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Mit der Reihe „IAB-Discussion Paper“ will das Forschungsinstitut der Bundesagentur für Arbeit den Dialog mit der externen Wissenschaft intensivieren. Durch die rasche Verbreitung von Forschungsergebnissen über das Internet soll noch vor Drucklegung Kritik angeregt und Qualität gesichert werden.

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Content

Abstract

In Germany, the labour force is ageing rapidly. At the same time, age heterogeneity within companies is rising. The literature on diversity argues that heterogeneity can have a positive as well as a detrimental effect on team outputs. Our paper sheds light on the impact of age diversity on the likelihood of a company to create product or process innovations. Based on our analysis of the Linked Employer-Employee-Data from the Institute for Employment Research (IAB) over the 2009-2013 period, we focus on different indicators of age diversity within a company's workforce (variety, separation and disparity). We find that a rise in the average age of a company's workforce has a negative impact on innovation, but age diversity measured by the standard deviation of age or the average age gap increases the probability of a company to create innovations. In addition, the uniformity of the age distribution does not affect innovativeness. Different results for age and tenure diversity suggest a higher importance of generalised human capital for creativity processes compared to company-specific knowledge gained during employment within a company.

Zusammenfassung

Die Erwerbsbevölkerung in Deutschland altert rasant, gleichzeitig nimmt aber auch die Altersheterogenität in den Belegschaften zu. In der Literatur finden sich sowohl Hinweise auf einen positiven wie auch einen negativen Einfluss der Altersheterogenität auf den Teamerfolg. Die vorliegende Studie untersucht, inwieweit die Altersheterogenität die Wahrscheinlichkeit eines Betriebs beeinflusst, Produkt- oder Verfahrensinnovationen hervorzubringen. Auf Basis von Linked Employer-Employee-Daten des Instituts für Arbeitsmarkt- und Berufsforschung (IAB) der Jahre 2009 bis 2013 werden verschiedene Indikatoren zur Messung der Altersheterogenität in der Belegschaft verwendet (Varietät, Separation, Disparität). Im Ergebnis findet sich ein negativer Effekt des Durchschnittsalters auf die Innovationsfähigkeit, allerdings erhöhen die Standardabweichung des Alters und die durchschnittliche Alterslücke die Wahrscheinlichkeit eines Betriebs, Innovationen hervorzubringen. Eine Gleichverteilung der Altersstruktur zeigt hingegen keinen Zusammenhang zur betrieblichen Innovationsfähigkeit. Die unterschiedlichen Ergebnisse zur Heterogenität des Alters und der Betriebszugehörigkeitsdauer weisen zudem auf eine höhere Bedeutung des allgemeinen Humankapitals für kreative Prozesse hin – im Vergleich zum Humankapital, welches betriebsspezifisch erworben wird.

Keywords

Age Diversity, Company Innovativeness, Linked Employee-Employer-Data

JEL Classification

J14, J24, M14

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This study uses the Linked Employer-Employee Data (LIAB) cross-sectional model 2 1993-2014 (LIAB QM2 9314) from the IAB. Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently remote data access.

1 Introduction

As the labour force is ageing rapidly in the majority of industrial countries, a better understanding of how a company's age pattern is related to its organisational outcomes gains in importance. The demographic change in Germany is reliably predicted (Deschermeier, 2017) and mainly driven by the ageing of the baby boomer generation as one of the largest groups within the current labour force. Other drivers can be found in recent institutional changes: In 2006, the Federal Government gradually increased the retirement age from 65 to 67 years. At roughly the same time, a lowering of the age of graduates entering the labour market was observed as a result of changes in the education system initiated by the Bologna Process. Consequently, the age structure within companies changed profoundly and workforces are nowadays older and more age-heterogeneous (Hammermann et al., 2017). This leads to enormous challenges for human resource managers in companies as well as for policymakers.

In times of skill shortages, it is not only essential for human resource departments to find appropriate candidates for job vacancies, but also to effectively compose working teams. Since every employee brings along her/his unique skillset, knowledge, experiences, attitudes and values, one of the main tasks for today's diversity management is to combine these characteristics and thereby strengthen a company culture in which differences translate into economic success. Building on this approach, the underlying questions are: Does labour (or age) diversity pay off? Provided each employee meets the requirements of her/his job, is there value added if working groups are composed diversely? If so, how can one effectively match employees with different personal characteristics and backgrounds? In particular, how does the age structure of a company's employees have to be composed to improve (overall) performance? Scientific research faces several challenges when attempting to address these questions.

The bulk of research in this field has so far focused on labour diversity and the performance of teams or organisations, which is frequently associated with productivity figures (see Boehm and Kunze, 2015). To the best of our knowledge, the link between several aspects of age diversity and innovation has not been investigated in detail, even though innovation is one of the most important factors in companies' long-term development and competitiveness. As innovation is highly dependent on a company's human capital resources, it could also be closely connected to labour diversity in that innovation "is an interactive process that often involves communication and interaction among employees in a firm and draws on their different qualities from all levels of the organisation" (Østergaard et al., 2011, 500).

In detail, it would appear that the link between age diversity and innovation measures is not fully understood: On the one hand, the underlying theoretical approaches, in principle, predict conflicting outcomes of labour diversity, and on the other hand, empirical evidence (also) indicates no clear or robust relationship. Obviously, this makes it difficult to establish a consistent theory of (age) diversity. With reference to the literature, several issues can be observed that make a comparison of research findings slightly complicated, insomuch as some studies rely on small samples and cannot produce far-reaching inferences (Pelled et al., 1999; Kilduff et al., 2000; Simons et al., 1999). Besides, different outcome variables are used to measure performance (e.g. value added, sales, the introduction of a new product (yes/no), a plant's total factor productivity; Grund and Westergård-Nielsen, 2005; Buche et al., 2013; Østergaard et al., 2011; Ilmakunnas and Ilmakunnas, 2011). In addition, some studies focus on the transmission channels between diversity and an outcome variable which points to moderating effects, whereas other studies put emphasis on the interaction of diversity dimensions and refer to diversity faultlines (e.g. Backes-Gellner and Veen, 2013, Breu et al., 2010). As many different intermediate causal relations in a given research setting are conceivable, it appears it is an ongoing task to reveal predominant interdependencies and to sharpen the picture of how transmission channels work. Moreover, the methods used to model the relationship partly differ; e.g., some studies account for endogeneity issues and/or use fixed-effects estimations to check for unobserved heterogeneity (Göbel and Zwick, 2013; Grund and Westergård-Nielsen, 2005; Backes-Gellner and Veen, 2013). As e.g., Göbel and Zwick (2012) show, different (significant) results for age dispersion (measured by the standard deviation of age) can be derived by switching from OLS models to System GMM estimates.

Our study contributes to the existing literature on the relationship between age diversity and innovation by applying multiple (diversity) indicators. In doing so, we strive to disentangle diverse transmission channels from age diversity to innovation. We concentrate on "variety", "separation" and "disparity" as three diversity types to find evidence of how a beneficial age structure might be composed. Therefore, we use the Linked Employer-Employee Data Set from the Institute for Employment Research (IAB, Klosterhuber et al., 2016) and employ distinct estimation models. The data set enables the derivation of various age diversity measures and the use of a broad set of company characteristics. However, detailed information about team composition and coordination, team output, relevant tasks, responsibilities etc. are not available. Hence, we adopt a holistic perspective and assume that the interaction between all employees in a company (together) facilitates innovation, even though this may be debatable (Woodman et al., 1993).

Our empirical findings show clear evidence of an ageing workforce along with a rising age heterogeneity within companies throughout the period of our analysis from 2009 to 2013. Whereas an increase of the average workforce age adversely affects a company's probability of being innovative by 0.7 to 1.3 per cent, two age diversity measures (standard deviation and the average age gap) show a significant positive impact of 1.2 to 1.5 per cent in GMM estimation models. The latter findings are in line with the assumed positive contribution of a broader set of information, problem solving strategies and experiences in age-diverse teams following the information-/decision-making perspective. However, we cannot rule out that the relationship is nonlinear. Logit estimates point to an inverted u-shaped relation but are in line with our basic result that a positive effect remains above a certain degree of age diversity. A particular uniform age distribution, however, shows no additional benefit for innovativeness. Interestingly, the heterogeneity of the employees' tenure does not show a significant impact on innovation at all. This leads us to the conclusion that general human capital gained during life and work experience in a broader sense might be more important for the innovativeness of age-mixed teams than company specific human capital.

