Economics Bulletin

Volume 45, Issue 4

Employee age structure and firm innovation

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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.

Funding from the HSE Support Foundation is gratefully acknowledged.
Citation: Pekka Ilmakunnas, (2025) "Employee age structure and firm innovation", *Economics Bulletin*, Volume 45, Issue 4, pages 1840-1849
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Submitted: May 28, 2025. **Published:** December 30, 2025.

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. Previous studies have used only some of them at the same time, and marketing and organizational innovations have not been examined before. Second, we compare different measures of age structure: average age and age group shares. Third, we analyze both age and age diversity effects. Fourth, we use ten waves of innovation data, which is a longer period than in previous studies and is essential in fixed effects estimation, as there are more firms with a change in the binary innovation measures over time. And fifth, we use both fixed effects and continuous treatment effect models.

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

2. Earlier research at the firm level

Previous firm-level 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

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

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

[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.

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 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. The firm data sets are merged using unique firm identifiers. 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. We also included year indicators. Worker characteristics were calculated from the FOLK data set of Statistics Finland, which covers the whole working-age population and has a link to the employer firm at the end of the year. This makes it possible to merge information on worker characteristics with the firm data. The FOLK 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. Using two-year lagged values is likely to weaken the relationship between average and innovation, since there can be employee turnover during the two years over which the innovation is measured. Descriptive statistics of the variables are in the Appendix.[4]

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 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

[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.

[4] The data sets can be accessed at Statistics Finland through a remote access system, subject to confidentiality agreements. For information on the terms of use, application for a user licence, pricing, etc., contact the Research Services unit at Statistics Finland (see https://stat.fi/tup/tutkijapalvelut/index_en.html).

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. The innovation indicators are correlated with each other, but not perfectly (Table 2).

Table 1. Descriptive statistics on innovation measures in different samples

	Product or service innovation	Process innovation	Marketing innovation	Organizational innovation	Turnover share of innovative products, %	R&D / employee
All firms						
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 2. Correlation matrix of innovation measures

	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%

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.

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. These are linear probability models for the binary indicators of innovation (product or service; process; marketing; organizational). The fixed effects estimates identify the impact of changes in the age structure over time within firms. In the case of the binary innovation measures, 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).

Since for always innovators and never innovators the innovative behavior, measured by a binary innovation measure, does not respond to the age structure, leaving these firms out of the analysis likely overestimates the relationship between average age and innovation. On the other hand, for the continuous measures, the share of innovative products and R&D/employee, there is no such effect, as all firms are included.

As an alternative method, we use continuous treatment effect estimation, where average age is used as a treatment variable. This makes it possible to include all firms in the analysis, but does not allow for fixed firm effects. Therefore, we use the linear fixed effects model as our preferred method.[5]

[5] Stata 18 (StataCorp LLC, Stata Statistical Software, Release 18, 2023) was used in data construction and estimation. The program codes are available in Zenodo (10.5281/zenodo.16902419).

To examine the relationship between age and innovation, we used the age variables in alternative forms: a polynomial of average age and age group shares. Panel A of Table 3 shows the estimation results with average age.[6] 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.

Table 3. Fixed effects estimation results

	Product or service innovation	Process innovation	Marketing innovation	Organizational innovation	Turnover share of innovative products, %	R&D / employee
Panel 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)
Panel 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%

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 in Panel A of Table 3. All firms are used in the estimation, but in the graphs, 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 are 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.

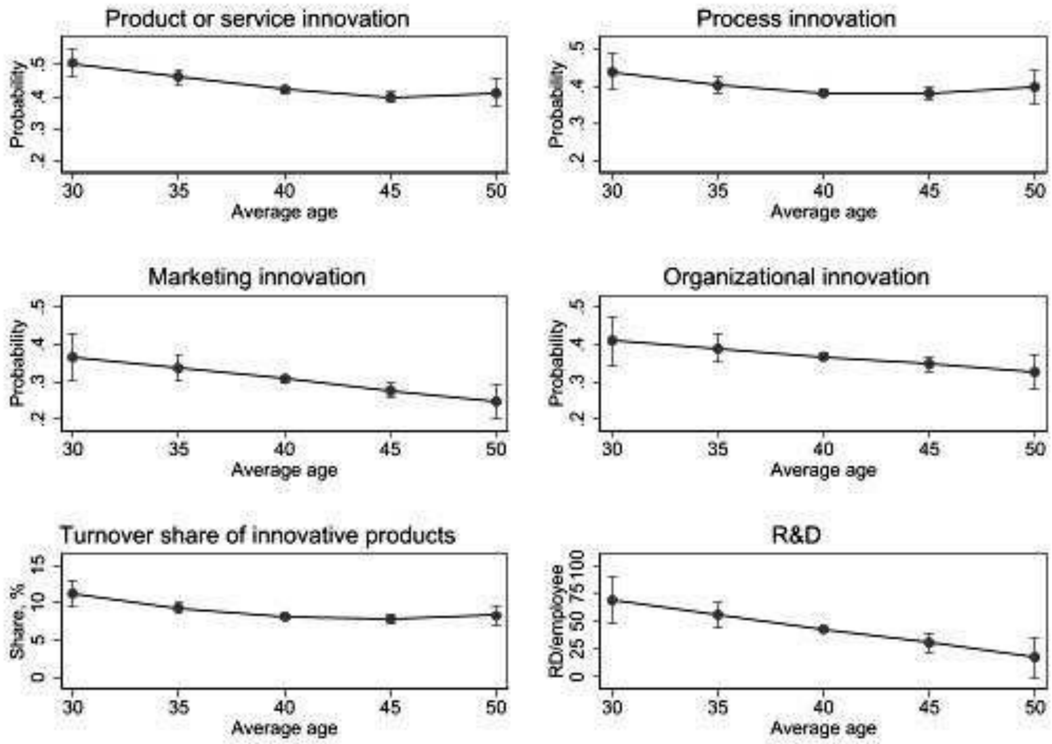
[6] The results on the control variables are not reported, but they are available from the author.

However, at older ages, the confidence intervals are large, so the change in innovativeness with age is not significant.

Although always innovators and never innovators are left out from the fixed effects analysis of the binary innovation measures, the results are similar to those with the continuous innovation measure, the share of innovative products. Therefore, leaving out the firms with no change in innovation has no significant impact on the results.

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 of Table 3), 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, the age group 31-40 already affects innovation negatively, compared to the reference group. Again, 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.

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



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 3 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.

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. In all cases, the relationship between average age and innovation was negative for a wide range of average ages, consistent with the fixed effects estimates.[7] The fact that the results are qualitatively similar justifies our use of the fixed effects method as the primary method of analysis.

5. 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.[8] 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.

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[7] The results are available in the discussion paper version of this article (Ilmakunnas, 2025).
[8] A negative connection between firm age and innovation was found, for example, by Huergo and Jaumandreu (2004), Balasubramanian and Lee (2008), and Cucculelli (2018).

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Appendix. 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.