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Age and gender composition of the workforce, productivity and profits: Evidence from a new type of data for German enterprises

by

Christian Pfeifer and Joachim Wagner

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Abstract

This empirical paper documents the relationship between composition of a firm's workforce (with a special focus on age and gender) and its performance (productivity and profitability) for a large representative sample of enterprises from manufacturing industries in Germany. We use unique newly available data that for the first time combine information from the statistics of employees covered by social security that is aggregated at the enterprise level and information from enterprise level surveys performed by the Statistical Offices. Our micro-econometric analysis confirms previous findings of concave age-productivity profiles, which are consistent with human capital theory, and adds a new finding of a rather negative effect of age on firms' profitability, which is consistent with deferred compensation considerations. Moreover, our analysis reveals for the first time that the ceteris paribus lower level of productivity in firms with a higher share of female employees does not go hand in hand with a lower level of profitability in these firms. If anything, profitability is (slightly) higher in firms with a larger share of female employees. This finding might indicate that lower productivity of women is (over)compensated by lower wage costs for women, which might be driven by general labor market discrimination against women.

Prof. Dr. Christian Pfeifer (corresponding author)
Leuphana University Lueneburg
and IZA, Bonn
Institute of Economics
P.O. Box 2440
D-21314 Lueneburg, Germany

e.mail: pfeifer@leuphana.de

Prof. Dr. Joachim Wagner
Leuphana University Lueneburg
and IZA, Bonn
Institute of Economics
P.O. Box 2440
D-21314 Lueneburg, Germany

e-mail: wagner@leuphana.de

1.   Introduction

Economic research has a long tradition in explaining differences in firm performance (e.g., Bartelsman and Doms 2000, Syverson 2011). Whereas some studies are interested in the effects of work practices (e.g., codetermination, training, incentive schemes) on firm performance, other studies are more interested in the relationship between the demographic structure of the workforce and firm performance. The latter stream of the literature has received increasing attention due to persistent inequalities in the labor market (e.g., wage differentials between men and women, employment problems of older workers), increasing female employment rates, and the demographic change which leads to an ageing workforce. In order to understand such inequality issues and to learn about potential aggregated productivity (welfare) changes in ageing societies with increasing female employment, micro-econometric studies on the effects of the age and gender composition of firms' workforces are important.

In the last two decades, several new databases have been made available for researchers such as establishment and linked employer employee data sets. These new data sources are usually large representative panel data sets, which are obtained by surveys or official statistics and which allow the application of advanced econometric techniques to the analysis of firm performance. In Germany, the most used data sets in this context are the IAB Establishment Panel (Fischer et al. 2009) and the linked employer employee data of the IAB (LIAB) (Alda, Bender and Gartner 2005), which combines the survey data of the IAB Establishment Panel with process produced employee data of the social security agencies. A disadvantage of such voluntary survey information is that information about firms' productivity, costs, profits, and other variables are often seen as confidential by firms and might include measurement errors that can distort the empirical link between explanatory variables and outcomes. In this paper, we use a new type of data (*KombiFiD* project) for German enterprises from the manufacturing sector that combines official statistics of

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employees covered by social security and information from mandatory enterprise level surveys performed by the German Statistical Offices. Therefore, we have more reliable information than most previous studies. Moreover, we can compute firms' rates of profit, which adds new insights into the firm performance literature as previous studies have primarily focused on productivity.

Table 1 presents a review of recent econometric studies that explicitly deal with the effects of age and gender on firm performance. Half of these papers has been published in the year 2011 in a special issue "Ageing Workforce" of De Economist (2011). All studies in Table 1 have in common that they use linked employer employee data to study productivity effects of age and gender. The used data sets stem from different countries (Germany, Netherlands, Denmark, Finland, Belgium, Portugal, Canada, USA, Taiwan). The main findings of previous research can be summarized as follows. Age-productivity profiles are mostly positive concave or inverse u-shape. The estimates differ however between different methods and specifications. The employment share of women has mostly significant negative effects on firm productivity in OLS (Ordinary Least Squares) regressions and non significant effects in GMM (General Method of Moments) regressions. Especially noteworthy are the last three papers in Table 1 by Cardoso, Guimarares, and Varejao (2011) for Portugal, van Ours and Stoeldraijer (2011) for the Netherlands, and Göbel and Zwick (2011) for Germany, because they are most comparable to our study with respect to data, variables, specifications, and methods. Although previous research has analyzed firm productivity and the productivity-wage gap, we do not know of any study that has yet analyzed explicitly the effects of age and gender composition of the workforce on firms' profitability.[1] Consequently, we present the first evidence for direct links between workforce composition and firm profits.

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[1] A paper by Lallemand, Plasman, and Rycx (2003), who focus on the effects of wage dispersion on performance of Belgian firms, provides an appendix table (page 28) with results of OLS regressions for profits (gross operating surplus) per employee. The employment share of women is negatively correlated with profits and the employment shares of broad age categories (<25, 25-50, >50 years) seem to have an inverse u-shape effect.

In our micro-econometric analysis, we use a balanced panel of 4,225 enterprises from German manufacturing for the years 2003 to 2006 and apply pooled OLS regressions, fully robust MM regressions to account for outliers, and GMM first difference regressions to account for unobserved heterogeneity and endogeneity issues. To anticipate our most important results, our analysis of this new type of German data confirms previous findings of positive concave age-productivity profiles and adds a new finding of a rather negative effect of age on firms' profitability. The finding for productivity is consistent with standard human capital considerations (amortization periods, depreciation). The finding for profit is consistent with deferred compensation considerations (underpayment of younger and overpayment of older employees). Whereas the concave age-productivity profiles do not support fears of declining productivity due to an ageing workforce and cannot explain the employment problems of older workers, the negative effect of age on firm profits highlights the employment barrier for older workers from a labor demand side. Our analysis furthermore reveals for the first time that the ceteris paribus lower level of productivity in firms with a higher share of female employees does not go hand in hand with a lower level of profitability in these firms. If anything, profitability is (slightly) higher in firms with a larger share of female employees. This finding might indicate that lower productivity of women is (over)compensated by lower labor costs for women, which in turn might indicate general labor market discrimination against women or lower reservation wages and less engagement in individual wage bargaining by women.

The rest of the paper is organized as follows. Section 2 describes the data used and the definition of variables and presents descriptive statistics. Section 3 presents and discusses the approaches for our micro-econometric investigation. Section 4 contains the results of our

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micro-econometric analyses. The paper concludes in Section 5 with a summary and discussion of our results as well as comments on the used newly available data for enterprises from German manufacturing.

2.   Data, definition of variables and descriptive statistics

The empirical investigation uses data for enterprises[2] from manufacturing industries that come from two sources. The first source is the cost structure survey for enterprises in the manufacturing sector. This survey is carried out annually by the statistical offices as a representative random sample survey stratified according to the number of employees and the industries (see Fritsch et al. 2004). The sample covered by the cost structure survey represents all enterprises with at least 20 employees from manufacturing industries. About 45 percent of the enterprises with 20 to 499 employees and all enterprises with 500 and more employees are included in the sample.[3] While firms with 500 and more employees are covered by the cost structure survey in each year, the sample of smaller firms is part of the survey for four years in a row only.

This survey is the source for information on productivity, profitability, firm size and industry affiliation:

Productivity is measured as labor productivity, defined as value added per head (in Euro and in current prices). Information on the capital stock of a firm is not available from the cost structure survey, so more elaborate measures of total factor productivity cannot be used

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[2] Data are for legal units (enterprises, or *Unternehmen*), not for local production units (establishments, or *Betriebe*). In this paper we use the term firm as a synonym for enterprise.