This study proceeds as follows: Section 3 gives an overview of the related literature on diversity. Section 4 sets out the econometric strategy, while section 5 introduces the data set and its preparation. Section 6 presents the empirical results, supplemented by sensitivity and robustness checks in section 7. A conclusion with a recapitulation of our findings is presented in section 8.

2 Literature and hypotheses

The question if, and to what extent, labour diversity affects the performance of a team or an organisation has given rise to a long series of studies. The basic objective is to find out if working together in a heterogeneous team will lead to a productivity surplus compared to the sum of the team members' individual productivity contributions.

In this section, we focus on the link between age diversity and a company's (or team's) innovativeness and performance. Tracing back to the fundamental approaches underlying the diversity literature, one has to deal with conflicting effects of higher degrees of labour (and age) diversity on team or company outcomes. On the one hand, positive outcomes can be assumed by arguing that a fruitful exchange between employees of different generations can foster innovation and other performance indicators. This argumentation coincides with the information-/decision-making perspective, whereby workforce heterogeneity may contribute to a team's performance because broader access to information, problem-solving strategies and different experiences is available. On the other hand, however, mixed age groups may give rise to adverse effects. In line with social categorisation processes and the similarity-attraction effect similarity attraction approach, one can argue that people tend to categorise themselves according to socio-demographic criteria, such as age, gender and ethnicity. As a result, they are more willing to cooperate with in-group members showing similar characteristics to their own while communication with outsiders is more complicated (Tajfel and Turner, 1986; van Knippenberg and Schippers, 2007; Williams and O'Reilly, 1998; Akerlof and Kranton, 2000; Hammermann et al., 2012; Prendergast and Topel, 1996).

The perspectives described above suggest that the effects of age diversity on innovativeness are ambiguous. Furthermore, one has to bear in mind that diversity measures, in principle, are only one icon in a (long) series of other explanatory factors that might interact with performance indicators. In this context, researchers have to deal with various issues extracted from previous findings.

Firstly, one would expect that teamwork is more likely to reap benefits if the team members' skills, capabilities and experiences are complementary (Lazear, 1999). As is well-known, employees of different ages usually differ in their abilities, attitudes and skills which might have different effects on productivity depending on the type of tasks that have to be performed (Backes-Gellner and Veen, 2013). In general, this raises concerns about taking moderating effects into account (here: type of tasks). Backes-Gellner and Veen (2013, 21) conclude – based on a cost-benefit framework – that "age diversity has a positive effect on company productivity if and only if a company engages in creative rather than routine tasks". In detail, one may think of other (moderating) factors accompanying task issues, such as task conflicts, which are, for example, conflicts about the distribution of resources, procedures, judgements and the interpretation of facts (De Dreu, 2006).

In addition, a high "correlation" of diversity dimensions within a team or institution, e.g. age, gender, ethnicity, education, may have adverse effects. If the underlying characteristics are closely interrelated, this can constitute diversity faultlines, which can foster subgroup conflicts (Lau and Murnighan, 1998). A strong diversity faultline occurs, for example, if a team consists of many old men and young women. Hence, the higher the degree of diversity in a team and the more this diversity is spread between two or more diversity dimensions, the higher the risk may be of subgroup formation. To capture these effects in multivariate settings and to isolate unbiased diversity effects, it seems reasonable to check for other diversity indicators or to use special faultline indices (for the latter see, for example, Breu et al., 2010).

Because various moderating effects can theoretically be assumed depending on a research question, it appears to be a very complex issue to prove which types of moderating effects will (quantitatively) dominate the interrelation of age heterogeneity and company performance (in certain settings). An intermediate step to be taken might be to look at different indicators of age diversity and to check whether they are associated with innovativeness (or other performance indicators). Some studies, as pointed out by Grund and Westergård-Nielsen (2005), are only based on a limited number of companies (e.g. Pelled et al., 1999; Zajac et al., 1991). Therefore, it is hardly possible to draw far-reaching inferences. If, for example, the focus is (only) on the top management team (Kilduff et al., 2000; Simons et al., 1999), related results may not be sufficient to explain how the age composition of teams affects the innovation outcome, because the creative processes to design new products or procedures are probably undertaken by specific departments/teams and at working level.

Grund and Westergård-Nielsen (2005) show – based on a large linked employer-employee data set for Denmark (1992-1997) – that mean age and the standard deviation of the workforce age are inversely u-shaped with company performance (value added per employee). Referring to the link of age diversity and innovation, Østergaard et al. (2011) obtain a different result (also for Denmark). Using combined data from an innovation survey and a linked employer-employee data set, they find some indications for a negative link between age diversity and innovation, but no significant effects for mean age, whereas in testing curvilinearity, age diversity exhibits a less significant negative impact on innovation. The results also show (slight) changes when considering other control variables (e.g. to examine the effects of gender diversity in detail or to test curvilinearity). Østergaard et al. (2011, 508) interpret their results carefully: "Diversity in age appears to have either negative or neutral effect, although average age has no significant impact". In addition, Parrotta et al. (2014) also use Danish data and investigate the nexus of labour diversity and companies' innovation activities. Among the diversity measures considered in their study, a demographic diversity index (consisting of a combination of gender and age groups) revealed no significant effect on the propensity to innovate or on a company's patent applications in various models, while ethnic diversity in particular seems to facilitate a company's patenting activities.

Ilmakunnas et al. (2004) present empirical evidence for Finland based on a matched employer-employee data set. Among other things, they use (ln) age, a quadratic, and a cubic term and the standard deviation of age as variables to explain plant total factor productivity (TFP). They derive an inverted u-shape age-productivity profile with a peak at about 40 years, while the standard deviation of age has no significant effect. In a more recent study, Ilmakunnas and Ilmakunnas (2011) use data from a Finnish Linked Employer-Employee Data Set (1990-2004). They provide evidence that average age has an adverse effect on TFP. Conversely, the standard deviation of age shows in almost all specifications a positive and highly significant coefficient with regard to TFP, which also remains stable in specifications with (log) value added per hour as a dependent variable.

Using an augmented company data set for Germany, Buche et al. (2013) investigate the effects of age and cultural diversity on (log) sales. For modelling age diversity, they include the mean age, age span and the average age gap in their calculations. The latter incorporates a pairwise comparison of each individual's age with that of all other (group) members (see also Dawson, 2012) and can be associated with social categorisation processes. However, their regressions show no significant effects of the age span and the average age gap on company sales, but a low negative significant effect for mean age. Thus, the results do not confirm an overall negative impact as predicted by social categorisation processes.

Göbel and Zwick (2012) also use German data to investigate the link of age and (log) value added. Besides variables for age groups and age cohorts, they also consider the standard deviation of age as a measure for age dispersion in their regressions. As their results show, age dispersion has significant adverse effects in some OLS-specifications, but not in any GMM estimates, which also raises awareness to model selection issues and checking for endogeneity. In another study, they examine the effects of specific staff measures to increase the productivity of older workers (Göbel and Zwick, 2013). For example, they find indications that establishments with mixed-age teams can boost the productivity of older and younger workers compared to establishments that do not apply this specific measure. Besides, the effect of age dispersion is not statistically significant in any team whether or not a certain human resource measure is applied for older employees.

As the evidence from the above-stated studies is not straightforward, the relation between age diversity (within a company) and a plant's innovativeness does not appear to be predetermined. However, since the majority of studies tend to give an indication of a negative sign of mean age, we assume the following:

Hypothesis 1: The average age of a company´s employees is negatively related to the likelihood of a company's innovativeness.

Regarding the effects of age diversity, we leave the answer open to the empirical investigation and formulate both (ambivalent) theses, keeping in mind that an inverted u-shape may also describe the relation of age diversity to innovation:

Hypothesis 2a: Age heterogeneity may foster innovation since different perspectives, knowledge and experiences enable creative exchanges within a company's workforce. (The theoretical ex ante relation is positive).

Hypothesis 2b: Age heterogeneity may lead to communication conflicts, which can reduce creative cooperation between young and older employees. (The theoretical ex ante relation is negative)

In addition, as we want to investigate the impact of age diversity on innovativeness in detail, we focus on the distribution of age within a company. Because this is rarely tested in existing studies, we can provide some new evidence about the relationship between age and innovation. We assume that a uniformly distributed age structure does not only represent a broad knowledge potential with complementary experiences, but also reduces the risk of subgroup formation and the emergence of age-related faultlines in the workforce:

Hypothesis 3: A uniformly distributed age structure is associated with a beneficial exchange between generations and consequently increases the company's innovativeness.

