UNIVERSITY OF TARTU
Faculty of Social Sciences
School of Economics and Business Administration

Christian Mentz

Innovation and Employment structure in Estonian firms

Master's Thesis

Supervisor: Prof. Urmas Varblane (cand)

Tartu, 23.05.2019

Name and signature of supervisor. . . . .

Allowed for defence on.. (date)

I have written this master's thesis independently. All viewpoints of other authors, literary sources and data from elsewhere used for writing this paper have been referenced. . . . . (signature of author)

Innovation and Employment structure in Estonian firms

Christian Mentz*

Abstract

This paper studies the impact of product and process innovation introduced by firms on the employment structure with respect to employee age on a sample of Estonian companies over multiple waves of Community Innovation Survey responses. We use a single equation model relaying company innovation activity to changes in the company and market age structure. Using fixed-effects panel data analysis, we find that introducing certain product or process innovations tends to decrease the share of young employees in favor of old employees, however this result might be strongly influenced by the selected time frame which includes the global economic crisis of 2008 which severely affected the Estonian economy and companies potentially aimed to secure short-term sustainability over long-term outlooks, since general employment levels also decreased for most groups of companies with different innovation activities.

Keywords: Innovation, Employment, Employment structure, Age

*Christian Mentz, M.A. Student, Tartu University, Faculy of Economics and Business Administration, 50409 Estonia. E-mail: christian.mentz@ut.ee
The author is grateful to Statistics Estonia for granting access to the data used in the paper. The datasets have been processed in accordance with the confidentiality requirements of Statistics Estonia. All the errors and omissions are the author's.
The author is also grateful to everyone who helped in the process of producing this thesis, especially: Urmas Varblane for supervision and guidance, Amaresh Kumar Tiwari for constructive criticism, and especially the author's better half for moral support.

1. Introduction

In the literature the different effects of different innovation activities and strategies are widely documented and their impact on the employment on company as well as market level is researched and discussed (see e.g. Hall, 2011 for an overivew). Certain types of innovation such as product innovation are seen as mostly employment enhancing on the company level, the results for other innovation activities such as process innovation are more ambiguous (see e.g. Dachs& Peters, 2011). While most of the literature on innovation and the effect on employment focuses on the change in the absolute value of employment, there are fewer papers and with more disagreement on how the innovative activity by companies influences the employment structure of the companies and the market as a whole in regards to certain characteristics of the employment (see e.g. Aubert et al., 2006). The discrepancy is caused by different factors, non-availability of suitable data-sets or the general disagreement of the direction of causality; innovation having a stronger influence on employment structure, or employment structure actually supporting and enabling innovation. The population as well as the workforce are ageing in our current time. This trend is global, affecting business sectors and companies around the world, who now have to adapt to this. This raises questions about company decisions and behavior to work with this change; also regarding innovativeness: Do companies adapt their innovative activities to the changing and aging labour supply or do they specifically hire people that fit their chosen innovation strategies?
Understanding the relationship of age and innovation and possible positive or negative effects of innovation on the age structure is of increasing importance in our ageing society and could contribute to a deeper understanding of innovation and where it can be improved and enhanced to further support beneficial age structures in different types of companies. This paper uses data from Estonian companies responding to the Community Innovation Survey as well as Estonian tax data to analyse the mentioned possible connections between innovations on products and processes and their effects on workforce composition; more specifically the age structure of companies and the market as a result of these product and process innovations.

2. Literature Review

This research draws on two topics of literature, with one being more generally researched and explored than the other one: The general topic of innovation activities and their influence on employment growth and size as well as the labour composition on the firm level and innovation activities as the influencing factor.
For a general overview on different innovation types see Appendix A or the Oslo Manual by the OECD, which refines the initial definition given by J.A. Schumpeter in 1934.

2.1. Types of innovation and employment

In this section we will discuss the most commonly researched and defined innovation types; product and process innovation and their connection to employment.
It is widely agreed on, both in older and more recent literature (see e.g. Van Reenen, 1997 or Harrison et al., 2014), that product innovation on the firm level is clearly associated with an increase in employment growth. The positive effect on the firm level is found to be of different magnitudes, which can be at least in part be attributed to varied availability to oftentimes different data sets and sometimes very different approaches and methods (Harrison et al. 2014). To give a quick example: in his 1997 paper, Van Reenen uses a database on innovation counts, which however does not allow an easy differentiation between product innovation and e.g. process innovation and finds a positive and significant effect of product innovation on employment growth. More recent works (e.g. Harrison et al. 2014) use for example the Community Innovation Survey data with its differentiated questions to distinguish between different types of innovation and find positive effects of product innovation on employment, but this type of data has other shortcomings, which will be discussed later. On the contrary, in their study on effects of innovation on employment, Lachenmaier and Rottmann (2011) find that product innovation does not have a significant positive effect on employment; only the second lag product innovation has a small positive significant effect on employment, but most authors agree on the positive effect of product innovation.
As mentioned above, product innovation has a direct and an indirect effect on employment growth. The direct effect describes the usually increased demand for the firms new or improved product as a result of the innovation activity and usually acts as employment-increasing factor, as new and higher demand needs more employees to supply the customers. This increased demand can come either from an overall market expansion or shrink competing firms market share in favour of the innovating firms, depending on competitors' reactions and the availability of substitute products. (Dachs, Peters 2013)
Besides the positive direct effect on employment growth, product innovation also has neg-

ative indirect effects which reduce employment. First there is the possibility, that the new product partially or totally replaces the firms existing product. This indirect demand effect leads to a decrease in labour demand for the old product and the overall effect can even be negative in bad situations; it differs from case to case. Contrary to this, it might be the case that the new and the existing product are complements, so that the demand of both products increases with the introduction of the new product. With increasing demand for both, the demand for labour to produce both goods should increase as well. (Dachs, Peters 2013)

Regardless of these direct and indirect effects, the new product could be easier or more difficult to produce, resulting in an increased or decreased labour demand with the same amount of output as before (Harrison et al. 2014). The overall effect needs to be determined empirically.

Lachenmaier and Rottmann (2011) mention a different aspect to product innovation however. They mention, that the direction of the employment shift also depends on a less obvious indirect effect: After a new product is introduced to a market, there is no competition yet, due to the nature of the product being new and the lacking availability of comparable alternatives, leaving the innovating firm in a temporary monopoly until other firms catch up, which can lead to negative effects due to misuse of monopoly power. In order to maximize its profits from their monopoly position, the innovating firm's actions can potentially lead to a reduction in outputs and a decreasing employment compared to the situation before introducing the new product. (Lachenmaier, Rottmann 2011)

As far as the influence of process innovation on employment is concerned, there is much less of a consensus in the literature on whether it is mainly positive or negative when compared to the case of product innovation. On the firm level, the introduction of new production processes has an influence on the productivity which is generally of positive nature, meaning the firm can produce the same output with less input and therefore less labour input (Greenan, Guellec 2000). This leads to a decrease in labour demand, which is dependant on the rate of substitution between the different input factors (Dachs, Peters 2013). That being said, the increase in productivity and therefore decrease in unit costs gives the firm the opportunity to lower the product price and attract more customers, thus possibly generating more demand and in turn more output. With the increased demand and output, the demand for labour rises again and employment increases, with the absolute size of the effect depending on multiple factors, such as the market position or the magnitude of the price reduction (Garcia, Calantone 2002).

Different studies on innovation and its influence on employment (growth) have found differ-

ent results of significance of process innovation. Greenan and Guellec (2000) find a positive and significant effect from process innovation on employment growth, which in their case and data is actually much bigger than the effect of product innovation on employment growth with the difference also being statistically significant. Lachenmaier and Rottmann (2011) also find a significant positive effect of process innovation on employment growth and conclude, that the saved inputs due to price reduction gained by the improved processes is then translated into higher output and increased employment.
Van Reenen (1997) on the other hand finds that "process innovations have insignificant and small (often negative) effects" (Van Reenen 1997, p. 20), while other authors find significant and negative effects of process innovation on employment (e.g. Harrison et al. 2014 refer to Ross and Zimmerman (1993)).

