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Old is Gold?

The Effects of Employee Age on Innovation and the Moderating Effects of Employment Turnover

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ABSTRACT

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JEL Code: D22, J21, J24, L25

Keywords: ageing, employee age, innovation, firm performance, R&D, human capital

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Abstract

There is consistent evidence in the literature that average employee age is negatively related to firm-level innovativeness. This observation has been explained by older employees working with outdated technological knowledge and being characterized by reduced cognitive flexibility. We argue that firms can mitigate this effect through employee turnover. In particular turnover of R&D workers is deemed a vehicle for transfer of external knowledge to the firm, which can compensate for lower cognitive flexibility and up-to-date knowledge among older workers. We use a matched employer-employee dataset based on three consecutive CIS surveys for Sweden to test our predictions. Our results suggest a) that overall employee age impacts negatively on product innovation activities (both in terms of propensity and success), b) that the effect of employee staying rate (measured by the share of employees that remain in the firm from one year to the next) on innovation follows an inverted U-shape implying an 'optimal' level of employment turnover, and c) that this 'optimal' value is lower for firms with older employees. The latter suggests that firms with older employees can at least partially compensate an aged workforce by increased employment turnover.

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1. Introduction

Recent analyses document a robust negative effect of average employee age on a wide range of innovation-related indicators, such as R&D expenditures, propensity to introduce product innovations and sales with new products (Pfeiffer and Reuß 2008, Pfeifer and Wagner 2012, Parotta et al. 2008, Østergard et al. 2011). The effect of age has also been analyzed in the context of technology adoption as well as in entrepreneurship and growth of new firms. Meyer (2011) shows for a sample of firms in Germany that an older workforce is negatively related to the probability of technology adoption. Several studies also show that new firms with younger employees grow faster (Ouimet and Zarutskie 2011, Andersson and Klepper 2013).

A common explanation for these empirical regularities is that the cognitive performance of individuals falls with age, which for example results in reduced ability and willingness to deal with new technology (Kaufman 2001, Schneider 2008, Friedberg 2003). Other explanations are sought in younger people's higher risk tolerance (Hensley 1977) or their more recent technological skills (Ouimet and Zarutskie 2011).

We focus in this paper on the relationship between employee age and firm-level innovation, and ask how the negative effects of employee age on firms' innovation can be mitigated.

A standard solution discussed in the literature is employee training (Binnewies et al. 2008), because continuous training keeps older employees' skills and knowledge up-to-date. This is somewhat problematic, however, because it can be shown that training becomes less effective for older employees (Mc Namara et al. 2008). One explanation is that shorter theoretical pay-off periods reduce the returns to training, implying the incentives to engage in training activities is lower for older employees (Pfeifer and Wagner 2011). Another is that negative stereotypes reduce the employers' willingness to admit older employees to training programs (Roth et al. 2007, Verworn 2009).In consequence it seems questionable that the statement that training can mitigate the age associated problems in firm innovativeness provides a satisfactory solution, because it does neither explain how to solve the workers incentive problems nor potential age-related discrimination by the employer. Thus, there remains a need for the analysis of further measures that can counteract the problems of ageing workforces for innovation.

Drawing on evolutionary economics and organization learning theory, we propose and empirically test the idea that employee mobility can reduce the adverse effect of employee age on innovation.

Evolutionary economics and organizational learning theory emphasize the crucial role played by knowledge variety for innovation (Nelson and Winter 1982, Dosi 1982, March 1991). Search for and absorption of new technology and knowledge are essential processes for maintaining knowledge variety within a firm. From this perspective, the negative effect of employee age can be understood as a consequence of reduced intensity of both search and absorption processes of new knowledge, which induces a reduction in firms' knowledge variety. Our argument is that employee turnover can compensate for this negative effect, because inflow of new workers implies inflow of new ideas, experiences and skills, which contributes to the variety of firms' knowledge base (cf. Feldman 1999, Power and Lundmark 2004). By being a vehicle for transfer of external knowledge into the firm, employee turnover should therefore mitigate some of the negative effects of an ageing workforce.

In order to test the hypothesis of employment turnover as a moderating factor in the employee age-innovation relationship, we make use of longitudinal matched employer-employee data for Sweden that comprise firms in three consecutive waves (2004, 2006 and 2008) of the Swedish Community Innovation Survey (CIS). We derive a measure for the share of workers that stay in the company as an inverse measure of employment turnover, which we call the 'staying rate'. We test whether the relationship between employee age and innovation is robust to controlling for this measure. Based on arguments in the organizational learning literature (March 1991), we allow for a non-linear effect of the staying rate.

The main results are as follows: we first verify results from previous studies using Swedish data. The average age of a firm's employees has a negative influence on the propensity to introduce product innovations as well as on the share of sales with new products. In line with our hypothesis, we find that the influence of staying rate on innovation follows an inverted U-shape, in particular for R&D workers. The inverted U-shaped relationship suggests the existence of an 'optimal' level of the staying rate. Most importantly, we show that this 'optimal' value is lower for firms with older employees. In other words, from the perspective of innovation, employee turnover is more important for firms with older employees. We conclude that the staying rate indeed moderates the employee age-innovation relationship in ways consistent with the hypothesis that employee turnover is one mechanism by which the adverse effects of employee age can be alleviated.

The remainder of the paper is organized as follows: in the following Section 2 we shortly present our theoretical arguments. In Section 3 we describe our data and the identification strategy. In Section 4 we present our results. In Section 5 we conclude and discuss the implications of our research results.

2. Theory and baseline hypotheses

According to Schumpeter (1934) innovation can be understood as the recombination of existing knowledge. Schumpeter's basic conjecture has received support from empirical work in innovation studies, which shows that technological innovations are in the majority based on recombinations rather than on the creation of totally new technology without predecessors (Usher 1954, Basalla 1988, Utterback 1996, Fleming 2001). The re-combinative element suggests that a prerequisite for successful technology development is the existence of variety in the knowledge base inside the firms (Mulder et al. 2001), and intentional search for new knowledge is an important mechanism creating this variety (Nelson and Winter 1982, Dosi 1982, Laursen and Salter 2006).