3 Methodology and estimation strategy

Technically, employee diversity can be defined by the distribution of differences among the members of a reference group (e.g. a company). These differences can be measured, in principle, according to three dimensions, i.e. variety, separation and disparity (Harrison and Klein, 2007).

Variety reflects, for example, the composition of differences in relevant knowledge or experience stemming from a categorical attribute. Hence, variety measures are inadequate for research on age as a metric variable. Basically, related indicators should have to disclose structural differences among specific age groups, such as differences between cohorts or generations (generation x and y). Nevertheless, it seems partly arbitrary to define these groups. The average age of the labour force within a company does not actually constitute a diversity index in this context, but is an essential measure for the location of the age distribution. Here, it represents a proxy for the general knowledge within a company – analogous to the role of the individual's working experience in explaining wages in human capital theory. Through the consideration of diversity indicators (see below), it seems reasonable to separate this effect from any distribution-related diversity measure.

The separation dimension implies, for example, measures to describe the composition of (horizontal) differences in the age distribution – that is, it focuses on the relative concentration within the age distribution (Harrison and Klein, 2007). Indicators of this group map the dispersion of the age distribution within a company.

In this context, we use (1) the standard deviation of the company's age distribution (e.g. Göbel and Zwick, 2013) and (2) the average age gap (e.g. Buche et al., 2013):

Equation 1:

$$sd_{AGE} = \sqrt{\frac{\sum_{j=1}^{n}(x_j - \bar{x})}{n}}$$

Equation 2:

$$gap_{AGE} = \frac{2}{N(N-1)} \sum_{j=1}^{N} \sum_{k<j} |x_j - x_k|)$$

The former is the square root of the variance and ranges from zero, when all members of a group have the same age, to a maximum, which is achieved when members of the group fall into two equal-sized subgroups with minimum and maximum age respectively. The age gap describes the average distance between the ages of two randomly chosen employees in a company, i.e. it measures the average absolute difference between one employee and every other employee for all pairwise combinations. This is expressed as the sum of absolute differences divided by the total number of pairs ½ N (N-1) (Dawson, 2012). It ranges from the lower limit of zero, if there is no age diversity within a company and, theoretically, to no set upper limit. Empirically, when assuming a common working age interval, a maximum is reached if all employees are uniformly divided into two age groups with ages at the outer margins of the distribution, e.g. between 16 and 64 years. As it compares each individual's age to that of other group members and not only to the mean like in the standard deviation, it can be associated more strongly with the social categorisation theory. In this context, it can be assumed that the lower the age gap in a company, the lower the risk will be for constituting age faultines.

In addition, the disparity dimension focuses on the shape of the age distribution with a special focus on the extreme (age) values in a company. In this context, a more equal distribution leads to a higher degree of diversity (Dawson, 2012). This group of diversity measures represents the balance or smoothness of the age distribution. We use (3) the evenness and (4) the spread as indicators (Harrison and Klein, 2007; Dawson, 2012) as they put special emphasis to the range of age in the whole workforce and the within age distribution, measured here by the maximum difference of adjacent ages:

Equation 3:

$$evenness_{AGE} = \frac{x_{max} - x_{min}}{max(x_j - x_{j-1})} \text{ } with \text{ } x_j \text{ } placed \text{ } in \text{ } order$$

Equation 4:

$$spread_{AGE} = \frac{(x_{max} - x_{min})^2}{max(x_j - x_{j-1})} \text{ } with \text{ } x_j \text{ } placed \text{ } in \text{ } order$$

Thus, for a given range of age in a company, the evenness and spread reach their maximum if the age of the employees is (de facto) completely equally distributed – that is, the denominator converges to zero. The evenness will reach its minimum (equals 1) if the range of age is equal to the maximum difference of adjacent ages, e.g. if the company consists of two age groups where every employee in each group has the same age and the ages between both groups differ. This also holds true for the spread, but only if the age in both groups differs by 1, in which case the minimum spread equals 1. The spread overemphasises the range of age and is thus more sensitive to the absolute range in the age spectrum of a company. Since both indicators increase with the range of age, given equally distributed ages, the available skills, abilities and knowledge of older and younger employees are supposed to increase and, thus, the richer age continuum highlights the resource approach of diversity. An empirical comparison between the two described disparity indicators reveals the relative importance of the range and equipartition.

These two, or respectively three groups of indices reflect the internal age structure of a workforce with regard to our formulated hypotheses. Based on those, we apply the following empirical strategy to evaluate the effects of age heterogeneity on innovation.

The theoretical estimation approach focuses on a modified knowledge production function (Machlup, 1984; Conte and Vivarelli, 2005). This implies the specification of an innovative output of company i in period t, denoted with $INNO_{it}$ in equation (5), and inputs like capital per worker (K_{it}), share of high-skilled employees and low-skilled employees (L_{it}) and, also, a matrix with several company-related characteristics (X_{it}). The set of control variables contains inter alia the share of migrants, share of women, competitive pressure (yes/no), and export orientation.[1] Our focus lies on the age-related diversity indices (AGE_{it}) of a company's labour force. This matrix comprises different settings of indices of the age distribution as described above, i.e. various combinations of the average age, standard deviation of age, average age gap, evenness and spread. The model in latent variable notation is given by

Equation 5:

$$INNO_{it}^{*} = K'_{it}\beta_K + L'_{it}\beta_L + AGE'_{it}\beta_{AGE} + X'_{it}\beta_X + \alpha_b + \alpha_r + \alpha_t + u_{it}$$

We estimate a baseline model by a static logit panel model with specific fixed effects, i.e.

Equation 6:

$$P(INNO_{it} = 1) = \Lambda(INNO_{it}^{*})$$

where $INNO_{it} = 1$ indicates that the company has introduced a product or process innovation and Λ is the cumulative distribution of the logistic distribution. By including invariant dummy variables for branches (α_b), region (α_r) and time (α_t) in the regression model, the estimates check for variations within branches, regions and across time, whereas year dummies check for overall economic fluctuations of innovation.[2] The term u_{it} includes unobserved characteristics like further company fixed effects, autocorrelation or idiosyncratic errors.

Beyond this baseline specification, we elaborate the estimation procedure by allowing dynamic state dependence of innovation propensity. This is motivated by the idea that the innovation propensity is highly dependent on past innovation. Put differently, the best predictor of what happens today is what happened

[1] This excludes the predictors of heterogeneity in tenure structures. Due to concerns of multicollinearity, we tried to capture these effects in our sensitivity and robustness subsection below. However, we want to keep the main part as short as possible and sophisticated with respect to implications of age diversity.

[2] The sample covers the period and aftermath of the Great Recession, which could have induced significant exogenous and temporary shocks to innovations in the economy or to the knowledge production inputs.

yesterday, and in this way, we try to take potential serial correlation in the error term into consideration and understand innovation persistence as a potential source of endogeneity. Thus, innovation persistence biases will be filtered out by conditioning on lagged innovations. The effect of the lagged dependant variables can reveal positive spillovers of knowledge to future innovation and indicates a 'standing on shoulders' of recent innovations. Alternatively, it is possible that the most obvious ideas are discovered at first, but when a company is already highly efficient, new ideas become increasingly harder to find over time, which can be interpreted as an adverse effect when 'fishing out' of innovation-driving possibilities (Jones, 1995). In this context, we also use the lagged share of expansion investments to establish a more causal relation, since said investments might be a prerequisite for innovation outcomes in the future.

