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Age-specific labour demand effect of technological innovation.

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(date)

We have written this master's thesis independently. All viewpoints of other authors, literary sources, and data from elsewhere used for the writing of this paper have been referenced.

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Abstract

This research examines the relationship between technological innovation and age-specific labour demand at the firm-level. A combined panel data set of Estonian firms is used in this study, namely merged version of 3 different data sets - (Community Innovation Survey, Business Registry data, Estonian Tax and Customs Office data) which consists of 5,785 unique firms over the 2006-2016 period. This paper uses a constant elasticity of substitution production function to derive labour demand equation for perfectly competitive firms and the system GMM approach for analysis on a panel data set. The results approve the theoretical expectations that there is a significantly positive impact of technological innovation on the total employment at the firm level and the negative relationship between innovation and the employment of older employees. However, the latter finding is the case only in low-tech firms. Moreover, adding organizational innovation to our estimation equations increased the coefficients of product innovation slightly, however all estimations show that both product and process innovations do not have an age-specific impact on labour demand in the long run.

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Contents

Introduction

Spreading computerization and artificial intelligence play an essential role in the effectiveness of production, followed by shifts in the labour demand in competitive global markets. In theory, technology affects labour demand in two ways. First view is labour substitution effect that technological innovation in the production process can reduce demand for low-skilled labour and thus increase unemployment in that group. Production costs are reduced as daily activities become more mechanized, hence technology increases productivity. This is a fact that the demand for the workforce is reduced due to the automation of the activities. For instance, the statistics in US revealed that 1.63 million technological devices replaced humans in different industries in 2015 (Frey and Osborne, 2017). Second view is compensation effect which increases demand for skilled labour through creating new job opportunities. The decrease in the costs of the country's products as a result of efficient production leads to an increase in demand, consequently new jobs are created in the labour market (Evangelista and Savona, 2003).

The studies on employment and innovation have covered several research questions, such as 'Is technological innovation skill-biased, routine-biased or age-biased?' (Dachs, 2018; Blanas et al.,2018). Despite the literature being quite voluminous, it still can be expanded to new countries using different data sources. Hence, this research will examine the effect of product and process innovation on the age-structure of workforce in Estonia. Previously, few authors (Michael 2007; Rønningen 2007) have investigated the age-biasedness of technological changes. It is generally assumed that young people can have higher innovation capabilities (Frosch, 2011). Although older workers have more experience compared to younger people, the implication of new technology to a company can be also against them. According to Aubert et al. (2006), there can be two main reasons behind this consequence. Firstly, the skills and experience of older workers might not be suitable for innovations. Secondly, the adaptation of older employees to mechanization can be much slower in comparison to younger coworkers.

Mentioned findings above make this topic more considerable in EU countries, namely in Estonia where massive technological innovations are applied to industries and companies as well as have aging population. The statistics from the United Nations (2017) report that approximately one-fourth of the EU population was 60 years old and above in 2017. Estimations reveal that this number will increase by 10 percentage points till 2050, so about 35 % of the population in Europe will consist of older people. Moreover, the employment rate of people between the ages of 55 and 64 in the EU was 58.7% in 2018 (Eurostat, 2019). This indicator stood at 68.9 % in Estonia, one of the highest indicators in the EU. In summary, analysis of the employment rate of those age groups in the age of rapid technological changes and finding solutions to these issues should be a concern for economic policies.

This research expands the existing empirical literature by analyzing the link between technological innovation and employees with different age structures in Estonian firms. A final unique combined data set is used in this study, namely 3 different data sets are merged for the study which consists of 5,785 unique firms in total. These are the Community Innovation Survey (CIS), Estonian Business Registry data and Estonian Tax and Customs Office data. As Estonian Customs and Tax Office data on payroll taxes contains information about firms starting from 2006, we dropped the first three waves of CIS (CIS3, CIS4, 2004-2006). Hence this data set gave an opportunity to apply thorough and advanced estimation strategy. Moreover, this paper uses a constant elasticity of substitution production function (CES) by Van Reenen (1997) to derive labour demand equation for perfectly competitive firms. Age-specific labour demand was regressed on the 3 years lagged technological innovation, lagged employment variable, the labour costs for each employee category (young, middle-aged, old), real capital stock, time and industry dummies for NACE 2-digit industries in final estimation equations. OLS, within group and system GMM (using Roodman's (2006) xtabond2 command in Stata) estimation methods are executed in the paper.

In summary, we investigated the effect of technological innovations on the total employment of companies in Estonia. Additionally, the innovation impact on different age categories of employment has been tested as it is the main question of the study. Thirdly, product and process innovation were added to the analysis to see the impacts of these specific types of new technologies separately. Next, we added organizational innovation to our estimations for robustness test. Finally, the companies are split into low, medium and high-tech sectors for more robustness.

The results approve the theoretical expectations that there is a significantly positive impact of technological innovation on the whole employment at the firm level and the negative relationship between innovation and older employees. However, the latter finding is the case only in low-tech firms. Moreover, adding organizational innovation to our estimation equations increased the coefficients of product innovation slightly, however all estimations show that both product and process innovations do not have an age-specific impact on labour demand in the long run. Finally, organizational innovation itself is not associated with the labour demand through different age structures.

The rest of the paper is organized as follows: The second section represents analysis of different theoretical and empirical literature comparing evidences of innovation effects on employment from all over the world. Section III. presents econometric model used in this paper covering the derivation of the labour demand equation (estimation strategies for the total number of workforce and for the employees from 3 different age groups) from production function introduced by Van Reenen (1997). Section IV. describes the sources of the data sets used in this study with the help of descriptive statistics. Section V. discusses empirical results obtained from analysis to show the linkage between technological changes and labour demand in terms of their age in Estonia. Finally, conclusions are presented summarizing the results in Section VI.

