Employee age structure and firm innovation

Ilmakunnas, Pekka

Aalto University School of Business

February 2025

Employee age structure and firm innovation

Pekka Ilmakunnas

Aalto University School of Business
pekka.ilmakunnas@aalto.fi

Abstract

The age-innovation relationship is studied at the firm level, using ten waves of Finnish innovation surveys linked to register data on firms and their employees. A negative age-innovation relationship exists for a wide range of average employee ages. This is robust to using employee age group shares instead of average age, using fixed effects and continuous treatment effects estimation, and using six different measures of innovative behavior. Employee age diversity is, however, not related to innovativeness.

Keywords: innovation, aging, age diversity, R&D

JEL codes: J11, J21, O31, O32

I am grateful to the HSE Support Foundation for funding the project.

1. Introduction

Population aging in many countries has increased worries about the possible decline in innovation and the consequent effects on productivity and growth (e.g., Aksoy et al., 2019; The Economist, 2023). Growth slowdown would, for example, create pressures on the sustainability of pension systems. Cognitive abilities and also motivation for innovation decline with age, and there is a long tradition of thinking that the relationship between age and achievements is, therefore, inverse U-shaped (see, e.g., the surveys by Frosch, 2011, and Salthouse, 2012). The effects of age likely depend on the type of occupation, work organization, firms' technology, etc. On the other hand, Salthouse (2012) argues that it is unclear whether the impact of cognitive decline on the overall level of functioning is great. Possible explanations are that cognitive decline may be compensated by more emphasis on quality than quantity in work and more reliance on accumulated knowledge. Indeed, a meta-analysis of individual-level studies (Ng and Feldman, 2013) showed that the relationship between age and innovative behavior is weak and mostly non-significant.

No meta-analyses of firm-level studies of employee age structure and innovation are available.[1] The existing research, briefly reviewed below in section 2, gives a somewhat more pessimistic view of the age-innovation relationship than the individual-level studies. Often, a negative relationship is found between employee age structure and innovation. Still, even many of the firm-level studies find non-significant results.

Innovation is argued to benefit from age diversity, as the younger and older employees may have complementary skills. On the other hand, when employees are attracted to working with similar colleagues, a diverse work group may not work as well as a homogeneous one. In a meta-analysis of research on teams, Schneid et al. (2016) showed that the relationship between age diversity and innovation is insignificant. Also, firm-level studies of the connection between age diversity and innovation give mixed results.

This article contributes in several ways to the firm-level studies of the connection between innovation and the age structure of employees. First, we use several measures of innovation: product or service innovation, process innovation, marketing innovation, organizational innovation, turnover share of new products, and R&D/Employee; second, we use several measures of age structure: average age and age group shares; third, we analyze both age and

[1] Many of the firm-level studies surveyed by Frosch (2011) deal with productivity rather than innovation.

age diversity effects; fourth, we use ten waves of innovation data; and fifth, we use alternative estimation methods: firm fixed effects and continuous treatment effects estimation.

We proceed as follows. In section 2, we briefly review previous firm-level studies. Section 3 introduces the data; section 4 presents fixed effects estimates, and section 5 presents continuous treatment effect estimates. Section 6 concludes the article.

2. Earlier research at the firm level

Previous firm-level studies are summarized in Table A1 in the Appendix. The research can be characterized by the measure of innovation, the measurement of age structure, and the estimation method.

In most studies, the dependent variable was a binary indicator of innovation, based on surveys of firms (Rouvinen, 2002; Verworn and Hipp, 2009; Söllner, 2010; Meyer, 2011; Østergaard et al., 2011; Schubert and Andersson, 2015; Ozgen et al., 2017; Hammermann et al., 2019; Mothe and Nguyen-Thi, 2021). Some studies concentrated on product innovations, some on process innovations, some lumped them together, and some modeled product and process innovations separately. Schneider (2008) uses an ordered variable based on the extent of the newness of innovation. Verworn and Hipp (2009), Schubert and Andersson (2015), and Koski (2015) had dependent variables based on sales due to new innovative products. The number of patents was used as a measure of innovation by Parrotta et al. (2014), Park and Kim (2015), and Derrien et al. (2023), and patent citations by Cui et al. (2019) and Derrien (2023). Pfeifer and Wagner (2014) used the R&D expenditure/revenues and R&D workers/all workers ratios to measure innovative behavior.

The most common age variable was average age (Rouvinen, 2002; Söllner, 2010; Østergaard et al., 2011; Schubert and Andersson, 2015; Hammermann et al., 2019; Cui et al., 2019; Mothe and Nguyen-Thi, 2021). Schneider (2008) and Park and Kim (2015) also included squared average age. Age group shares were also often used (Meyer, 2011; Parrotta et al., 2014; Koski, 2015; Ozgen et al., 2017; Pfeifer and Wagner, 2014). Verworn and Hipp (2009) used an indicator for a high share of old employees. Derrien et al. (2023) used the share of young employees and average age in the commuting zone where the firm's headquarters is situated as alternative measures.