2.2. Relationship between the innovativeness and age structure of employees

On the other side of this research thesis' spectrum is the dependant variable employment, or more specifically the structure of the employment present in the firms. Adding to that, there are authors that tried to analyse the influence of the labour turnover with respect to age and to some degree also wage, to get an idea of the importance of the change in worker structure, at what times firms employ what kind of labour and how the firm productivity benefits from it. (see e.g. Ilmakunnas and Maliranta, 2007 or 2016)
The most often employed view on labour turnover in firms is emphasizing the negative side of labour turnover, productive workers leaving the firm and creating costs in hiring and training new workers. On the other side, labour turnover can also be in the firm's best interest, if they can manage to lay off the lower-productivity workers and acquire higher-skilled new labour. (Ilmakunnas and Maliranta, 2016)
Judging by this, we have to further look into specifics of employee structure to make any statements on company productivity related to changes in the workforce. There are different factors according to which the structure in a company can be assessed. Due to the availability of age and wage in the data, the literature review on employment will focus on these factors. Other factors such as the type of tasks or which skills are applied at the workplace cannot be observed in the data, therefore it is assumed to be equal for all workers to simplify the research. This simplification should not be underestimated, as e.g. physical labour should definitely expect a decline in productivity with increasing age from a certain point, so the type of labour could be a rather big factor.
Skirbekk (2004) gives a good overview of the relationship of age and productivity, concluding in an inverted U-shaped relationship, despite some mixed reviews and possible issues with

considered studies and datasets. Roosaar et al. (2017) also confirm the inverted U-shape among employees of higher age compared to employess with average age across age groups. This means that on average, employees of medium age seem to be the most productive compared to younger employees and older employees, who are less productive respectively being on lower points of the inverted U-shape.

This general observation however needs to be adjusted based on a variety of factors. Vandenberghe (2017) writes, that one could argue for experience-related gains in productivity to make up for age-related decline in productivity. Skirbekk (2004) finds evidence of wages to decline from ages in the early 50s onwards, which could stem from experience-related gains becoming smaller than the age-related productivity losses. Vandenberghe (2017) then concludes after his analysis, that in his study he can't find any age-related productivity losses, but rather age-related (proxied by the share of older workers) productivity gains contributing highly to total factor productivity (TFP).

Backes-Gellner and Veen (2013) find a positive effect of increasing average age on the company productivity, should some factors such as non-routine tasks and age diversity be given. As the main result from their study emerges that given creative tasks, increasing age-diversity is beneficial to company productivity. They also suggest that one of the factors to have a positive effect on productivity of older employees and increasing average age could be innovative activity, which should further these mentioned more creative tasks.

Contrary to the finding that a higher average age increases productivity, Roosaar et al. (2017) find that increasing average age decreases productivity per employee. However, they couldn't find evidence of lower productivity of old workers in low-wage groups compared to middle-aged or young workers in the same wage group, and in the high-wage group they find that the most productive are the middle-aged workers, followed by old and young workers in that order. Additionally, they conclude in their findings also potential significant differences between sectors, such as the industry sector in their dataset of Estonian companies having a much lower difference in productivity between medium-aged and older employees than generally assumed in the literature. Similar thoughts were also already shared by Ilmakunnas and Maliranta (2007) who stated that "The role of aging employees for the performance of firms may clearly be an industry-specific issue" (Ilmakunnas and Maliranta 2007, page 1), meaning that in other sectors the prevalent aging of the workforce might not be detrimental to productivity, as other factors overpower the age-related losses in productivity.

Judging from these findings above it is important to analyse and understand how different innovation activities and innovation aims influence the employment in firms, both the absolute value of employed workers and the specific characteristics such as the age structure. For the scope of this research we will focus on the age structure in companies as the area of interest regarding the workforce.

After establishing the general effects of both product and process innovation on employment and employment growth as well as the importance of employee age as well as the age structure in a company, we will now consider the effect of innovations on the general age structure of companies.
As already hinted before, the general direction of the impact is unclear and being looked at from both sides; does the age structure have an influence on the innovation decisions and activities carried out by companies or does the fact that a company is investing in one or multiple types of innovation influence their choices regarding the age structure; do they hire more younger workers and employ fewer older employees?
To give a starting point, one paper in Aubert et al. (2006) reports their findings that "the wage-bill share of older workers is lower in innovative firms and that the opposite holds for younger workers (Aubert et al 2006, page 1). While this statement alone does not imply any direction of the impact, the general message should be that compared to non-innovative firms, we should find a higher share of young workers in innovative firms and hiring decisions, as innovation and new technologies generally negatively affect hiring opportunities for older workers and improve the chances of younger workers (Aubert et al 2006).
Other papers give a different view; e.g. Hammermann et al 2019 investigate the influence of the age structure and diversity as well as the average age on innovations in companies, finding that higher average age is detrimental to company innovations, but age diversity is beneficial to the probability of a company investing in innovations. While their research is considering the direction of causality opposing this research, the findings on higher age and lower innovativeness do confirm previous emerged and stated observations.
Other authors such as Machin and Van Reenen (1998) find that technological change does increase the demand for highly-skilled workers; however, determining the distinction of highly-skilled and other groups based on age is very difficult in the scope of this research as well as in general; wage should be a more reliable proxy for this subject. This view of "skill-biased technical change" increasing the demand for skilled labour was later taken up by Violante (2008) as well and if we aim to translate it to this research question, we would assume that innovation should increase the demand for capable workers which are both highly-skilled and experienced, therefore rather falling in a category of medium age as opposed to young, inexperienced workers or older workers of declining productivity.

3. Data and variables

The dataset used for this research is a combination of two different datasets.

3.1. *Community Innovation Survey*

Firstly, we have the Community Innovation Survey data, a questionnaire that is carried out every two years and is conducted by the national statistics office (or similar appointed institutions) in European countries and supervised by Eurostat. The survey targets a term of three years, e.g. CIS 2010 is for the years 2008 – 2010 (included). The core of questions posed in the questionnaire are common among the different countries (the term used is "harmonized") to make for some comparable results, while other, optional questions differ by country and might not allow comparisons between many countries for these specific questions. Usually the target companies for these questionnaires are companies in the manufacturing and service sector with a magnitude of at least 10 employees; though that might differ between countries as well.

The main questions in the CIS questionnaire aim at different types of innovation and information about company sales and employment levels, with questions about product and process innovation remaining mainly the same over different waves of CIS questionnaires as well as across different countries. The questions aim to identify if a company has invested in product and process innovation by e.g. introducing "new or significantly improved products" or "new or significantly improved processes". In case of a company responding with yes to the question about new or improved products they are asked to specify the share of sales at the end of the two-year period that is attributed to the new or improved products introduced in the previous years. This allows for rather simple comparison of the change in sales; how much the new or improved product has contributed to the total sales at the end of the two-year period, given the products are substitutes with the same combined demand. One important specification of the CIS data is that all responses are given by the companies representative(-s) themselves to the best of their knowledge. This means that all data is self-reported and might depend partially on the responding persons understanding and knowledge of their firm specifics and the survey as a whole. The survey encloses a guide on how e.g. different innovation types are defined and what would constitute as e.g. a product innovation, but in the end there might be some variance between different company responses and their interpretation of the survey questions.

From the employment levels directly reported in the CIS data we can deduct the net growth of employment for each firm over the questionnaire period, which is shown in the later table 2.