The age of firms' employees can have a decisive impact on such search processes in three important ways. First, as already argued in the introduction, older employees tend to invest less in training because the net present value of the investment made is lower due to a shorter pay-off period (Pfeifer and Wagner 2012). This means that older employees are less exposed to new ideas and knowledge. Second, cognitive capabilities (including intelligence, creativity, reasoning, and memory power) may fall with age (Kaufman 2001, Schneider 2008), which means that the ability to identify and absorb new knowledge may be reduced (Meyer 2011). As a consequence, search processes become less efficient for firms with older employees. Third, older employees may have lower incentives to promote technological change because older employees tend to have vested interests in the established technological base because they have invested in assets co-specialized with this technology. Technological change often turns these investments into sunk costs implying that older employees are more committed to existing technologies and knowledge bases than younger employees (cf. Behagel et al 2011). In view of these theoretical arguments and a large empirical literature, we form the following hypothesis:

> *H1: The propensity and the success of innovation are lower for firms with older employees.*

Our main argument is that this negative effect of age can be mitigated by employment turnover. To understand this we will now explain how this variable impacts on the on the knowledge variety in the firm. We use arguments made by March (1991), who demonstrates the crucial importance of employment turnover in turbulent environments.

The basic mechanics of March's (1991) model are as follows: employees hold certain (heterogeneous) beliefs about the state of the outside world. These can be right or wrong. The institutional code – as a representation of what the organization "knows" – learns from the employees' correct beliefs and the employees in their turn from the institutional code replacing the beliefs held by themselves. This leads to a convergence of individual and organizational beliefs reducing variety over time.

While this process is effective in stable environments, the quality of organizational and personal beliefs gradually deteriorates in turbulent setting because in the long run there is no variety left to learn from. March (1991) shows that employment turnover can solve this problem because it continuously recreates the variety that is needed for effective learning, i.e. organizational adaptation. In line with this, the literature has emphasized that knowledge, experiences, and competencies are embodied in people (Feldman 1999, Almeida and Kogut 1999). Therefore, inflow of employees with experiences from other firms and organizational contexts entails inflow of new knowledge and information (Almeida and Kogut 1999, Agrawal et al. 2006) Rosenkopf and Almeida 2003, Song et al. 2003 and Maliranta et al.2008), which increases variety..

At the same time, however, employment stability also offers benefits because the effectiveness of organizational learning also depends on the ability of the organizational code to transfer its embodied knowledge to the employees. Obviously, high turnover implies high variety i. But the ability to diffuse organizational knowledge within the firm effectively is low, because the employees leave the firm too quickly.

Because of this, March's (1991) model implies an inverted U-shape relationship between turnover and the effectiveness of organizational learning. Focusing on the staying rate (defined as 1-muns the employment turnover rate), we hypothesize the following with respect to innovation:

> *H2: There is a critical threshold value for the staying rate below which propensity and success of innovation increases and beyond which it decreases.*

The arguments above imply that employee age has negative influence on variety whereas employee turnover can have a positive influence on variety. Thus we suggest that firms with older employees – embodying under H1 a lower degree of technological variety – can compensate for this by a higher degree of employment turnover, i.e. lower staying rates. This will shift the optimal value of staying rate downwards in firms with on average older employees.

> *H3: The optimal level of the staying rate is lower in firms with older employees.*

3. Data and Identification Strategy

3.1 Data

We employ longitudinal matched employer-employee data on firms in three waves of the Swedish Community Innovation Survey (CIS), conducted the years 2004, 2006 and 2008. The Swedish CIS is part of the EU- wide harmonized CIS survey of firms' innovation activities. While the CIS is by construction a moving cross-section, many firms are surveyed in consecutive periods. This allows us to construct a panel data set including firms that are part of all three waves of the CIS.[1]

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[1]Some potential sources of bias need to be addressed: the stratification Statistics Sweden employs in the CIS may work towards larger firms being included (as all Swedish firms with 250 or more employees are included as long as they are in CIS-relevant sectors). To circumvent problems of identifying firms, we have disregarded those firms that may have changed ownership structure, since that would also imply changing organizational identifier.

The original Swedish data consists of 3,126 firms in 2004 (response rate 66%), 3,247 firms in 2006 (63%), and 4,624 firms in 2008 (85%) of which 1,113 firms are observed in all three surveys.

Concerning selection of firms Statistics Sweden creates a stratified, random sample based on firms with 10-249 employees, whereas all firms with 250 or more employees are always included in the survey. [2] The survey is then sent to the top managers of the firms, and all firms receiving the survey are obliged to answer it.

The survey contains most sectors from services and manufacturing. In specific, all firms from NACE 10 to 72 are included, which excludes agriculture and some service sectors, e.g. housekeeping. To keep the sample relatively homogenous, we restrict our sample to manufacturing firms and exclude services.

The use of CIS data is sometimes criticized on the grounds of potential selectivity issues in the sample of responding firms. Indeed it is known that in particular in countries where the participation is not mandatory for the firms, the response rate is 1) much lower (in Germany it is around 25%) and 2) the sample is biased towards innovating companies. In Sweden, however, the participation is mandatory and firms not answering in time have to pay fines. This induces both a relatively high response rate and reduces the likelihood of non-response bias, because it seems reasonable to assume that the willingness to pay the fine instead should be unrelated to the innovativeness of the firm. We thus assume that the Swedish CIS is be a roughly representative sample of the Swedish economy – though admittedly with a slight overrepresentation of larger firms.