Literature review

The literature on employment and innovation has covered several research questions, however it is one of the complex relationship addressed for many schools of economic thought. Some of them considered to have a positive effect on employment and economic growth but still the overall effect remains unclear on the side of theoretical contributions.

The analysis of innovation and employment presents a complex problem both from the theoretical and empirical perspective. Hereby, a general theoretical framework covers different schools of thoughts where the debate was already stated. To mention some, during the Classical period with David Ricardo, the labour class has already considered that the technological advance was detrimental to their interests. Marxism also considers it as a measure to increase unemployment, so introduction of new machines leads to displacement of workers in different fields. Following, the contributions of Schumpeter and Keynes enriched the understanding of innovation-employment nexus. Their findings highlight that a rise in demand induces higher employment rates. Making the necessary distinctions between product innovation and process innovation, Schumpeterian explains the first type as labour-friendly, the second one as labour-displacing (Pianta, 2005; Vivarelli, 2014; and Calvinoya & Virgillitoza, 2016). Product and process innovation become more important objects of studies among the four types of innovation. According to the Oslo Manual, product innovation is characterized as a good or service that is new or significantly improved. This includes significant improvements in technical specifications, components, and materials, software in the product, user-friendliness or other functional characteristics while process innovation is known as a new or significantly improved production or delivery method. This includes significant changes in techniques, equipment and/or software (Manual, 2018).

According to the general equilibrium view, when markets clearing assumption holds there is no place for overproduction and unemployment. Consequently, any technological innovation leads to only a temporal labour destruction. The main cause is not the lower level of available job opportunities, but not being able to finding a suitable low equilibrium salary that matches the decrease in the demand for labour (Calvinoya, Virgillitoza 2016). They examine how the employment dynamics is affected by the introduction of technical changes. The author reviews some papers that analyse the impact of R&D activities focusing on start-ups and fastest growing companies, and the positive impact R&D brings the creation of this kind of firms and therefore to the growth of employment.

At the micro level, the studies consider that there is a positive effect on employment due to the adoption of innovative activities, but this is not an obvious impact especially as concerns the firm level evidence, and these findings should be treated with caution (Brouwer et al., 1993; Greenan and Guellec, 2000). Studies that includes peculiar characteristic like firm age and firm size are relevant in offering a different perspective at microeconomic level to understand the employment dynamics with emphasize on high technology sectors.

Pianta (2003) examines the types of innovation and identify their effects on employment. There are generally found positive effects on job creation at the level of firms. However, the author also highlighted the differences between the findings of studies using micro level data and more aggregate level data. On the basis of empirical studies, Pianta concluded that current technological changes can lead to unemployment, but the type of innovation is important: product innovation, generally has a positive effect on employment while process innovation usually has a negative effect.

For Vivarelli (2015) instead, some innovations create jobs and some others displace labour that can be avoided. But it is possible that this job creating effect may be often limited to high tech sectors or high growth firms where normally it is evident that R&D expenditures have a positive impact on labour demand. So far, there is not a clear answer to the overall impact of process and product innovation to employment and the picture can become more complicated to analyses. Hence the real effect of them is not stable since it depends on other factors such as the elasticity of demand, the expectations of entrepreneurs and consumers, competition degree, etc. Thus, the importance in this case of the empirical studies analysed by Vivarelli (2015) to somehow give a response to this issue and the recent micro econometric studies support this positive link between technological change and employment. But of course, it is still necessary to take into consideration the complex interrelations between process innovation and product innovation.

The study of innovations surveys has become important over the time for the implementation of innovation policies, providing quantitative and qualitative information to monitor their performance and measure the impact on markets. This is a widely used data source for econometric analysis on the basis of appropriate indicators to establish the proper recommendations. The innovation surveys include detailed data on both innovators and non-innovators where firms are asked to provide information about their various kinds of innovative activities, both technological and non-technological. Mairesse and Mohnen (2010) make suggestions regarding the implementation of innovation surveys discussing several elements included (structure, content, characteristic, indicators and determinants) in the innovation to have an extended overview of innovation, selecting the ones that are based on the Oslo Manual recommendations, considered among the economists the most regularly used innovation survey and implemented in many countries. Large number of studies throughout the EU have been conducted using CIS data covering research questions, such as the links between technological changes and productivity or labour demand. The innovation surveys in some other countries like in Latin America follow the similar approach of CIS (Crespi and Peirano, 2007). It implies that the analysis based on CIS data are important for the decision-making process in the firms, industries etc., but it is difficult to apply it for a particular innovation project.

The paper by Frosch (2011) involves a specific discussion in terms of innovation performance according to workforce age. It is generally assumed that young people can have higher innovation capacities. In other words, young people are the carriers of up-to-date knowledge which is considered as the main contributor to the adoption of new products in a company. When it comes to the analysis of the age composition of the workforce, it can be hard to actually measure their performance. Thus, this study embraces empirical papers that established possible solutions to this issue. According to the author, the previous empirical findings suggest that people between the ages of 35 and 50 are the ones who embrace higher capacities to innovate and to achieve relevant abilities compared to the rest of age compositions. Consequently, it's said that these capacities tend to decrease at older ages, although most of these studies focus only on specific industries or firms' samples, thus they cannot be generalized to all industries and companies. Likewise, the results of analysis where a cross sectional data is used should be interpreted carefully, since unobserved heterogeneity and selectivity bias can lead to biased estimation having favourable results towards younger workers in detriment of the older ones.

However, different results from Feyrer (2008) propose that the age of patenting curve is more shifted to older ages, reaching the highest performance beginning from the end of the ages 30 till the mid-years of the ages 50. This means that is possible that the economies with older labour forces compared to young economies can have better performance in the number of inventions because these are still facing a process of building the necessary experience to level up their inventive activities. In case this performance is decreasing over time, it might be likely caused by a reduction in the number of workers in the economy rather than a decline in the performance at older ages.