Table 1: CIS responses per innovation group

Innovation group	2006	2008	2010	Total
Non-innovators	1,006	935	1,095	3,036
Process innovators	347	278	189	846
Product and process innovators	545	412	294	1,251
Product innovators	235	249	245	729
Total	2,133	1,874	1,823	5,830

For definition of innovation groups see appendix C

Table 1 shows the number of responses for each CIS wave. The observations are divided into four sub-groups according to their innovative activity in the two years leading up to the year specific the columns. The sub groups are based on if the company has partaken in only product innovation, only process innovation, not introduced any innovation or even responded positively to the questions for both innovation groups.
The samples are partly the same over the years, with a substantial number of firms participating in more than one wave of CIS reports. This is due to the fact that Estonia is a rather small country with only a limited number of companies to randomly select from for sending the CIS, so the chances of one company being selected multiple times are substantially higher than in other countries.
We can see that the number of responses from companies varies greatly over the years; with a very high number of firms responding in the first year and in later years the number of responses hovering around 1900 companies on average per CIS survey wave. CIS waves do overlap with e.g. the year 2008 both presenting the initial year for CIS 2008 as well as the final year for CIS 2006.
For the years 2006 to 2010 the number of non-innovative firms decreases at first and then rapidly increasing with a big increase of 10% from the year 2008 to 2010. This is potentially due to the global financial crisis in 2008, which affected many sectors all over the world and presumably a larger number of companies valued short term stabilization higher than investing in future changes which might prove worthless in case a company is unable to sustain through this financial crisis. A similar trend can be seen in process innovators, where the percentage share of the total peaked in 2006 and then dropped by 5% (equal to 33% of its total value) from 2008 to 2010. The same holds mainly true for the share of companies investing in both product and process innovation; a much higher share in 2006 with a substantial decrease in 2008 and mainly 2010. Product innovators in this data sample don't seem to be affected by the financial crisis and their share remains stable. Previous research has shown that in times of crisis the less innovative companies before the crisis are more likely to drop innovation and companies that were highly innovative already before the crisis tend to keep innovating and potentially increase their investments (see Archibugi et

al. 2013, Amore 2015)

3.2. Estonian Tax data

The second dataset used is a matched dataset from the records of employees' payroll taxes from the Estonian Tax and Customs Board that have been matched with companies' records from the Commercial Register of Estonia (dataset of firms' annual reports). This allows for a unique distinction to see which worker was employed at which company in each year and how the employment situation changed over the years 2006-2014. The information contained in this dataset includes among others the age of the employee which can roughly be translated to work experience and the taxes paid on income. From this we can form e.g. three groups of employees according to their age (young, average, old). Furthermore, due to having these absolute values of employees of a certain age group for each company allows to also create a new parameter for the percentage share of each age group from the total employment at each company for any given value of the variable "year" in the dataset.
The dataset also contains an identifier for the company the employees is employed at (this may change over the course of a year, so we consider them employed at the company they are employed at the longest for any given year). As the CIS datasets also include the same identifier values for companies as the matched dataset from employee payroll taxes and the company records, we can with the help of this parameter match the actual age groups (absolute value and percentage share) of employees for each company at each value of "year" to the corresponding entry for each company in the CIS dataset.

Table 2: Employment changes

		Year			
	Innovation group	2006	2008	2010	Total
Change in absolute numbers	Non-innovators	.	-.11	-8.26	-4.44
	Process innovators	.	-.70	13.02	-5.47
	Prod. and proc. innovators	.	15.53	-9.63	4.88
	Product innovators	.	5.68	-10.49	-2.37

Table 2 shows the average changes in absolute numbers of employees for the different innovation group categories over the years recorded in the tax office data, both for each year/CIS wave as well as the total change for all innovation categories over all the available data. The change is calculated as a change compared to the previous point in time, e.g. the value for Non-innovators at year 2008 is the change from the year 2006 to 2008 for this innovation group. and the missing value for year 2006 is due to this being the first available year in the dataset, so no previous entry to calculate the change in employment from.
It is notable, that over all these years the number of employees has not changed drastically

for all innovation groups except the most innovative group of product and process innovators, for which we can observe a big volatility between the year results. This potentially might be due to higher firm size for product and process innovators and therefore a larger number of employees to be able to make changes to; let go of less productive workers or hiring more workers and try to counteract degrading market conditions by more investment in innovation and employees. This however remains speculation without further analysis and further analyzing other factors, which will not be done at this point.
Change in employment numbers for companies in the Estonian tax office data merged with CIS data is only available for a few waves/years, with concrete, descriptive entries spanning from 2006 to 2010. As already noted above, this time period includes the highly influential global financial crisis in 2008, so the observed values are potentially influenced by this, whereas the differences between innovation groups in the same year should be mostly independent from the global economic situation.

Table 3: Change in company sales

		Year			
	Innovation group	2006	2008	2010	Total
In 1000 Euro	Non-innovators	.	750	-555	97
	Process innovators	.	3348	619	1984
	Prod. and proc. innovators	.	3448	642	2045
	Product innovators	.	2057	129	1094

The variable in table 3 is the change in turnover of firms participating in the CIS waves of this dataset. In most innovation groups we can see a steady increase up to the year 2006 with similar numbers in 2008, but most likely due to the financial crisis in 2008 the next entry for change in turnover as of 2010 is meaningfully lower for all innovative groups and even substantially negative on average for non-innovative companies. This clearly shows the (expected) negative impact caused by the financial crisis.

In the above table 4 we can see the percentage shares of different age groups from the total employee population for each respective innovation group over the years. From the table we can see clearly that middle-aged account for the biggest share of employees over all innovation groups, followed by old and finally young employees.
Over the years in the observed dataset, non-innovative companies tend to let go younger employees in favor of older employees; the share of the highest age group in non-innovative companies increased over the three time stamps while the share of the youngest age group decreased. Similar trends for the other innovation groups, except for product innovators, where the share of young employees increased slightly in 2010 compared to the significant drop in 2008. Looking at 2010 compared to 2008, companies seem to value middle-aged employees a lot higher, with substantial increases for all innovatie group averages.

Table 4: Age group shares

	Innovation group	2006	2008	2010	Total
		Year			
0 to 30	Non-innovators	.226	.204	.192	.207
	Process innovators	.230	.229	.204	.224
	Prod. and proc. innovators	.276	.261	.237	.248
	Product innovators	.278	.241	.250	.256
31 to 50	Non-innovators	.485	.481	.488	.485
	Process innovators	.494	.472	.517	.492
	Prod. and proc. innovators	.469	.482	.497	.482
	Product innovators	.480	.461	.489	.477
51 to 100	Non-innovators	.289	.314	.318	.308
	Process innovators	.275	.299	.278	.284
	Prod. and proc. innovators	.255	.256	.265	.279
	Product innovators	.241	.297	.260	.267

Overall it seems that companies value older employees of the two higher age groups more than young employees, potentially trying to counteract the effect of the financial crisis by parting ways with young, not yet fully productive employees which represent more of a long-term investment and replacing them with functioning, productive short-term solutions in the form of middle-aged and (for non-innovative and "product and process" innovative companies) even older employees. As explored in the literature review section above, we could be expecting this type of behavior due assumed higher productivity of older age groups compared to the youngest age group due to experience related gains as well as specific knowledge of the firm processes and requirements for staying workers.

4. Methodology

The methodology of this research is two-fold. Since we don't have all the data initially in one dataset, we first have to combine the two datasets to transfer all the necessary data from one dataset to another in order to correctly assess the impact and implications of innovative activities on employment as an absolute value on the firm level as well as potentially on the sector or country level and the change in epmployment structure; again on firm level and potentially on sector or country level. For this we take the information about employment from the estonian tax data and insert the needed values for the individual entries for each firm at any given year.

Employees are divided into three groups, workers up until the age of 30 (from now on called "young" workers), employees of the ages 31 to 50 (from now on called "middle-aged“ workers) and employees of the ages 51 and above (from now on called "old" workers) with age 100 as the upper boundary. For further analysis we then create variables to represent the percentage share of employees of each age group in any firm, as absolute values of employees might change drastically depending on the state of the company or the whole industry, while the share might not be affected by these kinds of fluctuations. This allows for the most specific analysis later on in the process of conducting regression analysis.

The first part of the methodology is mostly based on the methodology used by Harrison et al, 2014. However, a few adjustments might need to be made, as Harrison et al only had one wave of CIS data, but for different countries, while we have multiple waves of CIS data but only for the case of Estonia.

We can observe each company over a multitude of years denoted with t and accurately track their sales, employment growth and employment changes as well as the activity in regards to innovation; did they innovate a lot, only in some areas or rather attempted to boost their revenues by other means, which we however cannot accurately track here, besides changes in the absolute value of employment, which in turn can have different reasons and is not the most desciptive parameter and can't be further verified in the scope of this research.