To the CIS data we add information from several other sources including employment structure, balance-sheet data, ownership structure, international trade involvement and location. The final dataset comprises information from the following data sources:

- CIS (Community innovation survey 2004, 2006 and 2008, innovation information)
- LISA (Integrated database for labor market research 2002-2008, employees and regional variables)
- FEK (Business database 2004, 2006 and 2008, value added and business-related information)

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[2] Details on the CIS survey in Sweden may be found in statistical reports such as *Innovation activity in Swedish enterprises 2006-2008* by Statistics Sweden (SCB 2009).

- Database of business groups (2004, 2006 and 2008, states foreign vs. Swedish ownership)
- Export- and import-database (2002-2008, exporting experience)

A main novelty of the data is that the firms included in all three waves of the CIS are identified in the LISA-database. This database includes all individuals of age 16 and above in Sweden, which allows identifying which employees are employed in each firm. The longitudinal structure of LISA then enables us to trace their complete employment history including past occupations, the characteristics of their previous employers, and other personal characteristics (e.g. age, education).

3.2 Variables and descriptive statistics

The explanatory variables of main interest are "average age of the employees in each firm" and "staying rate". The latter is defined as the total employment minus hires relative to total employment. In formulae both variables are define as:

$$avage_{it} = \frac{1}{N_{it}} \sum_{j=1}^{N_{it}} age_{itj} \tag{1}$$

and

$$stayrate_{it} = \frac{N_{it} - hires_{it}}{N_{it}} \tag{2}$$

where N_{it} is the number employees (FTE) in firm i in year t, age_{itj} is the age of employee j in firm i and year t and $hires_{it}$ is the number of new employed people (FTE) in the respective firm and year.

Additionally, we differentiate these variables by total employment and for R&D-related workers. We understand R&D-related workers broadly as we allow employees to be characterized as such either on the grounds of their current position or based on their R&D-related experiences at previous employers. Specifically, we identify the subgroup of R&D-related personnel by three criteria:

1. R&D managers: *employees that worked as R&D managers at their previous employer. This corresponds to classification "1237" according to the four-digit level of the ISCO-88 in the LISA-database. Managers of this type are directly involved in R&D-related decisions*.

2. Other managers at R&D intensive firms: *employees that had a management position at their previous employer, according to the 1-digit ISCO-88. The employer was conducting R&D. These managers are generally the top- or middle-managers who are involved in decision-making and development of strategies and organization*.

3. Knowledge workers: *employees having a qualified (but not management) position at their previous employer according to the 1-digit ISCO-88. The employer was conducting R&D. A further requirement is that these employees have at least a university bachelor's degree.*

If an employee fulfilled either of these mutually exclusive requirements, he was considered to be an R&D-related worker. Analogously to (2) we defined the variable turnover of R&D workers as:[3]

$$stayrate_{it}^{R\&D} = \frac{N_{it}^{R\&D} - hires_{it}^{R\&D}}{N_{it}^{R\&D}} \qquad (3)$$

Hypotheses 1 to 3 relate the core independent variables, employee age and turnover, to innovation propensity and innovation performance. We focus on product innovation and make use of two commonly used variables in the context of CIS-data. In particular, we use a variable that indicates whether a firm is a product innovator, i.e. whether it has introduced a new or significantly improved product within the last three years. This variable measures the propensity to innovate. Additionally, we use the share of turnover with new products (share of innovation sales) as a success measure (see e.g. Laursen and Salter 2006, Grimpe and Kaiser 2010, Robin and Schubert 2012).

Additionally to the main explanatory variables "average age" and "staying rate" we include a set of potentially confounding factors. To control for size we use value-added. The discussion about the impact of size is still unresolved: On the one hand the Schumpeter Mark II hypothesis states that larger firms have an innovation advantage, for instance due to larger financial resources or other accumulated internal resource bases (cf. Breschi et al 2001). On the other hand virtues like

[3] Note that the staying rate was set to 1 for firms without R&D-related employees, because in this case the staying rate of 100% is deemed to capture that fact there is no inflow of new ideas and thus no additional creation of variety.

flexibility and adaptability are often attributed to smaller firms. Reflecting this indeterminacy of the impact of size we also include the squared value added in order to allow for potential non-linearities.

We also control for R&D intensity and a dummy for whether the R&D activities were on a continuous basis. R&D is a natural control variable and is often claimed to have a dual nature:: it is both an input into the innovation process (cf. Mairesse and Mohnen 2002, Robin and Schubert 2012) and it creates absorptive capacity (Cohen and Levinthal 1990). Additionally to the level of R&D also the organizational aspects influence the relationship between R&D and innovation. One important aspect is that of continuitity, because it is a measure of the institutionalization of the R&D activities, e.g. in a dedicated R&D department. Lööf et al (2012) argue that firms undertaking persistent R&D are better apt to develop routines and capabilities for their R&D operations, which adds to their innovativeness.

We further include a dummy variable for whether the firm is affiliated with a multinational company group. Multinationals are by definition active in many markets and therefore have access to dispersed knowledge bases (cf. Dachs et al. 2008, Nieto and Rodriguez 2011). MNEs also have strong internal capabilities pertaining to the development of proprietary information and knowledge within the corporation (Pfaffermayr and Bellak 2002). This suggests that affiliation to a multinational company group is a relevant factor in explaining a firm's innovativeness.

In addition we include a dummy which is one if the firm exports. International trade may stimulate innovation through exposure to stronger competition, requiring refinements of product lines and production processes. Interaction with foreign customers may also be a source of ideas and knowledge for new products (Andersson and Lööf 2009, Schubert and Simar 2011). This implies that firms active on international markets may have higher innovation propensities and innovations sales.

The local presence of R&D workers measured as the number of R&D workers as a fraction of the total employment in the region in which the firm has its main operations is also included as a control. A large literature suggests that local density of R&D activities can stimulate innovation (Feldman 1999, Glaeser 1994). A main argument is that the potential for and intensity of knowledge and information flows are greater in spatial contexts where R&D activity is high (cf. Baptista 2000).