There are different approaches used to analyse performance of labour and workforce, some might consider on measuring the impact of individual inventors which still lack information such as the knowledge transfers and about the inventor, while others take into consideration the contribution of companies' workforce to the overall innovative performance of the firm, and the value added per worker on the firm's innovativeness. This aggregate level of firms approach offers a solution to this deficiency in the existence analysis at the individual level by adding the direct contribution of the worker to an innovation.

The empirical evidence from micro-economic literature usually finds a positive relationship between employment and innovation. The results mostly differ in terms of the methodology, data source the authors used, and the type of innovation they investigated (see the Appendix A for the overview of empirical studies on technological change and employment). For instance, Roy et al. (2018) presents one of the most recent studies throughout Europe to measure the impact of innovativeness adopting citation-weighted patents as proxies for innovation output. They analysed the linkage in question using data which includes 20,000 patenting firms from 2003 to 2012 and found that new technologies has a positive impact on labour demand at the firm level. However, the positive effect can be considerably observed only in the high-tech manufacturing sector, not in the low-tech ones.

Disentangling the impact of different types of innovation, a group of authors have tried to quantify the effect of process and product innovations on employment growth separately. Within this strand of the literature, the study on German firms by Lachenmaier and Rottmann (2011) within 1982-2002 using panel dataset identifies the positive effect of both process and product innovation on employment. One of their contributions to existing literature was revealing the difference in the effects of process and product innovation, the effect of process innovation being much higher than that of the product innovation. Contrary to this, Hall et al. (2007) did not find significant impact caused by process innovation during the investigation of Italy. Analysing the dataset of manufacturing firms in Italy between the period 1995-2003, they indicated the employment growth as a result of both product innovation and the expansion in sales of old products.

Taking a similar perspective, Jaanika Merikull (2009) used Community Innovation Survey (CIS3 and CIS4) and Business Register data of Estonia over the period 1996-2006 at the firm and industry level and found a positive relationship between process innovation and employment in Estonian firms. However, the employment enhancing impact of product innovation can be seen at the industry level. Distinguishing between catching-up and high-income countries, the investigation indicates that the impact of technological change shows itself in medium and low-tech sectors, while no effect in high-tech sectors was revealed, probably because Estonia being a catching-up country.

In the next strand of literature, researchers added different aspect to employee diversity such as skills in order to see how skill-biased technological and organizational innovations are. The paper by Crespi and Tacsir (2014) researched manufacturing firms using innovation surveys of Argentina, Chile, Costa Rica, Uruguay, and the authors identified positive effect of product innovation in all countries except Costa Rica. In the case of process innovation, there is negative relationship only in Chile and no evidence in Costa Rica. Additionally, they focused on the relation between skill demand and innovative activities simultaneously, and found the skill-biased effect of product innovation, especially in high-tech sectors which is consistent with previous findings. Obviously, technological innovations increase a demand for skilled workforce, at least in the adoption phase of the new technologies. Similarly, Rønningen (2007) differentiated workers in terms of their education level. Analysing Norwegian manufacturing firms based on 1992-2003 data using OLS method, there was not found any statistically significant impact on wage bill shares of low-medium level educated people, however, the positive effects due to organizational changes was found only for people with high-level educational background in 30s (age group 30-40). In terms of the methodology, all the papers discussed above used either GMM approach or OLS estimation method.

Several researchers examined the impact of new technologies on the demand for employees through different age structures to see how age-biased technological changes are. Although, older workers are more experienced compared to younger ones, innovations may also be detrimental for the older workers from the perspective of adaptability requirements. For instance, Aubert et al. (2006) examined if technological and organizational innovations affect the wage bill shares of older employees in a sample of France. They detected a negative linkage between the innovativeness of the firm and the wage bill shares of older workers, and it holds both for women and men. Moreover, decreased hiring chances of elderly people stems from the introduction of new technologies to the firms, specifically from the case of computer usage. In contrast, Rønningen (2007) did not find any age-specific employment displacement due to organizational and technological changes. On the other side, technological innovations result in a decrease in the wages of individuals between the age of 50-60, while an increase when they are over sixty.

A group of authors explored the effect of workforce with different age structures on firm innovativeness and productivity. Generally, recent analyses reveal negative relationship between employee age and indicators of innovation. Bertschek and Meyer (2010) analysed German manufacturing firms and service sectors in 2004-2007 using nonlinear and linear probability models, thereby they presented positive interaction between IT and process innovation, whereas negative relation between technological changes and the demand for older workers, particularly those who lack proper IT skills. Thus occurrence of IT-enabled process innovation is rare at the companies with the high share of older workers, namely aged 50 years and over. However the older workers that have participated in specific IT trainings are not harmful for the innovativeness of the company. Similar to this finding, analysing manufacturing firms from the aspect of workforce experience, namely managers and workers, in Italy over the period of 2001-2003, Daveri and Parisi (2015) indicated that inexperienced workers can hinder the growth of both innovative and non-innovative firms, while if the company consists of mostly elderly managers, they will be disincentive for only highly innovative firms, not for non-innovative ones. To sum up, the direction of this particular effect depends on the innovation level of firms. Contrary to these papers, Verworn and Hipp (2009) who used German CIS data did not find that older workers have a negative impact on the innovativeness of companies. Nevertheless, they revealed that firms consisting of older people have not shown an inclination to invest in retraining. To sum up, no harmful effect of old people despite of the shortage of retraining was found. However, the findings in this paper do not mean the age structure of workforce should be ignored. Because their investigation was based on only 2001 data (lack of longitudinal data), consequently they could not analyse time lag effects of specific variables such as employment and innovation.