The results indicated negative age effects on innovation (Rouvinen, 2002; Söllner, 2010; Meyer, 2011; Pfeifer and Wagner, 2014; Schubert and Andersson, 2015; Ozgen et al., 2017; Hammermann et al., 2019; Mothe and Nguyen-Thi, 2021; Derrien et al. 2023), and sometimes an inverse U-shaped age-innovation relationship (Schneider, 2008; Parrotta et al., 2014; Koski, 2015; Park and Kim, 2015). An insignificant age effect was observed by Verworn and Hipp (2009), Østergaard et al. (2011), Ozgen et al. (2017), and Cui et al. (2019).[2]

Only a few of the studies mentioned above also examined the relationship between innovation and age diversity, measuring diversity with the coefficient of variation or standard deviation of age (Schneider, 2008; Söllner, 2010; Østergaard et al., 2011; Hammermann et al., 2019)), the Herfindahl and Blau indexes (Meyer, 2011; Parrotta et al., 2014; Park and Kim, 2015; Mothe and Nguyen-Thi, 2021), and other measures (Hammermann et al., 2019). The results were mixed. Mostly a negative or insignificant relationship was found between age diversity and innovation. Still, a few studies found a positive relationship.

Since innovation data are typically collected in surveys that are not conducted annually and may use rotating samples, most researchers have relied on cross-section data or only two or three survey waves. Moreover, policy changes do not affect the age structure, and it is hard to find variables that could be used as instruments. The causality of the results has seldom been discussed. Schubert and Andersson (2015), Ozgen et al. (2017), and Hammermann et al. (2019), however, used panel methods to account for unobservable time-invariant firm characteristics. Derrien et al. (2023) instrumented the age structure by commuting area births-based age structure. Parrotta et al. (2014) instrumented age diversity by past diversity in the commuting area and Mothe and Nguyen-Thi (2021) by lagged firm diversity but did not instrument average age or age group shares.

3. Data

We used 10 waves of Innovation Surveys by Statistics Finland, which are part of the Community Innovation Surveys (CIS) coordinated by Eurostat. The waves that we used are from the years 2000 to 2018. The surveys are conducted at two-year intervals, and the questions refer to innovations in the two years before the survey. We used the following innovation variables: 1) an indicator for product or service innovation (new or improved

[2] In related work, Frosch et al. (2011) found that inflows of younger employees and outflows of older ones were not related to innovative performance.

products or services); 2) an indicator for process innovation (new or improved methods of producing or developing goods or services); 3) an indicator for marketing innovation (new marketing methods for promotion, packaging, pricing, product placement); 4) an indicator for organizational innovation (new business practices, new methods for organizing work responsibilities and decision making, new methods of organizing external relations); 5) the percentage of turnover from new innovative products or services; 6) internal real R&D expenditure/employees.[3] Information on organizational and marketing innovations is available only starting from the 2008 survey.

In many studies, R&D is used to explain innovation. However, R&D is a "bad control" (Angrist and Pischke, 2009) since it is strongly related to the age structure. Indeed, for example, Pfeifer and Wagner (2014) used R&D itself as a measure of innovative behavior.

The innovation data were combined with register data on firms from the Business Register and R&D Statistics. As control variables, we used productivity (real sales per employee), growth (percentage change in the number of employees), industry (18 two-digit industries), firm size (7 size classes), indicators for exporters, importers, and publicly owned firms, and the number of plants. Worker characteristics were calculated from the FOLK data set of Statistics Finland that covers the whole working-age population and has a link to the employer at the end of the year. These data were used for calculating the age structure variables (average age, age group shares, standard deviation of age), the educational variables (average education years based on standard degree times, standard deviation of education years), and the share of female employees. Since the innovation variable refers to innovation in the two years before the survey, the firm and employee characteristics were lagged by two years. We also included year indicators. Descriptive statistics of the variables are in Appendix 2.

There is limited overlap between the surveys. The number of firms for which the dummy variable for product or service innovation and all the other variables are available is 10162, and the number of firm-year observations is 21501 (see Table 1). When only firms that are in at least two surveys are included, the number of firms drops to 4966 and the number of firm-year observations to 16305. Of the firms with at least two observations, 28 percent have only two, and nearly half have two or three observations. Even when there is more than one

[3] We did not use R&D/Turnover since this measure has many extreme values. For example, startups may have big R&D expenditures but still low turnover.

observation, there are gaps in the panel data, as not all firms are included in successive years. If we further drop firms that have innovated in all years when they are in the survey or have never innovated, there is a further drop in the number of firms to 3041 and the number of observations to 7725. The number of observations is smaller for marketing and organizational innovations, and the R&D data are missing for many firms.

The share of firm-year observations with a product or service innovation is 40 percent. The other innovation types are slightly less common. The share of observations with marketing innovation is less than 30 percent. When we restrict attention to firms with more than one observation or drop permanent innovators and non-innovators, the share of observations with innovation increases. This happens especially for marketing and organizational innovations which shows that many firms never have these kinds of innovations.