We furthermore include sales growth, labor costs and sector dummies based on the OECD technology levels classification which is widely applied in the context of innovation research. As already explained the sample is restricted to manufacturing firms, leaving us with a dummy for high-tech manufacturing, medium high-tech manufacturing, medium-low-tech manufacturing, as well as low-tech manufacturing (omitted base category).

Some descriptive summary statistics of the variables are presented in Table 1 and pairwise correlations between the variables are presented in Appendix A. With respect to our main variable we see that 40.44% of the firms in each year are product innovators. The average share of turnover with new products is 4.69%. Concerning average age of the employees, the mean value is about 43 years with a minimum of 26 years and a maximum of 60 years. The average share of common employees is 88.54% for total employment and 85.57% for R&D-related employment.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std. Dev.
Product innovator (y/n)	2532	0,4044	0,4909
Share of turnover new products	2532	0,0469	0,1251
Average age employees	2532	43,0791	4,4700
Staying rate R&D employees	2532	0,8557	0,1256
Staying rate total employees	2339	0,8854	0,1992
Group member (y/n)	2532	0,6635	0,4726
Exporter (y/n)	2532	0,0399	0,1957
Sales growth	1674	0,1881	0,3557
R&D share regional labor market	2524	0,1340	0,0491
Labor costs per turnover	2516	0,1895	0,1464
R&D intensity	2519	0,0339	0,4380
Value added in SEK	2532	238,1733	1472,0830
Continuity R&D engagement	2532	0,6560	0,7702
High-tech manufacturing (y/n)	2532	0,1019	0,3026
Medium high-tech manufacturing (y/n)	2532	0,2457	0,4306
Medium low-tech manufacturing (y/n)	2532	0,2145	0,4105
Low-tech manufacturing (y/n)	2532	0,4380	0,4962

Note: The table reports descriptive statistics for the variables in the empirical analysis.

3.3 Identification and estimation strategy

Our main goal is to empirically test the three hypotheses described in Section 2. Concerning H1 we are mainly interested in the linear effect of the age variable on either of the innovation variables. In particular, if H1 is true, we would expect that the estimated coefficient to be negative. Previous literature also confirms such a relationship and we expect it to hold for our sample of Swedish firms as well. We follow the strategy of Pfeifer and Wagner (2012) and thus estimate the influence of the age of the overall workforce of the firm on innovation. With respect to H2, we expect an inverted u-shape, implying the coefficient on the linear term of the staying rate to be positive and that a quadratic term to be negative. Given estimates of both coefficients, we are able to derive the optimal turning point based on straightforward calculus as a nonlinear function of these coefficients. H3 states that this turning point is lower for firms with one average older employees, because these firms need additional variety-generating employment turnover to compensate for the more aged workforce. In order to test these hypotheses we separate the sample into two subsamples of firms with below average employee age and above average employee age. For each subsample we calculate the optimal turning point separately and test whether the difference between the turning points is statistically significant. For this we need an estimate of the variance of the difference of estimates of the turning points, which is derived in the Appendix. A more straightforward and mathematically easier end to the same goal would have been to define age interaction terms for both the linear and the nonlinear terms of the staying rate and then test for differences in the turning point. However, it turned out that the so created interaction terms were so highly correlated with the main terms (above 0.7) that multicollinearity led to a collapse of almost all significances within the model. To circumvent this problem we chose the more complicated but eventually more stable method based on split samples.

Concerning the choice of appropriate regression models both innovation measures do not have continuous support on the complete real axis, rendering OLS-based panel estimation inconsistent. In the case of the product innovator model we employ a panel Probit model, because in this the case the dependent variable is a dummy, which is 1 of the firm has introduced a product innovation and 0 otherwise. In the case of the turnover due to new products we use a double-censored panel Tobit model, which is left-censored at 0 and right-censored at 1. The reason for this is that this variable is a fraction which by definition is bounded between 0 and 1.

Besides the limited dependent variable features, an important issue concerns the question of whether we assume fixed or random effects. While it is at least theoretically preferable to allow for firm-specific unobserved heterogeneity to be correlated with the explanatory variables, the corresponding within-estimation usually comes at the price of discarding any cross-section variance. In particular in the case of nearly time-constant variables this leads to very inefficient estimation and large influence of outliers or measurement error (Angrist and Pischke 2009). The main variables of interest in our context (average age, staying rate) however, display a low degree of within variance, which means that standard errors of the coefficients will be inflated when the within estimation is used. Furthermore, while there are fixed effects estimators for binary data (the fixed effects Logit), no such technique exists for the case of the Tobit model, depriving us of the possibility to employ a full within-technique. On the other hand, random effects estimation would lead to inconsistent estimates, when the individual effects are not independent of the explained variables.

In order to benefit from the properties of both fixed effects (robustness to correlated individual effects) and random effects (high efficiency), we decided to parameterize the fixed effects as suggested in Mundlak (1978) and include correction terms based on the firm-level means of the explained variables. This way of correcting for fixed effects is consistent in panel Probit and Tobit models under the assumptions that a) the fixed effects are linear in the firm-level means of the explained variables, b) the fixed effects to do not depend on other unobserved variables that are correlated with the explained variables.