Some of the empirical studies analysed the age and skill levels of different kinds of labour in comparison. According to the results of Hujer and Radić (2005) technology does not distinguish employees in terms of their age, the most important thing is whether the individuals have the required skills level for the particular position. More specifically, looking at the employment data between 1993-1997 companies in West Germany preferred high-skilled employees older than 50 years compared to low-skilled employees younger than 30 years. However, another study on West German firms in the same period by Beckmann (2007) found that both implementation of organizational and technological innovation considerably harm the perspective of older workers, because they will need new hard skills (required skills for computer users) and firms have no interest in to give additional training opportunities to them.

The impact of innovation in public sector differs from the consequences of technological changes in business sectors. Rizzuto (2011) found a positive relationship between older employees and technological innovation when analysing 18 governmental organizations in the US state, as a consequence, their response is much higher compared to younger individuals. Additionally, the author highlighted that both younger and older individuals, are more satisfied with new IT changes when there is age-diversity in departments.

Another study by Meyer (2009) explored small and medium-sized companies using 2005 quarterly business survey data by ZEW in Germany and compared older workers to younger counterparts who are under 30. Adaption to technological changes and older workers was found to be inversely related, while that was not the case for the young workforce. The investigation of Schubert and Andersson(2013) holds similar views with Meyer's. They analyzed manufacturing and service firms on the basis of CIS data of Sweden in 2004, 2006 and 2008, and confirmed conventional views that age and reaction to the technological innovation of the employees are negatively related. Obviously, companies try to hire young and skilled individuals instead of older ones to create an innovative environment in the company. As a consequence, it is more likely to have a higher employee turnover in the firms consisting of mostly older workers. However, an exception was found when Hujer and Radić (2005) checked for the impact of various types of innovation combinations using Linked IAB Establishment Panel dataset that the employment share of older workers are positively related to the introduction of organizational and product innovation together to the firm.

In sum, as can be seen from the studies which are stated above, the link between technological innovation and different age groups of labour still seem to be unclear, hence the results differ in terms of the methodology, data source the authors used, and the type of innovation they investigated. Generally, positive impact of both types of technological innovation (product and process innovation) on labour demand has been found. But, when it comes to the analysis of the age composition of the workforce, it can be hard to actually measure their performance. However, the majority of recent analyses reveal negative relationship between employee age and indicators of innovation. Considering all these investigations, our study aims to provide a better understanding of the age-biasedness of technological innovation.

Data and descriptive statistics.

The paper employs data from three different sources: Estonian Community Innovation Surveys (the waves cover the periods 1998 - 2000; 2002 - 2004; 2004-2006; 2006 - 2008; 2008 - 2010; 2010 - 2012; 2012 - 2014; 2014 – 2016, i.e. all of the innovation surveys cover a 3-year period); Estonian Commercial Registry (1998-2017); Estonian Tax and Customs Office on the employees' payroll taxes (2006-2017).

The study of innovations surveys has become important over the time for the implementation of innovation policies, providing quantitative and qualitative information to monitor the companies' innovation performance and measure the impact of innovations on markets, this being a widely used data source for econometric analysis on the basis of appropriate indicators to establish the proper policy recommendations. The innovation surveys are a conglomerate of data related to innovators and non-innovators where firms are asked to provide information about their innovative activities. The CIS surveys are performed every two years throughout the EU, several EFTA countries and EU candidate countries. Estonia has one of the highest response rates in CIS surveys among European countries directed by Statistics Estonia. For instance, response rates were 74% and 78% in CIS3 and CIS4, respectively, while average rate for EU was just 55% (Terk et. al. 2007). For later periods, the un-weighted non-response rate was only 20.8 % for Estonia in 2014, whereas it was much higher in others, such as 44% in Belgium, 49.2% in Germany and 47% in Austria (Eurostat, 2014). A large number of studies have been conducted using Estonian CIS data covering various research questions, such as the links between technological changes and productivity or labour demand (Meriküll, 2009; Masso and Vahter, 2012). This paper uses product and process innovation output indicators across 5 waves of CIS surveys.

The relationship between export orientation, innovation inputs and outputs can be estimated using CIS surveys. However, measuring innovation based on CIS surveys can lead to some errors during investigations. Firstly, the type of business in terms of innovativeness, namely innovative or non-innovative, is a binary variable. The issue is that the company is considered as an innovative regardless of the number of innovation activities implemented within a specific time. On the other hand, there is also a non-binary measure of innovations, such as the share of sales from new products. Of course, the measurement of innovativeness would be more precise if this complexity would be taken into account. Secondly, as every company reports innovation variable themselves, it may be ended up being misreported. Although the businesses have no interest in providing wrong information about innovativeness, they can have various understandings of the term in this context. However, the Estonian surveys had some additional examples of the innovativeness shown to respondents, thus theoretically it could lead to the better quality of the data. Moreover, each enterprise reports its innovation activity in the last year of the CIS surveys period. It means the indicator will be reported in CIS2014 for the years of 2012-2014, and in CIS2016 for the whole period of 2014-2016, etc. Therefore the third difficulty is that we can get this variable about the innovativeness of organizations over three years without knowing the accurate time of the innovation activity (Meriküll, 2009).

Table 1. The number of firms in the analysis across the years

Year	1998	2002	2004	2006	2008	2010	2012	2014	Total
Innovative firms	961	886	1,033	1,073	864	694	433	828	6,772
Non-innovative firms	2,200	861	891	953	872	1,029	1,450	874	9,130
Total number of firms	3,161	1,747	1,924	2,026	1,736	1,723	1,883	1,702	15,902
Firms with product innovation	717	683	713	673	522	439	276	428	4,451
Firms with process innovation	659	651	843	887	651	481	307	674	5,153
Firms with organizational innovation	930	488	519	362	281	263	158	229	3,230

Source: Estonian Business Registry data, Estonian Community Innovation Surveys (CIS3; CIS4; 2006-2008; 2008-2010; 2010-2012; 2012-2014; 2014-2016) and own calculations.