	Product or service innovation	Process innovation	Marketing innovation	Organizational innovation	Turnover share of innovative products, %	R&D / employee
All observations						
Mean	0.405	0.367	0.291	0.351	8.532	42.363
Standard deviation	0.491	0.482	0.454	0.477	18.477	176.678
Firm-year observations.	21501	21478	12889	12899	21372	14326
Number of firms	10162	10157	7052	7052	10140	7434
Firms with at least two observations						
Mean	0.425	0.389	0.297	0.361	8.433	41.415
Standard deviation	0.494	0.487	0.457	0.480	17.824	178.221
Firm-year observations	16305	16287	10072	10072	16198	11178
Number of firms	4966	4966	4233	4233	4966	4286
Firms with change in innovation						
Mean	0.492	0.479	0.544	0.575		
Standard deviation	0.500	0.500	0.498	0.494		
Firm-year observations	7725	9685	4699	5429		
Number of firms	2041	2550	1651	1927		

Table 1. Descriptive statistics on innovation measures in different samples

The innovation indicators are correlated with each other, but not perfectly (Table 2). Figure 1 shows the kernel density distributions of average age for innovators and non-innovators for the four binary measures of innovation. The distributions are fairly similar for all innovation types and show that non-innovators have a somewhat higher average age.

	Product or service innovation	Process innovation	Marketing innovation	Organiza-tional innovation	Turnover share of innovative products	R&D/ Employee
Product or service innovation	1					
Process innovation	0.468***	1				
Marketing innovation	0.463***	0.408***	1			
Organizational innovation	0.414***	0.501***	0.500***	1		
Share of innovative products	0.564***	0.300***	0.280***	0.260***	1	
R&D/Employee	0.120***	0.041***	0.083***	0.079***	0.177***	1

Note: Significance level: *** 1%

Table 2. Correlation matrix of innovation measures

Figure 1. Kernel densities of average age for binary innovation measures

4. Fixed effects estimates

We used firm fixed effects models to control for time-invariant firm unobservables that might be correlated with innovative behavior. For the binary indicators of innovation (product or service; process; marketing; organizational) these are linear probability models. To examine the relationship between age and innovation, we used the age variables in different forms: a polynomial of average age and age group shares. In the fixed effects models, firms that always innovate or never innovate do not contribute to the estimates, as in these cases, the deviation of the innovation indicator from the firm mean is always zero. This leads to a big loss of observations (see Table 1).

Panel A of Table 3 shows the estimation results with average age.[4] The standard errors are clustered by firm. We started with a cubic polynomial and dropped insignificant higher-order terms. It turned out that a cubic polynomial works in the case of product or service innovation, a quadratic age function in the case of process innovation and share of innovative products, and a linear age term for marketing innovation and R&D. For organizational innovation, even the linear age term is insignificant (p-value 0.014). The cubic and quadratic functions show a slightly U-shaped relationship between innovation and average age, and the linear terms show a steadily declining relationship.

		Product or service innovation	Process innovation	Marketing innovation	Organizational innovation	Turnover share of innovative products, %	R&D / employee
A	Average age	0.068	-0.031**	-0.006**	-0.004	-1.381***	-2.539***
		(0.045)	(0.013)	(0.003)	(0.003)	(0.498)	(0.989)
	Average age^2	-0.002*	0.0004**			0.015**	
		(0.001)	(0.0002)			(0.006)	
	Average age^3	-0.00002**					
		(0.00001)					
	Std. dev. of age	-0.003	0.001	-0.0002	0.003	-0.306**	-0.843
		(0.003)	(0.004)	(0.0045)	(0.005)	(0.137)	(2.075)
B	Share -30 (ref)						
	Share 31-40	-0.071	-0.057	0.067	0.010	-6.243**	-22.949
		(0.055)	(0.063)	(0.089)	(0.095)	(2.450)	(45.795)
	Share 41-50	-0.167***	-0.143**	-0.176*	-0.242**	-8.252***	-26.600
		(0.057)	(0.064)	(0.094)	(0.102)	(2.391)	(43.811)
	Share 51-	-0.156***	-0.112*	-0.180**	-0.145**	-5.445**	-72.442**
		(0.060)	(0.066)	(0.087)	(0.092)	(2.131)	(35.721)
	Std. dev. of age	-0.007*	-0.003	-0.00006	-0.00007	-0.576***	-0.273
		(0.004)	(0.004)	(0.00521)	(0.00554)	(0.140)	(1.184)

Note: Standard errors clustered by firm. Significance level: *** 1%, ** 5%, * 10%

Table 3. Fixed effects estimation results

The implied age-innovation relationships are shown in Figure 2. The graphs are average predicted means and their 95% confidence intervals at different levels of average age, based on models with the full set of controls and the coefficients of the average age terms reported

[4] The results on the control variables are not reported, but they are available from the author.

in Panel A of Table 2. (We restrict attention to average ages from 30 to 50 since the number of observations at the tails of the age distribution is small and the resulting confidence intervals wide.) The age-innovation relationships show that the main decline in innovativeness happens at ages 35 to 45. Before this age, although the curves are downward sloping, the confidence intervals are large. At older average ages, the curves either rise (in the cubic and quadratic cases) or continue to decline. However, also at older ages, the confidence intervals are large, so the change in innovativeness with age is not significant.