[3] For details see the quality report for the cost structure survey published by the Federal Statistical Office that is available on the web:

http://www.destatis.de/jetspeed/portal/cms/Sites/destatis/Internet/DE/Content/Publikationen/Qualitaetsberichte/ VerarbeitendesGewerbeIndustrie/Kostenstruktur,property=file.pdf

in this study.[4] Bartelsman and Doms (2000, p. 575) point to the fact that heterogeneity in labor productivity has been found to be accompanied by similar heterogeneity in total factor productivity in the reviewed research where both concepts are measured. In a recent comprehensive survey Chad Syverson (2011) argues that high-productivity producers will tend to look efficient regardless of the specific way that their productivity is measured.[5] Furthermore, Foster, Haltiwanger and Syverson (2008) show that productivity measures that use sales (i.e. quantities multiplied by prices) and measures that use quantities only are highly positively correlated. Labor productivity is computed as:

$$\text{value added per head} = \frac{\left(\begin{array}{l} \text{total sales (w/o sales taxes)} \\ - \text{ costs for materials (w/o sales taxes)} \\ - \text{ other costs} \\ - \text{ taxes (w/o sales taxes)} \\ + \text{ subsidies received} \end{array} \right)}{\text{number of employees}} \qquad (1)$$

Profitability of a firm is computed as a rate of return, defined as gross firm surplus (computed in line with the definition of the European Commission (1998) as gross value

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[4] Annual data for investments are available from a separate survey on investments (*Investitionserhebung*) that can be linked to the data used here. A careful inspection of these investment data revealed that they should not be used to construct estimates of the capital stock of the firm by using the perpetual inventory method. The crucial problem here lies in the fact that investment at the firm level tends to be highly volatile. Often very high values in some year and very low values (or no investments at all) in some other year are reported, and this leads to rather different values for the capital stock proxy variable depending on the year(s) used. A proxy for the physical capital used in a firm can be constructed using information based on the amount of depreciation reported in the cost structure survey (see Wagner (2010) for details). Depreciation, however, is governed by accounting rules, i.e., it is not necessarily representative for the true economic loss of value of investment goods.

[5] See International Study Group on Exports and Productivity (ISGEP) (2008) for a comparison of results for productivity differentials between exporting and non-exporting firms based on sales per employee, value added per employee and total factor productivity. Results proved remarkably robust.

added at factor costs minus gross wages and salaries minus costs for social insurance paid by the firm) divided by total sales (net of VAT) minus net change of inventories:[6]

$$\text{rate of profit} = \frac{\text{gross value added } - \text{ gross wages } - \text{ costs for social insurance}}{\text{total sales } - \text{ net change of inventories}} \qquad (2)$$

Firm size is measured by the number of people working in a firm. This measure is also included in squares in the empirical models to take care of non-linearity in the relation between firm size and firm performance.

Industry affiliation of a firm is recorded at the two-digit level.

The second source of data is the Establishment History Panel (*Betriebs-Historik-Panel*).[7] Details aside, this data set is built from individual level information for employees covered by social security.[8] In a first step for each year from 1975 onwards information for all employees working in a local production unit (establishment) was aggregated, and this is the standard version of the Establishment History Panel. In this study we use a different version of the Establishment History Panel. Here for multi-establishment enterprises information from all establishments of the enterprise was aggregated in a second step. The result is a data set with detailed information about the characteristics of the employees (covered by social security) in each enterprise in a year.

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[6] Note that the data set does not have any information on the capital stock, or the sum of assets or equity, of the firm, so that it is not possible to construct profit indicators based thereon like return on assets or return on equity.

[7] For an introduction to the Establishment History Panel see Spengler (2008); a detailed description of the current version is Hethey-Maier and Seth (2010).

[8] "All employees who are subject to at least one of the following compulsory insurances are liable to social security: health insurance, long-term care insurance, pension insurance, unemployment and accident insurance. However, not liable to social security and thus not included in the data are civil servants, conscripts, those doing alternative civilian service, self-employed, judges, scholars, students, pensioners, clergy and others." (Spengler 2008, p. 502)

Information reported to the social security system includes, among others, the sex of a person, the age and the qualification (educational level attained and vocational training concluded).

Share of employees from a certain age group is defined as the total number of employees (covered by social security) from the respective age group over the total number of employees (covered by social security) in an enterprise; the share is measured as a percentage.

Share of female employees is defined as the total number of females (covered by social security) over the total number of employees (covered by social security) in an enterprise; the share is measured as a percentage.

Share of medium qualified employees is defined as the total number of employees (covered by social security) with either the high-school diploma (*Abitur*) as the highest educational level attained or with vocational training concluded over the total number of employees (covered by social security) in an enterprise; the share is measured as a percentage.

Share of highly qualified employees is defined as the total number of employees with a polytech or university degree over the total number of employees (covered by social security) in an enterprise; the share is measured as a percentage.[9]

Share of part-time employees is defined as the total number of employees in part-time over the total number of employees (covered by social security) in an enterprise; the share is measured as a percentage.

The cost structure survey for enterprises in the manufacturing sector is conducted by the German statistical offices. The data can be accessed for scientific research via the Research Data Centres of the Federal Statistical Office and the Statistical Offices of the Federal States (see Zühlke et al. 2004). The Establishment History Panel is build from

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[9] Note that this information on the diversity of the employees is not available in more detail; for example, the number of female employees aged 30 to 34 with a university degree is not available from the data (although it would be possible to compute this figure from the individual level information available).

administrative data by the Research Data Centre of the Federal Employment Agency at the Institute for Employment Research. The data can be accessed via this Research Data Centre for scientific research (see Spengler 2008).

Linking these confidential firm level information across the borders of the data producers, however, is difficult. Details aside, it is technically not easy (but not impossible either) and it is legal only if the firm agreed in written form. The basic idea of the project *KombiFiD* (an acronym that stands for *Kombi*nierte *Fir*mendaten für *D*eutschland, or combined firm level data for Germany) that is in detail described on the web (see www.kombifid.de) is to ask a large sample of firms from all parts of the German economy to agree to match confidential micro data for these firms that are kept separately by three data producers (the Statistical Offices, the Federal Employment Agency, and the German Central Bank) in one data set. These matched data are made available for scientific research while strictly obeying the data protection law, i.e. without revealing micro level information to researchers outside the data producing agencies. In *KombiFiD* 54,960 firms were asked to agree in written form to merge firm level data from various surveys and administrative data for the reporting years 2003 to 2006. 30,944 firms replied and 16,571 agreed. These 16,571 firms are in the *KombiFiD Agreement Sample*.

The sample of enterprises used in the empirical investigation performed here consists of all firms from manufacturing industries in West Germany[10] in the *KombiFiD Agreement Sample* for which information from both data sources – the cost structure survey and the Establishment History Panel - could be linked in the *KombiFiD* project. Enterprises that do

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[10] The sample is limited to firms from West Germany. There are large differences between enterprises from West Germany and the former communist East Germany even many years after the unification in 1990. Therefore, an empirical study should be performed separately for both parts of Germany. The *KombiFiD Agreement Sample* for East German manufacturing firms, however, contains only a small number of firms, and this sample turned out to be not representative for the population of firms in a replication study that compares results based on the complete cost structure survey data and data from the *KombiFiD Agreement Sample* (see Wagner 2011).

not have complete information for each year from 2003 to 2006 were dropped from the computations.[11] This leads to a balanced panel data set with 16,900 observations for 4,225 firms and 4 years.

Descriptive statistics for all variables and the pooled data are reported in Table 2. It is evident from these descriptive statistics that the variation of the share of females and of the share of employees in the two large qualification groups are small over the four years covered compared to the variation between the firms in the sample. The same holds for the variation of firm size. Therefore, the within firm variation of important dimensions of diversity of the employees over time cannot be used in fixed effects models to sufficiently identify any relationship between changes in firm performance over time and diversity of employees.

[Table 2 near here]

Furthermore, a comparison of the mean and the standard deviation of the variables indicate that some firms may have characteristics that differ by orders of magnitude from the rest of the firms in the sample. Unfortunately, due to strict data protection rules it is not possible to report the minimum and maximum values of the variables in Table 2 (because these are figures for a single firm that may not be revealed). This is less a problem for all the variables that are defined as shares, because the values of these variables are bound between zero and one hundred percent by definition. For value added per head, the rate of profit and

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[11] Firms with incomplete information for any variable in at least one year were dropped from all computations because there are, on the one hand, by construction no entries due to the fact that the firms taking part in the cost structure survey were sampled before the start of the survey in 2003. On the other hand, exits cannot be identified because firms with information in, say, 2003 but not in 2004 might have closed down – they might have, however, relocated out of manufacturing (or out of Germany) or they might have shrunk below the cut-off point relevant for the cost-structure survey.

firm size, however, we know from (unpublished) results of investigations of the *KombiFiD Agreement Sample* that for some firms there are extremely low or high values of these variables. These extreme observations, or outliers, may be highly influential in any empirical investigation. This aspect of the data, therefore, should be taken care of.

