficits of older employees.

The results of our study suggest that the expected impact of an ageing workforce on the economic performance is hardly influenced by the industrial structure of the economy.

Das Wichtigste in Kürze

Im Laufe der letzten Jahre stieg das Durchschnittsalter der Beschäftigten in fast allen entwickelten Industrieländern stark an. Falls der Alterungsprozess die Produktivität der Beschäftigten in verschiedenen Wirtschaftssektoren unterschiedlich beeinflusst, hängen die zu erwartenden Folgen für die Leistungsfähigkeit der Volkswirtschaften auch von ihrer jeweiligen Industriestruktur ab. Vor diesem Hintergrund geht diese Studie der Frage nach, ob Änderungen in der Altersstruktur der Belegschaften in unterschiedlichen Wirtschaftszweigen unterschiedliche Wirkungen auf die Produktivität haben. Dazu messen wir den Produktivitätsbeitrag der Beschäftigten in einzelnen Altersgruppen für den Dienstleistungssektor, das verarbeitende Gewerbe sowie die metallverarbeitende Industrie. Mit repräsentativen Paneldaten für Deutschland kann hierbei zusätzlich der Einfluss zahlreicher Charakteristika der Betriebe und ihres Personals auf die Produktivität über die Zeit hinweg berücksichtigt werden.

Die berechneten Alters-Produktivitätsprofile sprechen dafür, dass zwischen den ausgewählten Sektoren keine signifikanten Unterschiede in der altersabhängigen Produktivität bestehen. Dies scheint zunächst erstaunlich, da beispielsweise die mit dem Alter abnehmende körperliche Leistungsfähigkeit je nach Sektor eine unterschiedlich starke Rolle spielen sollte. Einen möglichen Erklärungsansatz für dieses Ergebnis liefern die sektoralen Unterschiede bei der Anwendung spezifischer Personalmaßnahmen für ältere Beschäftige. Möglicherweise gelingt es den Betrieben, die unterschiedlichen Anforderungen an ihre älteren Beschäftigten durch gezielte Maßnahmen zu kompensieren.

Vor dem Hintergrund dieser Ergebnisse ist zu erwarten, dass der Einfluss von alternden Beschäftigten auf die gesamtwirtschaftliche Leistungsfähigkeit entwickelter Industrieländern kaum von deren spezifischen Industriestruktur abhängt.

Age and Productivity – Sector Differences[♦]

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Abstract

In most industrialised countries, the workforce is ageing rapidly. If ageing workforces affect sectors differently, the total impact of ageing will depend on the industrial structure of an economy. This paper measures the impact of changes in the age structure of establishments on productivity using representative linked employer-employee panel data. We argue that establishment age-productivity profiles might differ for various reasons. For example, the importance of physical strength and possibilities to compensate deficits in skills differ between sectors. We investigate differences in the age-productivity profiles between the (metal) manufacturing and services sectors. However, in our preferred specification that controls for several potential sources of estimation biases, we find no significant differences in the age-productivity profiles between these sectors.

Key-Words: ageing workforce, age, productivity, linked employer employee data, sectors

JEL Codes: J11, J14, J21

1 Introduction

In most industrialised countries, the average age of the workforce has been growing rapidly during the recent years, and this trend is likely to continue (Toosi, 2007). The literature points to various aspects of the relationship between ageing workforce and the competitiveness of establishments. In the field of medicine and psychology, many contributions show that the relationship between age and performance indicators depends on the performance dimension investigated. For example, most dimensions of physical performance decline constantly with age for virtually all types of measures, at least beyond the age of 30 to 35 years (Stones and Kozma, 1985). For psychological performance measures, the results are varying (Ng and Feldman, 2008), and there seem to be various productivity related dimensions of psychological performance that even show a positive relationship with age (Waldman and Avolio, 1986; Mc Evoy and Cascio, 1989; Sturman, 2003). Given these results, it is not astonishing that we find mixed evidence of dependencies between occupations or professions, age and productivity. Veen (2008), for example, provides results on occupations and professions that have on average an increasing productivity during the entire career, occupations that are age neutral, and occupations that have declining productivity with age.

Since establishments differ with respect to the skills, experience and knowledge of their employees, these results suggest that the effects of an ageing workforce on productivity might vary between economic sectors. If the impact of ageing workforces differs between sectors, the total impact of ageing would depend on the industrial structure of economies. Since the industrial structure varies widely between countries, and since there is a trend towards the service sector in most industrialised countries, knowledge about the relationship between ageing and sector productivity is of high economic importance.

A series of recent papers tackles the question of whether an ageing workforce reduces the productivity of establishments. Several contributions estimate the average relationship between the age structure of the workforce and establishment productivity for the whole economy (see for example Göbel and Zwick, 2009). Other studies are based on data that are restricted to a subset of sectors (Malmberg et al., 2008, for example, use data on manufacturing and the mining industry). Some papers split their samples into subgroups of sectors. Here, the separation is usually not motivated by hypotheses which explain the expected differences in age-productivity profiles, however (Crépon et al., 2003; Aubert and Crépon, 2006; Schneider, 2007; Van Ours and Stoeldraijer, 2010; Cardoso et al., 2010). To our knowledge, only Daveri and Maliranta (2007) and Lallemand and Rycx (2009) split their sample on the basis of explicit hypotheses about differences in age-productivity profiles between economic sectors.

In this paper, we estimate the age-productivity profiles for different sectors. The choice of the sectors is based on considerations on how these sectors might differ. More specifically, we estimate the relative productivity impact of different age groups separately for the services, manufacturing and metal manufacturing sectors. Similar to Aubert and Crépon (2006), we derive our estimates from a Cobb-Douglas production function framework. In our estimations, we take unobserved heterogeneity of firm characteristics and the likely simultaneity of the age structure and the production decision into account. We compare the results of pooled OLS and GMM (instrumental) estimates and test the validity of the hypotheses used in the different specifications. In order to control for the characteristics of the establishments as well as the characteristics of the employees, we use German representative linked employer-employee panel data entailing an unusually rich list of control variables. These data allow to control for part-time work, differences in the qualification structure and tenure of the employees and to separate age from cohort effects.

The remainder of this paper has the following structure. The next section provides hypotheses on differences between the age-productivity profiles in our sectors and an overview of the empirical literature on the impact of age on establishment productivity in different sectors. In the third section, we discuss our empirical strategy, and the fourth section provides a description of our representative linked employer-employee panel data set. The fifth section contains the empirical evidence on the impact of age on productivity in different sectors; and section six concludes and provides some policy implications of our results.

2 Background

A high share of older employees can be beneficial for the productivity of establishments because on average older employees have more experience, are more loyal, and have a higher quality conscience and working morale. On the other hand, older age is frequently associated with less technical knowledge, creativity, innovativeness, flexibility, openness to new knowledge, and physical as well as psychological resilience (Boockmann and Zwick, 2004). In addition, studies of psychologists and medical scientists argue that so-called "fluid" cognitive abilities such as the performance and speed of solving tasks related to new material tend to deteriorate with age. Other, "crystallised" abilities such as felicity and word fluency improve with accumulated knowledge and remain at a high functional level at least inside the age-bracket that is relevant for employment (Skirbekk, 2008).

Depending on the specific production processes in different sectors and professions, employees might differ with respect to their age-productivity profiles. Veen (2008), for example, names brick layer, tiler or administrator with basic jobs as occupations that are likely to become less productive when the employees age. Age-neutral occupations are those of bank or commercial clerks and electronic engineers. Finally, examples for occupations that might even have a higher productivity when employees are old are lawyer, professor, manager, medical doctor or engineer. However, no clear hypothesis on differences in relative productivity between age groups in different sectors can be drawn from these findings because in most sectors occupations with increasing and decreasing productivity potential are employed.