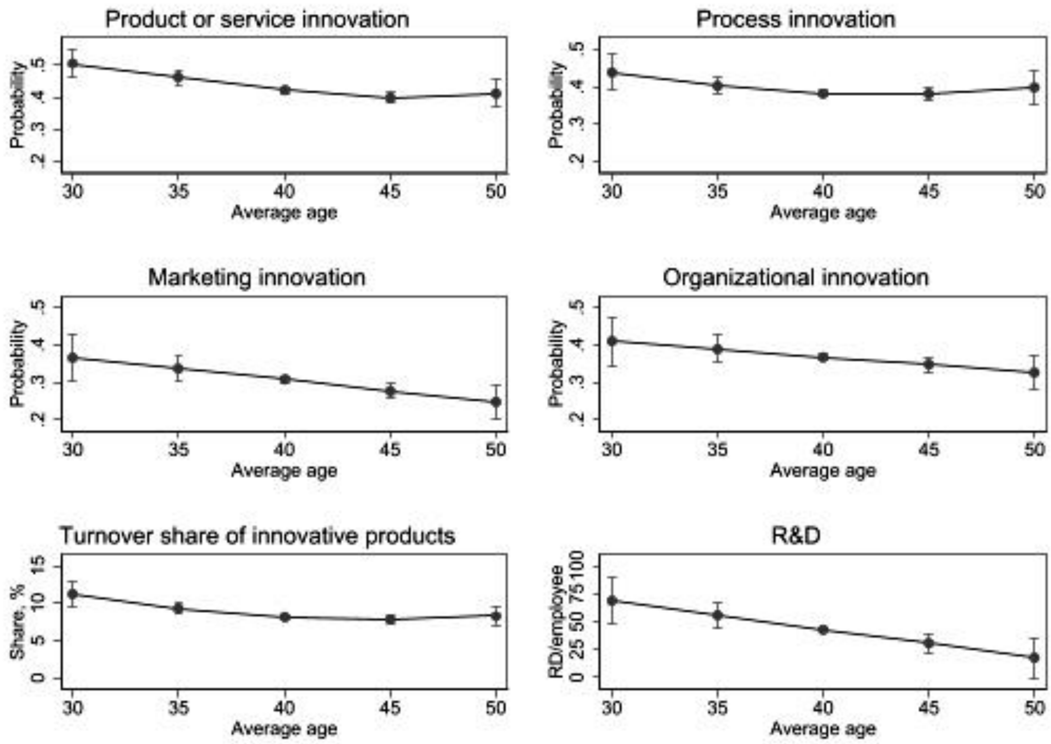

Figure 2. Age-innovation relationships, fixed effects models with average age

When the age group shares 30 or below (reference group), 31-40, 41-50, and 51 or above were used as the age variables (Panel B), the coefficient of the 31-40 years age group is not significantly different from the reference group, those 30 or younger, in the linear probability models for the binary innovation measures. The share of 41-50-year-olds is negatively related to innovation, and the share of 51-year-olds or older is also negatively related to innovation, but slightly less so than the share of 41-50-year-olds. This shows that after age 40, innovation declines, but at older ages, the decline slows down. When the turnover share of innovative products is the innovativeness measure, already the age group 31-40 affects innovation negatively, compared to the reference group. Also here, the decline slows down in the oldest age group. For R&D, only the oldest age group is significantly negatively related to innovativeness. Overall, the results are mostly consistent with those obtained with the average age variable.

The results support the view that cognitive decline with age reduces innovativeness. Although experience can compensate for cognitive declines at the individual level, it may be that when all are aging, the firm-level effect is still negative.

The models of Table 2 also include the standard deviation of employee ages as a measure of age diversity. The results indicate that the point estimates of the coefficient of age diversity are mostly negative but insignificant. However, there is a negative and significant relationship between age diversity and the turnover share of innovative products. The coefficient is also significant in the case of product innovation but only when age group shares are used. These results are consistent with the findings of Schneid et al. (2016) for teams and support the view that there are no age-based complementarities. It seems that age diversity alone does not contribute positively to innovativeness.

We also used the Fair and Dominguez (1991) approach to model the age effects. Age-specific shares are collapsed into two terms, from which the age-specific coefficients can be calculated (see Appendix 3). The results were very close to those obtained with the average age variable.

To analyze the sensitivity of the results, we used probit models instead of linear probability models for the four binary innovation measures and estimated the models with pooled data. It turned out that the polynomial of the average was reduced to a linear term with a significant negative coefficient in all four cases. In the age share approach, the coefficients of the oldest age group were negative and higher in absolute value than the coefficient of the age group 41-50, so there was no slowdown in the decline at older ages. These results show that not accounting for unobservables may exaggerate the decline in innovativeness by age.

5. Continuous treatment effect estimates

The fixed effects method eliminates time-invariant unobservables, but there may be time-varying unobservables that affect the results. To investigate further the causal effect of average employee age on innovation, we also used the continuous treatment effect model suggested by Imai and van Dyk (2004) (see also Zhao, van Dyk, and Imai, 2020). We used pooled data as the method cannot handle fixed effects.