3.   Approaches for the micro-econometric investigation

The investigation of the link between diversity of employees (especially the composition of the workforce by age and gender) and two dimensions of firm performance (productivity and profitability) uses empirical models that regress the performance variable on the shares of employees from different age groups, the share of female employees[12], the shares of highly and medium qualified employees, the share of part-time employees, and on the firm size (number of employees) which is also included in squares to take care of a non-linear relationship, a set of dummy variables for years and industries, and a constant. We consider two variants of this empirical model. Model 1 includes two variables for the share of employees aged 30 to 49 years and for the share of employees aged 50 years or older (taking the group of employees which are less than 30 years old as the reference group). Model 2 includes ten variables for the shares of employees aged 15 – 19 years, 20 – 24 years, 25 – 30 years, etc. up to the share of employees aged 65 or older.[13] We decided to include the group

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[12] As a robustness check all models were re-estimated with an additional squared term of the female share. The estimates were not significantly affected. The coefficients of the squared terms are non significant whereas the coefficients of the linear terms remain their size and significance. It should however be kept in mind that the mean female employment share is about 30 percent across all firms in our sample and that most manufacturing firms have a male dominated workforce. Consequently, our sample does not allow to draw conclusions about female dominated workforces and further increases of the female employment share. To economize on space results are not reported here but are available from the corresponding author on request.

[13] As a robustness check all models were estimated with the median age of the employees and its squared value instead of the shares of employees for various age groups. Results for the other variables in the empirical model did not reveal a different picture. To economize on space results are not reported here but are available from the corresponding author on request.

65 or older separately in order to account for potential anomalies (e.g., motivation, remaining paid holidays) in the last year before retirement and among the few employees working beyond the legal retirement age of 65 years.

Note that these regression equations are not meant to be an empirical model to explain labor productivity or profitability at the enterprise level; the data set at hand here is not rich enough for such an exercise. They are just a vehicle to test for, and estimate the size of, the relation between firm performance and one dimension of workforce diversity controlling for other firm characteristics. Furthermore, note that productivity differences at the firm level are notoriously difficult to explain empirically. "At the micro level, productivity remains very much a measure of our ignorance." (Bartelsman and Doms 2000, p. 586) Syverson (2011) surveys the recent literature on determinants of productivity at the firm level. Inter alia, he mentions effects of competition, organizational structures within firms, payment systems, other human resources practices, managerial talent, human capital, higher-quality capital inputs, information technology (IT) and R&D. All these determinants of productivity matter for profitability, too, and they cannot be looked at here with the data at hand. These limitations should be kept in mind when putting the results into perspective.

In a first step, the empirical models were estimated for the pooled data from 2003 to 2006 by Ordinary Least Squares (OLS). The descriptive statistics presented above revealed that the variation of the share of females and of the share of employees in the two large qualification groups are small over the four years covered compared to the variation between the firms in the sample. The same holds for the variation of firm size. Therefore, the within firm variation of important dimensions of diversity of the employees over time cannot be used to identify any relationship between changes in firm performance over time and diversity of employees by adding fixed firm effects. To take care of the dependence of the error term

between observations from one firm over the four years the standard errors of the estimated regression coefficients are clustered at the firm level.[14]

In a second step, we take care of the fact (mentioned in the discussion of the descriptive statistics for the data used here) that some firms have values for some variables (value added per head, the rate of profit and firm size) that are extremely low or high compared to the other firms in the sample. This often happens when one investigates a sample of heterogeneous firms. These extreme values might be the result of reporting errors (and, therefore, wrong), or due to idiosyncratic events or to firm behavior that is vastly different from the behavior of the majority of firms in the sample.

Observations of this kind are termed outliers. Whatever the reason may be, extreme values of productivity or profitability may have a large influence on the mean value of the performance variable and on the estimates of the coefficients that show the link between firm performance and a dimension of diversity of the workforce. Conclusions, therefore, might be influenced by a small number of firms with extremely high or low values of productivity or profitability.

Researchers from the field of micro-econometrics of firm activities usually are aware of all of this. Given that due to confidentiality of the firm level data single observations as a rule cannot be inspected closely enough to detect and correct reporting errors, or to understand the idiosyncratic events that lead to extreme values, a widely used procedure to keep these extreme observations from shaping the results is to drop the observations from the top and bottom one percent of the distribution of the variable under investigation. A case in point is the international comparison study on the exporter productivity premium by the International Study Group on Exports and Productivity (ISGEP) (2008, p. 610).

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[14] As a robustness check we have also performed OLS regressions for the four separate years, which did not show noteworthy differences. To economize on space results are not reported here but are available from the corresponding author on request.

Dropping the firms from the top and the bottom one percent of the productivity distribution and comparing the results of empirical investigations with and without these firms with extremely high or extremely low values of labor productivity might be considered as a first and useful step to check the sensitivity of results. However, although this approach seems to be rather popular it is in some sense arbitrary. Why the top and bottom one percent? Why not choose a larger or smaller cut-off point?

There are alternative approaches to deal with extreme observations (outliers) that are substantiated in statistics. One approach that is advocated in the literature is Quantile regression. As Yasar, Nelson and Rejesus (2006, p. 682) put it: "Quantile regression estimates are considered robust relative to least squares estimates. In contrast to the least squares estimator, the quantile regression estimates place less weight on outliers and are found to be robust to departures from normality." Quantile regression at the median is identical to least absolute deviation (LAD) regression that minimizes the sum of the absolute values of the residuals rather than the sum of their squares (as in OLS). This estimator is also known as the L_1, or median regression, estimator. LAD regression, however, is not a panacea against outliers. To see why, following Rousseeuw and Leroy (1987) we distinguish three types of outliers that influence the OLS estimator: vertical outliers, bad leverage points, and good leverage points. Verardi and Croux (2009, p. 440) illustrate this terminology in a simple linear regression framework (the generalization to higher dimensions is straightforward) as follows: "Vertical outliers are those observations that have outlying values for the corresponding error term (the y dimension) but are not outlying in the space of explanatory variables (the x dimension). Their presence affects the OLS estimation and, in particular, the estimated intercept. Good leverage points are observations that are outlying in the space of explanatory variables but that are located close to the regression line. Their presence does not affect the OLS estimation, but it affects statistical inference because they do deflate the estimated standard errors. Finally, bad leverage points are observations that are both outlying in the

space of explanatory variables and located far from the true regression line. Their presence significantly affects the OLS estimation of both the intercept and the slope."

Using this terminology one can state that the median regression estimator protects against vertical outliers but not against bad leverage points (Verardi and Croux 2009, p. 441; Koenker 2005, p. 268). Full robustness can be achieved by using the so-called MM-estimator that can resist contamination of the data set of up to 50 percent of outliers (i.e., that has a breakdown point[15] of 50 percent compared to zero percent for OLS). A discussion of the details of this estimator is beyond the scope of this paper (see Verardi and Croux (2009) for this estimator and for Stata commands to compute it). Suffice it to say here that this estimator combines a breakdown point of 50 percent with a high efficiency (the degree of which can be chosen by the researcher). An explicit formula for the estimator is not available, it is computed by numerical optimization.

Given that the presence of outliers can be expected to be the rule in data sets for heterogeneous firms it is important to document the extent to which estimation results are influenced by extreme observations. Therefore, the two empirical models for productivity and profitability are estimated using the fully robust MM-estimator, too.[16]

In a third step, we estimate GMM (General Method of Moments) first difference regressions (see Roodman (2009) for this estimator and for Stata commands to compute it). Due to the short panel and low within variance of most explanatory variables, our GMM estimates serve only as a robustness check and we expect imprecise estimates with large

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[15] The breakdown point of an estimator is the highest fraction of outliers that an estimator can withstand, and it is a popular measure of robustness.

[16] Computations were done using the ado-files provided by Verardi and Croux (2009) with the efficiency parameter set at 0.7 as suggested there based on a simulation study; details are available on request. As a further robustness check all models were estimated using quantile regression at the median, too. While in the estimation for model 2 for profitability no convergence was achieved, results from the other model were very similar to the results from the other estimation methods reported below. Details are available from the corresponding author on request.

standard errors. Nevertheless, it is important to check for potential endogeneity issues as our previous estimates might only be interpreted as descriptive evidence for between firm differences that need not to represent causal effects.