The second dataset used in this research is Estonian Business Registry data covering the period from 1995 to 2017. Business Registry gives information about 20 - 50,000 firms each year in Estonia. The financial data based on profit or loss, cash-flow statements, balance sheets is included in the dataset. Additionally, it informs about enterprise size (the number of workers), firm entry and exit in several years, and economic activity codes of companies. We merged Business Registry data with CIS to get the number of employees, employment costs, and capital stock variables for each firm, as CIS data does not cover these variables. Both data sets include employment variable, but register data is preferred as a source of observations on employment.

The total number of observations after merging Estonian Business Registry and Estonian Community Innovation Surveys data sets is 15,902 which covers information about 5,785 enterprises. The share of innovative firms regardless of the company's innovation type consists of about 43% of all enterprises as shown in Table 2. In more detail, the share of firms with product and process innovations is 28% and 32%, respectively. The enterprises with any innovative activities have higher employment, labour cost, and capital stock level compared to non-innovative companies. Labour cost and real capital stock show deflated (by GDP deflator) yearly average wage cost per employee in thousands of euros in a company and deflated (by GDP deflator) average capital stock per company in millions of euros, respectively. Both of these are higher for innovative companies as compared to non-innovative companies.

Table 2. Descriptive statistics of innovative and non-innovative firms.

	All firms		**Innovators** [a)]		**Non-innovators** [b)]	
	Mean	Std.dev.	Mean	Std.dev.	Mean	Std.dev.
Share of innovative firms	0.426	0.494				
Share of firms with product innovation	0.279	0.449				
Share of firms with process innovation	0.324	0.468				
Share of firms with organizational innovation[1]	0.309	0.462				
Employment	64	203	94	281	42	112
Labour cost *(in thousands of euros)*	18	188	23	292	14	15
Real capital stock *(in millions of euros)*	3.5	29.7	5.5	37.2	2.04	22.6
No. of observations	15,902		6,772		9,130	

Source: Estonian Business Registry data, Estonian Community Innovation Surveys (CIS3, CIS4, 2006-2008, 2008-2010, 2010-2012, 2012-2014, 2014-2016).

a) Innovators represents firms either with process or product innovations.

b) Non-innovators means firms without both product and process innovations.

[1] We added the share of firms with organizational innovation afterwards, as we included it in our robustness check.

The last data set used in this paper is employee and employer level Estonian Customs and Tax Office data on payroll taxes (Statistics Estonia) covering the years 2006 – 2017. The data includes personal level variables. These are: 1) gender – variable (M – male; F- female); 2) Date of birth. In addition, the dataset covers information about the social tax payments of employees by employers. The date of birth was used to calculate the individuals' age. The paper uses the records of employee age for each year in January. The other months' data are also available for companies. We categorized employees in three different age groups: 1) young (employees less than 30 years old) 2) middle-aged (employees between 31-50 years old) 3) old (employees between 51-100 years old). This classification coincides with that of Beckman's (2007) and eases to assess the impact of innovations on the workforce with different age structures. Consequently, the final combined data set to investigate the effect in question consists of 5,785 unique firms. Considering that Estonian Customs and Tax Office data on payroll taxes have information about firms starting from 2006, we dropped the observations from the first three waves of CIS (CIS3, CIS4, 2004-2006). Additionally, we excluded some observations after checking for the outliers using scatter plot and summarizing the observations for specific variables (employment, labour cost, capital).

Table 3. Descriptive statistics of age groups.

	All firms		Innovators [a)]		Non-innovators [b)]	
	Mean	Std.dev.	Mean	Std.dev	Mean	Std.dev.
Number of young employees	14	34	22	48	8	15
Share of young employees (%)	0,213	0.179	0.236	0.176	0.197	0.179
Number of middle-aged employees	33	78	48	111	21	34
Share of middle-aged employees (%)	0.484	0.484	0.482	0.158	0.485	0.177
Number of old employees	21	56	29	77	14	31
Share of old employees (%)	0.303	0.205	0.282	0.191	0.318	0.213

Source: Estonian Customs and Tax Office data and own calculations.

a) Innovators represents firms either with process or product innovations.

b) Non-innovators mean firms without both product and process innovations.

The average number of young employees in Estonian companies is 14 as presented in Table 3. However, we can observe that this number is higher (22) than average in innovative firms and lower (8) in non-innovators ones. This tendency is consistent with the other age groups. Overall, the average share of young employees is 21% in Estonian firms, while for innovative and non-innovative companies this indicator is 24% and 20%, respectively. The share of middle-aged workers is the same (48%) for both types of firms. Additionally, we can find out from Table 3 that the share of older workers is higher in non-innovative companies (32%) compared to innovative ones (28%).

Table 4. Shares of age groups in Estonian firms grouped by field of activity

NACE [2]	All firms			Innovators [b)]			Non-innovators [c)]		
	Young	Middle	Old	Young	Middle	Old	Young	Middle	Old
A	0.175	0.467	0.358	0.206	0.447	0.347	0.151	0.484	0.365
B	0.170	0.492	0.338	0.235	0.462	0.303	0.112	0.518	0.370
C.	0.130	0.507	0.363	0.155	0.501	0.344	0.113	0.511	0.376
D	0.196	0.473	0.331	0.217	0.479	0.304	0.178	0.476	0.355
E	0.101	0.421	0.478	0.104	0.414	0.482	0.1	0.424	0.476
F	0.288	0.416	0.296	0.343	0.412	0.245	0.247	0.419	0.334
G	0.233	0.505	0.262	0.253	0.516	0.231	0.221	0.499	0.280
H	-	-	-	-	-	-	-	-	-
I	0.358	0.503	0.139	0.396	0.491	0.113	0.325	0.513	0.162
J	0.32	0.537	0.143	0.322	0.541	0.137	0.318	0.535	0.147
K	0.331	0.417	0.252	0.325	0.404	0.271	0.335	0.425	0.24
L	-	-	-	-	-	-	-	-	-
M	-	-	-	-	-	-	-	-	-
N	-	-	-	-	-	-	-	-	-
O	0.167	0.496	0.337	0.163	0.479	0.358	0.171	0.511	0.318