The average age was used as a continuous treatment, and innovation as the outcome. The method is based on two assumptions. First, the distribution of potential outcomes for a unit (firm) is independent of the potential treatment status of the other units, given the observed covariates (Stable Unit Treatment Value Assumption, SUTVA). This "non-interference" assumption means, in our case, that the innovation probability of a firm does not depend on the age structure of the other firms once we control the observed firm characteristics. Second, the distribution of the actual treatment does not depend on the potential outcomes, given the observed covariates (Strong Ignorability of Treatment Assignment Assumption). That is, the distribution of average ages does not depend on the probability of innovation, conditionally on the observed characteristics of the firms. (Note that Figure 1 shows that the distribution of average age is somewhat different for innovators and non-innovators when firm characteristics are not controlled.)

Imai and van Dyk (2004) showed that potential outcomes and actual treatment are independent, conditionally on the propensity function. The propensity function is the conditional distribution of the treatment, given the covariates X. Assuming the distribution to be normal $N(X\beta, \sigma^2)$, the propensity function can be characterized by the parameter $\theta = X\beta$. This can be estimated with a linear regression of average age on X, which includes all other variables. We estimated the effect of average age on innovation from a probit model for each binary innovation measure, where average age, the estimated $\hat{\theta} = X\hat{\beta}$ and the X variables were included. We used linear models for the turnover share of innovative products and R&D per employee. To allow for nonlinear age effects, we used a quadratic function with average age, its square, $\hat{\theta}$, $\hat{\theta}^2$, and the interaction of average age and $\hat{\theta}$. As an alternative, we used a spline function with 5 knots for $\hat{\theta}$, and interacted the spline with average age, but the results did not differ much from the quadratic specification. Standard errors were estimated from 100 bootstrap replications of both the regression for $\hat{\theta}$ and the outcome model.

Covariate balance was checked using the regression-based method suggested by Imai and van Dyk (2004). Each variable was explained by the treatment variable average age. For continuous variables, the logarithm of the variable was regressed on average age, and for binary variables, a probit model was used[5]. The left-hand side of Figure 3 shows a standard

[5] The logarithmic form and probit are used because given $\hat{\theta}$, the untransformed variables would be uncorrelated with average age.

normal quantile plot of the t-values from these estimations. Some of the t-values are quite large, indicating that average age is correlated with the variables. Next, the regressions were repeated, also controlling for the estimated $\hat{\theta}$. The resulting t-values are on the right-hand side of Figure 3. The graph shows that the t-values are considerably lower, so the covariate balance has improved.

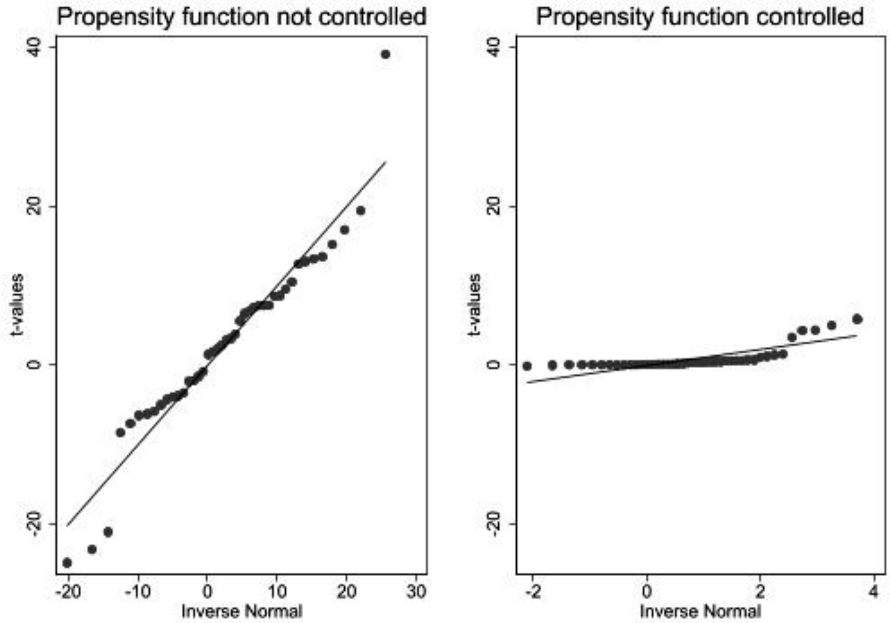

Figure 3. Covariate balance

Figure 4 shows the relationship between average age and innovation for each innovation measure. The graphs show the average predicted values and their 95% confidence intervals at different levels of average age. In all cases, the relationship is negative for a wide range of average ages. For product innovation and organizational innovation, the curves are increasing at low average ages. However, the standard errors are so large in the tails of the graphs that there is no significant increase. Correspondingly, at high average ages, the standard errors are so large that the further decline in innovativeness is insignificant, consistently with the fixed effects estimates.