Due to several complications and biases occurring from nonlinear dynamic panel estimation, i.e. the so-called Nickell Bias (Nickell, 1981), we cannot easily insert the lagged dependant variable $INNO^*_{it-1}$ in the logit model. Instead, we checked the results with the System GMM technique (Blundell and Bond, 2000; Roodman, 2006). By doing so, we also tackle some endogeneity problems and check for unobserved heterogeneity. The literature stresses that individual fixed effects are usually correlated with time varying explanatories in dynamic estimations. Furthermore, by construction, the lagged dependant variable is usually correlated with individual fixed effects, meaning that unobserved heterogeneity affects the innovation outcome. Thus, innovations are highly dependent on unobserved aspects within a company. It must also be noted that the regressors may also exhibit a nonzero correlation with the idiosyncratic errors – unobserved innovation shocks affect production inputs. The dynamic panel estimator by Blundell and Bond (2000) is designed especially for those situations with

i) 'small T, large N', meaning lots of individuals and few time periods,
ii) linear functional relationship,
iii) single left-hand-side variable that is dynamically depending on its own past realisations,
iv) independent variables that are not strictly exogenous, meaning correlation with past and possibly current realisations of the error
v) fixed individual effects, and
vi) heteroscedasticity and autocorrelation within units but not across them

to tackle the weak spots of the logit model. The System GMM estimates the equation in first differences (orthogonal transformation of the original equation) and in levels simultaneously, whereby it imposes exogenously additional orthogonality conditions to offset biases from dynamic panel estimations. Endogenous and predetermined explanatories are instrumented with their lagged differences and levels, respectively. The transformation of all regressors, by forming first differences, assumes that the first differences of the instrumental variables are uncorrelated with the fixed effects. By using internal instruments constructed from lagged variables, this estimation rules out biases from dynamic panel models with potential endogenous variables. These additional orthogonality conditions of the system GMM estimator do not come without a cost: Initially, our nonlinear model collapses into a linear one that is nonetheless more robust and addresses endogeneity problems arising from the explanations above (Wooldridge, 2002; Arellano and Carrasco, 2003). Besides, instrumenting the lagged dependant variable with their own lags may evoke the weak instrument problem, since lagged levels as instrument may convey little information on future or contemporaneous changes respectively (Bun and Windmeijer, 2009). Our implemented GMM estimation equation in level form is equation (5) adding the lagged dependant variable $INNO^*_{it-1}$ on the right hand side and assessing it with two different timing assumptions for the identification of the regressors' effects: First, we treat the lagged dependent variable as endogenous and all other variables as strictly exogenous which means that they are uncorrelated with past, contemporaneous and future innovation errors. This is unambiguously a strong assumption that we will ease in the next step. The second timing assumption addresses the fact that both the inputs of capital and labour are determined by companies' decisions, i.e. the explanatories are associated with K_{it}, and L_{it}. Thus, inputs are correlated with the error term – that is, when a company faces an innovation shock more/less workers are hired, which positively/adversely affects the relationships between demographic composition and knowledge production inputs, and, in turn, boosts/diminishes innovation activity. Therefore, we treat all standard production inputs as predetermined and instrument them implicitly with their own lagged differences and levels. On the other hand, the remaining variables are assumed to be strictly exogenous, i.e. to be uncorrelated with the error term. This implies that companies cannot directly alter the age composition in the workforce, because they are not able to or aware that they can take advantage of a diversified workforce. By treating some explanatories as predetermined, we additionally deal with concerns of reverse causality in which we suppress the theoretical mechanism that innovations induce more/less production inputs.

4 Data

This paper uses the Linked Employer-Employee Data of the Institute for Employment Research (LIAB, cross-sectional model 2). It contains company data from the annual waves of the IAB Establishment Panel (EP) and individual data from the process-generated data of the Federal Employment Agency (Klosterhuber et al., 2016, 8)[3]. The data can be merged via a unique establishment identifier that is available in both data sources. As the establishment panel constitutes the sampling unit (of the EP), additional variables drawn from or calculated based on the individual data can be appropriately aggregated on the establishment level. In this context, we constructed the diversity indices (see next section) based on individual data for each company and then assigned the data to the establishment level and merged the resulting variables to the EP. Table 1 portrays how the explanatory variables are computed.[4]

We excluded the agriculture sector and companies with fewer than five employees to ensure valid analyses when calculating age diversity indices. Because of considering lagged terms for the dependent variable and due to the panel structure, our sample collapses to the period from 2009 to 2013, covering on average 2,331 companies.

[3]In detail, the EP focuses on establishments as sampling units rather than companies, but, hereafter, we will use each term as synonym.

[4]Some measures are not directly observed but approximated, i.e. capital per worker, which may systematically produce some measurement error in the regression analysis.

Table 1: Variable definition

Variables	Data Source	Description
innovation (dependent variable)	EP	binary variable indicating whether a company introduced an innovation during the current year (yes=1)
capital per worker	EP	calculated from an approximated capital stock (sum of replacement investments) per full-time equivalent in 1,000 Euro
share of expansion investment	EP	per cent proportion of total investments in the current period
technical status	EP	categorical variable describing the technical state (outdated, intermediate, modern) of companies' capital
payroll per worker	EP	calculated from salary documentation per full-time equivalent in 1,000 Euro
qualification level of workers	EP	three variables indicating the share of high, middle and low skilled in full-time equivalents
company size	BHP	categorical variable describing how much workers (5-20, 21-50, 51-200, 200+) are employed in the company unit
share of migrants	BHP	share of employees with non-German citizenship
share of women	BHP	share of female employees
share of part time	EP	share of part-time workers
age of the company	EP	binary variable indicating whether a company was founded less than 15 years ago (yes=1)
R&D unity	EP	binary variable constructed from an imputation since the IAB documents only biennially whether a company is research-orientated (yes=1)[5]
competitive pressure	EP	binary variable indicating whether a company feels exposed to medium or high competitive pressure (yes=1)
export orientation	EP	binary variable indicating whether a company sells their product or services in other countries (yes=1)
industries	EP	categorical variable aggregating 17 sectors to five industries: [1] manufacturing, [2] commercial services, [3] finance and communication, [4] social services, [5] non-profit
Western Germany	EP	binary variable indicating whether the company is situated in Western Germany (=1)
tenure: average	BHP	average employment duration of all employees in a company
tenure: standard deviation	BHP	average standard deviation in the duration of employment of the workforce in a company
tenure: average gap	BHP	average gap of the duration of employment of the workforce in a company (equivalent to the age gap, defined subsequently)

EP – IAB Establishment Panel, BHP – Establishment History Panel.

Source: Own illustration

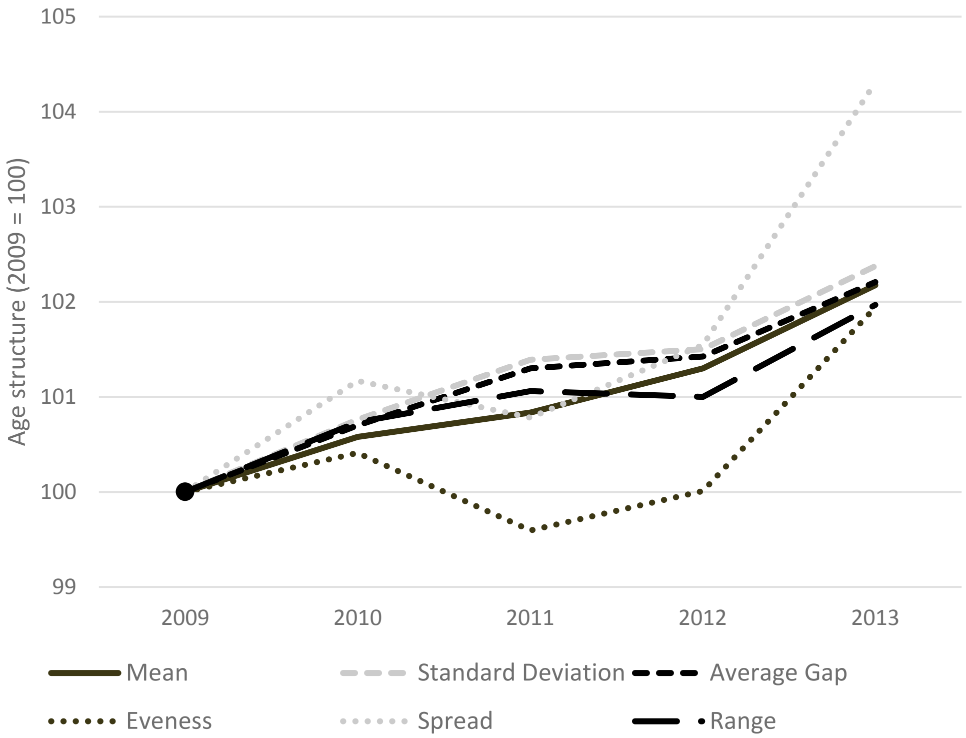
5 Results

Our sample reveals the current developments in labour force ageing trends in Germany (Figure 1). The average age increased by roughly two per cent during the years 2009 and 2013. In addition, it can be seen in particular that the average standard deviation and average age gap constantly increased – implying that demographic change not only affects mean age in the companies, but also age diversity. This type of heterogeneity rose by a little more than two per cent in this period (Hammermann et al., 2017). It is worth mentioning that the evenness of age distribution increased after the shortfall in 2010/2012.[6] Thus, a more separated workforce existed due to more/less new young or older employees in this period.