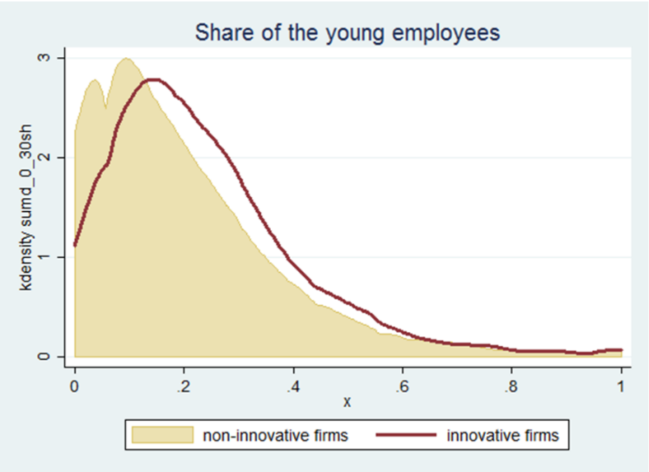
Source: Estonian Community Innovation Surveys (CIS3, CIS4, 2006-2008, 2008-2010, 2010-2012, 2012-2014, 2014-2016), Estonian Customs and Tax Office data, Estonian Business Register and own calculations.

a) Innovators represents firms either with process or product innovations.

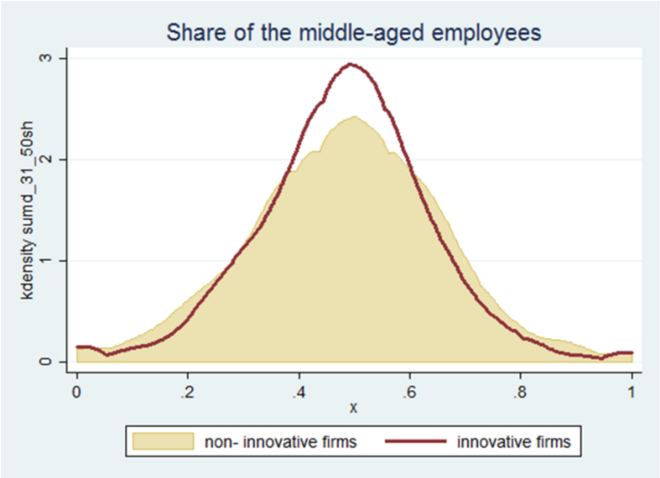
[2] The NACE acronym is used for the European standard statistical classification of productive economic activities. (Eurostat, 2008). Explanations of the industry letters: A-Agriculture, hunting and forestry; B-Fishing; C-Mining and quarrying; D-Manufacturing; E-Electricity; F-Construction; G-Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles; H-Hotels and restaurants; I-Transportation and Storage; J-Financial Activities; K-Real Estate Activities; L-Public Administration and Defence; Compulsory Social Security; M-Education; N-Human Health and Social Activities; O-Other Service Activities; P-Activities of Households as Employers; Q-Extraterritorial Organisations and Bodies.

b) Non-innovators means firms without both product and process innovations.

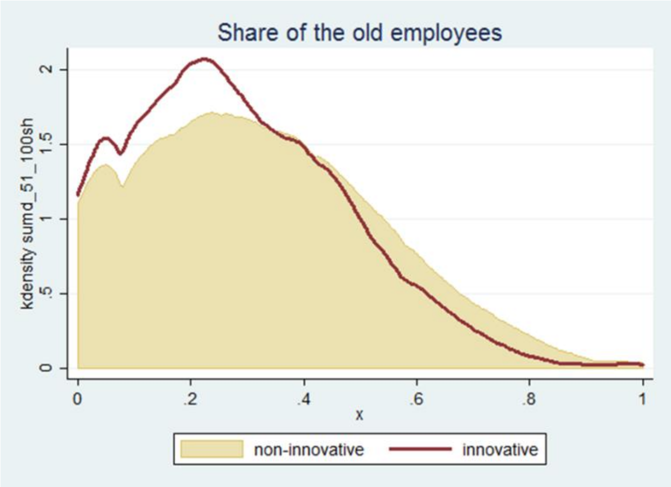
Table 4 presents the shares of different age groups in Estonian companies by field of activity. We find out that the statistics are consistent with Table 3, hence the share of young employees are higher in innovative companies compared to non-innovative companies. For instance, manufacturing firms (NACE code - D) cover the major share of all firms and the average share of young employees in technologically innovative manufacturing firm (22%) is higher than the one which had not implemented technological innovation activity at all (18%).



Graph 1. Kernel density plot of the distribution of young employees in innovative and non-innovative firms.



Graph 2. Kernel density plot of the distribution of middle-aged employees in innovative and non-innovative firms.



Graph 3. Kernel density plot of the distribution of old employees in innovative and non-innovative firms.

The 3 graphs above are Kernel density plots of the distribution of employees by different age structures in innovative and non-innovative firms. Hence, we can observe visually the higher share of the younger employees in the innovative companies throughout the distribution. In other words, the share of young workers in innovative companies is higher compared to non-innovative firms. Apparently, in the case of older workers the share is vice versa, so the share of older employees in non-innovative companies is larger than in innovation-friendly firms. Additionally, we employed two-sample Kolmogorov-Smirnov (KS) tests to compare the distribution of 3 different age groups in innovative and non-innovative firms where the difference was statistically significant for all 3 comparisons. According to the results of KS tests in terms of the distribution of young and old employees, we may reject the null hypothesis of equal distribution in both types of firms at the 1 % significance level as expected. Hence, these results justify looking at the decompositions of labour demand in terms of the various age groups in innovative and non-innovative firms.