The first source of endogeneity might stem from an omitted variable bias. In order to deal with this problem, first differences are used to cancel out unobserved time invariant firm heterogeneity. The second source of endogeneity is concerned with reverse causality, because short-term productivity shocks should affect workers in- and out-flows differently across demographic groups and consequently affect the composition of the workforce. For example, a negative shock is likely to lead to relatively more layoffs of younger than older workers (e.g., due to employment protection legislation or internal labor markets) and a positive shock to the recruitment of relatively more younger than older workers. Therefore, employment shares of older workers could be negatively correlated with productivity shocks, which would lead to a downward bias in OLS if endogeneity is not taken into account properly. The same logic might be applicable to the gender composition. If men have on average a lower layoff probability than women (e.g., due to on average longer tenure, more investments in human capital, being the main contributor to household income, or taste-based and statistical discrimination), the employment share of women could be positively correlated with productivity shocks, which would lead to an upward bias in OLS. However, if firms reduce female employment in case of negative shocks, the still employed women are likely to be a positive selection, i.e., they should on average be more productive than the laid of women and might even be more productive than male counterparts. From this follows a downward bias if endogeneity is not taken into account properly. Thus, two opposing effects can bias estimates of female employment on firm performance. In order to deal with this kind of endogeneity, we follow the standard approach in the literature where the first differences are instrumented with the second and third lags of their own levels.

Comparable GMM identification strategies have been used in several previous studies (see Table 1 in the Introduction). Due to our four year panel, the GMM first difference regressions are estimates for changes in firm performance and employment share variables from 2005 to 2006, which are instrumented with their own levels from 2004 and 2003 because the past workforce composition cannot be affected by current short term productivity shocks.

4.   Results of the micro-econometric investigation

Our main empirical results for the links between dimensions of workforce composition and firm productivity (value added per head in Euro) are reported in Table 3 for pooled OLS and robust MM regressions. The estimated OLS parameters for Model 1, in which the employee share of workers aged below 30 years is the reference group, indicate an inverse u-shape relationship between age and productivity. The share of employees aged 30-49 years is significantly positively correlated with productivity. A one percentage point increase in the employment share of these middle aged workers increases productivity by about 204 Euros per head. The employment share of older workers aged 50 years or older has also a positive coefficient, which is however not statistical significant at conventional levels. The share of female employees has the significant negative impact on productivity known from previous studies. A one percentage point increase in female employment decreases productivity by about 219 Euros per head. Since women work on average fewer hours than men, this negative effect could be simply the result of fewer working hours and not of lower productivity. In order to deal with this problem, we control for the share of part-time employees in a firm, which has also a significant negative effect and should at least partly take out differences in working hours. Moreover, our results are consistent with Cardoso, Guimarares, and Varejao (2011) and Ilmakunnas and Ilmakunnas (2011), who find in their OLS regressions negative correlations between the female share and productivity per hour, which explicitly deals with

gender differences in working hours. Our results further reveal the plausible result that firms with a more qualified workforce have a higher average labor productivity and that the relationship between firm size and productivity is concave.

[Table 3 near here]

In order to check for potentially influential outliers, we re-estimated Model 1 with the robust MM regression technique that supports our main findings from OLS. The estimated coefficients are slightly smaller and the estimated standard errors are substantially smaller for most variables in the robust MM regression, which leads to higher significance levels. Although the coefficient for the oldest age group is now significant and positive, we still find an inverse u-shape relationship between age and productivity. The estimated negative coefficient of the employment share of women is 189 Euros in the robust MM regression compared to 219 Euros in OLS. A noteworthy difference arises for firm size, which is likely driven by influential outliers. Whereas OLS indicates a positive concave relationship, as the maximum is reached at more than 70,000 employees, the robust MM regression suggests an inverse u-shape with a maximum at about 4,000 to 5,000 employees.

As we are especially interested in age-productivity profiles, Model 2 with less aggregated age groups is also estimated with OLS and robust MM regressions. The results in Table 3 show no noteworthy changes in the estimated parameters for the other variables so that we focus on age. In order to facilitate interpretation, we plotted the estimated coefficients and corresponding 95% confidence intervals for OLS in Figure 1 and for robust MM in Figure 2. Note that the share of employees aged below 20 years serves as reference group and that we neglect the oldest age group with workers aged 65 years and older, because they might be not normal workers anymore. Both plotted age-productivity profiles show in principal the same pattern. Productivity increases for younger workers approximately until age 30 and does

not significantly change afterwards. Thus, we find rather a positive concave than an inverse u-shape age-productivity profile that does not support potential negative productivity effects due to an ageing workforce.

[Figure 1 near here]

[Figure 2 near here]

Table 4 presents our main empirical results for the links between workforce composition and firm profitability (rate of profit in percent) for pooled OLS and robust MM regressions. Note that the explained variance of profits is rather low (R^2=0.041 for Model 1, R^2=0.047 for Model 2), which indicates that firm profits are more influenced by random shocks than is firm productivity. The descriptive statistics (see Table 2 in Section 2) also reveal that the coefficient of variation for the rate of profit (CV=9.55/8.12=1.18) is substantially larger than for the value added per head (CV=30320.34/57812.53=0.52). Our empirical models are not meant to indentify business strategies to increase profitability but to analyze if firms with different workforce compositions differ in their profitability. In fact, the overall low explanation power of our models strengthens the few significant findings, even if they are rather small from a quantitative perspective. Again, we will at first discuss the results for Model 1, before we will discuss the age-profit profiles obtained for Model 2.

[Table 4 near here]

The OLS results for Model 1 in Table 4 indicate a negative correlation of age and the rate of profit. Compared to the reference group of young employees, a one percentage point increase in the share of employees aged 30 to 49 years decreases the rate of profit by about

0.044 percentage points.[17] The share of workers aged 50 years or older has even a negative impact of 0.117 percentage points. The share of female employees is positively correlated with profitability. A one percentage point increase in female employment is correlated with a 0.03 percentage point higher rate of profit. For our further employment structure variables no significant coefficients have been estimated, except for a surprisingly negative coefficient of highly qualified employees with college degrees. The estimated coefficients and standard errors are again smaller in the robust MM than in the OLS regressions, but the main findings do not change noteworthy. Estimates for Model 2 also do not show noteworthy differences. Model 2 allows however to look more precisely at the age-profit profiles, which are plotted in Figure 3 for OLS and in Figure 4 for robust MM regressions. It can be seen that profitability increases until age 30, as was the case for productivity, and decreases afterwards, compared to rather flat productivity profiles.

[Figure 3 near here]

[Figure 4 near here]

Our results from pooled OLS regressions and robust MM regressions, which take care of influential outliers in the data, are in principal only correlations and need not to be causal due to potential endogeneity issues stemming from omitted variables and reverse causality. Therefore, we perform GMM first difference regressions for Model 2 as robustness checks. The results are presented in Table 5. As expected, the estimated parameters are imprecise (and large) and have large standard errors, which is likely to occur because we can only analyze the differences between 2006 and 2005 due to our four year panel. Hence, we stress again that the

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[17] The effects might seem small at first glance. If we compute relative effects (coefficients divided by mean of dependent variable), the size of the coefficients have also economic relevance. For example, a coefficient of 0.1 is a relative effect of approximately 0.1/8=1.25%, i.e., a ten percentage point increase in an employment share is correlated with a 12.5 percent higher rate of profit.

results of our GMM regressions should not be overemphasized and serve only as a robustness check.

[Table 5 near here]

In the GMM productivity regressions (see Table 5), only the female share and the employment shares of age groups have significant effects. Compared to our previous results, the female share has now turned from a significant negative to a significant positive effect on productivity. Although we can only speculate, this finding could indicate a downward bias in pooled OLS and robust MM regressions that is driven by a positive selection of the remaining women in case of negative productivity shocks. Figure 5 plots the age-productivity profile, which is again positive concave. The GMM regressions for profitability (see Table 5) reveal a positive coefficient for the female employment share, which is however not significant. The age-profit profile in Figure 6 shows an increase until age 30 and a slight decline afterwards, although differences between age groups are not statistically significant. Despite low statistical significance, the overall GMM results support our previous findings from pooled OLS and robust MM regressions, except for the relationship between female employment and productivity.

[Figure 5 near here]

[Figure 6 near here]

5.   Discussion and concluding remarks

We start our discussion with a short summary of our basic findings about age and gender effects on firm performance. In line with previous research, we find concave age-productivity profiles that increase until age 30 and are flat afterwards. The age-profit profiles indicate an

increase until age 30 and a decline afterwards. The employment share of women and productivity are significantly negatively correlated in our pooled OLS and robust MM regressions but significantly positively correlated in the GMM regressions. Profitability seems to be positively correlated with the share of female employees in all our regressions, though not significantly in the GMM regressions. Overall, most of our findings on firm productivity are in line with findings from previous research, which has been summarized in Table 1, and we have also provided new findings on firm profitability.