[5] The propensity of a company to innovate is inherently connected to the R&D performances. The IAB Establishment Panel documents only biennially whether a company is research-orientated with a binary characteristic of 'being an R&D unit' (2009, 2011, 2013). To overcome this problem of missing data, we used a rule-of-thumb imputation, which might induce a measurement error, i.e. backward-looking continuation, which inspects the R&D variable in the prior year whenever the current year experiences a missing value.

[6] In 2011, this heterogeneity index shrinks due to a broader age range in the companies and a less equal age distribution in the companies (the range [numerator] increased continuously, while the denominator of the evenness index must have increased more strongly, but less than the square of the range, because the evenness decreased compared to 2010 and spread increased compared to 2010).

Figure 1: Ageing workforces within companies in Germany



Source: Own illustration based on LIAB data

In Table 2, descriptive evidence is presented for the year 2013 and split according to the notation in equation (5) – except for panel "R", where tenure figures are shown. The latter will be used as part of the robustness checks in section six.

Complementary to the data in Figure 1, Table 2 displays the absolute values of the age diversity indicators for the year 2013. They characterise a typical company's diversity, which e.g. is on average 43 years. The standard deviation of age is between 1.1 and 26.6, which indicates a rather broad spectrum of age heterogeneity across companies, but as the mean standard deviation is 11.9 (at a mean age of 42.8), it can be assumed that – on average – age structures within the companies are rather diverse. Interestingly, the (mean) age gap is only slightly greater than the (mean) standard deviation and, obviously, shows that the mean distance between the age of one employee and every other employee (in her/his company) approximately equals the mean distance between each value and the mean age. This confirms our assumption that both indicators can be used for robustness checks on each other (section 7).

For a further robustness check, we replace the standard deviation of age by the standard deviation of tenure. Tenure is chosen because it measures working experience within a company in particular, rather than general working and life experience measured by age. Company-specific knowledge can be assumed a significant driver for the development of new product or process innovations. As can be seen in Table 2, mean tenure is about 6.7 years with a standard deviation of 4.6, which also indicates a fairly mixed picture of mean tenure across companies. In addition, average standard deviation and the average tenure gap are closer to each other in absolute and relative terms compared to standard deviation and the average age gap, which also makes them appropriate (alternative) measures in robustness checks.

Table 2: Descriptive statistics for 2013

	Variable	Mean	Sd	Min	Max	Obs
	innovation	0.41	0.492	0	1	8625
AGE	workforce age: mean	42.8	6.655	19.2	68.9	10867
	workforce age: sd	11.9	3.070	1.1	26.6	10867
	workforce age: gap	13.8	3.652	1.2	31.5	10867
	workforce age: evenness	4.8	4.778	1.1	62.0	10867
	workforce age: spread	196,4	238.586	6.3	3844.0	10867
K	capital per worker	5.5	19.108	0	401.7	5285
	share of expansion investment	0.24	0.356	0	1	5499
	technical status					
	outdated	0.03	0.178	0	1	10634
	indeterminate	0.30	0.459	0	1	10634
	modern	0.66	0.472	0	1	10634
L	payroll per worker	25.78	13.83	0	155.8	8562
	qualification level of workers					
	low skilled	0.24	0.293	0	1	8906
	medium skilled	0.67	0.310	0	1	8906
	high skilled	0.09	0.202	0	1	8906
X	share of migrants	0.07	0.140	0	1	10687
	share of women	0.52	0.316	0	1	10687
	share of part-time workers	0.35	0.282	0	1	10580
	age of the company (foundation)					
	more than 15 ago	0.36	0.481	0	1	10525
	less than 15 ago	0.64	0.481	0	1	10525
	RandD unity	0.07	0.259	0	1	10637
	competitive pressure					
	no or low	0.25	0.431	0	1	10658
	medium or high	0.75	0.431	0	1	10658
	export orientation					
	exporting	0.16	0.371	0	1	6897
	non-exporting	0.84	0.371	0	1	6897
	company size					
	5 to 19	0.71	0454	0	1	10678
	20 to 49	0.18	0.386	0	1	10678
	50 to 199	0.09	0.283	0	1	10678
	200 and more	0.02	0.141	0	1	10678
	industries					
	manufacturing	0.24	0.424	0	1	10147
	commercial services	0.35	0.476	0	1	10147
	finance and communication	0.15	0.362	0	1	10147
	social services	0.22	0.413	0	1	10147
	non-profit	0.05	0.211	0	1	10147
	Western Germany	0.82	0.386	0	1	10687
R	workforce tenure: mean	6.66	4.568	0.3	28.7	10678
	workforce tenure: standard dev.	4.83	3.428	0	16.6	10678
	workforce tenure: average gap	5.40	3.887	2.2	19.8	10678

Source: Own calculations from LIAB data

In Table 3, we report the point estimates and significance levels for the average age, the standard deviation of age and the age gap within the workforces. The terms in brackets denote robust standard errors or corrected standard errors, respectively. We consider unbalanced panel estimates. All models are based on at least 7,043 observations covering on average 2,331 companies. The complete estimation results are displayed in Table A 1 in the Appendix. As can be seen in Table 3, static logit, System GMM with strictly exogenous inputs, and System GMM with predetermined production inputs support our hypotheses 1 and 2a, i.e. that mean age is negatively related to innovation, whereas age diversity – measured by standard deviation of age and the age gap – is positively related to innovation. Since both coefficients (age sd and age gap) show the same results, we assign them a high reliability.

Table 3: Estimation results for age: mean, standard deviation and gap

Dependent variable: product or process innovation? (yes/no)	M1 Logit	M2 System GMM (ex)	M3 System GMM (pr)	M4 Logit	M5 System GMM (ex)	M6 System GMM (pr)
workforce age: mean	-.043*** (0.0114)	-.007*** (0.0027)	-.013*** (0.0031)	-.043*** (0.0113)	-.007*** (0.0027)	-.013*** (0.0031)
workforce age: sd	.065*** (0.0210)	.012** (0.0052)	.015*** (0.0059)			
workforce age: gap				0.047*** (0.0174)	.009** (0.0043)	.011** (0.0049)
innovation (lagged)	-	.125*** (0.0468)	.101** (0.0405)	-	.127*** (0.0470)	.101** (0.0407)
Pseudo R^2	0.1157			0.1143		
AR(1)		0.000	0.000		0.000	0.000
AR(2)		0.260	0.173		0.264	0.174
# of Instruments		48	198		48	198
Overidentification test		0.108	0.194		0.106	0.190
Observations	7,044	7,043	7,043	7,044	7,043	7,043

Significance levels: *** p< 0.01 per cent, ** p< 0.05 per cent, * p<0.10 per cent; robust (M1, M4) or corrected (M2-3; M5-6) standard errors in parentheses

Source: Own calculations based on LIAB data

Table 4 presents our age diversity estimates for the evenness and spread in addition to the age mean. Whereas the estimations for the mean age support the results of Table 3, we do not find evidence regarding hypothesis 3, i.e. that a uniformly distributed age structure might affect innovation.