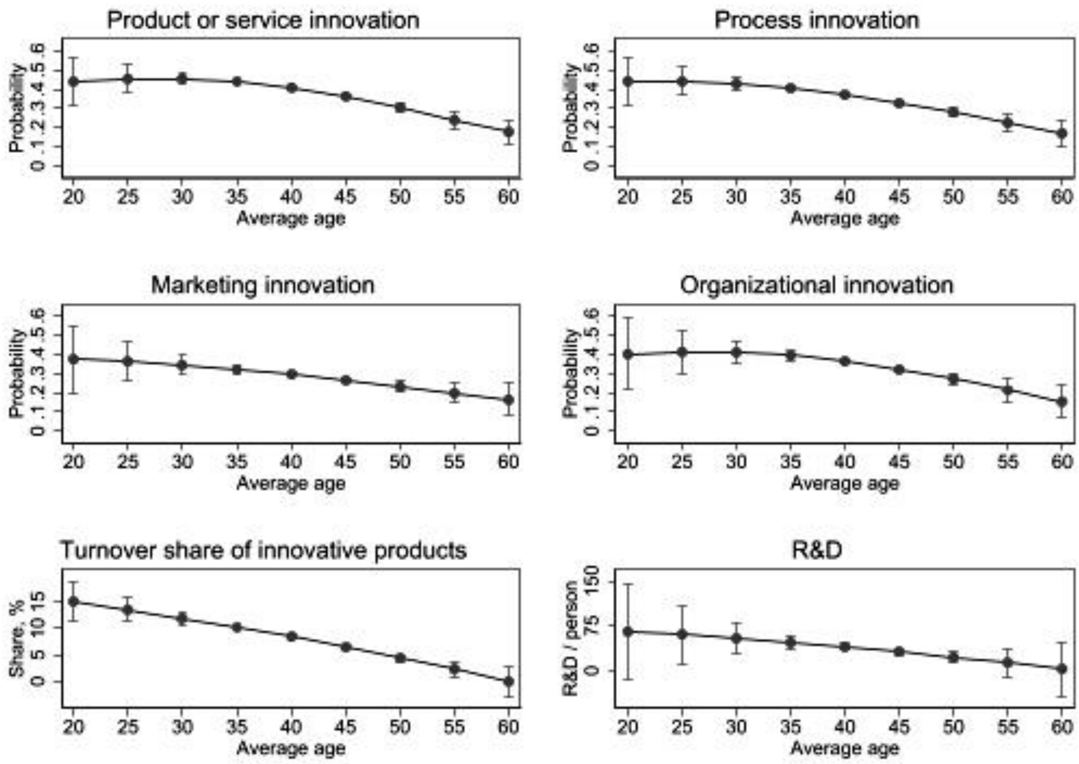

Figure 4. Age-innovation relationships, Imai and van Dyk approach

6. Conclusions

Overall, our results indicate that for a significant part of the workforce age distribution, innovativeness decreases with age, and age diversity is not significantly related to innovation. This supports the concern that workforce aging may have detrimental effects on the economy.

It is possible, however, that the age effect is overestimated since firm age and average employee age are likely correlated (Coad, 2018). This means that the result of a negative connection between average employee age and innovation may partly be due to old firms having old technology and old products.[6] Therefore, their employees perhaps have fewer possibilities and incentives for innovation. Upgrading the technology in older firms can, therefore, counteract the effects of workforce aging.

[6] A negative connection between firm age and innovation was found, for example, by Huergo and Jaumandreu (2004), Balasubramanian and Lee (2008), and Cucculelli (2018).

References

Aksoy, Y., Basso, H.S., Smith, R.P., and Grasl, T., Demographic structure and macroeconomic trends, American Economic Journal: Macroeconomics 11, 2019, 193–222.

Angrist, J.D. and Pischke, J.-S., Mostly Harmless Econometrics, Princeton University Press, 2009.

Balasubramanian, N. and Lee, J., Firm age and innovation, Industrial and Corporate Change 17, 2008, 1019–1047.

Coad, A. Firm age: A survey, Journal of Evolutionary Economics 28, 2018, 13-43.

Cucculelli, M., Firm age and the probability of product innovation. Do CEO tenure and product tenure matter? Journal of Evolutionary Economics 28, 2018, 153–179.

Cui, V., Ding, W.W., and Yanadori, Y., Exploration versus exploitation in technology firms: The role of compensation structure for R&D workforce, Research Policy 48, 2019, 1534-1549.

Derrien, F., Kecskés, A., and Nguyen, P.A., Labor force demographics and corporate innovation, Review of Financial Studies 36, 2023, 2797–2838.

Fair, R.C. and Dominguez, K.M., Effects of the changing U.S. age distribution on macroeconomic equations, American Economic Review 81, 1991, 1276- 1294.

Frosch, K.H., Workforce age and innovation: A literature survey, International Journal of Management Reviews 13, 2011, 414–430.

Frosch, K., Göbel, C., and Zwick, T., Separating wheat and chaff: age-specific staffing strategies and innovative performance at the firm level, Journal of Labour Market Research 44, 2011, 321–338.

Hammermann, A., Niendorf, M., and Schmidt, J., Age diversity and innovation: Do mixed teams of 'old and experienced' and 'young and restless' employees foster companies' innovativeness?, IAB Discussion Paper 4|2019.

Huergo, E. and Jaumandreu, J. (2004) How does probability of innovation change with firm age? Small Business Economics 22, 2004, 193–207.

Imai, K. and van Dyk, D.A., Causal inference with general treatment regimes: Generalizing the propensity score. Journal of the American Statistical Association 99, 2004, 854-866.

Koski, H., Commercial success of innovation. The roles of R&D cooperation and firm age, ETLA Working Papers No. 30, 2015.

Meyer, J., Workforce age and technology adoption in small and medium-sized service firms, Small Business Economics 37, 2011, 305–324.