Production in the manufacturing sector is frequently characterised by a relatively rigid and monotonous pace dictated by the conveyor belt (Berg, 1994) and is often physically demanding. The same applies to metal manufacturing where conveyor belts in the production sector are very common. However, jobs in the service sector are often characterised by the absence of physically demanding production methods. They are frequently psychologically demanding, however, because the individual output is easy to measure, such as in the banking and insurance industry. Jobs in the service sector often imply a high degree of social interaction and communication skills. A priori, we expect a decline in the relative productivity of older workers in the production sectors, while we expect the productivity for the service sector to decline at a slower pace.

The technology and production processes should determine to which degree human capital investments drive the productivity contribution of employees. If production requires a lot of firm or sector-specific human capital, one would expect to have a steep learning curve, particularly for young employees who enter the labour market and on whom training investments are concentrated. Since the manufacturing sector typically requires more specific knowledge than the service sector (Mohrenweiser and Zwick, 2009), we expect a steeper learning curve in this sector. More specifically, the relative productivity for young workers in comparison to old and prime age workers is likely to be lower in the manufacturing sector. The higher importance of continuing training in addition might reduce the relative productivity of older employees in the manufacturing sector – older employees take part in training less often. An important reason for the decline in training participation over the life cycle might be that personnel managers perceive older employees to be less able and willing to learn (Boockmann and Zwick, 2004). When older employees take part in training, their participation seems to be less effective than for younger employees (Göbel and Zwick, 2010). Therefore, we would expect a decline in relative productivity of older employees in sectors that need continuous training efforts.

Many contributions stress the impact of information and communication technology (ICT) on labour productivity. For example, firms in the service sector frequently use ICT more intensively than manufacturing enterprises (O´Mahony and Van Ark, 2003). Older employees being less able to cope with the specific demands of ICT usage might reduce the relative productivity of older employees in ICT intensive enterprises (Lallemand and Rycx, 2009; Bertschek and Meyer, 2009). Despite the introduction of ICT, there are many service sectors where technological shocks play only a minor role, however, since the core of the production processes remains virtually unchanged over time. On the contrary, ICT has been introduced in selected production processes in manufacturing. From a theoretical point of view, the role of technology shocks on the age-productivity profiles of service or manufacturing sectors is therefore not determined.

A final point that has hardly been investigated until now is that human resource management measures vary among different sectors. For example, the application of specific measures that are targeted on older workers could vary significantly between different sectors. Weichel et al. (2008), for instance, report that measures specifically aiming at improving the relative productivity of older employees are more frequently used in (metal) manufacturing.

To summarise our considerations so far, there are many theoretical arguments that suggest that the age-productivity profiles of manufacturing and service sector might differ. The extent and the direction of the differences remain an empirical question, though. As metal manufacturing is one of the most important economic sectors in Germany and frequently has been in the focus of the discussion concerning negative impacts of an ageing workforce (Weichel et al., 2008), we estimate the age-productivity profiles for this sub-sector as well.

During recent years, there has been a growing interest in estimating the causal relationship between workforce age and establishment productivity. Börsch-Supan et al. (2005), Skirbekk (2008), and Göbel and Zwick (2009) provide extensive literature surveys of this quickly emerging field. In the following lines, we therefore only briefly review the relatively scarce empirical literature on differences in the impact of ageing workforces on establishment productivity between economic sectors.

Crépon et al. (2003) split their sample into the French manufacturing and non-manufacturing sector and drop the construction sector. They hardly find any differences in the relative impact of age groups on productivity for both sector groups besides a larger productivity disadvantage of young employees in the manufacturing sector than in the non-manufacturing sector. The authors therefore do not discriminate between the sectors in the discussion of their results.

Aubert and Crépon (2006) separately consider the impact of age groups on productivity for the French manufacturing, trading, and services sectors. In their preferred estimation version, they stress that relative productivity increases until age 35 in all three sectors. In manufacturing, there is no statistically significant difference between the age group 35-39 and older workers. In trading, workers aged 40-59 are significantly more productive, whereas in services only workers aged 45-54 are more productive than younger workers.

Daveri and Maliranta (2007) differentiate between the Finnish electronics sector, the forest industry and the production of machinery and equipment industry. They justify this distinction by the assumption that the usage of ICT leads to a stronger increase in productivity of young employees than of older employees. They argue that the electronics industry already has been hit by an information and technology shock, which may negatively affect the relative productivity of older employees, and the other two industries would follow in adopting a higher ICT intensity probably leading to a similar age-productivity pattern in the future. The authors find that age has a negligible impact on productivity in comparison to experience and seniority. In addition, the impact of these age-related factors is inversely u-shaped for the electronics industry and increasing in the two more traditional sectors.

Schneider (2007) differentiates between the manufacturing and services sector. He uses the German LIAB data we also employ and finds a stronger negative impact of younger employees on productivity in the manufacturing than in the services sector. The age effects derived in OLS regressions disappear completely in his fixed effects regressions, however.

Lallemand and Rycx (2009) split their sample of Belgian firms into sectors with high and low ICT intensity based on aggregate sector specific information. They argue that sufficient cognitive skills and the possibility to adjust quickly and flexibly to new forms of work organisation are crucial for an intensive ICT usage. In addition, they claim that these characteristics decline stronger with age than other personal traits. The authors indeed find that ICT intensive firms suffer more from an increase in the share of older workers. Bertschek and Meyer (2009) do not find a negative relationship between ICT intensity and age shares on productivity in a German data set, however.

Vandenberghe and Waltenberg (2010) split their Belgian enterprise sample into the sectors industry, services and trade. On the basis of FGLS and OLS estimations, they find a stronger productivity disadvantage of older workers aged 50-65 in the service industry than in their entire sample.

Cardoso et al. (2010) show separate age productivity profiles for the Portuguese manufacturing and service sector. In their preferred GMM version, productivity of older workers is slightly higher in services than in manufacturing. The differences are not significant, however, because the variance is relatively high.

Van Ours and Stoeldraijer (2010) show separate age productivity profiles for the following sectors in the Netherlands: construction, wholesale trade, retail trade, commercial services, and manufacturing. They find clear differences in the age-productivity patterns between the sectors – for manufacturing value added increases until the age group 50-56; for all other industries the age-productivity patterns are essentially flat. One reason might be that for the manufacturing sector, a GMM instrumental variables estimation is used, and for the other sectors a fixed effects regression is used. With the exception of manufacturing, in all sectors the share of the age groups has been found to be exogenous – the authors, however, admit that their tests might have little power because they have relatively few observations. Another (unobserved) difference between the sectors might be the qualification structure by age. In some sectors older employees might be relatively lower educated than younger employees. As the authors do not have data on qualification, they cannot differentiate between the effects of age and qualification.

Summing up, the empirical literature so far suggests that there might be differences in the age-productivity profiles between sectors – younger employees seem to be less productive in the manufacturing than in the services sector because specific human capital acquired in the job seems to be more important here. ICT usage seems to negatively affect the relative productivity of older employees mainly in the service sector. The results are frequently not very robust with respect to changes in the estimation technique and tend to disappear in estimates that control for unobserved heterogeneity or endogeneity of the age shares in production functions.

3 Estimation Strategy

This paper uses standard estimation strategies of Cobb-Douglas production functions including shares of age groups. This approach is discussed in detail in Aubert and Crépon (2006) and Göbel and Zwick (2009). Therefore, we resort to a short intuitive and graphical depiction of our main arguments.