In the first year at any point observed over the survey time span, the output of any given company is for simplification purposes assumed to only be one product, with the potential of producing two types of product at the end of the second year; which then turns into one product if the span of the next two years is being investigated. This leads to the situation, where the output in any year beyond the first is divided into output of the old product in combination with the potential output for the new product. This output for the new product is to be zero if the company has not invested in any product innovation in the past year.

For simplification we assume that the production technology for both products, old and new, remains the same; two seperate production functions with constant returns to scale for all inputs (capital K, labour L, other intermediate inputs M). Furthermore, we assume Hicks-neutral productivity technology; meaning old products can become more efficient in their production over time or in bad cases the productivity can also decrease.

Harrison et al. 2014 first measure the output of a company at t1 and t2 and then the labour demand as a function of costs (wages), output and production efficiency. Assuming that costs stay the same with prices for inputs to the production of old and new product staying roughly at the same level Harrison et. al reach an equation which measures the employment growth of production efficiency and output. This research will not go more into detail at this point, as the steps can be easily observed in the original article and the equation steps will not be reproduced here.

The regression equation to investigate the effect of product and process innovation on employment as presented by Harrison et. al could look like follows if we adjust for the fact that more than one CIS wave is available:

$$l_i - y_1 i = \alpha_0 + \alpha_1 d_{1t} + \beta y_{2i} + u_i \tag{1}$$

Here the l_i stands for the employment growth in the period i, which is the time frame of the CIS survey being investigated, e.g. 2006 to 2008 for CIS2008. y_1 and y_2 are the outputs of the old and new product respectively with the parameter β being the relative efficiency in production of the old good and the new good, with the term including y_2 only being relevant in case the company does indeed invest into product innovation and has any new or improved goods being distributed by the end of the survey time frame. α_0 stands for the average efficiency growth in production of the old good over the survey time frame, while α_1 stands for the additional effect of product innovation on the efficiency in producing the old good. The variable d determines whether the company has indeed introduced any process innovation not connected directly to a product innovation over the survey time frame or not. If the company has introduced said process innovation, the variable d has the value of 1; otherwise it has the value of 0 in case of only process innovations concerning a new or improved product or no process innovation at all.

Based on this equation this research attempted to create similar equation to disentangle the effect of innovation on the percentage change of employment into the effect of innovative activities on each age group of employment in a separate equation. The equation the author came up with based on Harrison et al 2014 is the following:

$$S_{j,t} = alpha_{0,t-1} + \alpha_1 d_t + \beta y_{2,i,t} + u_{i,t} \tag{2}$$

S stands for the change in share of the employee age group from the total with j having the values 1 to 3, for each of the three age groups respectively. t stands for the time; in this case rather the time range of the survey waves, e.g. 2004 to 2006 for CIS2006. α_0 represents the efficiency growth of the production for the old good, while α_1 covers the increased efficiency of production for the old good in case of a firm investing in process innovation. d_i is a binary variable which has the value of one in case of a firm did introduce process innovation and in this case the variable will influence the equation. If a company did not introduce any process innovation the variable d_i has the value zero and the whole term is zero.
β_1 is the relative efficiency of producing the old product, for which the output growth is denoted by y_1. Similar to this, β_2 refers to the relative efficiency of producing the new product compared to the old product and unsurprisingly y_2 refers to the output growth of the new product. If the company made efforts into product innovation, y_2 will be positive and therefore impact the equation, whereas if there was no new or improved product introduced

in the time period in question, the only output growth will be of y_1, as the output growth for the new product y_2 will be zero.

However, due to various reasons the above equation did not translate well into actual attempts at estimating the impact of innovative activities on the change in percentage shares of employment age groups as opposed to a change in the absolute value of empoyment. For the scope of this research then the author adopted a different equation and estimation method, based mainly on singular CIS questions and the implication of the responses on the company innovation activity directly, rather than levied through changes in company productivity or output level of different products. We can adopt this method by looking at previous research of e.g. Aubert et al 2005, who found that different types of innovative activity had an influence on age structure, so in this research we compare directly the self-reported answers from companies on different types of product and process innovation, which were specified earlier and are explained in more detail in the appendix as well.

It is noteworthy, however, that other authors generally tend towards a methodology more similar to Harrison et al. 2014, in which the innovative activites are not directly integrated but rather through the instruments of changes in sales and the shares of new and old products. This might help in accounting for the variance in self-reported responses and personal interpretation of the respondant, as well as another issue that innovations are very different in nature and importance of innovations. Some innovations might be small and not very influental to the company or a specific product, while others might be of a large importance to the company and change a product drastically. (Hall, 2011) Nevertheless, this research employs the following single equation estimation method:

$$S_{i,t} = \alpha_1 d_{1,t} + \alpha_2 d_{2,t} + \beta_1 d_{3,t} + \beta_2 d_{4,t} + \beta_3 d_{5,t} + o_t + u_{i,t} \tag{3}$$

The dependent variable S_{it} is the change in percentage share of an employee age group across all companies over the dataset. t stands for the time, however not as discussed above the time frame of a CIS survey wave (e.g. 2006 to 2008 for CIS2006) but rather one of the time stamps which occur every two years at the end of one survey wave and also the beginning of the next. α_1, α_2, β_1 and β_2 are coefficients of their respective binary variables which have the value of 1 if a company responded positively to the question captured by the second part of their respective term and 0 if the company responded negatively. d_{1t} represents the impact of a company responding yes or no to the question in the CIS survey which asks about the company introducing product innovations in the form or new or improved manufacture goods in the time frame of the survey, the previous 2 years. The variable d_{2t} captures a similar question, asking about a company introducing product innovation in the form of new or improved services. Similarly to the two previous variables, d_{3t} and d_{4t} represent the

similar questions on the topic of process innovations; specifying different types of process innovation.
Lastly the o_t stands for the change in output over the time frame of the survey, more specifically the change in total amount of sales before any deductions, the change in gross revenue. This is to see how well companies are doing over the time frame observed in the data set and if there clear tendencies can be observed in how well companies are doing from a sales standpoint and how this changes the employment structure keeping in mind the innovative activities by the company.

Speaking about expected results for the regression analysis, there is little research which explores the particular question of how innovative activities influence the actual structure of the workforce; mostly limited by the access to said data. As explained in the previous section, there are very few countries which can offer such data about company innovation on company level and the actual structure of the workforce in these companies; on one hand in regards to age and gender, but also as another point, which is not being explored in this research, in regards to wage or potentially other factors on the employee level. After consulting previous literature on innovation as well as employee age and their productivity we can still set some expectations to what is to be expected as a potential outcome from this research, taking into account the economic situation in Estonia, the initial age group distributions, expected effects of hiring different aged employees and in which situations companies hire what kind of employees.
Young, recently founded companies seem to be more prone to carry out innovative activities and present new products to the market as well. Previous research has shown that so called start-ups tend to employ proportionally more younger people, since they are more likely to fit their company culture and work better together with other younger people, as opposed to older, more settled workers who might not be as flexible anymore in their views and habits. For this reason it is expected that the share of older workers (age group 51-100 in the dataset) should be negatively affected by a company introducing innovations, potentially even more by new to the company or new to the market innovations, which however is not included in the model for now (see section 5 for further discussion). As Aubert et al 2005 stated, the share of older workers was smaller in innovative firms when compared to non-innovative firms. Regarding the two age groups under 51 years the expected results are more ambiguous, as the age groups are relatively large and attributing middle-aged workers of 31 to 50 years of being "too old" for innovative firms would be a large oversight; therefore we expect the impact of companies introducing process innovations and especially product innvations to be of positive effect on the midlle-aged employee share and a smaller, but still