With these assumptions the panel Probit model can be written as:

$$
\begin{aligned}
& y_{it}^{*} = x_{it}\beta + \overline{x}_{i}\gamma + v_{it} + u_{it} \qquad v_{it} + u_{it} \mid x_{it} \sim N(0,1) \\
& y_{it} = \begin{cases} 1 & y_{it}^{*} > 0 \\ 0 & y_{it}^{*} \leq 0 \end{cases}
\end{aligned} \tag{4}
$$

The 0-1-double-censored panel Tobit model has the following structure:

$$
\begin{aligned}
& y_{it}^{*} = x_{it}\beta + \overline{x}_{i}\gamma + v_{it} + u_{it} \qquad v_{it} + u_{it} \mid x_{it} \sim N(0,\sigma) \\
& y_{it} = \begin{cases} 0 & y_{it}^{*} \leq 0 \\ y_{it}^{*} & 0 < y_{it}^{*} < 1 \\ 1 & y_{it}^{*} \geq 0 \end{cases}
\end{aligned} \tag{5}
$$

where in both cases the vector $\overline{x}_{i}$ contains the Mundlak-correction terms. The analyses in Section 4 are based on the Mundlak-correction using the R&D-intensity.[4] The models are then estimated by Random Effects.

4. Results

4.1 The main effects

In Table 2 we present the main results referring to hypotheses 1 and 2, where several variants of our models are reported. Models (1) and (2) include the linear terms of the age variable and the staying rate both for total employment and for the subgroup of R&D workers separately. (1a) refers to the Probit model where we analyze the influence of the variables on the likelihood of product innovation. (2a) refers to the Tobit model where the dependent variable is the share of turnover with new products. (1b) and (2b) additionally include the squared terms for the staying rate in the Probit and Tobit models, respectively.

[4] We checked alternative specifications (see the robustness section 4.2).

From (1a) and (2a) we observe that the average age of the employees in the firm has significantly negative effects on both the probability to introduce product innovations as well as the turnover share with new products. This result lends support for H1. The terms on the staying rate are neither significant for any of the innovation indicators nor for any of the subgroups of employees.

This is expected since in H2 we argued for an inverted u-shape relationship of these variables, which implies that the coefficient on the linear term is positive while it is negative for the squared term. In (1b) and (2b) we have therefore additionally included these quadratic effects. While there once again seems to be no effect for the staying rate referring to all employees, we indeed find the expected effects with respect to R&D workers, i.e. the important group of workers in the context of innovation. The estimates imply an inverted U-shape, which also means the existence of a turning point that can be calculated from the data given the formulae in the Appendix. We find that this value is 62% in the case the product innovator dummies and 56% in the case of share of new products. A literal interpretation is that firms below these levels can increase their innovation performance by reducing their staying rate (increasing their employment turnover). In contrast, firms beyond this level should increase it. The variable on average age is as before negative in both (1b) (product innovator) and (2b) (share of turnover with new products).

With regard to our control variables, we find that firms with large value-added have higher innovation propensities and sales, since in three out of 4 models the linear term is positive significant, while the non-linear term remains insignificant. This provides indeed some evidence for the Schumpeter Hypothesis in our sample of firms. Further, firms that are affiliated with multinationals do not appear to have higher innovation propensity, though they do show higher shares turnover with new products. This may be interpreted to imply that multinationals are in a better position to introduce novelties through their established global sales networks. We also find that firms undertaking R&D on a continuous basis are more likely to introduce product innovations. Continuous R&D also appears to raise the share of turnover with new products. The estimated influence of the other controls is inconclusive.

Turning to H3 we hypothesized that the turning points are lower for firms with younger employees and higher for firms with older employees. To analyze this we run regressions similar to those in (1b) and (2b) but separate the samples by firms with above and below average employment age across all firms in the sample. In these estimations we focus on R&D workers as the results in Table 2 shows that these are the relevant group of workers in our empirical context. The results are reported in Table 3. In the table, *young employees* refer to the sample of firms with *below* average age of their employees and *aged employees* refers to the sample of firms with *above* average age of their employees.

Table 2. The effect of employee age and turnover on innovation.

	(1) Product innovator	(2) Share of turnover new products	(3) Product innovator	(4) Share of turnover new products
Average age employees	-0.0233**	-0.00380*	-0.0221**	-0.00336
	(-2.13)	(-1.83)	(-1.97)	(-1.56)
Staying rate all employees	0.565	0.0518	0.530	0.668
	(0.92)	(0.45)	(0.09)	(0.53)
Staying rate R&D employees	-0.237	-0.0701	2.588***	0.366*
	(-0.99)	(-1.54)	(2.65)	(1.77)
Staying rate all employees^2			0.0685	-0.370
			(0.02)	(-0.49)
Staying rate R&D employees^2			-2.102***	-0.324**
			(-3.00)	(-2.22)
Group member (y/n)	0.149	0.0625***	0.112	0.0548***
	(1.51)	(3.37)	(1.13)	(2.99)
Exporter (y/n)	0.191	0.0156	0.196	0.0179
	(0.97)	(0.46)	(0.99)	(0.53)
Sales growth	-0.0270	0.0307	-0.0117	0.0333
	(-0.24)	(1.46)	(-0.11)	(1.60)
R&D share regional labor market	-1.771*	-0.177	-1.925*	-0.200
	(-1.75)	(-1.01)	(-1.84)	(-1.13)
Labor costs per turnover	-0.621	0.231	-0.539	0.241
	(-1.31)	(1.34)	(-1.19)	(1.46)
L.R&D intensity	-2.041**	-0.0320***	-1.977**	-0.0314***
	(-2.13)	(-6.31)	(-2.10)	(-5.87)
Value added in mln. SEK	0.000156*	0.0000323***	0.000111	0.0000283***
	(1.66)	(3.35)	(1.19)	(2.94)
Value added in mln. SEK^2	-3.80e-09	-6.48e-10	-2.01e-09	-5.13e-10
	(-1.11)	(-1.31)	(-0.51)	(-1.04)
Continuity R&D engagement	0.827***	0.138***	0.821***	0.137***
	(15.42)	(11.11)	(15.26)	(10.94)
Sector dummies	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES
Mundlak correction	YES	YES	YES	YES
Observations	1543	1543	1543	1543

Marginal effects; *t* statistics in parentheses

(d) for discrete change of dummy variable from 0 to 1

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3. The effect of employee age and turnover on innovation by firms with above and below average employee turnover, respectively.