First, we argue that cross-section estimations of the relationship between the establishment age-structure and productivity are likely to give biased age-productivity profiles. Assume that the productivity-contribution of employees aged 20-30 years is lower than that of the prime age workers (those aged 30-40 years). Moreover, the relative productivity of those 40-50 years and those 50-60 years is on the same level as relative productivity of the 30-40 years old employees. This means that the relation between age share and productivity can be represented as shown in the lowest line in Figure 1. Furthermore, let us assume that there is an exogenous technical improvement induced by learning and innovations that increases total establishment productivity uniformly over time for all age groups.[1] In other words, the technical improvement does not particularly favour a certain age group but shifts the productivity of all age groups upwards, as shown in the second lowest line in comparison to the lowest line in Figure 1. We finally assume that there are no age composition effects on productivity[2], i.e. the productivity of employees of a certain age group does not depend on the size of the other age groups. In this case, the lowest line of Figure 1 represents the true age productivity profile of the employees of one cohort. This profile represents what

[1] The described upwards shift would for example occur when later birth cohorts are better educated or when they work with newer, more productive technologies or machines. The shift could apply for birth cohorts at the level of employees and for cohorts of establishments that are founded at the same moment in time.

[2] Veen (2008), for example, argues that age heterogeneity might have an additional (negative)

researchers would obtain if they could directly observe the productivity development of this cohort for 40 years. The second lowest line is the analogous age-productivity profile for another cohort that enters the labour market ten years later. From the longitudinal perspective, observing age productivity over time, we obtain several trajectories of age-productivity curves in an inverted L-shape.

Now suppose that we compute age-productivity profiles from cross-sectional data, observing differences in age and productivity between our four cohorts at one point in time. This approach cannot take into account the productivity trend over time because technological shocks usually cannot be observed in available data sets. The cross-section approach results in an inverted U-shaped age-productivity profile as indicated by the bold line in Figure 1.

In our empirical approach, we imitate the longitudinal and cross-sectional estimation approaches depicted in Figure 1. First, we calculate an age-productivity pattern in a pooled OLS approach that is driven by cross-sectional variation in the data. Then we take into account unobservable time invariant heterogeneity between establishments (probably induced by unobservable technological shocks over time) in a longitudinal within approach. Our preferred specification exploits changes in productivity and the age structure over time within the same firms and takes into account that third factors such as the business cycle might have an impact on both productivity and the age structure (endogeneity). In addition, our data allow us to separate cohort from age effects. The simultaneous identification of age-, cohort- and calendar-effects is often awkward in empirical models. The fundamental issue is here that at the individual level the year of birth plus the age is equal to the calendar time. This equality can lead to multi-collinearity also when analysing establishment data. Here, the share of employees with a specific year of birth is equal to the corresponding share of employees with the corresponding age in years. Therefore, additional requirements have to be met for the simultaneous identification of cohort-, age- and calendar-effects with establishment data. First, the chosen time windows for age groups and cohort groups are not allowed to completely overlap. Complete overlap would lead to perfect collinearity and would

impact on establishment productivity beyond the pure shares of age groups.

render any estimation impossible. This implies that one has to decide on the width of the time windows, which can put constraints on the empirical specification.[3] Second, sufficient variation over the possible age and cohort shares is required. The use of panel data at the establishment level is certainly helpful to provide this variation, since there is typically ample variation over age and cohort composition within the enterprises over time (compare Göbel and Zwick, 2009). This variation is the result of an aging workforce combined with employees that quit and enter the establishments in the course of the observation period.

We estimate a structural Cobb-Douglas production function and include a broad range of relevant establishment specific information besides capital and age shares. It is especially important to control for age related variables such as tenure (Haegeland et al., 1999; Schneider, 2007; Daveri and Maliranta, 2007), qualification (Van Ours and Stoeldraijer, 2010), the age of the firm (Daveri and Maliranta, 2007; Cardoso et al., 2010), and the birth cohorts of the employees in order to avoid biased results. Otherwise, age might capture part of the influence of these factors on productivity.[4] Assuming perfect substitution among workers of different age groups, one can write the production function per head, for establishment *j* in year *t* as:

$$\ln(p_{j,t}) \approx c + \sum_k \alpha_k \ln(p_{j,t-k}) + \beta \ln(k_{j,t}) + \sum_{i-\{0\}} \gamma_j \left(\frac{L_i}{L}\right)_{j,t} + \phi X_{j,t} + \varepsilon_{j,t} \, .$$

Value added (value of sales minus the value of intermediate inputs) per head *p* is a function of capital per head *k*, a broad range of establishment characteristics *X*, and the fraction of the number of employees in age groups *i*, L_i of the total number of employees in the establishments *L*. Here, γ_j is the effect of a marginal increase of the share of age group *j* when at the same time decreasing the share of the reference age group. We use age classes in five-year brackets and only report the coefficients of employees between 20 years of age and 60 years of age. The estimates for the other age classes are summarised in a separate variable, but they are not reported because they are

[3] Since in empirical applications time windows typically comprise several years, this requirement often does not put serious constraints on the specification. In order to analyze the sensitivity of the results, however, it is advisable to test different specifications of the window widths.

[4] Please note that so far, only contributions on the basis of the German LIAB panel data set can simultaneously control for qualification, tenure and cohort effects in production functions because other suitable data sets do not provide this information.

likely to reflect unobserved characteristics of employees at the fringes of the age distribution – very young employees and very old employees are usually specific individuals. In addition, they represent only a small fraction of the population of all employees.[5] In order to allow for persistence in the level of productivity, we specify a dynamic model where the production of one year is allowed to be a function of its past values $p_{j,t-k}$.

We consider various ways of estimating the production function. In a first step, we estimate pooled ordinary least squares (OLS) of equation (1) without the lagged dependent variables. However, the OLS estimates are likely to be biased by endogeneity because the value added and the age structure are determined simultaneously (Griliches and Mairesse, 1998). Successful establishments, for example, recruit more workers, and job entrants tend to be younger than those who leave the enterprise (Heywood et al., 2009; Zwick, 2008a). In addition, the variation between the establishments is likely to drive the results, and we can only observe part of the heterogeneity between establishments (Prskawetz et al., 2006). For example, establishments with better industrial relations might be able to bind their employees longer, while they enjoy a higher productivity (Addison et al., 2010). Since we cannot control for all establishment characteristics, estimates from OLS estimates of the age-productivity profile are likely to be biased.

Therefore, we switch from a between estimation to a within estimation in a next step. In order to control for endogeneity, we apply dynamic GMM methods and use lagged values of the explanatory variable to instrument contemporary values (Arellano and Bover, 1995; Blundell and Bond, 1998; Bond, 2002). In order to find the correctly specified model, we start with moment conditions that require relatively mild assumptions and augment the set of instruments systematically. The validity of the additional instruments is tested by means of the standard Sargan/Hansen test for overidentifying restrictions. We also apply a test for serial correlation in the disturbance term in order to check whether the dynamic specification of the model is correct (for

[5] In 2005, the last year of our observation period, only 3.5% of the employees are younger than 20 years and only 3.8% are older than 60 years old (OECD, 2005).

details see Göbel and Zwick, 2009). Finally, we use the model with the smallest number of instruments and lags that satisfies all necessary test statistics.

4 Data

We estimate the impact of the age structure on establishment productivity using the waves 1997-2005 of the linked employer-employee data set (LIAB) of the *Institute for Employment Research (IAB).* We choose a version of the LIAB that provides one observation per year for establishment characteristics and virtually all employees of the observed establishments on June 30th of the respective year (see Jacobebbinghaus, 2008 for details).[6] On the establishment level, the LIAB uses the survey data of the IAB establishment panel. This panel entails questions on value added, investments, sector, average employee characteristics and on many other aspects of the establishment. These data can be linked to the administrative files for the employees by the means of a common identifier. The employee data set uses official data of the IAB employment register. Yearly information on earnings, qualification, gender, tenure, birth year, and age for each employee of the firm is therefore available. Altogether, our version of the LIAB covers almost 7 million employees who work in more than 8,500 establishments.