positive effect on the share of young employees.
As for the change in company sales turnover, it is expected to see a positive effect of higher sales over the period on both the shares of young and middle-aged employees, while the oldest age groups share is expected to simultaneously take the decrease to even out the company workforce due to companies in a favorable economic situation being more likely to invest in the future and be able to afford take younger employees onboard and survive the period of their lower productivity in the beginning due to a strong market position. On the other hand, we have to keep in mind the overall economic situation and stability of the market at that time. It is slightly unfortunate that the data sample happened to be gated to these few CIS survey waves which include the global financial crisis and potentially overthrow large portions of the expected results of this research. Geroski and Walters (1995), found that economic changes and the position in the business cycle indeed impact the companies innovation activity, so it can be expected that innovative activity would be less prevalent. Previous research has shown that there are companies that persist through unfavorable economic downtimes by increased focus on innovation to counteract the crisis by new, innovative ideas and products that could help the company weather the storm and emerge from the crisis in a potentially improved position due to their persistence in innovation (see e.g. Filippetti and Archibugi 2011). Regardless, the overall effect of innovative activities on the different age groups should remain the same, positive impact on middle-aged employee share and potentially also young employees, negative on older workers, though it can be a consideration that the overall share of older, more productive workers can increase in times of crisis, at least for non-innovative companies, as also seen in our data. Innovative companies however are still expected to increase at least the share of middle-aged employees, who are widely seen as the most productive due to not yet declining in their cognitive capabilities (see e.g. Grund and Westergaard-Nielsen (2005) on age structure and firm performance; Maliranta (2007) or (2016), or Lallemand and Rycx (2009) on age and firm performance) but also being more experience and “refined” if one might say that than younger employees. To summarize for a general view leaving out a number of factors such as sector specifics and business cycle influence; innovative companies and therefore innovative activities are expected to increase the share of middle-aged employees and therefore be positively correlated as well as to some extent increase the share of young employees, while subsequently the share of older workers in innovative companies has to decrease as a result and innovative activities are to be of negative impact on the share of older workers.

5. Encountered problems and future improvements of the research

As already touched in the previous sections, there are some problems which arose during the conduction of this research. In this section we want to further specify the problems and issues as well as discussing some potential solutions that could be applied in further research on this topic. There were some significant topics which should be discussed already at this point instead of expanding the conclusion at the end of this paper.

5.1. Explanatory variables and sample size

In the results section this topic was already discussed, but some further insight will be given in this paragraph. Combining the datasets of CIS survey data and Estonian tax data is not perfect in the sense that it is done for each company available on each point of time (year) available. However, due to randomness in selecting companies for CIS responses as well as the responses not always being complete and other factors such as e.g. companies being founded or going bankrupt, the merging of the data sets by matching a specific company identifier present in both datasets is not perfect in the sense of not being able to match every company and leaving a lot of variables blank which can't be used for further evaluation then. In our case due to data availability we lost a big portion of the sample and had to continue with only the years 2006 to 2010 for the questions that were asked to the data. If we were to include further variables and ask different questions or try and involve more versatile questions and variables about e.g. other innovation types like marketing innovation or sources of innovation (e.g. in-house R&D or external R&D) it would only narrow the sample down even more to unusable levels. To give a specific example, including the variable asking if any of the innovations were new to the firm or the market for both product and process innovation does cut down the observations to only 888 observations over the two years, which makes the results very unsatisfying and severely limits any conclusions drawn from the regressions. This issue makes choosing the right balance of explanatory variables to get significant, meaningful results while still keeping the actual observation count high enough surprisingly challenging.

5.2. Innovation timing

Innovative activity does not always take immediate effect and therefore some innovations that were introduced or started shortly before the end of a CIS wave period or the time of the survey being conducted might be counted into the innovations for the current CIS wave but have not had any effect on the current results, but rather influence the next CIS wave. This leads to the current CIS data being skewed and not accurately accounting for the effects of innovation from this period. On the same note, this can effect all periods in two ways: prior CIS wave innovations skewing the current results by the innovative activity not being taken into account in the current CIS results, leading to potentially higher output (if we assume positive effects of innovation) in the data than the results should display or as mentioned before, current innovation only taking effect in the next CIS wave period but the innovative activity being conducted an recorded in the current CIS wave, therefore reducing the net effect of innovation on the current CIS wave response. One way of trying to account for this would be to include lagged variables in the regression, but this again has different issues that require sorting out. The magnitude of the time lag needs to be decided on and set, but choosing and moving forward with a higher lag can potentially contribute to the above mentioned diminishing number of observations given more restrictions is the timing of innovations. This of course depends on the data availability, but in our case with only three points in time having information on innovative activity that can be used effectively, even a lag of one removes one third of the observations and severely limits the explanatory power of the results, making the results even more dependent on the economic situation which in our case would fall in the period of economic crisis.

5.3. Firm sector differences

The last potential improvement that will be discussed at this point is the differentiation and differences in companies depending on their produced output. Companies in the manufacturing sector of producing physical goods do have different requirements and specifics compared to service companies. This differentiation is likely to also be shown in the available data; companies in the service sector might have a different work force composition, different innovation preferences and the shares of employee age groups therefore would potentially also react differently to innovative activities. The first two variables in the regression do in fact ask about product innovations for produced goods and services respectively and it can be assumed that positive responses to the questions behind the variables are given by mostly companies of the respective sector, but this is only a potential indicator and should not be taken for a confirmed result. As many of the problems encountered during this research, accounting for this specification would further restrict the available data and observations and further limit the explanatory power of the results found due to a decreasing number of observations, so it was left to be included in future versions of this research with more extensive data and potentially new, adjusted methods.

6. Results

Tables 5,6,7 and 8 below show the results of the panel data fixed effects regressions run with the previously explained method. For reasons of completeness we ran two different versions of regressions on a slightly altered version of the model, once leaving out the change in company sales compared to the previous version. In general, it turned out to be a reasonably large problem of adding a large quantity of variables to the model or regression without diminishing the observations and sample size down to insignificant values. Unfortunately, the tax dataset does not include the complete information for all companies' employees over all the years that are observed in the CIS survey; but rather only for the years 2006 to 2010. This fact or criterion alone decreases the number of observations (company responses to CIS survey for any year/wave) from 13770 entries for the whole dataset to 5830 over the years 2006 to 2010. Adding further variables or required parameters such as a response to a specific question to the model further narrows down the sample size, as can be seen in the number of observations used for the regression with and without the change in company sales, decreasing to 2471 due to the regression method and the dependent variable being a change variable as well.

Besides the above explained issue of decreasing sample size we also applied one further distinction when running the regressions. Due to Estonia being an objectively small country, we do have a substantial number of companies responding multiple consecutive times to the CIS survey questions, meaning the data allows us to run a panel data regression testing for company fixed effects as it can be seen with the number of unique firms in the tables 6 and 8 as opposed to only considering time points as the way of grouping the observations and checking for time fixed effects as can be seen in tables 5 and 7. Having a larger number of companies respond for consecutive years also allows to ask different questions which can be potentially explored in the scope of other research projects; for this research however this possibility was explored but will not be further treated here due to again narrowing down the number of observations to levels of even stronger insignificance of results.

For comparison of model fit we also ran a standard pooled OLS model first, whose results can be found in appendix D. Tests and comparison with panel data regression however quickly established OLS as the inferior regression method in this case.

We also ran a Hausman test to confirm whether a fixed effects model would be preferred over random effects. The result was clear, the H0 of individual-level effects being adequately modeled by random-effects model was soundly rejected, meaning the difference in coefficients is systematic and a fixed effects model will yield better results. This finding was also confirmed by the Breusch and Pagan LM test for random effects.