Our finding for age and productivity is consistent with standard human capital considerations. Human capital theory (Mincer 1974) implies that incentives to invest in human capital decrease with age as the amortization period decreases. Moreover, human capital is usually subject to depreciation. Both arguments lead to concave or even inverse u-shape age-productivity profiles. Our finding for age and profit is consistent with deferred compensation considerations (Lazear 1979). In deferred compensation models with long-term employment contracts, younger workers are paid below their marginal product and older workers are paid above their marginal product in order to provide work incentives. Consequently, firms' short term profits are positively affected by younger workers with short tenure, who pay loans to the firm, and negatively by older workers with long tenure, who get the repayments of their loans. Although we cannot explicitly analyze tenure effects due to missing information in the data, age can be interpreted in this context because the German manufacturing sector is characterized by stable employment so that age and tenure are quite collinear. Moreover, seniority arrangements with respect to age are usually part of collective contracts, which are binding to most firms in the German manufacturing sector. Whereas the concave age-productivity profiles cannot explain the employment problems of older workers, the negative effect of older workers on profits highlights the employment barrier for older workers from a labor demand side that might be explained by deferred compensation schemes (Hutchens 1986; Heywood, Jirjahn and Tsertsvardze 2010). A similar conclusion can be

drawn from previous studies that analyze the productivity-wage gap (e.g., Cardoso, Guimarares, and Varejao 2011; Cataldi, Kampelmann, and Rycx 2011; van Ours and Stoeldraijer 2011). Moreover, our findings are important as they do not support the fear of declining productivities in ageing societies.

Although our findings for gender and productivity are not clear from a causal perspective, we could document that firms with higher shares of female employees do not have lower levels of profitability. If anything, profitability is (slightly) higher in firms with a larger share of female employees. This finding might indicate that the often reported lower productivity of women is (over)compensated by lower labor costs for women, which in turn might indicate general labor market discrimination against women. The related rationale based on taste-based discrimination (Becker 1988) would be that owners need to be compensated with higher profits, if they employ women whom they dislike because of their gender. This discrimination argument is in principal valid for all employees with profit sharing schemes and not only for owners, who are unlikely to have personnel contact with employees in larger firms. Another rationale based on labor supply considerations is that women are willing to accept lower wages due to lower reservation wages (Humpert and Pfeifer 2011) and less engagement in individual wage bargaining (Babcock and Laschever 2003; Bertrand 2010).

Based on our results, we can speculate about effects of affirmative action policies, which are unlikely to be clear-cut. Enforced increases of female employment via legal employment quotas might have the perverse effect of increasing profits for capital owners and of decreasing the productivity in an economy, which is likely to reduce welfare due to lower wages and higher prices. Equal pay legislation might lead to the adverse effect of reducing female employment, if owners or other employees with profit sharing insist on a compensation for their utility loss from distaste. However, if firms' profits would be only larger due to an underpayment of women reasoned by lower reservation wages and fewer

wage bargaining activities, equal pay legislation might not have adverse effects on female employment but on firms' profits. Overall, a combination of female quotas and equal pay legislation might be necessary to effectively improve the employment situation of women and to reduce gender wage gaps. If such a policy would be efficient, is however questionable and needs more research (e.g., natural experiments). Moreover, new gender inequalities and injustices in the labor market might arise in favor of young women and to the disadvantage of young men.

To conclude our paper, we want to shortly discuss the new type of enterprise data (*KombiFiD*) that we have used in this paper. We could demonstrate that the newly available *KombiFiD*-Data (described in detail in Section 2) that combine for the first time enterprise level data produced by the Statistical Offices and by the Federal Employment Agency are a highly valuable data base for economic research. The data are of a high quality, and participation of the enterprises in the cost structure survey and in the delivery of information on the employees covered by social security is mandated. Instead of opinions and "guesstimates" collected in surveys with voluntary participation, the *KombiFiD*-Data have reliably information on variables like value added per head and the rate of turnover profitability that are difficult to collect in interviews or questionnaires without mandatory participation. Evidently, the *KombiFiD*-Data have shortcomings. The panel is short (covering only four years from 2003 to 2006), the information on the enterprises is far from comprehensive (for example, no information on the presence or not of a works council is available, and the same holds for international firm activities except exports) and the enterprise data are not linked with individual level data for the employees in a linked employer-employee data set. That said, in our view the *KombiFiD*-Data should at least be carefully looked at by researchers from various fields in economics (including labor economics, industrial organization and international economics) interested in working with

firm level data. The access is easy and costless (for details, see www.kombifid.de) and the expected payoff might be high.

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Table 1: Review of recent econometric studies on the effects of age and gender on firm performance

Study	Country, years, data	Estimation methods	Firm performance indicators	Workforce composition measures	Main findings
Haltiwanger, Lane, and Spletzer (1999)	USA, 1985-1997, linked employer employee data	OLS: pooled levels 1990 & 1994, pooled differences 1986-1990 & 1990-1994 with lag of productivity level	Productivity: log sales per head	Age: employment shares (<30, 30-55, >5) Women: employment share	Age: negative for levels, positive for differences Women: negative but not significant for differences
Grund and Westergaard-Nielsen (2008)	Denmark, 1992-1997, linked employer employee data	OLS: pooled, fixed effects GMM: dynamic model with first lag of productivity	Productivity: log value added per head	Age: mean Women: employment share	Age: inverse u-shape (max at age 37) Women: negative
Lallemand and Rycx (2009)	Belgium, 1995 & 2003, linked employer employee data	OLS for cross sections	Productivity: log value added per head	Age: employment shares (<30, 30-49, >49)	Age: negative
Liu, Tsou, and Wang (2010)	Taiwan, 1998-2003, linked employer employee data	OLS: pooled, fixed effects	Productivity: log sales per head, Solow residual, Levinsohn-Petrin	Age: employment shares (<30, 30-55, >55) Women: employment share (of men)	Age: inverse u-shape Women: negative
Parrotta, Pozzoli, and Pytlikova (2010)	Denmark, 1995-2005, linked employer employee data	OLS: pooled, IV	Productivity: log total factor productivity	Age: employment shares (<33, 33-41, 42-50, >50) Women: employment share (of men)	Age: inverse u-shape Women: negative
Dostie (2011)	Canada, 1999-2005, linked employer employee data	OLS	Productivity: log value added, Levinsohn-Petrin	Age: employment shares (<35, 35-54, >54)	Age: positive concave, inverse u-shape
Vandenberghe (2011)	Belgium, 1998-2006, linked employer employee data	OLS: pooled, first difference GMM: first difference, second and third lags as instruments	Productivity: log value added per head	Age, women: separate employment shares (18-29, 30-49, 50-64) for men and women	Age: negative Women: negative

Cataldi, Kampelmann, and Rycx (2011)	Belgium, 1999-2006, linked employer employee data	OLS: pooled, first difference GMM: first difference, second lags as instruments	Productivity: log value added per hour	Age: employment shares (<30, 30-50, >50)	Age: positive concave for pooled OLS, negative after age 50 for first difference OLS, not significant in GMM
Ilmakunnas and Ilmakunnas (2011)	Finland, 1995-2004, linked employer employee data	OLS: pooled, fixed effects GMM: system, dynamic models with first lag of productivity	Productivity: log total factor productivity, log value added per hour	Age: mean, employment shares (<31, 31-50, >50) Women: employment share	Age: negative Women: significantly negative only in pooled OLS
Cardoso, Guimarares, and Varejao (2011)	Portugal, 1986-2008, linked employer employee data	OLS: pooled, fixed effects GMM: first difference, second and third lags as instruments	Productivity: log sales per hour	Age: employment shares (5 year grouping) Women: employment share	Age: inverse u-shape for pooled OLS (max at age 40-44), negative for fixed effects OLS after age 35, and positive concave for GMM until age 50 Women: significantly negative for OLS (pooled and fixed effects), but non significantly positive for GMM
van Ours and Stoeldraijer (2011)	Netherlands, 2000-2005, linked employer employee data (manufacturing)	OLS: pooled, first difference GMM: first difference, at least second lags as instruments	Productivity: log value added per head	Age: employment shares (<25, 5 year grouping, >56) Women: employment share	Age: inverse u-shape for pooled OLS (max at age 35-39), not significant for first difference OLS, and positive concave for GMM Women: significantly negative for pooled OLS, but not significant for first difference OLS, non significantly positive for GMM
Göbel and Zwick (2011)	Germany, 1997-2005, linked employer employee data (LIAB: manufacturing and service)	OLS: pooled GMM: difference, dynamic models with first and second lags of productivity	Productivity: log value added per head	Age: employment shares (5 year grouping) Women: employment share	Age: inverse u-shape in manufacturing sectors for OLS, but not significant in service sectors and for GMM Women: negative in manufacturing, but not significant in service sectors for OLS and for GMM