Table 4: Estimation results for age: mean, evenness and spread

Dependent variable: product or process innovation? (yes/no)	M1 Logit	M2 System GMM (ex)	M3 System GMM (pr)	M4 Logit	M5 System GMM (ex)	M6 System GMM (pr)
workforce age: mean	-.044*** (0.0112)	-.007*** (0.0028)	-.013*** (0.0032)	-.044*** (0.0112)	-.007*** (0.0028)	-.013*** (0.0032)
workforce age: evenness	-.013 (0.0101)	-.002 (0.0018)	-.002 (0.0019)			
workforce age: spread				.000 (0.0002)	.000 (0.0000)	-.000 (0.0000)
innovation (lagged)		.127*** (0.0476)	.095** (0.0410)		.128*** (0.0477)	.096** (0.0411)
Pseudo R^2	0.1108			0.1106		
AR(1)		0.000	0.000		0.000	0.000
AR(2)		0.276	0.178		0.279	0.179
# of Instruments		48	198		48	198
Overidentification test		0.098	0.162		0.097	0.160
Observations	7,044	7,043	7,043	7,044	7,043	7,043

Significance levels: *** p< 0.01 per cent, ** p< 0.05 per cent, * p<0.10 per cent; robust (M1, M4) or corrected (M2-3; M5-6) standard errors in parentheses

Source: Own calculations based on LIAB data

Concerning the estimation quality of the System GMM, the Arellano-Bond autocorrelation test indicates that for the estimation models displayed in Table 3, no second-order autocorrelation is present (for the estimation models of System GMM with strictly exogenous inputs the test is significant at the 10 per cent level), but for all GMM estimation models there is first-order autocorrelation. Hansen tests do not reject the validity of overidentifying restrictions in the usual System GMM, where all lags up to the first period in the data are used as instruments. However, this test should not be seen as highly reliable, since it can be weakened when many instruments are included. Difference Sargan tests for various instrument subsets (not reported) lead to the acceptance of the hypothesis of exogeneity of the instruments in most cases.

As we cannot interpret the coefficients of the logit estimates quantitatively, however, we can interpret the signs and significance levels. Fortunately, the estimates of the System GMM reveal directly interpretable effects.

As the coefficients of the age diversity measures reveal, mean age is negatively associated with innovation output, that is, the propensity to innovate declines when the workforce becomes older. A one-unit rise in the average age leads ceteris paribus to a 0.7 to 1.3 per cent decrease in the innovation propensity. In contrast, the age separation effects are always positive. GMM estimates imply an increase of approximately 1.2 to 1.5 per cent in a company's innovativeness due to a one-unit increase in the standard deviation of age. Additionally, the effects of the average age gap show only small deviations, i.e. the estimates suggest an increase of roughly 1.0 per cent (for a one-unit increase from the average age gap). Hence, we can conclude that companies face opposing effects between age diversity and mean age when looking to their age structures to foster innovation activities. The estimate for the lagged innovation reveals that companies pursuing innovative activities in the past (previous period) also show a higher propensity (on average) to engage in innovation activities in the present (current period). Therefore, indications for a path dependency in innovation can be found, i.e. a company 'stands on the shoulders' of past engagement in innovation, and hence has a higher propensity for developing innovation activities in the future.

Further results of the explanatory variables are displayed in the Appendix, in Table A 1 and Table A 2. The capital endowment of a company hardly affects the innovation outcome. According to the estimates, the capital per worker, the share of expansion investments and the technical status of the machines do not have any statistical robust effect on innovation. This seems completely intuitive because small start-ups with low capital resources (per worker) can generate innovations just as well as high-tech companies with extensive capital resources. In contrast, labour inputs contribute positively to a company's innovativeness. System GMM estimates show that an increase of the average payroll per worker is positively correlated with innovation activities. This might be associated with a higher share of high-qualified workers, which also seems an important factor. A one percent increase in the share of high-qualified workers would translate into a 0.232 per cent increase in the propensity to innovate (see M2 of Table A 1 in the Appendix). However, this effect is not significant in System-GMM models with predetermined K_{it} and L_{it}, that is, when a more causal relation is assumed.

Among the other controls, we also find significant positive effects for the share of women[7], if a company was founded less than 15 years ago, if a company is engaged in R&D, if a company is exposed to medium or high competitive pressure and if a company has a high export orientation. In addition, larger companies and companies in West Germany are more likely to provide innovations. In this context, these results offer many starting points for future research to uncover the interdependencies between the propensity to innovate and a company's workforce and structural characteristics.

6 Robustness checks

In this section, we test our main results of Table 3 with modified model specifications and potential predictors for innovativeness. We mainly address two topics: curvilinearity of diversity and a collinearity problem. The first issue stems from hypotheses about the effects of age diversity allowing for decreasing or increasing marginal diversity effects (Buche et al., 2013; Østergaard et al., 2009, 2011). The second issue is to check whether the main innovation driver is the heterogeneity of employees' tenure – instead of age diversity.

Testing for curvilinearity

Based on the previously described diversity approaches, one may expect contradicting effects of age diversity on innovation. Therefore, it seems obvious that nonlinear effects of diversity may play a role when considering a transmission to innovation. Evidence on this issue is presented in Table 5. We use quadratic terms to depict a nonlinear relation. Accordingly, a more flexible functional structure is assigned to the logit model, as it is nonlinear by definition. The adoption of a squared term puts the age effects into a curvilinear form, whereby we test an inverted u-shape relationship with innovation (e.g. Østergaard et al., 2011). We abstained from inserting higher polynomials as we have no indication for other functional relations between age diversity and innovation.

[7] It would be a separate research issue to investigate the relationship of other diversity dimensions to age diversity in detail, since interaction effects and faultlines may also play a role in the propensity to innovate.

Table 5: Testing for curvilinearity

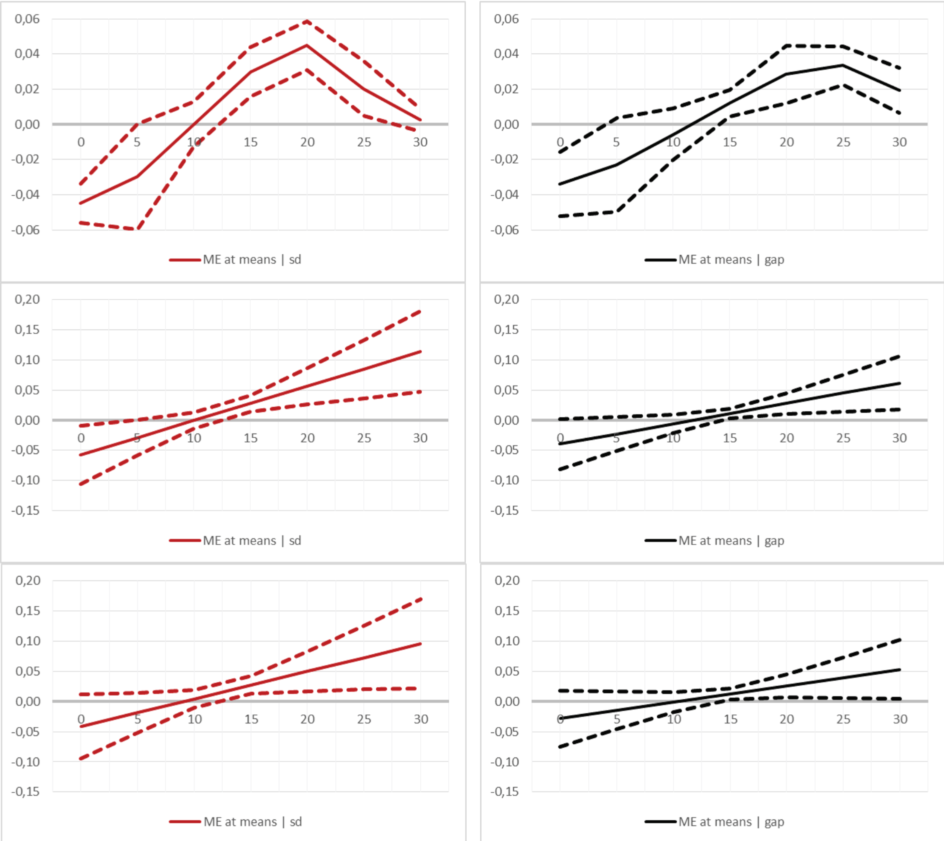
	Logit		System GMM (ex)		System GMM (pre)	
workforce age: mean	-.043*** (0.0113)	-0.044*** (0.0113)	-.007*** (0.0027)	-.007*** (0.0027)	-.012*** (0.0031)	-.012*** (0.0031)
workforce age:sd	-.282** (0.1246)		-.057** (0.0245)		-.041 (0.0273)	
workforce age: sd²	.014*** (0.0050)		.003*** (0.0009)		.002** (0.0011)	
workforce age gap		-.193* (0.1032)		-.040* (0.0212)		-.028 (0.0238)
workforce age: gap²		.008** (0.0035)		.002** (0.0007)		.001* (0.0008)
F-test (H_0: β_{poly1}=β_{poly2}=0)	0.000	0.002	0.000	0.004	0.001	0.009
Observations	7,044	7,044	7,043	7,043	7,043	7,043

Significance levels: *** p< 0.01 per cent, ** p< 0.05 per cent, * p<0.10 per cent; The controls for the model specifications are displayed in Table 2; robust or corrected standard errors in parentheses.