Mothe, C. and Nguyen-Thi, T.U., Does age diversity boost technological innovation? Exploring the moderating role of HR practices, European Management Journal 39, 2021, 829-843.

Ng, T.W.H. and Feldman, D.C., A meta-analysis of the relationships of age and tenure with innovation-related behaviour. Journal of Occupational and Organizational Psychology 86, 2013, 585–616.

Østergaard, C.R., Timmermans, B., and Kristinsson, K., Does a different view create something new? The effect of employee diversity on innovation, Research Policy 40, 2011. 500–509.

Ozgen, C., Nijkamp, P., and Poot, J., The elusive effects of workplace diversity on innovation, Papers in Regional Science 96, Supplement 1, 2017, S29-S49.

Park, J. and Kim, S., The differentiating effects of workforce aging on exploitative and exploratory innovation: The moderating role of workforce diversity, Asia Pacific Journal of Management 32, 2015, 481–503.

Parrotta, P., Pozzoli, D., and Pytlikova, M., The nexus between labor diversity and firm's innovation, Journal of Population Economics 27, 2014, 303–364.

Pfeifer, C. and Wagner, J., Is innovative firm behavior correlated with age and gender composition of the workforce? Evidence from a new type of data for German enterprises. Journal of Labour Market Research 47, 2014, 223–231.

Rouvinen, P., Characteristics of product and process innovators: some evidence from the Finnish innovation survey, Applied Economics Letters 9, 2002, 575-580.

Salthouse, T., Consequences of age-related cognitive declines, Annual Review of Psychology 63, 2012, 201–226.

Schneid, M., Isidor, R., Steinmetz, H., and Kabst, R., Age diversity and team outcomes: a quantitative review, Journal of Managerial Psychology 31, 2016, 2-17.

Schneider, L., Alterung und technologisches Innovationspotential. Eine Linked Employer-Employee Analyse, Zeitschrift für Bevölkerungswissenschaft 33, 2008, 37–54.

Schubert, S. and Andersson, M., Old is gold? The effects of employee age on innovation and the moderating effects of employment turnover, Economics of Innovation and New Technology 24, 2015,95-113.

Söllner, R., Human capital diversity and product innovation: A micro-level analysis, Jena Economic Research Papers 2010 – 027.

The Economist. Ageing and innovation. The old and the zestless, June 3 – 9, 2023, 16-18.

Verworn, B. and Hipp, C., Does the ageing workforce hamper the innovativeness of firms? (No) evidence from Germany, International Journal of Human Resources Development and Management 9, 2009, 180-197.

Zhao, S., van Dyk, D.A., and Imai, K. Propensity score-based methods for causal inference in observational studies with non-binary treatments. Statistical Methods in Medical Research 29, 2020, 709–727.

Appendix 1. Previous firm-level studies

Authors	**Dependent variables**	**Data type**	**Estimation method**	**Age structure measure and results**	**Age diversity measure and results**
Rouvinen 2002	Product innovation; process innovation	Cross section (Finland)	Bivariate probit	Average age: negative for process, not significant for product innovation	
Schneider 2008	Product innovation, 4 categories (no innovation, product improvement, new product for firm, new product for market)	Cross section (Germany)	Ordered logit	Average age, average age squared: inverse U-shaped	Coefficient of variation of age: negative
Verworn & Hipp 2009	Innovation (product or process); market novelties; high turnover share (>20%) due to product innovations	Cross section (Germany)	Probit	Dummy for high share (>20%) of old (50+): not significant	
Söllner 2010	Product innovation; new product	Panel (Germany)	Random effects probit	Average age: negative	Coefficient of variation of age: not significant
Meyer 2011	Adoption of new or improved technology	Cross section (Germany)	Probit	4 age group shares (-29, 30-39, 40-54, 55-): negative	Herfindahl index of age: not significant or negative
Østergaard, Timmermans & Kristinsson 2011	Product innovation	Cross section (Denmark)	Logit	log of average age: not significant	Standard deviation of age: negative
Parrotta, Pozzoli & Pytlikova 2014	Patenting; number of patents	Panel (Denmark)	Probit; Poisson. Past diversity in commuting area as instrument	4 age group shares (15-28, 29-36, 37-47, 48-65): inverse U-shaped	Herfindahl index of 4 age groups by gender: not significant
Pfeifer & Wagner 2014	R&D expenditure/revenues; R&D workers/all	Panel (Germany)	Fractional logit	3 age group shares (-30, 30-49, 50-): negative for 50-	
Schubert & Anderson 2015	Product innovation; turnover share due to new products	Panel (Sweden)	Probit; Tobit. Mundlak approach	Average age: negative	
Koski 2015	Turnover per employee due to new or improved products	Pooled cross sections (Finland)	OLS	5 age group shares (16-24, 25-34, 35-44, 45-54, 55-70): inverse U	
Park & Kim 2015	Sales/R&D; patents	Cross section (Korea)	OLS; negative binomial	Average age, positive for S/R&D; Avg. age, avg. age squared: inverse U-shaped for patents	Blau index: positive, interaction with average age negative