Table 2: Descriptive statistics

Variables	Mean	Standard deviation		
		Overall	Between	Within
Value added per head (Euro)	57812.53	30320.34	27734.55	12257.83
Rate of profit (%)	8.12	9.55	8.28	4.76
Share of employees aged less than 30 years (%)	17.16	9.39	8.98	2.75
Share of employees aged 30 – 49 years (%)	57.57	9.33	8.72	3.32
Share of employees aged 50 years or older (%)	25.25	10.10	9.66	2.94
Share of employees aged 15 – 19 years (%)	3.10	3.92	3.60	1.55
Share of employees aged 20 – 24 years (%)	6.46	4.59	4.13	2.01
Share of employees aged 25 – 29 years (%)	7.60	4.58	4.11	2.02
Share of employees aged 30 – 34 years (%)	10.84	5.05	4.30	2.64
Share of employees aged 35 – 39 years (%)	16.00	5.43	4.63	2.84
Share of employees aged 40 – 44 years (%)	16.72	5.18	4.36	2.80
Share of employees aged 45 – 49 years (%)	14.01	5.11	4.42	2.56
Share of employees aged 50 – 54 years (%)	11.44	5.04	4.47	2.31
Share of employees aged 55 – 59 years (%)	8.20	4.80	4.28	2.18
Share of employees aged 60 – 64 years (%)	4.06	3.59	3.04	1.92
Share of employees aged 65 years or older (%)	1.55	2.79	2.55	1.13
Share of female employees (%)	30.12	20.76	20.63	2.38
Share of low skilled employees (%)	22.44	18.56	18.33	2.95
Share of medium qualified employees (%)	61.52	20.54	20.24	3.47
Share of highly qualified employees (%)	6.03	7.85	7.70	1.50
Share of part-time employees (%)	18.18	14.60	14.23	3.27
Firm size (number of employees)	429.68	3649.52	3644.74	192.87

Note: The data are from a balanced panel (4 years from 2003 to 2006) with a total of 16,900 yearly observations for 4,225 enterprises. For the definitions of the variables see text.

Table 3: Pooled estimates for productivity

	Pooled OLS regressions		Robust MM regressions	
	Model 1	Model 2	Model 1	Model 2
Employees 30 – 49 years (%)	204.2723***		195.3816***	
	(51.5160)		(17.5726)	
Employees 50 years or older (%)	61.4791		103.2042***	
	(41.3389)		(15.9103)	
Employees 20 – 24 years (%)		-6.7506		166.0262***
		(139.1245)		(53.4369)
Employees 25 – 29 years (%)		512.3296***		388.5230***
		(128.5867)		(51.4711)
Employees 30 – 34 years (%)		523.4095***		437.0036***
		(110.3084)		(44.6775)
Employees 35 – 39 years (%)		493.5080***		452.1762***
		(107.6693)		(42.5120)
Employees 40 – 44 years (%)		321.7099***		363.9478***
		(104.4426)		(41.9210)
Employees 45 – 49 years (%)		266.7672**		309.0789***
		(104.3467)		(43.7561)
Employees 50 – 54 years (%)		361.9286***		319.3821***
		(115.4942)		(43.0461)
Employees 55 – 59 years (%)		440.9448***		439.5134***
		(121.2577)		(46.4363)
Employees 60 – 64 years (%)		290.9312**		359.5496***
		(138.9901)		(57.1610)
Employees 65 years or older (%)		-245.7238*		-62.2619
		(138.9297)		(50.3271)
Female employees (%)	-219.2244***	-233.3700***	-188.9776***	-196.9950***
	(27.6394)	(27.3801)	(9.7427)	(9.7185)
Medium qualified employees (%)	83.4892***	76.7838***	44.5350***	38.7050***
	(17.9452)	(17.7453)	(6.8354)	(6.7999)
Highly qualified employees (%)	848.7500***	801.4342***	679.7042***	644.4257***
	(72.3017)	(69.1437)	(31.2364)	(29.1600)
Part-time employees (%)	-369.7626***	-268.8039***	-304.9767***	-240.7307***
	(30.4742)	(33.6020)	(11.0463)	(12.0111)
Firm size (number of employees)	0.9604**	0.9326**	7.8397***	7.5201***
	(0.4818)	(0.4612)	(0.4700)	(0.4617)
Firm size (squared)	-6.54e-6*	-6.33e-6*	-0.0009***	-0.0008***
	(3.49e-6)	(3.35e-6)	(0.0001)	(0.0001)
Constant	49982.4919***	29116.3618***	50986.4554***	30202.4348***
	(6772.1374)	(10927.3514)	(3658.1811)	(4789.2448)
Number of observations	16900	16900	16900	16900
Number of enterprises	4225	4225	4225	4225
R²	0.2593	0.2658		

Note: The dependent variable is value added per head (Euro). All models include dummy variables for years and 2digit-level industries. Standard errors clustered at the firm level are in parentheses. Coefficients are significant at * $p<0.10$, ** $p<0.05$, and *** $p<0.01$.
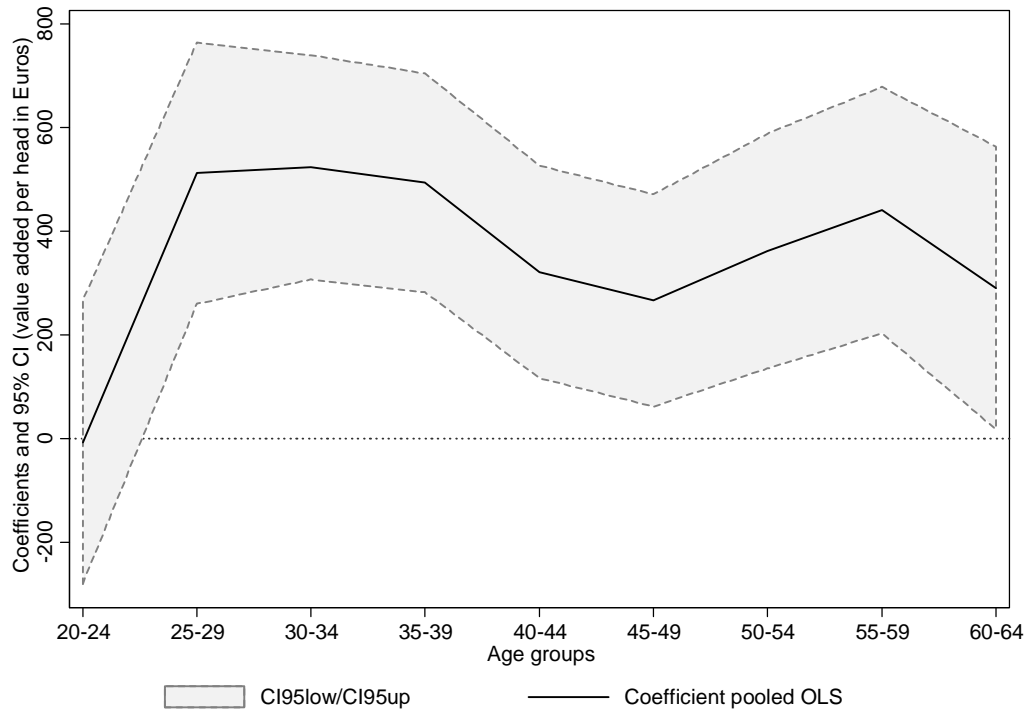
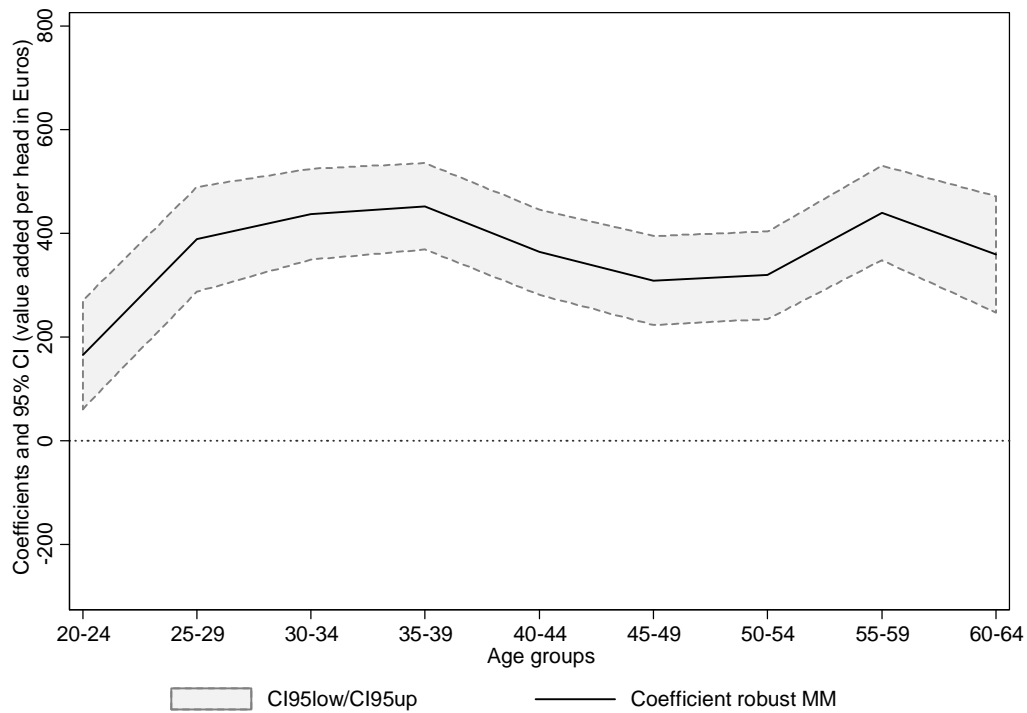Figure 1: Age-productivity profiles (model 2) for pooled OLS regression