Labour market participation of older employees is about OECD average in Germany. It was relatively stable during our observation period and started to slightly increase in 2004, however, mainly as a reaction to decreased early retirement possibilities (OECD, 2010). Early retirement is associated with steep cuts in old age pensions when the employer does not offer and financially support measures such as old age reduced working time (*Altersteilzeit*) that frequently is chosen in the so-called block model (Zwick, 2008a). This frequently means that employees work full time during their two last employment years and retire two years earlier instead of working half-time for four years. The official retirement age was 65 during the observation period, and the actual average retirement age was approximately 62 (for males and females alike). In general, labour market participation of old employees significantly decreases just beyond the age of 60 (Boockmann et al., 2011). The unemployment rate oscillated around nine percent

[6] This version of the LIAB-data is called “cross section version”, despite the fact that the data set

between 1997 and 2005. Older employees are hit more than proportionally by unemployment, and, once unemployed, they remain longer in unemployment than younger employees in Germany (OECD, 2010). A clear sign of the relatively weak labour market position of older unemployed and relatively high wages of older employed are strong seniority wage increases and increasing wage losses of re-entering unemployed with age (Zwick, 2008a; Zwick, 2008b). The employment share in the service sector continued its secular increase during the observation period from about 65% to 70%.

Only establishments with more than five employees are included. Since either the measure of the outcome variable or the measure of the capital variable have a different meaning in certain sectors, the public sector, the non-profit sector and the financial sector are excluded. In order to have a proxy for the capital stock, we use the yearly information on investment and the depreciation rates on the two-digit sector level according to the perpetual investment method (Zwick, 2004). For the starting value, we use the average of real investment and divide it by the sum of the depreciation rate and the average growth rate of investment (Hempell, 2006). For the following periods, we compute value of capital as the value of capital in the previous period plus investments and minus depreciation. About eight percent of the establishments never report an investment during our observation period. For theses firms, we impute the missing values for capital stocks.

The variables on individual tenure are censored in some cases. For employees in West Germany, we know the exact date for tenure since January 1st 1975 and for East Germany, the dates are known since January 1st 1990. For employees with longer tenure, the censored date is given. This means that between 16% (1997) and 10% (2005) of the West German and between 46% (1997) and 27% (2005) of the East German employees have censored values for tenure. We account for censoring by multiply imputing their values (compare Gartner, 2005). We define 20 cells for different gender, qualification (five groups), and nationality. For each cell, we estimate censored Tobit regressions separately including the covariates tenure, tenure squared, age, age

provides panel data.

squared, a dummy for East Germany and the level of education; see also Addison et al. (2010). Yearly imputation of the values for tenure could lead to excess variance in these variables, and, therefore, for each employee, only the first value for tenure and experience is imputed. For each additional year the employee stays in the same establishment, we update the value for experience and tenure by adding one year to the imputed value of the last year.

Since we are interested in the productivity per head, we have to compute the input per head. To cope with workers that only have part-time contracts, we count each part-time employed worker by one-half. Apprenticeships are included in the sample, but since they can be expected to have a lower productivity than other workers, we include the share of apprenticeships as an additional control variable. We split our sample according to the NACE03 classification into manufacturing (codes 0-49), metal manufacturing (codes 29, 30, 31, 34 and 35), and service sector (codes 50-99). The manufacturing sector therefore consists of agriculture and mining, timber, production of machinery, and energy and water supply. The services sector consists of trade, traffic and communication, real estate, renting, industrial services, training and education, and other public and personal services. The metal manufacturing services consists of metal products, production of machinery, and production of automobiles. For a short description of the variables and their mean values, we refer to Tables 1 and 2 in the appendix.

5 Results: The Age-Productivity Profile – Sector Differences

The pooled OLS estimations lead to age-productivity patterns that are roughly comparable to the bold line in Figure 1; compare Table 4. Figures 2 to 4 provide a visual representation of the age-productivity profiles obtained for the manufacturing, metal manufacturing, and services sectors. For manufacturing, the age productivity profile increases until the age group 30-35 years and then decreases until the age group from 55-60 years. Young workers and workers older than 50 years have a significantly smaller productivity than the reference group. In the services sectors we do not find significant effects of the age structure on productivity. The steeper increase in relative productivity for young versus prime-age employees and the stronger productivity decline for the oldest age groups in the manufacturing sector in comparison to the services sector has also been found in the literature (Aubert and Crépon, 2006; Skirbekk, 2008). In metal manufacturing, we find significant negative effects for the age groups 50-60 in comparison to the reference age group. Different from our hypothesis, the relative productivity of the youngest age groups is not lower than that of prime age workers here. However, as argued above, OLS estimates have several well-known deficiencies. Most notably, these estimates are likely to suffer from the endogeneity of the age structure, and we should control for unobserved time-invariant heterogeneity between establishments and lagged productivity effects. Therefore, one should not over-interpret these results but control the sources of estimation bias.

Figures 5 - 7 illustrate the age-productivity profiles for our difference GMM estimations based on Table 5. Here, we do not find any significant impact of the age structure of the establishment on productivity for all three sectors. Moreover, the point estimates for older age groups are above the reference group and peak at the age 50-55 in the manufacturing sector and the metalworking sector (in contrast to the services sector where all age groups seem to have a lower productivity impact than age group 35-40). Although on first sight there are differences between the sectors, these are not significant because the variance of the estimators is too large. Vandenberghe and Waltenberg (2010) and Cardoso et al. (2010) do also stress large variances of age group estimators that make inter-sectoral comparisons problematic. In order to test the validity of the instruments, we apply the standard Sargan/Hansen tests of overidentifying restriction separately for the variables of interest, the share of the different age groups, and for the control variables. Our tests indicate that all instruments are fine. In addition, the test for autocorrelation in the residuals indicates that the model is correctly specified. We also calculated age-productivity profiles without controlling for tenure, qualification and/or birth cohorts. Probably mainly caused by the large variances, these profiles did not significantly differ from those depicted here. In order to analyse the sensitivity of our results with respect to the consideration of birth-cohorts and the specification of the size of the time windows we conducted the following estimations: Estimates without calendar time dummies, estimates where we have 10-year windows for the age and 5-year windows for the birth-cohort and estimates without birth cohorts. The key results in the specification without calendar time dummies and with altered windows size are virtually the same as those presented in this paper. The exclusion of birth cohorts leads to slightly different age-productivity profiles, however these differences are not significant and the main message of this paper is unaltered.[7]

We believe that our findings support the hypothesis that differences in estimates between the cross-sectional and longitudinal approaches are driven by misspecifications in the cross-sectional empirical model. In our preferred GMM specification, we do not find support for an inverse U-shaped form of the age-productivity profile – this is in accordance to previous findings on the basis of within estimations; see Aubert and Crépon (2006), Malmberg et al., (2008), Göbel and Zwick (2009), and Stoeldraaijer and Van Ours (2010). A flat age-productivity profile suggests that the foreseeable increase in the share of older employees will not damage establishment productivity. Moreover, we do not find support for strong differences in the shape of the age-productivity profile between sectors. In the service sector as well as in the manufacturing sector, the young age groups have the lowest productivity contribution.

Our results suggest that there are no pure age affects on productivity in the three sectors analysed here. We have to take into account, however, that these results are obtained from the relationship between age structure and establishment productivity given human resource management measures used by establishments to enhance the relative productivity of older employees and given selectivity of older employees. One argument in favour of this might be that the manufacturing and the metal manufacturing sector invest in human resource measures more extensively in order to improve the performance of older employees. There are several measures associated with higher relative performance of older employees in Germany (Wegge et al., 2008; Göbel and Zwick, 2010).[8] Establishments offer age specific jobs in order to put employees on

[7] The estimates of the sensitivity analysis are available on request, from the authors.