Econometric Strategy

The existing empirical literature has used various empirical approaches to investigate the link between technological changes and labour demand. Derivation of the labour demand can be obtained both from production function introduced by Van Reenen (1997) and cost function by Christensen et al. (1973). Following the former one, this paper uses a constant elasticity of substitution production function (CES) to derive labour demand equation for perfectly competitive firms.

$$Y = T\ \left[(AL)^{\frac{\sigma-1}{\sigma}} + \ (BK)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}\ . \qquad (1)$$

Here, *Y* represents output, *L* is labour and *K* is capital stock. *T* denotes Hicks-neutral technology; *A* and *B* are respectively labour augmenting Harrod-neutral and capital-augmenting Solow-neutral technology parameters. The term σ shows elasticity of substitution between employment, *L* and capital, *K*. Substituting marginal product of labour with real wage (*W/P*), and taking the first-order condition with respect to labour, our equation will be as follows:

$$\log L = \log Y - \sigma \log \frac{W}{P} + (\sigma - 1)\log A\ . \qquad (2)$$

Considering the fact that marginal cost (MC) is the economic measure of determining the price, labour-saving technology elasticity of labour demand can be given by:

$$\frac{\partial \log L}{\partial \log A} = \left(\frac{\partial \log Y}{\partial\ \log P}\right)\left(\frac{\partial \log MC}{\partial\ \log A}\right) + (\sigma - 1), \qquad (3)$$

or

$$\eta_{NL} = \eta_P \theta\ + (\sigma - 1).$$

Here η_{NL} , θ and η_P show the labour-technology elasticity, the technological change elasticity of MC and the elasticity of demand with respect to price, respectively. The impact of technological innovations on labour demand depends on the level of substitutability of labour and capital for a fixed production. Hence, labour demand will increase when the elasticity of substitution - σ - is higher than 1. If capital and output can be varied, positive labour demand impact can be still observed even in the case of low elasticity (σ - 1) since decrease in prices will lead to rise in demand for products. The greater η_P and the larger θ make the positive labour demand effects more likely to be (Neary, 1981; Dowrick and Spencer, 1994; Van Reenen, 1997).

Following, substituting output with marginal product of capital (equals to the cost of capital (*R*)), the simple labour demand relationship in formula 2. can be rewritten as follows:

$$\log L = (\sigma - 1)\log\left(\frac{A}{B}\right) - \sigma\log\frac{W}{P} + \log K + \sigma \log R\ . \qquad (4)$$

Next, innovation *(INNO)* replaces unobserved technology variables. Technological changes have led to rise in labour demand, not in capital in the last 150 years according to the Acemoglu's argument (2002b), i.e. the technological change has been rather labour augmenting than capital augmenting.[3] Hence, the substitution of technology terms for innovation is understandable indicating that technological innovation must enter to the model through labour augmenting technology, not capital augmenting one. Consequently, the labour demand function's stochastic form should be as below:

$$l_{it} = \alpha_1 INNO_{it} + \beta_4 w_{it} + \beta_5 k_{it} + \tau_t + u_{it}\ , \qquad (5)$$

where lower case letters represent logarithms, *INNO* variable stands for innovation, τ_t and u_{it} are the vectors of time and industry dummies and a white noise error term respectively. Index 'i' indicates the firm and 't' the time. The cost of capital (R) is assumed constant across all the firms and only differs over time.

The impact of technological innovation on labour demand shows itself gradually and this is considered in the lag structure of the model. This paper uses the data set where innovation is reported over eight 3-year periods. Hence, we should lag innovation variable by 3 year time periods. Additionally, considering that the previous year's employment has an effect on current labour demand, one year lag of labour is added into the model (Meriküll, 2009; Piva and Vivarelli, 2005). Longer time lags turned out to be statistically insignificant in the paper of Meriküll (2009). Taking into account the adjustments, the above labour demand equation can be written as below:

$$l_{it} = f_i + \alpha_1 INNO_{it-3} + \beta_1 l_{it-1} + \beta_2 w_{it} + \beta_3 k_{it} + \tau_t + u_{it}\ . \qquad (6)$$

Considering the aim of this research is to reveal the effect of innovation on employment through different age groups, dynamic estimating equations can be written as follows (Prskawetz et al., 2008):

$$y_{it} = f_i + \alpha_1 INNO_{it-3} + \beta_1 y_{it-1} + \beta_2 yw_{it} + \beta_3 mw_{it} + \beta_4 ow_{it} + \beta_5 k_{it} + \tau_t + u_{it}\ . \quad (7)$$

[3] According to Acemoglu's paper (2002b), there is an apparent growth difference in the prices of labour and capital in last 150 years. Considering evidences from the Western European countries and U.S., he highlighted the fact that rental rates had been almost stable over the given period. However, the price of labour had risen consistently. It reveals that technological innovation has mostly labour augmenting effects, not capital one.

$$m_{it} = f_i + \alpha_1 INNO_{it-3} + \beta_1 m_{it-1} + \beta_3 mw_{it} + \beta_2 yw_{it} + \beta_4 ow_{it} + \beta_5 k_{it} + \tau_t + u_{it} . \quad (8)$$

$$o_{it} = f_i + \alpha_1 INNO_{it-3} + \beta_1 o_{it-1} + \beta_4 ow_{it} + \beta_2 yw_{it} + \beta_3 mw_{it} + \beta_5 k_{it} + \tau_t + u_{it} . \quad (9)$$

In these formulas, *y*, *m* and *o* describe young (below 30 years old), middle-aged (31-50 years old), and older (above 50 years old) workforce respectively. This kind of employee classification have been used in the papers of several authors such as Mahlberg et al. (2013 a, b), Vanderberghe (2011). Moreover, yw_{it}, mw_{it} and ow_{it} are the labour costs for each employee category calculated from the tax data. Every equation includes wages for all the 3 categories of workforce, since all of them affect hiring decisions of the companies (Meschi et al., 2015). Additionally, for the age part of analysis we dropped first three waves of CIS from our data, as Estonian Customs and Tax Office data on payroll taxes contains information about firms starting from 2006.