Figure 2: Age-productivity profiles (model 2) for robust MM regression

Table 4: Pooled estimates for profitability

	Pooled OLS regressions		Robust MM regressions	
	Model 1	Model 2	Model 1	Model 2
Employees 30 – 49 years (%)	-0.0438***		-0.0231**	
	(0.0161)		(0.0101)	
Employees 50 years or older (%)	-0.1169***		-0.0903***	
	(0.0159)		(0.0089)	
Employees 20 – 24 years (%)		0.0329		0.0372
		(0.0448)		(0.0275)
Employees 25 – 29 years (%)		0.1236***		0.0838***
		(0.0408)		(0.0246)
Employees 30 – 34 years (%)		0.0838**		0.0654***
		(0.0388)		(0.0218)
Employees 35 – 39 years (%)		0.0548		0.0542**
		(0.0383)		(0.0213)
Employees 40 – 44 years (%)		-0.0265		-0.0037
		(0.0364)		(0.0213)
Employees 45 – 49 years (%)		-0.0102		-0.0082
		(0.0385)		(0.0211)
Employees 50 – 54 years (%)		-0.0460		-0.0571**
		(0.0393)		(0.0226)
Employees 55 – 59 years (%)		-0.0527		-0.0241
		(0.0388)		(0.0222)
Employees 60 – 64 years (%)		-0.0043		-0.0095
		(0.0413)		(0.0254)
Employees 65 years or older (%)		0.1004*		0.0969***
		(0.0518)		(0.0291)
Female employees (%)	0.0299***	0.0304***	0.0292***	0.0314***
	(0.0082)	(0.0081)	(0.0047)	(0.0047)
Medium qualified employees (%)	0.0004	0.0020	0.0027	0.0041
	(0.0058)	(0.0058)	(0.0033)	(0.0033)
Highly qualified employees (%)	-0.1121**	-0.1191***	-0.0332***	-0.0363***
	(0.0453)	(0.0460)	(0.0126)	(0.0115)
Part-time employees (%)	0.0033	-0.0009	0.0081	0.0004
	(0.0104)	(0.0127)	(0.0060)	(0.0067)
Firm size (number of employees)	-0.0001	-4.13e-5	-0.0001***	-0.0001***
	(0.0001)	(7.51e-5)	(2.86e-5)	(2.74e-5)
Firm size (squared)	2.30e-10	4.13e-11	4.92e-10**	4.46e-10**
	(5.13e-10)	(5.06e-10)	(2.12e-10)	(2.04e-10)
Constant	12.6804***	5.4955	11.2843***	5.7021**
	(2.4176)	(3.7994)	(2.2085)	(2.5967)
Number of observations	16900	16900	16900	16900
Number of enterprises	4225	4225	4225	4225
R^2	0.0406	0.0471		

Note: The dependent variable is rate of profit (%). All models include dummy variables for years and 2digit-level industries. Standard errors clustered at the firm level are in parentheses. Coefficients are significant at * $p<0.10$, ** $p<0.05$, and *** $p<0.01$.
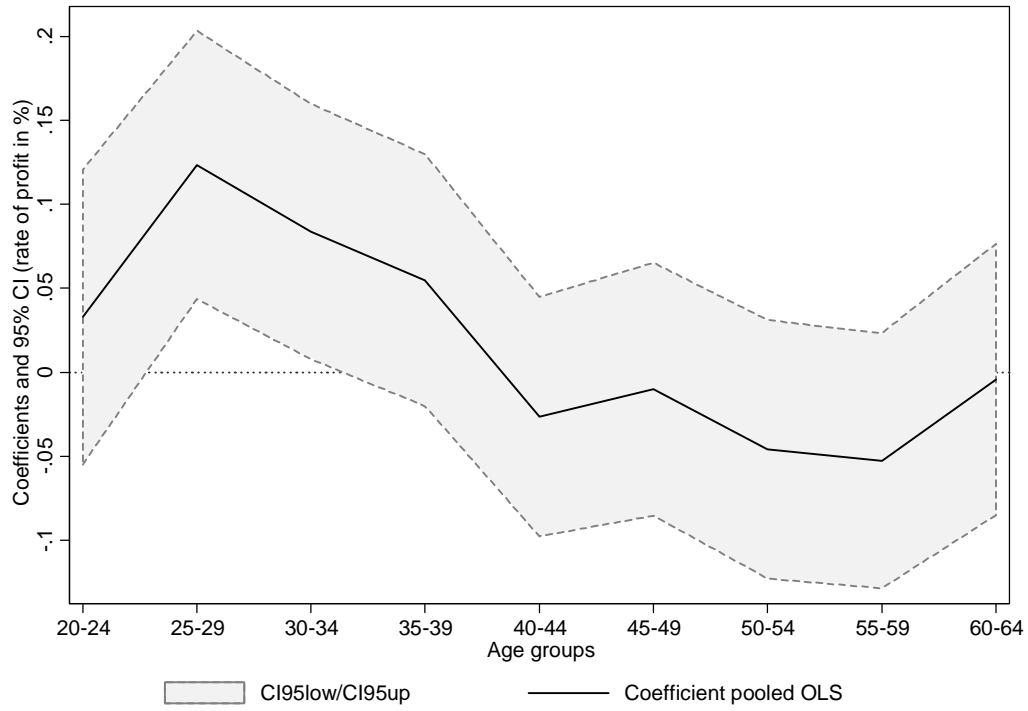
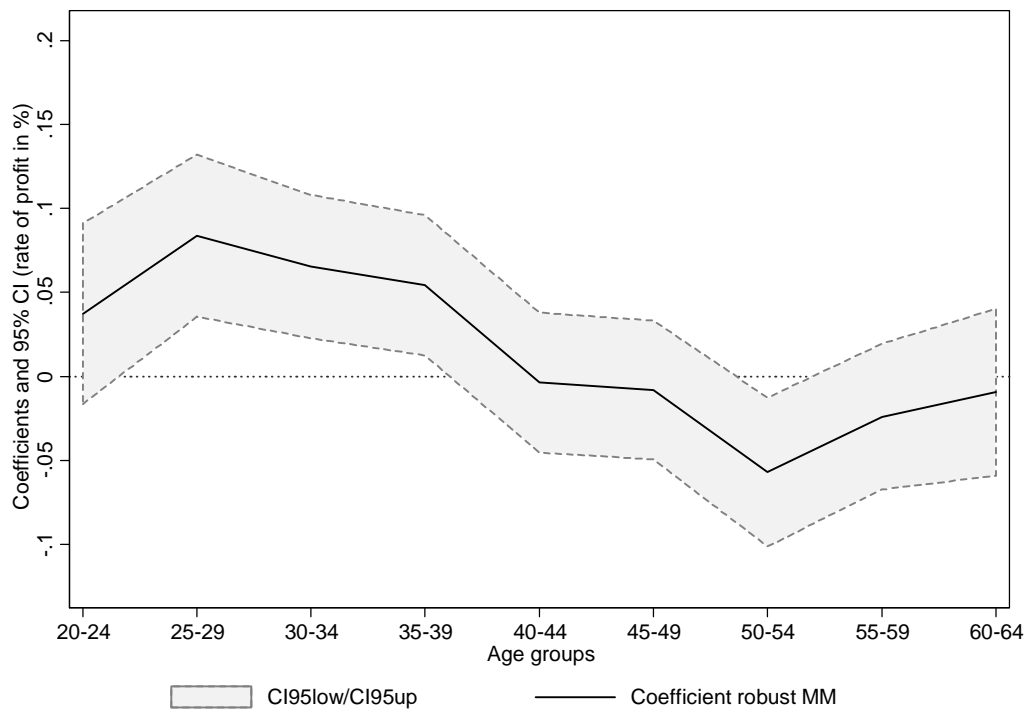Figure 3: Age-profit profile (model 2) for pooled OLS regression