[8] The other two human resource measures listed in Table 3 are not effective. Working time reductions for old employees are mainly used for early retirement instead of a gradual working time reduction in Germany (also see data section). Training of older employees is less effective because less effective training forms are used, and the goals associated with training are less ambitious for older employees than for young employees.

activities they are most competent in. Furthermore, they establish mixed age teams to reap synergy effects from combining specific skills and advantages old and young employees have. Some establishments also provide a special equipment of workplaces for older workers such as larger signs, better colour contrast or better chairs. The manufacturing sector and particularly the metal manufacturing sector do in fact use the effective measures mentioned above more often than enterprises in the services industry (see Table 3). However, the differences between the sectors are small, and it remains unclear whether specific measures for old employees are indeed driving our results. Therefore, we do not have a powerful argument that the good performance of old employees in the manufacturing sector is predominantly based on investments in (observed) specific measures for old employees.

Specific human resource measures aimed at older employees also might have an impact on their quitting behaviour. Enterprises might be able to motivate and retain their most able older employees by specifically investing in them (Pfeffer, 1981). As a matter of fact, there are indications that German enterprises with the measures specifically aimed at older employees described above (except training and age mixed teams) can keep their old employees longer (Boockmann et al., 2011). Another explanation could be that one answer to the high physical demands in some jobs in the manufacturing sector is a stronger selection of workers. Only old employees who have above-average productivity might still be present at the workplace. On average, we do not find large turn-over and quitting rates for employees younger than 60 years of age in Germany, however (Boockmann et al., 2011). Therefore, also the scope of the differences in selectivity between sectors seems limited because our age sample only takes employees into consideration until age 60.

6 Conclusions

This paper shows that the share of employees in different age groups hardly has an impact on establishment productivity in the manufacturing, services and metal manufacturing sectors. On first sight, these findings contradict the notion that physically demanding, rigid and monotonous jobs might reduce the relative productivity of older employees in the (metal) manufacturing sector, or that higher flexibility and speed increase the productivity of younger employees in the services sector. However, one has to be aware that only the productivity of those employees who are actually working in the establishment is measured. We do not find strong evidence that our results reflect differences in the selectivity of older workers or in investments in old employees between sectors.

This paper paints a positive picture of the relative productivity of older employees in different sectors of the German economy. It remains an interesting question of whether the predicted strong increase in the share of old employees that goes far beyond the increase during the observation period will change the picture. In a related paper, we show that specific human resource measures for old employees are associated with improved relative productivity of old employees. These investments, such as age mixed teams, specific equipment of workplaces of older employees or age specific jobs are applied to a different extent in different sectors (see Table 3). In future research, it seems interesting to investigate to which degree the age-productivity profiles in different sectors are influenced by the application of specific human resource measures for old employees.

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Table 1: Descriptions of variables

Variable	Description
log(value added)	Log of (sales minus value of intermediate goods) per head
log(capital)	Log of (capital) per head
export	Dummy, 1 if establishment indicates that it is exporting
number of workers	Number of workers per establishment expressed in full-time equivalents
East-Germany	Dummy, 1 if the establishment is located in East Germany
sector	50 Sector dummies derived from the 2 level NACE-classification
good equipment	Dummy, 1 if the establishment indicates that their equipment/capital-stock is in good shape
women	Dummy, 1 if gender of employee is female
German	Dummy, 1 if nationality of employee is German
apprenticeships	Dummy, 1 if the employee participates in apprenticeship training
unskilled	Dummy, 1 if employee is not formally qualified
lowskilled	Dummy, 1 if employee is a formally qualified worker
highskilled	Dummy, 1 if employee is a formally qualified worker in a leading position
white-collar	Dummy, 1 if employee is white-collar worker
parttime	Dummy, 1 if worker has a part-time contract
average employee age	Average age of employees
age-dispersion	Standard deviation of age
cohort[1900,1930)	Dummy,1 if employee is employees born 1900 – 1930
cohort[1930,1940)	Dummy,1 if employee is employees born 1930 – 1940
cohort[1940,1950)	Dummy,1 if employee is employees born 1940 – 1950
cohort[1950,1960)	Dummy,1 if employee is employees born 1950 – 1960
cohort[1960,1970)	Dummy,1 if employee is employees born 1960 – 1970
cohort[1970,1980)	Dummy,1 if employee is employees born 1970 – 1980
cohort[1980,1999)	Dummy,1 if employee is employees born 1980 – 1999
tenure[0,10)	Dummy,1 if employee is employees with tenure 0 - 10 years
tenure[10,20)	Dummy,1 if employee is employees with tenure 10 – 20 years
tenure[20,30)	Dummy,1 if employee is employees with tenure 20 – 30 years
tenure[30,40)	Dummy,1 if employee is employees with tenure 30 – 40 years
tenure[40,50)	Dummy,1 if employee is employees with tenure 40 – 50 years

Table 2: Descriptive statistics by sectors

	manufacturing		services		metal manufacturing		all sectors	
Variable	**mean**	**s.d.**	**mean**	**s.d.**	**mean**	**s.d.**	**mean**	**s.d.**
log(value added)	10.83	0.70	10.85	0.82	10.90	0.65	10.84	0.75
log(capital)	10.16	1.38	10.01	1.66	10.26	1.19	10.10	1.50
age_[20,25)	0.07	0.08	0.09	0.10	0.06	0.06	0.08	0.09
age_[25,30)	0.08	0.08	0.10	0.09	0.08	0.06	0.09	0.08
age_[30,35)	0.12	0.09	0.13	0.10	0.12	0.08	0.13	0.09
age_[35,40)	0.16	0.09	0.15	0.10	0.16	0.08	0.16	0.09
age_[40,45)	0.16	0.09	0.15	0.10	0.16	0.08	0.16	0.09
age_[45,50)	0.14	0.08	0.13	0.09	0.15	0.08	0.14	0.09
age_[50,55)	0.11	0.08	0.11	0.09	0.12	0.07	0.11	0.08
age_[55,60)	0.08	0.07	0.08	0.07	0.09	0.07	0.08	0.07
age_[60,65)	0.06	0.07	0.06	0.07	0.06	0.06	0.06	0.07
age dispersion	10.43	1.94	10.21	2.13	10.47	1.72	10.32	2.04
number workers	224.17	889.76	104.14	407.53	338.92	1090.70	176.18	738.22
parttime	0.06	0.26	0.20	0.54	0.05	0.15	0.12	0.40
women	0.23	0.42	0.46	0.50	0.18	0.39	0.32	0.47
Germans	0.95	0.21	0.95	0.21	0.95	0.22	0.95	0.21
apprentice	0.05	0.23	0.06	0.23	0.04	0.20	0.06	0.23
unskilled	0.20	0.40	0.15	0.35	0.19	0.39	0.18	0.38
lowskilled	0.44	0.50	0.19	0.39	0.45	0.50	0.34	0.47
highskilled	0.03	0.16	0.01	0.11	0.03	0.16	0.02	0.14
white-collar	0.24	0.43	0.45	0.50	0.26	0.44	0.32	0.47
East-Germany	0.43	0.50	0.31	0.46	0.41	0.49	0.37	0.48
good equipment	0.67	0.47	0.73	0.45	0.67	0.47	0.70	0.46
export	0.35	0.48	0.11	0.31	0.50	0.50	0.23	0.42
cohort[1900,1930)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
cohort[1930,1940)	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.02
cohort[1940,1950)	0.15	0.09	0.15	0.10	0.16	0.09	0.15	0.10
cohort[1950,1960)	0.28	0.11	0.27	0.13	0.29	0.11	0.28	0.12
cohort[1960,1970)	0.31	0.11	0.30	0.13	0.31	0.10	0.31	0.12
cohort[1970,1980)	0.17	0.10	0.20	0.13	0.16	0.09	0.18	0.11
cohort[1980,1999)	0.08	0.08	0.08	0.10	0.07	0.07	0.08	0.09
tenure[0,10)	0.67	0.27	0.74	0.25	0.67	0.28	0.70	0.27
tenure[10,20)	0.22	0.19	0.18	0.18	0.22	0.19	0.21	0.19
tenure[20,30)	0.09	0.11	0.07	0.10	0.09	0.11	0.08	0.11
tenure[30,40)	0.02	0.04	0.01	0.03	0.02	0.04	0.02	0.04
tenure[40,50)	0.00	0.01	0.00	0.01	0.00	0.00	0.00	0.01
N	2393		1477		788		3870	

Note: Descriptive statistics based on the 2002 wave of the LIAB.