	(1) Product innovator	(2) Product innovator	(3) Share of turnover new products	(4) Share of turnover new products
Average age employees	-0.0102	0.000216	-0.00178*	-0.000109
	(-0.92)	(0.02)	(-1.85)	(-0.09)
Share common R&D employees	1.644*	1.027*	0.239***	0.0604
	(1.69)	(1.94)	(2.97)	(1.13)
Share common R&D employees^2	-1.095*	-0.924**	-0.175***	-0.0613
	(-1.69)	(-2.28)	(-3.23)	(-1.52)
Group member (y/n) (d)	0.0557	0.0239	0.0131***	0.0109*
	(0.86)	(0.37)	(2.64)	(1.85)
Exporter (y/n) (d)	0.0279	0.126	-0.00146	0.00765
	(0.19)	(0.91)	(-0.12)	(0.60)
Sales growth	-0.0906	0.0447	0.00112	0.0108**
	(-1.06)	(0.69)	(0.16)	(2.07)
R&D share regional labor market	-0.289	-2.040**	-0.0183	-0.134*
	(-0.51)	(-2.36)	(-0.42)	(-1.69)
Labor costs per turnover	-0.373	-0.209	0.0745*	-0.0136
	(-1.39)	(-0.59)	(1.80)	(-0.41)
L.R&D intensity	-1.123***	-1.030*	-0.00858***	0.0517
	(-3.08)	(-1.90)	(-7.60)	(1.05)
Value added in mln. SEK	0.000466***	-0.0000102	0.0000117***	-0.0000115
	(3.33)	(-0.08)	(4.62)	(-1.03)
Value added in mln. SEK^2	-1.40e-08***	-6.06e-09	-2.89e-10**	1.71e-09
	(-2.63)	(-0.21)	(-2.44)	(0.73)
Continuity R&D engagement	0.438***	0.332***	0.0298***	0.0360***
	(9.69)	(8.68)	(10.23)	(7.66)
Sector dummies	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES
Mundlak correction	YES	YES	YES	YES
Observations	856	687	856	687

Marginal effects; *t* statistics in parentheses

(d) for discrete change of dummy variable from 0 to 1

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The inverted U-shape is confirmed in almost all specifications. The only exception is the case of turnover with new products for firms with aged employees, though the marginal effects at least have the expected signs. This basically corroborates the results obtained in (3) and (4). However, by calculating the optimal turning points by age-group (Table 4) we see as expected that there are significant differences between firms with young and old workers. In the case of the product innovator regression, the respective numbers are 55% (older employees) vs. 75% (younger employees). In the case of the turnover due to the products the numbers are 47% and 69%, respectively. Hence the optimal level of employee stability is *lower* for firms with older employees. This provides evidence also for H3.[5]

Table 4. Optimal turning points

	Optimal staying rate young	**s.e.**	**Optimal staying rate share aged**	**s.e.**	**Diff. z-stat.**
Product innovator	0.7511	0.0848	0.5561	0.0796	1.6767*
Share of turnover new products	0.6961	0.0553	0.4744	0.1534	1.3595

In summary, our estimates provide empirical support for all three hypotheses. We find that employee age has a negative influence on both innovation propensity and turnover with new products. Employment turnover yet appears to have a moderating effect, where the optimal level of employee turnover is higher for firms with older employees.

4.2 Robustness

We have performed a couple of robustness analyses to corroborate the stability of our results. First, we have experimented with different specifications for the Mundlak terms. Indeed we find great stability of our results. The exception pertains to the inclusion of Mundlak terms for almost time constant variables, in which case the significance levels dropped. This, however, clearly was expected, because the Mundlak correction for virtually time constant variables reduces just like to the full fixed effects model the efficiency of estimation primarily because it induces multicollinearity between the Mundlak correction terms and the variables that they are based on. We also checked our results by dropping the Mundlak corrections altogether, i.e. by running random effects models. In this case we observed an increase in the significance of all of our results.

5 While this evidence is, given the significance levels, somewhat marginal, this is certainly also due to the fact that we had to split samples.

Second, the negative effect of lagged R&D expenditures seems somewhat counterintuitive. This is likely due to multicollinearity, because the two variables lagged R&D and continuity of R&D engagement are highly correlated. We experimented with dropping either of the one. Two observations are important. First, the remaining variable became positive and significant. Second, the results concerning the main variables of interest remained robust.

Third, a question may be raised why the mobility variables differentiates between R&D workers and other workers, whereas employee age is measured on the total number of employees. An argument could be made that R&D employees are more important in innovation, implying that it is the age of these workers that matters more. The reason we focus on the general employee age is (i) to corroborate previous findings in the literature and (ii) that not all firms have R&D employees according to our definition. For these firms the age is undefined. As a robustness test of the results, we have run models only with the sample of firms that have R&D employees according to our definition and in which we discriminate between the age of R&D employees and other workers. These estimations show that the age of R&D workers is positive but, though close to significance, insignificant, while the general effects of employee age on product innovation remains. These results can be corroborated when using a Heckman selection model to control for sample selection bias, where in fact that the coefficient on the inverse Mills Ratio was insignificant, implying the absence of sample selection. The positive effect of the R&D workers' age, even though insignificant, could be of potentially interest for future work, because it might imply that there might be some kind of age complementarity effect b across functional divisions. Indeed although not significantly different from zero, it could be corroborated that it is significantly larger than the coefficient on the overall age variable. We will raise this issue in the conclusion again. Concerning our main variables of interest, we can in any case conclude that the results are robust.

Fourth, the results on differences in the turning points concerning the staying rate were based on a sample splitting technique. The results clearly depend on the sample value where we split the sample. In the main model we used the mean value, but we have also experimented with other values, e.g. the median. We did not observe qualitative changes.