Table 5: Relationship between the change of the shares of different age groups and types of innovation; regression results for company fixed effects

	Change of the share of age group from total employment		
	(1)	(2)	(3)
VARIABLES	Up to 30 years	Between 31 and 50 years	Above 50 years
Product innovation - products	-0.00640	0.0130	-0.00663
Product innovation - services	-0.00552	-0.00123	0.00675
Process innovation – methods	0.000329	0.00313	-0.00345
Process innovation – logistics	-0.0264**	0.0228*	0.00360
Process innovation - administrative	-0.00798	0.0237**	-0.0157*
Change company sales	5.71e-10**	-5.96e-10**	0
Constant	0.0617*	-0.116***	0.0541*
Observations	2,471	2,471	2,471
Unique companies	1,478	1,478	1,478

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Interpreting the results, we do see some relationships that are not always in line with what was predicted to be the expected outcome, but also other, more expected results that confirm some of our initial expectations. Firstly when looking at the variable that is not directly measuring innovative activity, the change in turnover compared to the previous point in time, we can see that indeed, companies that have increasing sales and therefore a more favorable economic position tend to employ more younger workers, as the impact is positive and statistically significant for both regressions, taking $p<0.05$ as the standard threshold of statistical significance. The numbers are in fact slightly difficult to read and should be adjusted to not look at improvements of units counting in 1 Euro steps but rather a much larger quantity to make the results more readable. The share of medium-aged workers is negatively influenced by increasing company sales; confirming the expected result we raised earlier, also with the same statistical signifiance as the change in share of young employees.

Table 6: Relationship between the change of the shares of different age groups and types of innovation; regression results for time fixed effects

	Change of the share of age group from total employment		
	(1)	(2)	(3)
VARIABLES	Up to 30 years	Between 31 and 50 years	Above 50 years
Product innovation - products	0.00289	-0.00598	0.00309
Product innovation - services	-0.000537	-0.00879	0.00933*
Process innovation – methods	-0.00261	-0.00849	0.0111**
Process innovation – logistics	-0.0166**	0.00963	0.00693
Process innovation - administrative	-0.00223	0.00226	-2.17e-05
Change company sales	5.44e-10***	-2.71e-10	-2.73e-10
Constant	0.0112	0.0176	-0.0288*
Observations	2,471	2,471	2,471
Years	2	2	2

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

When looking at the different questions posed in the CIS survey and the impact of a company responding yes to these, lets first look at the results for the regression including the change in company sales, which are shown in tables 5 and 6. Interestingly, we don't see any statistically significant impact by a company introducing product innovations for manufactured goods as opposed to not doing so except for a small statistically significant increase in the change of share for old employees by a company innovating in services when controlling for time fixed effects. Overall, a company investing in product innovation for either products or services when compared to a company that does not invest into them does not seem to have any meaninful statistically significant impact on the change in age group shares. The general direction of the coefficients tends towards a negative impact on shares of mostly young and sometimes also middle-aged employees in favor of older employees, but no statistical significance to back this trend. It is likely, that this change is more caused by the general economic situation and the generally bad economic conditions overshadow any potentially small significance in the effect of product innovation on age group share changes. The lack of statistically significant results for product innovation could be influenced by the fact that potentially there is no need to change the workforce that much when introducing (marginal) improvements to products or services. Besides that, there is again the impact of the general economic situation overshadowing the results with general economic downturn. Looking at the results for process innovation variables impact on age group shares, we can see that some types of process innovation tend to have a statistically significant impact on the different age shares. Introducing new or improved ways of manufacturing or producing

goods or services does have a statistically significant impact on the change in share of old employees in case of time fixed effects, with the share of young and medium-aged employees (however statistically not significant) decreasing and simultaneously the share of old employees increasing. Introducing new or improved logistics, delivery or distribution methods does show a statistically significant decrease in the share of young employees for both company as well as time fixed effects in favor of an increased share of medium-aged and old employees, the former having some statistical significance while the latter does not.
Lastly, innovation of administrative processes does lead to a statistically significant small increase in the change of the age share of medium-aged employees at the cost of old employees when considering company fixed effects in table 5; potentially hinting that administrative technology could be harder to adapt to for employees of the highest relative age group. As for the general impact of innovation on changes of age group shares in tables 5 and 6 the effects are rather small and do not present strong structural causality for most innovative activities influence. Nevertheless, there are some statistically significant changes for types of process innovations and the change in company sales, mainly finding increasing shares of employees not in the youngest age group; potentially hinting at companies aiming at older employees for their process innovations; perhaps due to their previous knowledge of processes both at the current company or from competitors to improve their internal processes by comparing and adapting to successful competitor processes.

Table 7: Relationship between the change of the shares of different age groups and types of innovation; regression results for company fixed effects (excluding change in company sales variable)

		Change of the share of age group from total employment	
	(1)	(2)	(3)
VARIABLES	Up to 30 years	Between 31 and 50 years	Above 50 years
Product innovation - products	-0.00831	0.0150	-0.00671
Product innovation - services	-0.00401	-0.00280	0.00682
Process innovation – methods	-0.000201	0.00368	-0.00348
Process innovation – logistics	-0.0283**	0.0248*	0.00351
Process innovation - administrative	-0.00963	0.0254**	-0.0158*
Constant	0.0704*	-0.125***	0.0545*
Observations	2,471	2,471	2,471
Unique companies	1,478	1,478	1,478

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Tables 7 and 8 present the results of the regression leaving out the variable measuring the change in company sales. As for the coefficients of the different variables and their significance there are no real changes or improvements observed, rather the results do stay of similar significance and the direction of the coefficient stays the same in almost all cases and no changes in coefficient direction for statistically significant variables impact on changes in certain age shares.

Table 8: Relationship between the change of the shares of different age groups and types of innovation; regression results for time fixed effects (excluding change in company sales variable)

VARIABLES	(1) Up to 30 years	Change of the share of age group from total employment (2) Between 31 and 50 years	(3) Above 50 years
Product innovation - products	0.00243	-0.00575	0.00332
Product innovation - services	-3.15e-05	-0.00904	0.00907*
Process innovation – methods	-0.00313	-0.00823	0.0114**
Process innovation – logistics	-0.0174**	0.0100	0.00733
Process innovation - administrative	-0.00320	0.00274	0.000461
Constant	0.0157	0.0154	-0.0311*
Observations	2,471	2,471	2,471
Years	2	2	2

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Looking at the fit of the model, having run a fixed effects model, the results give a rather clear picture. Grouping only by the (unbalanced) year variable and considering time fixed effects gives a very high r^2 for between effects, meaning a large amount of the changes in effect of the independet variables on the dependent variables from one value of the year variable to the next one can be explained by the different time periods. This holds true whether the change in company sales is included or not. Similarly, grouping by both year and the company identifier value, meaning looking at companies as a group over the years and considering company fixed effects, gives very low r^2 results for both within and between effects with a simultaneously exceptionally high ρ value. This results in most of the variance in the results in fact being explained by the error term itself and the results could be more or less disregarded as the actual results of these specific regressions can be classified as more or less random.

Looking at the results of the regression as a whole, we can summarize that there are some small, significant effects of individual types of innovations on some changes in certain age shares, however, it can be discussed how much it makes for a convincing argument for an impactful finding as a whole. The mechanisms behind these changes could be much more reasonably explained if more results were statistically significant, however in the current state the results when considering company fixed effects seem to be mostly influenced by the error term itself. On the contrary, the different time periods do seem to have a strong impact on the changes in age shares across all age groups. This further hintson the strong impact of the financial crisis in Estonia, which was hit severely and much harder than many other countries, alongside its neighbouring countries of Latvia and Lithuania (e.g. Purfield and Rosenberg 2010).

7. Conclusion

This research uses a single equation model to explain the changes in age shares of the workforce composition of Estonia over some waves of the CIS survey; mainly by variables relating to the effects of different innovative activities regarding product and process innovations on the change in age shares.

As a whole, the results point towards innovative activity of any sort, if statistically significant, decreasing the share of young employees in favor of mainly old-aged employees. This result does come as a surprise, given the expectation of younger, more innovative companies also employing a younger workforce. However, the results seem to be highly influenced by the general economic situation, as the time frame of the available dataset includes the global economic crisis from 2008 in the middle section and any results from there on might be stronlgy skewed due to this. The general descriptive data also supports this, as over all innovation groups from non-innovators to companies introducing both product and process innovation the share of young employees significantly decreased from the point of the global economic crisis onwards in favor of medium-aged or even old employees; potentially to ensure short-term company stability and ensure survival through immediate results instead of focusing on future times. This view on innovation groups and their respective age share distribution however was to the best of my knowledge not explored before and does pose a suitable area worth exploring further in future research, given the availability of innovation activity and company specifics with the possibility to merge the data per company.