Table 3: Descriptive statistics for specific measures for old employees by sectors

	manufacturing		services		metal manufacturing		all sectors	
Variable	**mean**	**s.d.**	**mean**	**s.d.**	**mean**	**s.d.**	**mean**	**s.d.**
Reduced working time	0.36	0.48	0.27	0.44	0.45	0.50	0.32	0.47
Specific equipment of workspaces	0.06	0.23	0.03	0.17	0.08	0.27	0.05	0.21
Age specific jobs	0.06	0.24	0.05	0.23	0.08	0.28	0.06	0.24
Mixed-age working groups	0.21	0.41	0.16	0.37	0.23	0.42	0.19	0.39
Training for old employees	0.18	0.38	0.17	0.37	0.23	0.42	0.17	0.38
Other measures for old employees	0.03	0.17	0.03	0.16	0.04	0.19	0.03	0.17
No measure for old employees	0.51	0.50	0.57	0.49	0.43	0.50	0.53	0.50
N	2393		1477		788		3870	

Note: Descriptive statistics based on the 2002 wave of the LIAB.

Table 4: OLS estimates

Dependent variable: log(value added)

	Manufacturing		Services		Metal Manufacturing	
Variable	**Coef.**	**t**	**Coef.**	**t**	**Coef.**	**t**
log(capital)	0.12***	29.18	0.12***	24.21	0.10***	14.66
age_[20,25)	-0.32***	-2.63	0.13	0.88	-0.33	-1.31
age_[25,30)	0.11	1.01	0.09	0.65	-0.10	-0.41
age_[30,35)	0.20***	2.46	0.16	1.51	0.02	0.14
age_[35,40)			reference			
age_[40,45)	-0.05	-0.60	0.01	0.10	0.11	0.67
age_[45,50)	-0.16	-1.47	-0.03	-0.19	-0.38*	-1.72
age_[50,55)	-0.39***	-3.51	0.00	0.02	-0.58**	-2.63
age_[55,60)	-0.47***	-3.29	-0.25	-1.32	-0.71**	-2.55
women	-0.11***	-9.12	-0.01	-0.96	-0.04*	-2.11
Germans	-0.02	-1.10	-0.01	-0.20	-0.07	-1.99
apprenticeships	0.08***	3.76	0.09***	3.09	0.09**	2.72
unskilled	-0.01	-1.14	-0.09***	-4.39	-0.05*	-2.09
highskilled	0.03	1.16	0.08	1.53	0.00	0.08
whitecoll	0.13***	10.99	0.13***	8.15	0.12***	6.16
parttime	0.06***	3.43	0.01	0.70	0.03	0.59
good equipment	0.07***	7.44	0.08***	5.14	0.10***	6.11
age-dispersion	0.00	-0.12	-0.01***	-3.51	-0.02***	-2.90
export	0.15***	12.66	0.13***	6.86	0.13***	7.17
number of workers	0.00***	6.08	0.00	1.19	0.00**	2.60
East-Germany	-0.29***	-26.06	-0.29***	-19.33	-0.32***	-16.64
Constant	10.05***	86.41	10.77***	35.94	10.19***	50.46
cohort[1900,1930)	-12.58	-1.17	-7.09	-1.12	-31.96***	-24.66
cohort[1930,1940)	0.23	1.16	0.36	1.40	0.27	0.72
cohort[1940,1950)	0.17*	1.71	0.07	0.53	0.43**	2.34
cohort[1950,1960)			reference			
cohort[1960,1970)	0.01	0.14	0.01	0.09	0.00	-0.01
cohort[1970,1980)	-0.47***	-4.16	-0.29*	-2.05	-0.14	-0.61
cohort[1980,1999)	-0.62***	-4.81	-0.53***	-3.40	-0.63**	-2.37
tenure[0,10)			reference			
tenure[10,20)	-0.03	-1.02	0.06	1.43	-0.03	-0.59
tenure[20,30)	0.11**	2.19	0.06	0.67	-0.03	-0.34
tenure[30,40)	0.14	1.03	0.11	0.46	0.38	1.59
tenure[40,50)	1.98**	2.09	-0.28	-0.12	0.32	0.16
50 sector dummies included						
9 year dummies included						

Manufacturing	Services	Metal Manufacturing
Linear Regression	Linear Regression	Linear Regression
Number of obs = 19510	Number of obs = 12989	Number of obs = 5994
F(67, 19442) = 95.16	F(56, 12932) = 82.64	F(44, 5949) = 104.07
Prob > F = 0.0000	Prob > F = 0.0000	Prob > F = 0.0000
R-squared = 0.2433	R-squared = 0.2425	R-squared = 0.2136
Root MSE = .61041	Root MSE = .71785	Root MSE = .57639
Arellano-Bond test for AR(1):	Arellano-Bond test for AR(1):	Arellano-Bond test for AR(1):
z = 44.40 Pr > z = 0.0000	z = 36.71 Pr > z = 0.0000	z = 23.93 Pr > z = 0.0000
Arellano-Bond test for AR(2):	Arellano-Bond test for AR(2):	Arellano-Bond test for AR(2):
z = 33.06 Pr > z = 0.0000	z = 27.80 Pr > z = 0.0000	z = 18.34 Pr > z = 0.0000

Significance levels: ***<0.01, **<0.05, *<0.1

Table 5: Diff- GMM estimates

Dependent variable: log(value added)

	Manufacturing		Services		Metalworking Sector	
Variable	**Coef.**	**t**	**Coef.**	**t**	**Coef.**	**t**
Lag 1 of dep. var.	0.05	0.99	0.08	1.62	-0.04	-0.85
Lag 2 of dep. var.	0.01	0.40	-0.02	-0.48	-0.05	-1.50
log(capital)	0.16**	2.07	0.27***	2.88	0.18*	1.71
age_[20,25)	-0.58	-1.55	-0.67	-1.46	-0.41	-0.73
age_[25,30)	-0.62**	-2.05	-0.37	-0.75	-0.64	-1.39
age_[30,35)	-0.05	-0.27	-0.08	-0.27	-0.31	-0.90
age_[35,40)			reference			
age_[40,45)	-0.02	-0.10	-0.11	-0.42	0.17	0.52
age_[45,50)	0.26	0.96	-0.18	-0.53	0.19	0.43
age_[50,55)	0.41	1.25	-0.09	-0.21	0.63	1.26
age_[55,60)	0.22	0.59	-0.58	-1.11	0.27	0.46
women	-0.03	-0.74	0.02	0.46	0.03	0.83
Germans	-0.06	-0.86	-0.01	-0.11	-0.09	-1.39
apprenticeships	-0.02	-0.33	0.16*	1.73	-0.01	-0.15
unskilled	-0.01	-0.26	-0.13**	-2.21	0.03	0.79
highskilled	-0.12	-1.32	0.15	1.27	-0.10	-1.19
whitecoll	-0.04	-0.80	0.02	0.52	0.00	0.10
parttime	0.09*	1.95	0.14*	1.69	0.03	0.23
good equipment	-0.03	-0.67	0.02	0.33	-0.05	-1.19
age-dispersion	0.00	-0.31	0.03	1.44	-0.02	-0.92
export	-0.01	-0.11	0.00	-0.02	-0.06	-1.26
number of workers	0.00**	2.45	0.00	-0.65	0.00***	2.91
cohort[1930,1940)	-0.46	-0.55	1.22	1.09	2.41**	2.28
cohort[1940,1950)	-0.23	-0.49	0.01	0.01	-0.22	-0.34
cohort[1950,1960)			reference			
cohort[1960,1970)	0.00	-0.01	-0.23	-0.45	0.69	1.10
cohort[1970,1980)	0.63	1.28	-0.29	-0.49	0.85	1.19
cohort[1980,1999)	0.08	0.16	-1.16*	-1.89	1.10	1.30
tenure[0,10)			reference			
tenure[10,20)	0.12	1.02	0.17	1.03	0.01	0.09
tenure[20,30)	-0.01	-0.01	0.09	0.19	-0.26	-0.50
tenure[30,40)	0.35	0.46	1.12	1.08	0.03	0.03
tenure[40,50)	-0.14	-0.05	4.92	1.17	-2.06	-0.43
6 year dummies included						