Ozgen, Nijkamp & Poot 2017	Product innovation; process innovation	Panel (Netherlands)	Pooled and fixed effects logit, fixed and random effects linear probability	Share of young (25-44): positive or not significant	
Hammermann, Niendorf & Schmidt 2019	Innovation (product or process)	Panel (Germany)	Logit, GMM linear probability	Average age: negative	Standard deviation of age: positive, average age gap: positive
Cui, Ding, & Yanadori 2019	Exploratory patents, originality (proportions based on citations)	Panel (US)	Fractional logit	Average age in R&D division: not significant	
Mothe & Nguyen-Thi 2021	Product innovation; process innovation	Panel (Luxembourg)	Instrumental variables probit; Lagged diversity as instrument	Average age: negative	Age polarization index negative and age variety (1-Herfindahl) positive for product innovation, both non-significant for process innovation
Derrien, Kecskés, & Nguyen 2023	Patent count, patent citations	Panel (US)	Instrumental variables; Commuting area births-based instrument	Share of young (20-39): positive, average age: negative; Age structure measured in commuting area	

Appendix 2. Descriptive statistics

Variable	N	Mean	Standard deviation
Product or service innovation	21501	0.405	0.491
Process innovation	21478	0.367	0.482
Marketing innovation	12891	0.291	0.454
Organizational innovation	12891	0.351	0.477
Turnover share of innovative products, %	20153	6.032	14.756
R&D/employee	14326	42.363	176.678
Average age	21501	40.394	5.058
Standard deviation of age	21501	10.412	2.216
Share age 15-30	21501	0.236	0.165
Share age 31-40	21501	0.272	0.130
Share age 41-50	21501	0.262	0.121
Share age 51-70	21501	0.230	0.151
Average education years	21501	12.825	1.534
Standard deviation of education years	21501	2.190	0.558
Female share	21501	0.279	0.224
Productivity	21501	0.460	0.582
Employment growth	21501	0.161	2.162
Number of plants	21501	3.309	12.946
Exporter	21501	0.472	0.499
Importer	21501	0.565	0.496
Publicly owned	21501	0.039	0.194
Size 0-10	21501	0.085	0.278
Size 11-20	21501	0.261	0.439
Size 21-50	21501	0.247	0.431
Size 51-100	21501	0.165	0.371
Size 101-200	21501	0.101	0.301
Size 201-500	21501	0.089	0.285
Size 501-	21501	0.052	0.221

Note. Industry and year indicators are not shown.

Table A1. Descriptive statistics of the variables

Appendix 3. Fair-Dominguez approach

In principle, we could include in the model 54 age group shares for ages from 17 to 70 with coefficients α_j , j = 1,…,54 (with group 1 denoting 17 years old, etc.). Fair and Dominguez (1991) suggested an approach where, using some assumptions on the coefficients of the age group variables, the age effects can be estimated from the coefficients of just two terms, which are combinations of the age shares. The estimation involves using variables (omitting firm and time subscripts for simplicity)

$$Z_1 = \sum_{j=1}^{54} j s_j - \left(\frac{1}{54}\right) \sum_{j=1}^{54} j \sum_{j=1}^{54} s_j$$

$$Z_2 = \sum_{j=1}^{54} j^2 s_j - \left(\frac{1}{54}\right) \sum_{j=1}^{54} j^2 \sum_{j=1}^{54} s_j$$

where s_j is the share of age group j (in a firm in a particular year). Their coefficients are γ_1 and γ_2 , respectively. Note that since we calculate the shares of each one-year age group of the total number of employees aged 17 to 70 for each firm, the sum of the shares in the above equations is one, $\sum_j s_j = 1$. The coefficients of the age group shares are obtained as

$$\alpha_j = \gamma_0 + \gamma_1 j + \gamma_2 j^2$$

where

$$\gamma_0 = -\gamma_1 \left(\frac{1}{54}\right) \sum_{j=1}^{54} j - \gamma_2 \left(\frac{1}{54}\right) \sum_{j=1}^{54} j^2$$

The fixed effects estimation results are in Table A1. The coefficients of the Z_2 terms were insignificant for marketing and organizational innovation and R&D and were dropped. In these cases, the resulting coefficients of Z_1 are close to the results with average age in Panel A of Table 3. The estimates imply a slightly U-shaped relationship for product and process innovations and the share of innovative products, again echoing the results in Panel A. The pattern of the implied age-innovation relationships, i.e., the pattern of the α_j coefficients plotted against age is very close to the pattern in Figure 3 and, therefore, not shown here.

	Product or service innovation	Process innovation	Marketing innovation	Organizational innovation	Turnover share of innovative products, %	R&D / employee
Z1	-0.019**	-0.016**	-0.006**	-0.004	-0.763**	-2.510***
	(0.008)	(0.008)	(0.003)	(0.003)	(0.309)	(0.979)
Z2	0.0002*	0.0002*			0.008**	
	(0.0001)	(0.0001)			(0.004)	
Std. dev. of age	-0.007**	-0.003	-0.0003	0.003	-0.493***	-0.829
	(0.003)	(0.004)	(0.0046)	(0.005)	(0.130)	(2.073)

Note: standard errors clustered by firm. Significance level: *** 1%, ** 5%, * 10%

Table A2. Fixed effects estimation results, Fair-Dominguez approach