Figure 4: Age-profit profile (model 2) for robust MM regression

Table 5: GMM first difference estimates for productivity and profitability

	Productivity	Profitability
Employees 20 – 24 years (%)	370.1960	0.3039
	(433.5095)	(0.1883)
Employees 25 – 29 years (%)	990.7642*	0.6243***
	(560.1271)	(0.2252)
Employees 30 – 34 years (%)	1447.2803**	0.6047**
	(612.4988)	(0.2362)
Employees 35 – 39 years (%)	1167.7536*	0.3894*
	(608.8043)	(0.2332)
Employees 40 – 44 years (%)	1217.1934*	0.3380
	(635.3015)	(0.2417)
Employees 45 – 49 years (%)	1557.7039**	0.4178*
	(656.1437)	(0.2410)
Employees 50 – 54 years (%)	1309.6891*	0.3195
	(675.2281)	(0.2468)
Employees 55 – 59 years (%)	1094.0228	0.1959
	(697.9981)	(0.2457)
Employees 60 – 64 years (%)	1497.1742**	0.3894
	(701.7014)	(0.2646)
Employees 65 years or older (%)	2109.1828*	0.4270
	(1238.7614)	(0.3429)
Female employees (%)	1309.8010**	0.1403
	(652.0186)	(0.1750)
Medium qualified employees (%)	-294.2409	-0.3238***
	(329.8124)	(0.1122)
Highly qualified employees (%)	1862.4764	-0.4977
	(2028.0992)	(0.5378)
Part-time employees (%)	-168.9521	-0.2050
	(390.1211)	(0.1470)
Firm size (number of employees)	-0.0196	0.0010
	(4.3593)	(0.0010)
Firm size (squared)	1.95e-6	-3.56e-9
	(2.03e-5)	(-3.56e-9)
Number of observations	12675	12675
Number of enterprises	4225	4225
Sargan test of overidentifying restrictions: $\chi^2(32)$; prob$>\chi^2$	62.30; p=0.0011	30.92; p=0.5212

Note: Twostep GMM first difference regressions for model 2. The dependent variables are value added per head (Euro) and rate of profit (%). First differences are instrumented with second and third lags of their own levels. Robust standard errors are in parentheses. Coefficients are significant at * p<0.10, ** p<0.05, and *** p<0.01.
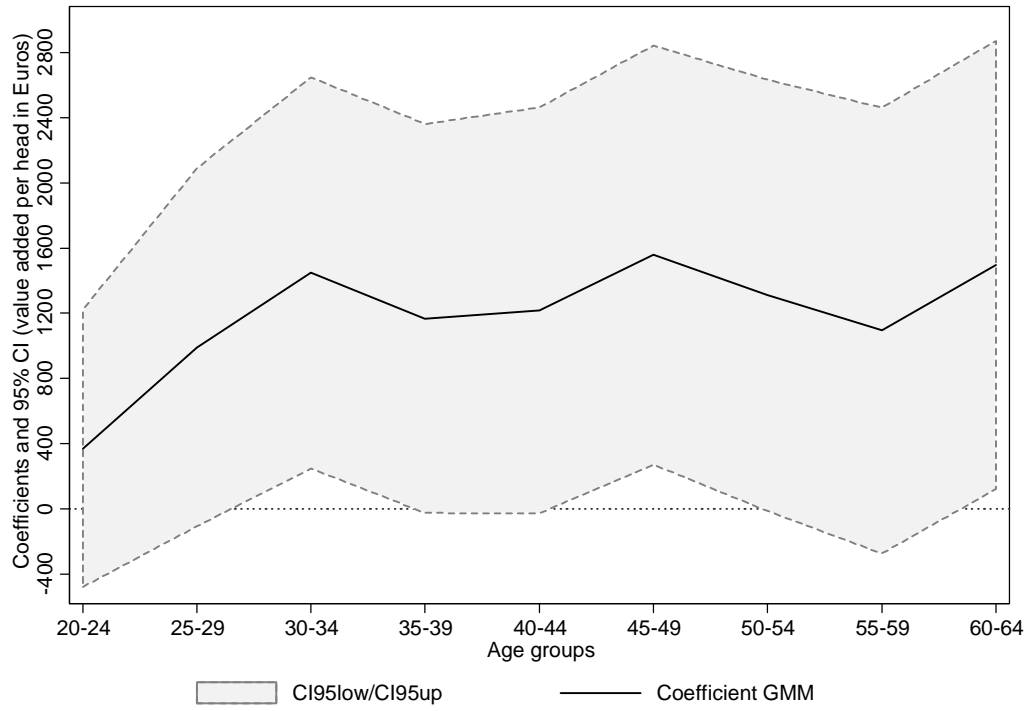
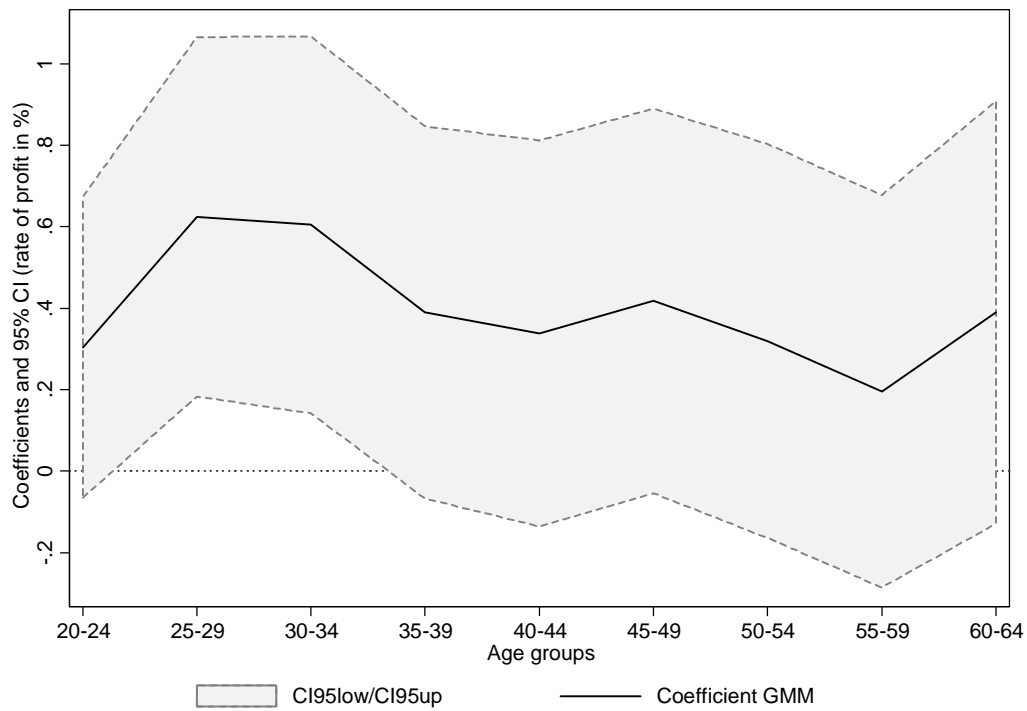Figure 5: Age-productivity profile (model 2) for GMM regression

Figure 6: Age-profit profile (model 2) for GMM regression

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