Number of obs = 5592	Number of obs = 2982	Number of obs = 1800
One-step, robust estimates	One-step, robust estimates	One-step, robust estimates
Number of instruments = 628	Number of instruments = 628	Number of instruments = 628
Wald chi2(37) = 58.98, Prob > chi2 = 0.012	Wald chi2(37) = 61.49, Prob > chi2 = 0.007	Wald chi2(37) = 62.13, Prob > chi2 = 0.006
Arellano-Bond test for AR(1) in first differences: z = -5.51 Pr > z =0.000	Arellano-Bond test for AR(1) in first differences: z = -5.67 Pr > z =0.000	Arellano-Bond test for AR(1) in first differences: z = -5.20 Pr > z =0.000
Arellano-Bond test for AR(2) in first differences: z = -0.43 Pr > z =0.669	Arellano-Bond test for AR(2) in first differences: z = -1.17 Pr > z =0.241	Arellano-Bond test for AR(2) in first differences: z = -0.38 Pr > z =0.703
Instruments for all orthogonal deviations equation:	**Instruments for all orthogonal deviations equation:**	**Instruments for all orthogonal deviations equation:**
Sargan test of overid.	Sargan test of overid.	Sargan test of overid.

restrictions: chi2(591)= 612.22 Prob > chi2 = 0.265 Hansen test of overid. restrictions: chi2(591) = 579.20 Prob > chi2 = 0.628	restrictions:chi2(591) = 650.15 Prob > chi2 = 0.046 Hansen test of overid. restrictions: chi2(591) = 590.82 Prob > chi2 = 0.494	restrictions:chi2(591) = 618.59 Prob > chi2 = 0.209 Hansen test of overid. restrictions: chi2(591) = 551.16 Prob > chi2 = 0.878

Figure 1: Longitudinal vs. cross-sectional observations of age and productivity

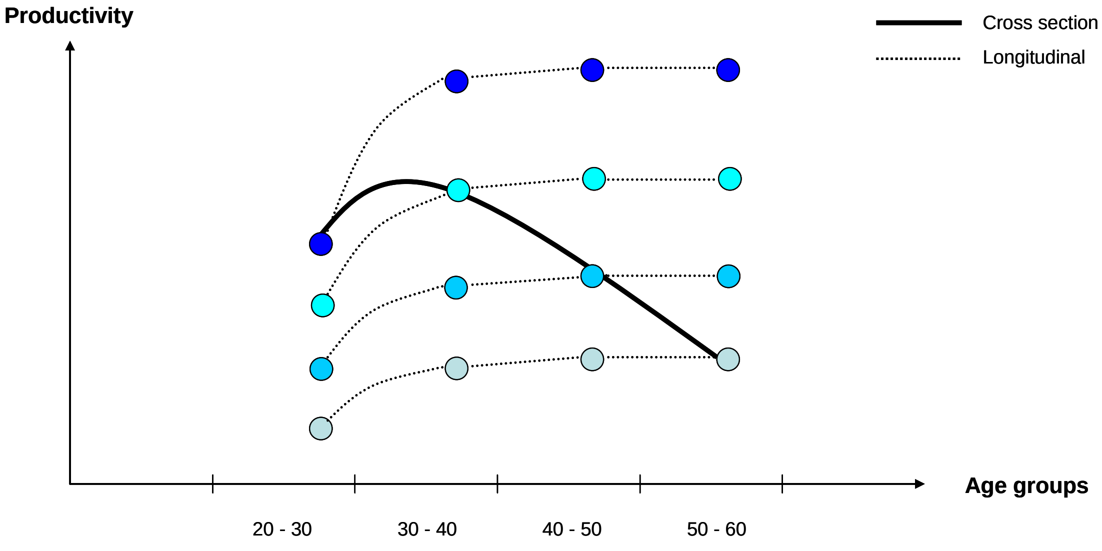
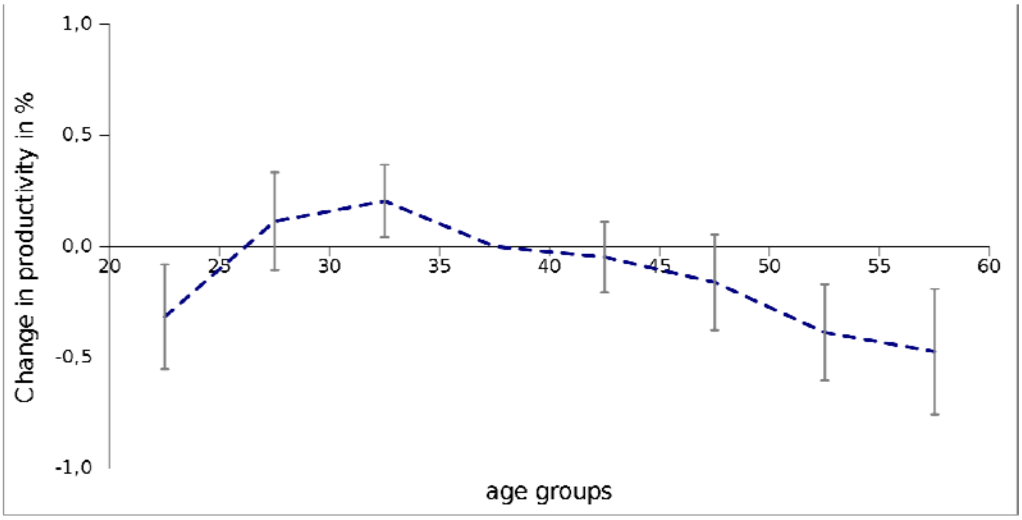
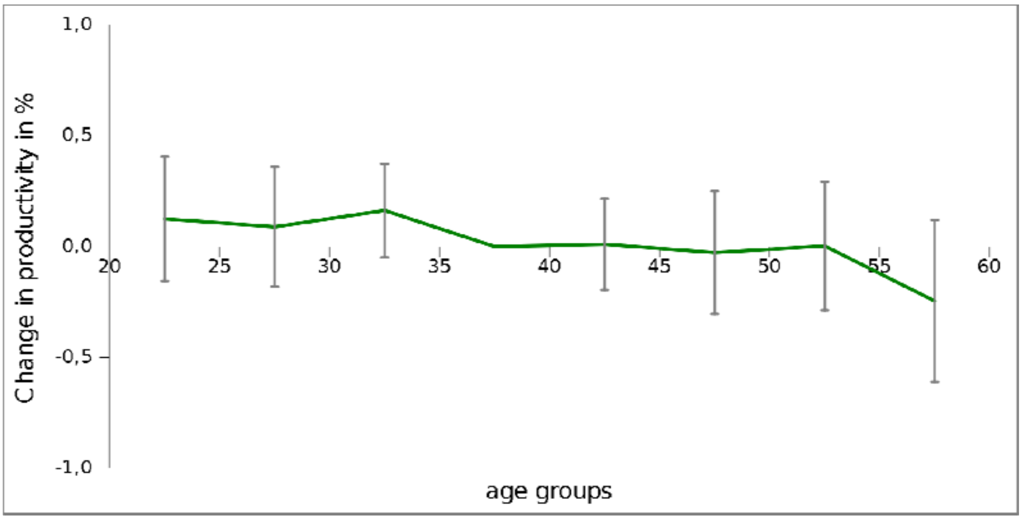