5. Conclusion

We analyzed the effect of employee age on innovation and the interplay of age of the employees and employment turnover with respect to innovation performance. Our analyses corroborate findings in the literature that suggest that overall employee age is negatively related to innovation performance. We yet show that employee turnover is a moderating factor in the employee age-innovation relationship and can alleviate the negative effects of employee age on innovation. The relationship between employment turnover and innovation has the form of an inverted U-shape, providing evidence for theoretical considerations that highlight the importance of the variety-creating effects of employment turnover in turbulent environments. Our analyses demonstrate that the employees and the optimal employment turnover are linked together, because the optimal turnover is higher for firms with employees that are on average older. We explained that by increased need of additional variety that firms with older employees have.

These findings have important implications. First, ageing of the workforce is a dominant trend for many Western economies. In Sweden, for instance, estimates indicate that the share of the population aged 65 years and above will jump from 17% in 2007 to 25% a quarter century later (Brunner 2007). The consequences of ageing societies are primarily discussed in terms of its feedbacks on the social security systems or on macroeconomic growth (c.f. Brunner 2007, de la Croix et al. 2009). A negative effect on innovation provides additional perspectives, because the demographic change can potentially become a threat for firms that are dependent on innovation on the welfare generation in Western economies, which is largely based on technological advantages. According the argument that innovation is one of the central drives of competitive advantage, the returns on investment in R&D are found as high as 15% (cf. (Lööf et al. 2012, Hall et al 2010, Andersson et al. 2012). In a classical paper Geroski et al. (1993) show that innovation can induce non-transitory increases in profitability by leveraging the ability to gain from spillovers. They also show that innovating firms are less affected by adverse economic shocks. Eventually this implies that the Western societies should start discussing the impact of demographic change not only in terms of the stability of the social security systems but also in terms of the wider impacts it has on innovation. This argument is emphasized by the fact that also the private returns to innovation are often very high.

Second, our results have also implications for management and policy. We have highlighted that employment turnover can potentially mitigate the variety-decreasing effects of an ageing workforce. Therefore, at least to some degree, firms may seek to increase their employment turnover in order to guarantee a sufficient level of variety, which is needed for successful innovation. For policy, our results suggest that labor market dynamics and general mobility is important to foster innovation, especially in the context of an ageing workforce. Labor market regulations which ensure flexibility and reduce rigidities and inertia appear as important in ageing societies.

There are many avenues for further research on the relationship between employee age and innovation. Two issues that were not addressed explicitly in this paper concerns the possibility of age complementarities between categories of workers and endogeneity. Regarding the age complementarities, we followed the strategy of previous papers (in particular Pfeifer and Wagner 2012) and focused on the influence of the average age of employees at large. While we did robustness test and distinguished between R&D workers and other workers, these were constrained by data issues. There are many conceivable ways in which age complementarities could manifest. For example, it may be argued that it is favorable to have young employees with new technological skills working with older more experienced co-workers than only working with other young co-workers. Another perspective would suggest that in some functional divisions optimal age is higher than in others. As already argued in the robustness section, there might be some promising venues to analyze these issues further, since the R&D age variable was significantly larger than that for the overall age variable. Since, these estimations were based on very small samples, further analyses of the role of the age of employees for different types of skills or occupations are warranted. Furthermore, the analyses in this paper did not pay explicit attention to endogeneity issues. One could argue that both employment turnover and the overall age of employees may be outcome variables of innovation. For instance, an increase in product innovation or in the share of turnover originating from new products affect the turnover rates and the age composition of the firms due to difficulties in implementing new technology. While we addressed selectivity issues and the influence of unobserved heterogeneity (through panel Mundlak correction) and found results consistent with our hypotheses, further work should dig deeper into endogeneity between employee age, turnover and innovation.

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	Product innovation	Share of turnover new products	Average age of employees	Staying rate all employees	Staying rate R&D employees	Group member	Exporter	Sales growth	R&D share regional labor market	Labor costs per turnover	R&D intensity	Value-added	Value-added^2	Contonuity in R&D engagement
Product innovation	1													
Share of turnover new prod-ucts	0,4144	1												
Average age of employees	-0,0674	-0,0574	1											
Staying rate all employees	0,0623	-0,0128	0,2773	1										
Staying rate R&D employees	-0,0269	-0,0122	0,0042	0,5076	1									
Group member	0,1034	0,0645	0,0329	0,0599	-0,0841	1								
Exporter	0,0103	0,0054	-0,0117	-0,0053	0,0284	-0,0005	1							
Sales growth	0,0137	0,0352	-0,116	-0,3264	-0,0635	-0,0008	0,0142	1						
R&D share regional labor market	-0,0554	0,0132	-0,0329	-0,0601	-0,0659	0,0729	0,0072	-0,0084	1					
Labor costs per turnover	-0,0455	0,0289	-0,0385	-0,0764	-0,0215	-0,1097	-0,0198	-0,1192	0,0586	1				
R&D intensity	0,0301	0,1361	0,0161	0,0231	0,0049	0,0129	-0,0041	0,0227	0,0046	0,1044	1			
Value-added	0,1039	0,1432	-0,0093	0,043	-0,0239	0,0865	0,0369	-0,012	0,057	-0,0556	-0,0047	1		
Value-added^2	0,0679	0,135	-0,0167	0,0263	-0,0038	0,0338	0,0298	-0,0084	0,0389	-0,0235	-0,0008	0,9225	1	
Contonuity in R&D engagement	0,4726	0,2392	-0,0454	0,0567	-0,0237	0,0923	0,0018	0,0132	-0,0276	-0,002	0,0112	0,0581	0,0265	1

Appendix B

We start by deriving the extremum conditions for the expected values of the explained variables in the Probit and Tobit models as a function of the parameters. We will show that it is in sufficient to maximize the linear index $x\beta$ in both cases.