Source: Own calculations based on LIAB data

The relationship is obviously nonlinear, since most estimates indicate a statistically negative relation of the standard deviation (sd) which is overcompensated by its effect of the second polynomial at higher age separation levels. Figure 2 illustrates the nonlinearity of age diversity by mapping marginal effects at sample means, evaluated at flexible values of age heterogeneity. Dashed lines show the 95 per cent confidence interval. The first row presents the results from the logit model and in the second (third) row, the results from System GMM with exogenous predictors (with predetermined production inputs) are displayed.

Figure 2: Marginal effects at means evaluated at a given age diversity



Results in row 1 / 2 / 3 are based on the following models: Logit / System GMM with exogenous predictors / System GMM with predetermined production inputs.

Source: Own illustration based on LIAB data

Concisely, age heterogeneity has a substantial and highly nonlinear effect on innovation from a statistical point of view. For instance, at very low levels of sd and the age gap we find a negative relation to innovation in all specifications. Nevertheless, the "good news" is that we can derive "break-even levels" of age heterogeneity in all models where the negative marginal effect turns into a positive effect. In detail, logit estimates point to an inverted u-shape relationship, whereas the results of System GMM models – not surprisingly – suggest a linear relation (but with varying confidence intervals).

Turning these results into practical implications, one would assume that companies could profit significantly from extending age heterogeneity if it exceeds a certain threshold. Indeed, the upper kink in the logit model suggests a turnaround. However, the average effect only enters the negative area at heterogeneity levels, which are (generally) out of the working age range. Hence, the optimal age mix would be a combination of old and young employees within a bounded range of age heterogeneity (logit) or which exceeds a certain threshold of heterogeneity (System GMM).

Age versus tenure heterogeneity

Human capital theory suggests that company-specific knowledge plays an integral role in accumulating higher pay-offs for individuals and, in a broader sense, one can assume that it also triggers productivity due to its heterogeneity within companies. Theoretically, the age structure could only be a proxy for another driving force for innovation, where the true relations depend on company-specific human capital, namely the structure of tenure among the employees. By excluding the tenure structure in the previous analyses, we intend to eliminate collinearity concerns between the age and tenure measures. Table 6 pins down the effects when focusing on System GMM models with predetermined inputs.

Table 6: Testing for tenure heterogeneity

	System GMM with predetermined inputs (K_{it}, L_{it})					
	R1	**R2**	**R3**	**R4**	**R5**	**R6**
workforce age: mean	-.013*** (0.0031)		-.013*** (0.0031)		-.010*** (0.0033)	-.010*** (0.0033)
workforce age: sd	0.015*** (0.0059)				.015** (0.0061)	
workforce age: gap			.011** (0.0049)			.011** (0.0052)
workforce tenure: mean		-.019*** (0.0069)		-.020*** (0.0070)	-.011* (0.0066)	-.011* (0.0069)
workforce tenure: sd		.007 (0.0107)			.0004 (0.0096)	
workforce tenure: gap				.008 (0.0093)		.002 (0.0090)
F-test **(H_0: β_{sd}=β_{gap}=0)**					0.045	0.090
F-test **(H_0: β_{AGE}=β_{TENURE}=0)**	0.000	0.002	0.000	0.002	0.000	0.000
Observations	7,043	7,032	7,043	7,032	7,032	7,032

Significance levels: *** p< 0.01 per cent, ** p< 0.05 per cent, * p<0.10 per cent; The controls for the model specifications are displayed in Table 2, robust or corrected standard errors in parentheses.

Source: Own calculations based on LIAB data

Apparently, the tenure structure seems to measure other effects than age diversity. In fact, the innovation propensity of companies decreases with increasing mean tenure just as it does for the mean age. A diversified compilation of employees with high and low tenure has no significant effects. From this, we conclude that innovation predominantly comes from working together in age diverse teams and this, in particular, enables a fruitful exchange based on differing life experiences (independent of tenure). In this sense, age-homogenous teams need a combination of experienced employees as well as young employees in order to foster innovation activities.

7 Conclusion

There is growing evidence that company workforces are becoming increasingly diverse in Germany. Yet, the divergent effects of age heterogeneity on output measures at company level are still not investigated to a satisfying extent. Our study provides new evidence on the relevance of different aspects of the age composition to companies' innovativeness. In detail, we find indications to the following three hypotheses: Companies with – on average – older workforces are less innovative (hypothesis 1), companies with more diverse workforces are more innovative (hypothesis 2). Essentially, our results suggest that companies need to exceed a minimal threshold of age diversity to realise innovation potentials. This is also true when applying nonlinear (logit) models but in this case, an inverted u-shape relationship can be observed. With respect to this model, we can deduce that the positive effect of age diversity again decreases above a certain degree but remains positive for higher degrees of age diversity if we assume a standard range for working age. A robust relation between a uniform age distribution and innovation cannot be found in our data (hypothesis 3).

As discussed in section 7, we are aware of several shortfalls in our analytical design. Wherever possible, we applied alternative methods to check the robustness of our results. The most profound limitation, however, may be the measurement of innovation itself. Innovation is only available as a binary variable indicating if a company has achieved a product or process innovation within the previous year of the survey. Furthermore, we do not have any information on diversity and the interaction at team unit level. Therefore, further research is needed to disentangle the different channels of diversity affecting innovation within a company. However, the dataset used in this study provides comprehensive information about companies and enables us to shed light on the age structure of the workforces in detail.

Our research results highlight the importance of age-related human capital for creativity processes and, consequently, for companies' innovativeness. However, the ambiguous propositions regarding the interdependences of age heterogeneity and innovation suggest that the effect could work both ways. Thorough management of diversity within companies might probably be a moderating factor determining the success or failure of heterogeneous teams (Hammermann and Schmidt, 2014).

Human resource managers face a complicated trade-off when they try to bolster a company's innovation capacities. On the one hand, a company probably gains from a mix of young employees' higher inclination towards modern techniques and the vast experience of older employees. On the other hand, experienced employees contribute to a rising average age, which seems to reduce innovativeness. As the optimal composition of the workforce is unknown, our results suggest that the effect of age diversity overcompensates the effects of a higher mean age and, hence, we can conclude that (above a certain threshold) "diversity pays off". The absence of an effect of tenure on innovation should lead human resource managers to rethink team composition, insomuch as it might be more beneficial to foster age diversity than to put emphasis on tenure diversity when aiming to boost innovation activities. More specifically, with regard to a rapidly changing digital landscape and rising skill shortages in many branches, companies need new strategies to address the upcoming challenges using the knowledge sets already at their disposal. Optimising work in age-diverse teams could be a successful starting point. Preferably, further research would provide additional guidelines in this context about the drivers and pitfalls of managing age diversity.