Figure 2: OLS estimates for the manufacturing sector



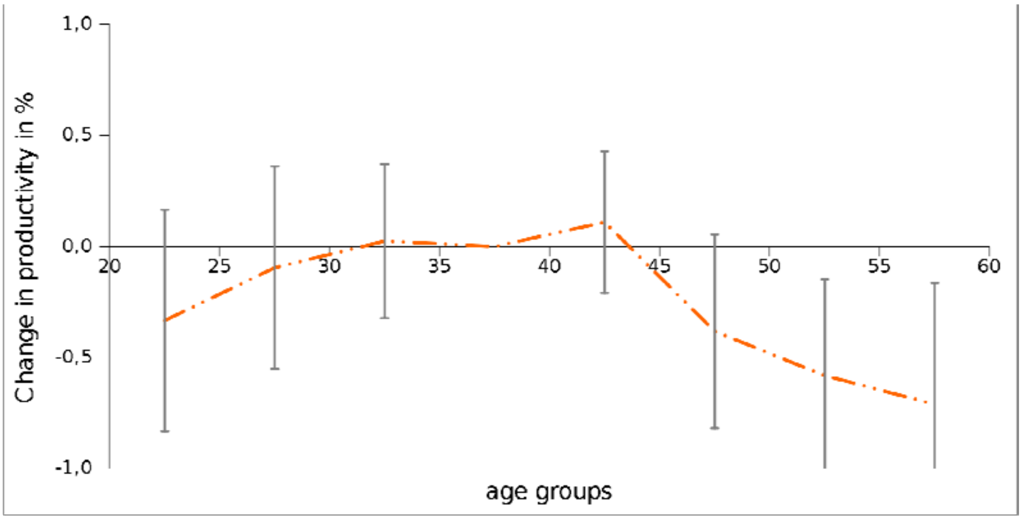
Note: The bars indicate the 95% confidence intervals.

Figure 3: OLS estimates for the service sector



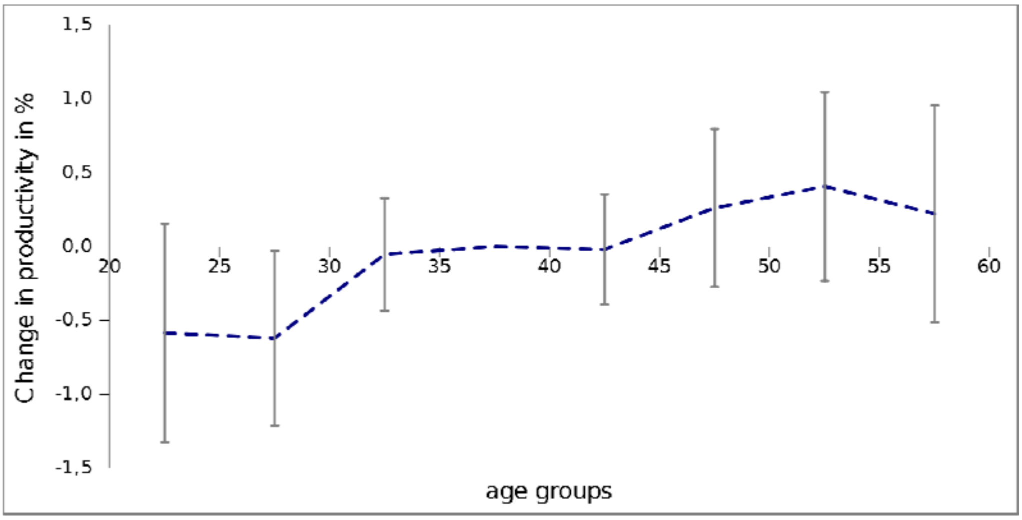
Note: The bars indicate the 95% confidence intervals.

Figure 4: OLS estimates for the metalworking sector



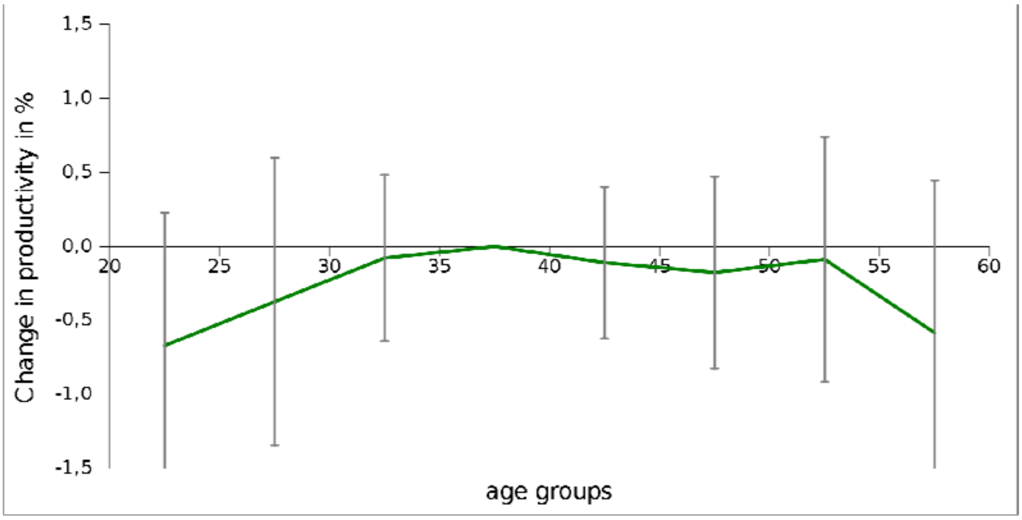
Note: The bars indicate the 95% confidence intervals.

Figure 5: Difference GMM estimates for the manufacturing sector



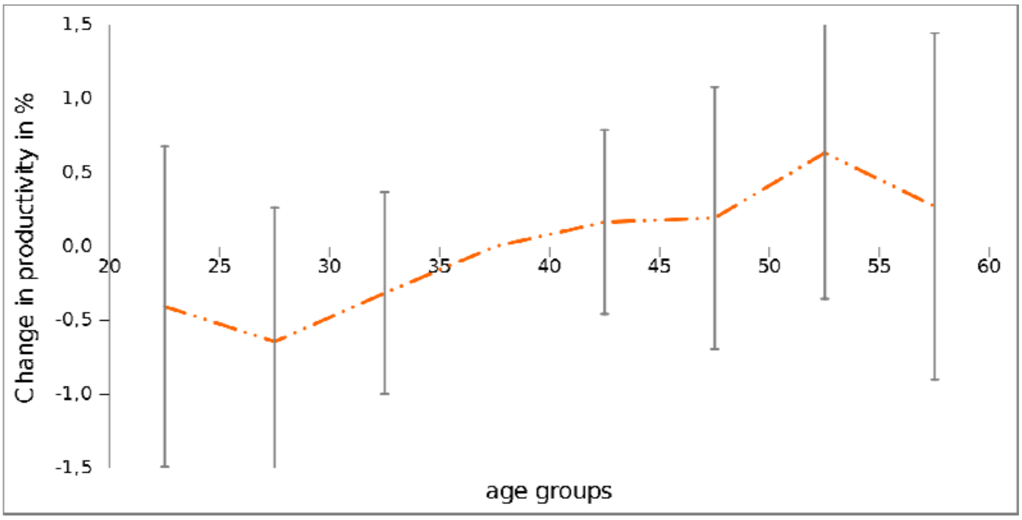
Note: The bars indicate the 95% confidence intervals.

Figure 6: Difference GMM estimates for the service sector



Note: The bars indicate the 95% confidence intervals.

Figure 7: Difference GMM estimates for metalworking sector



Note: The bars indicate the 95% confidence intervals.