There are certain other points that can be continued and improved in future research on this topic; a longer time frame with results also in more favorable economic times as well as some improvements to the model itself, which are explained in section 5. Expanding on next potential steps gives some clear ideas such as also testing a different dataset of potentially other countries and also attempting to reverse the causality; both for the current dataset of Estonian companies from 2006 to 2010 as well as others. This could allow to further confirm or deny the direction of the impact; can we confidently say that innovation does have an impact on the changes in employee age shares and companies deliberately adapt the workforce to their innovation activites and strategies, or are in fact companies more depending on the changes in the workforce when it comes to planning and executing their innovations and innovation strategies?

Adding to this, one could also try to disentangle the age share changes into what is attributed to changes due to hiring and firing of employees; it could very well be possible (and looking at the general change in employment over the time frame it also seems likely), that the increase of the shares of older employees is in part also due to companies laying off their young, less productive workers compared to older, more experienced workers.

Overall, this research does give some hints on the potential effects of innovative activities on employment age shares, but especially the time frame and the economic situation present during this time frame puts a noticeable questionmark behind the findings for now.

Appendix A. References

- Amore, Mario Daniele, (2015), Companies learning to innovate in recessions, Research Policy, 44, issue 8, p. 1574-1583, https://EconPapers.repec.org/RePEc:eee:respol:v:44:y:2015:i:8:p:15 1583
- Archibugi, Daniele; Filippetti, Andrea and Frenz, Marion (2013), Economic crisis and innovation: Is destruction prevailing over accumulation?, In Research Policy, Volume 42, Issue 2, 2013, Pages 303-314, ISSN 0048-7333, https://doi.org/10.1016/j.respol.2012.07.002
- Archibugi, Daniele, (2001) Pavitt'S Taxonomy Sixteen Years On: A Review Article, Economics of Innovation and New Technology, 10:5, 415-425, DOI: 10.1080/10438590100000016
- Aubert, P. , Caroli, E. and Roger, M. (2006), New technologies, organisation and age: firm-level evidence*. The Economic Journal, 116: F73-F93. doi:10.1111/j.1468-0297.2006.01065.x
- Backes-Gellner, U. and Veen, S. (2013), Positive effects of ageing and age diversity in innovative companies – large-scale empirical evidence on company productivity. Human Resource Management Journal, 23: 279–295. doi:10.1111/1748-8583.12011
- Crépon, Bruno, Duguet, Emmanuel and Mairesse, Jacques, (1998), Research, Innovation And Productivity: An Econometric Analysis At The Firm Level, Economics of Innovation and New Technology, 7, issue 2, p. 115-158, https://EconPapers.repec.org/RePEc:taf:ecinnt: 158.
- Dachs, Bernhard and Peters, Bettina, (2014), Innovation, employment growth, and foreign ownership of firms, Research Policy, 43, issue 1, p. 214-232, https://EconPapers.repec.org/RePEc 232.
- Filippetti, Andrea and Archibugi, Daniele, (2011), Innovation in times of crisis: National Systems of Innovation, structure, and demand, Research Policy, 40, issue 2, p. 179-192, https://EconPapers.repec.org/RePEc:eee:respol:v:40:y:2011:i:2:p:179-192
- Garcia, Rosanna & Calantone, Roger. (2002). A Critical Look at Technological Innovation Typology and Innovativeness Terminology: A Literature Review. Journal of Product Innovation Management. 19. 110-132. 10.1111/1540-5885.1920110.
- Greenan, Nathalie & Guellec, Dominique. (2003). Technological Innovation and Employment Reallocation. LABOUR. 14. 547 - 590. 10.1111/1467-9914.00146.
- Grund, Christian & Westergaard-Nielsen, Niels. (2005). Age Structure of the Workforce and Firm Performance. International Journal of Manpower. 29. . 10.1108/01437720810888553.
- Geroski, Paul and Walters, Chris, (1995), Innovative Activity over the Business Cycle, Economic Journal, 105, issue 431, p. 916-28, https://EconPapers.repec.org/RePEc:ecj:econjl:v:105:y: 28

- Hall, Bronwyn H., Innovation and Productivity (June 2011). NBER Working Paper No. w17178. Available at SSRN: https://ssrn.com/abstract=1879040
- Hall, Bronwyn H. and Lotti, Francesca and Mairesse, Jacques, Innovation and Productivity in Smes: Empirical Evidence for Italy (December 2008). NBER Working Paper No. w14594. Available at SSRN: https://ssrn.com/abstract=1320840
- Hammermann, Andrea; Niendorf, Matthias; Schmidt, Jörg (2019): Age diversity and innovation: Do mixed teams of old and experienced and young and restless employees foster companies innovativeness? (IAB-Discussion Paper, 04/2019), Nürnberg, 31 S.
- Harrison, Rupert, Jaumandreu, Jordi, Mairesse, Jacques and Peters, Bettina, (2014), Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries, International Journal of Industrial Organization, 35, issue C, p. 29-43, https://EconPapers.repec.org/RePEc:eee:indorg:v:35:y:2014:i:c:p:29-43.
- Hyytinen, Ari & Maliranta, Mika. (2013). Firm lifecycles and evolution of industry productivity. Research Policy. 42. 1080–1098. 10.1016/j.respol.2013.01.008.
- Ilmakunnas, Pekka; Maliranta, Mika and Vainiomäki, Jari, (2005) Worker turnover and productivity growth, Applied Economics Letters, 12:7, 395-398, DOI: 10.1080/13504850500109790
- Ilmakunnas, Pekka; Maliranta, Mika, (2003) "The turnover of jobs and workers in a deep recession: evidence from the Finnish business sector", International Journal of Manpower, Vol. 24 Issue: 3, pp.216-246, https://doi.org/10.1108/01437720310479714
- Ilmakunnas, Pekka; Maliranta, Mika (2007) : Aging, labor turnover and firm performance, ETLA Discussion Papers, The Research Institute of the Finnish Economy (ETLA), No. 1092
- Ilmakunnas, Pekka & Miyakoshi, Tatsuyoshi. (2013). What are the drivers of TFP in the Aging Economy? Aging labor and ICT capital. Journal of Comparative Economics. 41. 201–211. 10.1016/j.jce.2012.04.003
- Ilmakunnas, P. & Maliranta, M. How does the age structure of worker flows affect firm performance? J Prod Anal (2016) 46: 43. https://doi.org/10.1007/s11123-016-0471-5
- Lachenmaier, Stefan and Rottmann, Horst, (2011), Effects of innovation on employment: A dynamic panel analysis, International Journal of Industrial Organization, 29, issue 2, p. 210-220, https://EconPapers.repec.org/RePEc:eee:indorg:v:29:y:2011:i:2:p:210-220.
- Lallemand, T. & Rycx, F. Are Older Workers Harmful for Firm Productivity? De Economist (2009) 157: 273. https://doi.org/10.1007/s10645-009-9126-5
- Machin, Stephen and van Reenen, John, (1998), Technology and Changes in Skill Structure: Evidence from Seven OECD Countries, The Quarterly Journal of Economics, 113,

issue 4, p. 1215-1244, https://EconPapers.repec.org/RePEc:oup:qjecon:v:113:y:1998:i:4:p:1215-1244..