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Appendix

Table A 1: Estimation results for age: mean, standard deviation (sd) and gap

Dependent variable: product or process innovation? (yes/no)	M1 Logit	M2 System GMM (ex)	M3 System GMM (pr)	M4 Logit	M5 System GMM (ex)	M6 System GMM (pr)
workforce age: mean	-.043*** (0.0114)	-.007*** (0.0027)	-.013*** (0.0031)	-.043*** (0.0113)	-.007*** (0.0027)	-.013*** (0.0031)
workforce age: sd	.065*** (0.0210)	.012** (0.0052)	.015*** (0.0059)			
workforce age: gap				0.047*** (0.0174)	.009** (0.0043)	.011** (0.0049)
innovation (t-1)	-	.125*** (0.0468)	.101** (0.0405)	-	.127*** (0.0470)	.101** (0.0407)
share of expansion investments (t-1)	.283 (0.1689)	.061 (0.0357)	.012 (0.0383)	.282 (0.1686)	.061 (0.0358)	.012 (0.0384)
capital per worker	-.001 (0.0023)	-.000 (0.0006)	.001 (0.0008)	-.001 (0.0023)	-.000 (0.0006)	.001 (0.0008)
technical status						
indeterminate	-.504 (0.4088)	-.077 (0.0911)	-.108 (0.1044)	-.484 (0.4069)	-.073 (0.0907)	-.107 (-.1163)
modern	-.338 (0.4041)	-.068 (0.0942)	-.118 (0.1109)	-.317 (0.4023)	-.064 (0.0938)	-.116 (0.1112)
payroll per worker	.012** (0.0056)	.003** (0.0013)	.006*** (0.0022)	.012** (0.0056)	.003** (0.0013)	.006*** (0.0022)
qualification level of workers						
low skilled	-.061 (0.2555)	.008 (0.0618)	.138 (0.1364)	-.053 (0.2551)	.009 (0.0618)	.141 (0.1366)
high skilled	1.233*** (0.3615)	.232*** (0.0771)	.147 (0.1460)	1.215*** (0.3609)	.229*** (0.0772)	.145 (0.1452)
share of migrants	-.785 (0.8439)	-.251 (0.1290)	-.369** (0.1657)	-.819 (0.8381)	-.258* (0.1290)	-.376** (0.1661)
share of women	.993*** (0.2600)	.210*** (0.0628)	0.233*** (0.0731)	.980*** (0.2597)	.208*** (0.0628)	.232*** (0.0733)
share of part time	-.227 (0.3312)	-.096 (0.0816)	-.074 (0.0969)	-.207 (0.3313)	-.094 (0.0819)	-.074 (0.0968)
foundation						
less than 15 ago	.423*** (0.1325)	.093*** (0.0340)	.089** (0.0391)	.415*** (0.1323)	.092*** (0.0341)	.087** (0.0393)
RandD unity	1.605*** (0.2412)	.214*** (0.0361)	.233*** (0.0409)	1.589*** (0.2413)	.212*** (0.0361)	.232*** (0.0408)
competitive pressure						
medium or high	.496*** (0.1489)	.082** (0.0351)	.093*** (0.0347)	.489*** (0.1487)	.081** (0.0352)	.092*** (0.0347)
export orientation						
exporting	.596*** (0.1407)	.106*** (0.0354)	.085** (0.0400)	.600*** (0.1406)	.106*** (0.0355)	.086** (0.0401)
company size						
20 to 49	.085	0.011	-.036	.098	.013	-.032

Dependent variable: product or process innovation? (yes/no)	M1 Logit	M2 System GMM (ex)	M3 System GMM (pr)	M4 Logit	M5 System GMM (ex)	M6 System GMM (pr)
	(0.1378)	(0.0318)	(0.0408)	(0.1376)	(0.0320)	(0.0409)
50 to 199	.392*** (0.1338)	.065* (0.0345)	.042 (0.0422)	.406*** (0.1336)	.068 (0.0346)	.046 (0.0423)
200 and more	.951*** (0.1762)	.145*** (0.0365)	.097** (0.0459)	.967*** (0.1762)	.148*** (0.0367)	.102** (0.0459)
industries	Yes	Yes	Yes	Yes	Yes	Yes
years	Yes	Yes	Yes	Yes	Yes	Yes
Western Germany	.398*** (0.1204)	.085*** (0.0305)	.058 (0.036)	.399*** (0.1204)	.086*** (0.0306)	.059* (0.0364)
Pseudo R^2	0.1157			0.1143		
AR(1)		0.000	0.000		0.000	0.000
AR(2)		0.260	0.173		0.264	0.174
# of Instruments		48	198		48	198
Overidentification test		0.108	0.194		0.106	0.190
Observations	7,044	7,043	7,043	7,044	7,043	7,043

Significance levels: *** p< 0.01 per cent, ** p< 0.05 per cent, * p<0.10 per cent; robust (M1, M4) or corrected (M2-3; M5-6) standard errors in parentheses

Source: Own calculations based on LIAB data

Table A 2: Estimation results for age: mean, evenness and spread

Dependent variable: product or process innovation? (yes/no)	M1 Logit	M2 System GMM (ex)	M3 System GMM (pr)	M4 Logit	M5 System GMM (ex)	M6 System GMM (pr)
workforce age: mean	**-.044*** (0.0112)**	**-.007*** (0.0028)**	**-.013*** (0.0032)**	**-.044*** (0.0112)**	**-.007*** (0.0028)**	**-.013*** (0.0032)**
workforce age: evenness	**-.013 (0.0101)**	**-.002 (0.0018)**	**-.002 (0.0019)**			
workforce age: spread				**.000 (0.0002)**	**.000 (0.0000)**	**-.000 (0.0000)**
innovation (t-1)		.127*** (0.0476)	.095** (0.0410)		.128*** (0.0477)	.096** (0.0411)
share of expansion investments (t-1)	.297* (0.1679)	.065* (0.0363)	.010 (0.0393)	.298* (0.1676)	.065* (0.0363)	.010 (0.0394)
capital per worker	-.001 (0.0023)	-.000 (0.0005)	.001 (0.0008)	-.001 (0.0023)	-.000 (0.0006)	.001 (0.0008)
technical status						
indeterminate	-.448 (0.4083)	-.064 (0.0937)	-.110 (0.1106)	-.452 (0.4085)	-.064 (0.0935)	-.111 (0.1102)
modern	-.271 (0.4039)	-.054 (0.0965)	-.115 (0.1172)	-.276 (0.4043)	-.055 (0.0963)	-.117 (0.1170)
payroll per worker	.010* (0.0055)	.002* (0.0013)	.006*** (0.0022)	.010* (0.0055)	.002* (0.0013)	.006*** (0.0021)
qualification level of workers						
low skilled	-.043 (0.2554)	.011 (0.0624)	.146 (0.1377)	-.040 (0.2549)	.011 (0.0623)	.148 (0.1381)
high skilled	1.148*** (0.3653)	.219*** (0.0793)	.133 (0.1461)	1.158*** (0.3646)	.220*** (0.0795)	.133 (0.1466)
share of migrants	-1.015 (0. 8106)	-.304** (0.1254)	-.437*** (0.1625)	-1.03 (0.8134)	-.305** (0.1255)	-.440*** (0.1632)
share of women	.953*** (0.2623)	.206*** (0.0641)	.237*** (0.0757)	.950*** (0.2616)	.205*** (0.0641)	.236 (0.0759)
share of part time	-.196 (0.3298)	-.091 (0.0837)	-.065 (0.0984)	-.184 (0.3299)	-.090 (0.0837)	-.065 (0.0986)
foundation						

Dependent variable: product or process innovation? (yes/no)	M1 Logit	M2 System GMM (ex)	M3 System GMM (pr)	M4 Logit	M5 System GMM (ex)	M6 System GMM (pr)
less than 15 ago	.391***	.089***	.081**	.393***	.090***	.082**
	(0.1321)	(0.0343)	(0.0403)	(0.1322)	(0.0344)	(0.0406)
RandD unity	1.539***	.205***	.233***	1.533***	.203***	.231***
	(0.2430)	(0.0367)	(0.0421)	(0.2424)	(0.0369)	(0.0424)
competitive pressure						
medium or high	.455***	.076**	.085**	.452***	.075**	.085**
	(0.149)	(.0363)	(0.0365)	(0.1489)	(0.0363)	(0.0364)
export orientation						
exporting	.604***	.109***	.086**	.599***	.107***	.084**
	(0.1412)	(0.0364)	(0.0412)	(0.1410)	(0.0364)	(0.0412)
company size						
20 to 49	.124	.018	-.028	.077	.011	-.034
	(0.1404)	(0.0327)	(0.0411)	(0.1427)	(0.0326)	(0.0415)
50 to 199	.512***	.087**	.069	.367**	.065*	.049
	(0.1544)	(0.0365)	(0.0437)	(0.1652)	(0.0372)	(0.0458)
200 and more	1.217***	.1938***	.150***	.896***	.145***	.107*
	(0.2644)	(0.0515)	(0.0575)	(.2791)	(0.0552)	(0.0647)
industries	Yes	Yes	Yes	Yes	Yes	Yes
years	Yes	Yes	Yes	Yes	Yes	Yes
Western Germany	.420***	.092***	.065*	.422***	.092***	.065*
	(0.1187)	(0.0308)	(0.0372)	(0.1189)	(0.0309)	(0.0372)
Pseudo R^2	0.1108			0,1106		
AR(1)		0.000	0.000		0.000	0.000
AR(2)		0.276	0.178		0.279	0.179
# of Instruments		48	198		48	198
Overidentification test		0.098	0.162		0.097	0.160
Observations	7,044	7,043	7,043	7,044	7,043	7,043

Significance levels: *** p< 0.01 per cent, ** p< 0.05 per cent, * p<0.10 per cent; robust (M1, M4) or corrected (M2-3; M5-6) standard errors in parentheses

Source: Own calculations based on LIAB data

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