In the case of the Probit model, this is relatively straighforward. The expected value of y given x is $\mathrm{E}(y \mid x) = \Phi(x\beta)$. Because $\Phi(\cdot)$, the standard normal cumulative distribution function, is a monotonic transformation of the index $x\beta$, it is sufficient to find the maximum of this linear index with respect to the employment turnover.

The same result holds for the Tobit model. But here the derivation is more complicated. An economically meaningful distribution characteristic is the expected value of the explained variable, given that it is larger than zero. This turns out to be $\mathrm{E}(y \mid y > 0, x) = x\beta + \sigma\lambda(\frac{x\beta}{\sigma})$, where σ is the standard deviation in (3) and $\lambda(\frac{x\beta}{\sigma})$ is the inverse Mills ratio. Differentiating this quantity with respect to one of the explanatory variables yields:

$$\begin{aligned}\frac{\partial\,\mathrm{E}(y \mid y > 0, x)}{\partial x_j} &= \frac{\partial x\beta}{\partial x_j} + \sigma \frac{\mathrm{d}\lambda(\frac{x\beta}{\sigma})}{\mathrm{d}\frac{x\beta}{\sigma}} \frac{\partial \frac{x\beta}{\sigma}}{\partial x_j} \\ &= \frac{\partial x\beta}{\partial x_j} \underbrace{\left(1 - \lambda(\tfrac{x\beta}{\sigma})\left(\frac{x\beta}{\sigma} + \lambda(\tfrac{x\beta}{\sigma})\right)\right)}_{>0} \end{aligned} \tag{A1}$$

where the second term follows from the properties of the inverse Mills ratio. Furthermore in the second term in the second line is strictly larger than zero, an internal extremum requiring the derivative to become zero can only exist, if the term outside brackets becomes zero. This implies that like in the Probit model the maximum of the quantity of interest is identical to the maximum of the linear index $x\beta$. We can therefore simplify our calculations and focus on the latter.

Having proved this we now turn to the derivative of the extremum conditions in our models relating to H3. Consider two sets of firms a and b, where a given firm i is in set b, if its employees have below average age, and is in set a, if it their employees have above average age. We run the basic regression model separately by each set of firms for both the Probit and the Tobit model, but as said it is sufficient to concentrate on the linear index in both cases.

Including the Mundlak-correction terms, this can be written as:

$$x_i\beta = \begin{cases} \alpha_l^b \cdot \mathrm{e}mpturn_i + \alpha_{sq}^b \cdot \mathrm{e}mpturn_i^2 + x_{1i}\beta_1^b & i \in b \\ \alpha_l^a \cdot \mathrm{e}mpturn_i + \alpha_{sq}^a \cdot \mathrm{e}mpturn_i^2 + x_{1i}\beta_1^a & i \in a \end{cases} \tag{A2}$$

The main interest lies the optimal turning point with respect to employment turnover by group. This function obviously satisfies the first order condition for an extremum at $-\alpha_l^b/\left(2a_{sq}^b\right)$ and $-\alpha_l^a/\left(2a_{sq}^a\right)$ respectively. Furthermore, a sufficient condition for this to be a maximum is that $\alpha_l^b, \alpha_l^a > 0$ and $a_{sq}^b, a_{sq}^a < 0$.

If H3 is true, $t^b(\alpha) \equiv -\alpha_l^b/\left(2a_{sq}^b\right)$ should be significantly smaller than $t^a(\alpha) \equiv -\alpha_l^a/\left(2a_{sq}^a\right)$, or in other words the Null-hypothesis is: $t^a(\alpha) - t^b(\alpha) \leq 0$. Both $t^a(\alpha)$ and $t^b(\alpha)$ can be estimated from the data by plugging in the coefficient estimates derived from the regression in (4) and (5). Furthermore, the turning point estimates are smooth functions of the asymptotically normal parameters. Therefore, they are themselves asymptotically normal with a variance that can estimated from the data using the delta method (Wooldridge 2002).

In particular, we use the mean value theorem and write:

$$t^j(\alpha) = t^j(\alpha) + \frac{\partial t^j(\alpha^{j*})}{\partial \alpha^j}\left(\alpha^j - \alpha^j\right) \qquad j = b, a \tag{A3}$$

where $\frac{\partial t^j(\alpha^j)}{\partial \alpha^j} = \left(-1/\alpha_{sq}^j, \alpha_l^j/\left(\alpha_{sq}^j\right)^2\right)$. Because $\alpha^{j*} \in \left]\alpha^{j*}, \alpha^j\right]$ and $\alpha^j \xrightarrow{p} \alpha^j$, it follows immediately that:

$$\sqrt{N}\left(t^j(\alpha) - t^j(\alpha)\right) \xrightarrow{d} N\left(0, \left(\sigma^j\right)^2 \equiv \left(\frac{\partial t^j(\alpha^j)}{\partial \alpha^j}\right) \operatorname{cov}(\alpha^j) \left(\frac{\partial t^j(\alpha^j)}{\partial \alpha^j}\right)'\right) \tag{A4}$$

All terms in the variance on the right-hand-side are estimable from the data, when we replace the parameters by their coefficient estimates. Therefore, the asymptotic distribution of each of the turning points is retrievable.

The difference of the estimates of the turning points is also estimable, because given the separation in the two independent samples also the estimates of turning points are independent of each other. It follows that a valid asymptotic test-statistic for the hypotheses that $t^a(\alpha) - t^b(\alpha) \leq 0$ is the following:

$$T = \frac{t^a(\alpha) - t^b(\alpha)}{\sqrt{\left(\sigma^a\right)^2 + \left(\sigma^b\right)^2}} \tag{A5}$$

where the critical value of this one-sided test significance level ϕ is the $1-\phi$-quantile of the standard normal distribution.