- Masso, Jaan and Vahter, Priit, The Link Between Innovation and Productivity in Estonia's Service Sectors (February 21, 2011). The University of Tartu Faculty of Economics and Business Administration Working Paper No. 80-2011. Available at SSRN: https://ssrn.com/abstract=1765846 or http://dx.doi.org/10.2139/ssrn.176584
- Meriküll, Jaanika. (2010). The Impact of Innovation on Employment: Firm and Industry-Level Evidence from a Catching-Up Economy. Eastern European Economics - EAST EUR ECON. 48. 25-38. 10.2753/EEE0012-8775480202.
- Mohnen, Pierre and Hall, Bronwyn, (2013), Innovation and Productivity: An Upedate, Eurasian Business Review, 3, issue 1, p. 47-65, https://EconPapers.repec.org/RePEc:spr:eurasi:v:3:y: 65.
- Purfield, Catriona & Rosenberg, Christoph. (2010). Adjustment Under a Currency Peg: Estonia, Latvia and Lithuania During the Global Financial Crisis 2008-09. IMF Working Papers. 10. 10.5089/9781455205448.001.
- Roosaar, L., Masso, J., Varblane, U.;"THE STRUCTURAL CHANGE AND LABOUR PRODUCTIVITY OF FIRMS: DO CHANGES IN THE AGE AND WAGE STRUCTURE OF EMPLOYEES MATTER?" University of Tartu - Faculty of Economics and Business Administration Working Paper Series, No. 103, 2017
- Roosaar, L., Varblane.U., Masso, J. (2019) Age-related productivity decrease in high-waged and low-waged employees. International Journal of Manpower (earlycite)
- Schumpeter, Joseph A., The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle (1934). University of Illinois at Urbana-Champaign's Academy for Entrepreneurial Leadership Historical Research Reference in Entrepreneurship. Available at SSRN: https://ssrn.com/abstract=1496199
- Skirbekk, Vegard. (2003). Age and Individual Productivity: A Literature Survey. Vienna Yearbook of Population Research. 1. 10.1553/populationyearbook2004s133.
- Syverson, Chad. 2011. "What Determines Productivity?" Journal of Economic Literature, 49(2): 326-65. DOI: 10.1257/jel.49.2.326
- Vandenberghe, Vincent. (2012). Are Firms Willing to Employ a Greying and Feminizing Workforce?. Labour Economics. 22. . 10.1016/j.labeco.2012.07.004
- Vandenberghe, Vincent. (2017). The productivity challenge. What to expect from better-quality labour and capital inputs?, Applied Economics, 49:40, 4013-4025, DOI: 10.1080/00036846.2016.1273504
- Van Reenen, John, (1997), Employment and Technological Innovation: Evidence from U.K. Manufacturing Firms, Journal of Labor Economics, 15, issue 2, p. 255-84,

https://EconPapers.repec.org/RePEc:ucp:jlabec:v:15:y:1997:i:2:p:255-84.

- Violante, Giovanni. (2008). Skill-Biased Technical Change. 10.1057/978-1-349-95121-5_2388-1.

Appendix B. Definition of innovation

First it would be helpful to make clear what is defined as an innovation or innovation activity. In his famous work from 1934, Joseph Alois Schumpeter divides innovation into five different types:

- The introduction of a new good that the consumers are not yet familiar with, or an improved version of a previously existing good. This type of innovation is later mostly referred to as product innovation
- A new method of production, improved or streamlined processes that enhance the production. This is later referred to as process innovation
- Entering a new market, either into an existing one or opening a completely new market
- Gaining access to a new source of production input, regardless of it being raw materials of half-manufactured goods
- Reshaping the organization of an industry, like breaking up existing monopoly positions or establishing a monopoly situation

Over the years these five types were adjusted or changed until in 2005 the OECD gave an updated and contemporarily used definition in their Oslo Manual, which aims to generalize the collection and use of innovation data:

"An innovation is the implementation of a new or significantly improved product (good or service), or process, a new marketing method, or a new organisational method in business practices, workplace organisation or external relations." (OECD 2005, p. 46)

This definition includes the previously mentioned product and process innovation, but also incorporates organizational innovation and marketing innovation. Organizational innovation is explained at targeting cost reductions in supply acquisition, transactions, and administration, as well as improving labour productivity through workplace satisfaction, and "gaining access to "non-tradable assets (such as non-codified external knowledge)" (OECD 2005, p. 51). Marketing innovations are classified as significant changes to existing marketing strategies, be it through e.g. product promotions or changes in product design. (OECD 2005).

The relationship between innovation activities and employment has been studied and discussed by a relatively large number of authors and papers by now and can be analysed at either the firm, the sector, or the macro level. This paper will focus on the firm level due to the available data which will be explained in a later section. The distinction between different types of innovation that is usually focused on in recent publications is the one between the effect on employment of product innovation and process innovation, which both incorporate effects that potentially stimulate and increase employment, as well as employment reducing effects (Dachs, Peters 2013). Other strands of research focus on e.g. the importance and the distinction between different innovation strategies, and their effect on employment growth, or on organizational or marketing innovations.

Appendix C. Variables and parameters

C.1. Variables

- Product innovation - products
  - Introduction of new or significantly improved goods (excluding resale of solely aesthetically changed goods purchased from other companies); binary answer options (yes-no)
- Product innovation - services
  - Introduction of new or significantly improved services, binary answer options (yes-no)
- Process innovation - methods
  - Introduction of new or significantly improved methods of manufacturing or producing goods or services, binary answer options (yes-no)
- Process innovation - logistics
  - Introduction of new or significantly improved logistics, delivery or distribution methods for your inputs, goods or services, binary answer options (yes-no)
- Process innovation - administrative
  - Introduction of new or significantly improved supportng activities for your processes, such as maintenance systems or operations for purchasing, accounting or computing, binary answer options (yes-no)

All definitions are from CIS survey questionnaires and did not change much, if at all, over the discussed time frame. Furthermore it includes also a preamble to help identify and classify company output as products or services based on tangibility, ownership over time, and durability. These conditions are then discussed and examples are given; but will not be further discussed here.

C.2. Parameters

- Innovation groups
  - Non-innovative: Company has not responded with yes to any of the question about introducing a product or process innovation
  - Product innovators: Company has responded with yes to at least one of the questions about introducing a product innovation and not responded with yes to any of the questions about introducting a process innovation
  - Process innovators: Company has not responded with yes to any of the question about introducing a product innovation and responded with yes to at least one of the questions about introducting a process innovation
  - Product innovators: Company has responded with yes to at least one of the question about introducing a product innovation and also responded with yes to at least one of the questions about introducting a process innovation

Appendix D. OLS results for comparison

Table 9: OLS results (excluding change in company sales)

	Change of the share of age group from total employment		
VARIABLES	(1) Up to 30 years	(2) Between 31 and 50 years	(3) Above 50 years
Product innovation - products	0.00233	-0.00555	0.00322
Product innovation - services	-0.000294	-0.00849	0.00878
Process innovation – methods	-0.00423	-0.00591	0.0101**
Process innovation – logistics	-0.0183**	0.0119	0.00633
Process innovation - administrative	-0.00361	0.00360	5.83e-06
Constant	0.0208	0.00470	-0.0255
Observations	2,471	2,471	2,471

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: OLS results

	Change of the share of age group from total employment		
VARIABLES	(1) Up to 30 years	(2) Between 31 and 50 years	(3) Above 50 years
Product innovation - products	0.00286	-0.00593	0.00306
Product innovation - services	-0.000835	-0.00810	0.00894
Process innovation – methods	-0.00351	-0.00643	0.00994**
Process innovation – logistics	-0.0172**	0.0112	0.00604
Process innovation - administrative	-0.00247	0.00279	-0.000324
change_turnover_cis	6.16e-10***	-4.38e-10*	-1.78e-10
Constant	0.0151	0.00872	-0.0238
Observations	2,471	2,471	2,471

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Non-exclusive licence to reproduce thesis and make thesis public

I, *Christian Mentz*

(*author's name*)

1. herewith grant the University of Tartu a free permit (non-exclusive licence) to

reproduce, for the purpose of preservation, including for adding to the DSpace digital archives until the expiry of the term of copyright,

Innovation and Employment structure in Estonian firms,

(*title of thesis*)

supervised by: *Urmas Varblane*

(*supervisor's name*)

2. I grant the University of Tartu a permit to make the work specified in p. 1 available to the public via the web environment of the University of Tartu, including via the DSpace digital archives, under the Creative Commons licence CC BY NC ND 3.0, which allows, by giving appropriate credit to the author, to reproduce, distribute the work and communicate it to the public, and prohibits the creation of derivative works and any commercial use of the work until the expiry of the term of copyright.

3. I am aware of the fact that the author retains the rights specified in p. 1 and 2.

4. I certify that granting the non-exclusive licence does not infringe other persons' intellectual property rights or rights arising from the personal data protection legislation.

Christian Mentz

Tartu, 23.05.2019