In terms of the short and long run impacts of the new technologies, in EU15 and in the industrial countries, technological innovations usually have a negative short run and a positive long run impact on labour demand (Severgnini, 2009). However, according to the characteristics of the innovation variable used in our analysis, it is impossible to forecast the short-run effects as innovation is reported over 3-year periods. Hence, our study focuses only on the long-term (3 years) impact of technological innovation on the total employment and the employment of the different age groups.

Apparently, dynamic estimation models will lead to some problems. There may be positive correlation between lagged employment variable and the firm specific part of the error term (u_{it}). Hence, estimation using simple OLS will result in biased coefficient. Within group estimator or first difference method can be used to solve this problem instead of OLS estimation method. However, analysis with within group estimator will be biased (negative correlation between transformed version of lagged employment and error terms) again because of limited time period. The biasedness in case of this method would decrease if time would go to infinity (Nickell, 1981). In the case of the first difference method, the endogeneity problem will arise because of the positive correlation between lagged differenced employment variable and the error term. But, adding instrumental variables to lagged differenced employment can solve this correlation issue. To apply this technique for dynamic panel data estimations, mostly GMM estimation methods are used (Difference GMM, System GMM) (Arrelano, 1989; Arrelano & Bond, 1991; Arrelano & Bover, 1995; Ahn & Schmidt, 1995; Blundell & Bond, 1998). There can be reverse causality issues since the age structure of employment can have an effect on the innovativeness of the firm. Using GMM estimator will resolve the issue of biased results arising from endogeneity or reverse causality. (Leszczensky and Wolbring, 2019) It is also applicable for our analysis considering discrete time period and large number of observations. In addition, Blundell and Bond (1998) and Blundell et al., (2000) revealed that the difference GMM has a weak predictive power in the finite sample, so the coefficient estimates will be biased. They found that the system GMM's estimation power is higher. Therefore, the study uses the system GMM approach, which is stated to be a better predictor compared to other GMM predictors.

Empirical results

This section discusses empirical results obtained from analysis to show the linkage between technological changes and labour demand in Estonia. Firstly, we checked the effect of new technologies on the companies' total employment in Estonia (Table 5.1). Secondly, the innovation impact on different age categories of employment has been investigated as it is the core aim of the study (Table 5.2; 5.3; 5.4). Thirdly, different types of innovation, namely product and process, were added to the analysis to see the impacts of these separately (Table 5.5; 5.6.; 5.7). Next, we added organizational innovation to our estimations for robustness test (See Appendix B, C, D). Finally, the companies are split into low, medium and high-tech ones for more robustness in this study (See Appendix E, F, G). Our analyses take into consideration the effects in questions only in firm-level, not the effects in industry-level or on the whole Estonian economy.

The OLS and within group estimation method are expected to give overestimated and downward biased results of lagged variables, respectively (Baltagi, 2008). Moreover, the results of system GMM model should be lying between the coefficients of OLS and within group estimator. Hence, we can consider OLS as an upper bound and within group estimator as a lower bound of coefficients.

We performed a number of tests to check for the autocorrelation (Arellano–Bond autocorrelation test); the validity of the estimated models, instruments and the robustness of the results. The Wald Chi-Squared test was used to test the significance of the explanatory variables: rejecting the null hypothesis results in removing insignificant variables. The Hansen test was performed to check for the overall validity of instruments. It is preferred to Sargan test in two step estimations to prevent overidentification issues (Labra and Torrecillas, 2018). The number of groups (in our case firms) or observations should be higher than the number of instruments to avoid from overidentifying. Roodman's (2006) xtabond2 command in Stata was used for our system GMM estimations. Xtabond2 command provides more options in terms of the usage of instruments and enables to investigate endogeneity problems of both dependent and independent variables separately. Moreover, the command can use the lags of endogenous variables as instruments in levels and in differences. Thus, since innovation is reported over 3-year periods in our data set, we lag the innovation by 3 years to avoid the biased estimation, namely the impact of the future new technologies on current labour demand. In addition, as wage and capital can have an impact on employment structure of the next period, they are considered to be endogenous.

Table 5.1. The impact of technological innovation on labour demand (2006 - 2017).

	Pooled OLS		Within estimator		Two-step GMM-SYS	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Innovation *(t-3)*	0.031***	0.006	0.026***	0.007	0.091***	0.082
Employment *(t-1)*	0.901***	0.004	0.729***	0.017	0.887***	0.022
Labour cost per employee	-0.415***	0.081	-0.195**	0.032	-0.375**	0.111
Real capital	0.029***	0.002	0.058***	0.006	0.164**	0.016
Hansen test					53.55	
Hansen p-value	`				0.530	
AR (1)					-0.93	
AR (1) p-value					0.350	
Number of observations	10,526		10,526		10,519	
Number of groups			4,161		4,169	

As can be seen from Table 5.1, positive and significant impact of technological innovation on the whole employment was found from all the estimation methods (OLS, WG, GMM-SYS). This result is consistent with the evidences from other countries such as Germany, Italy, Turkey (Lachenmaier and Rottmann, 2011; Van Roy et al., 2018; Evangelista and Savona, 2003; Meschi et al., 2015). The coefficient of the lagged innovation in GMM-SYS is much higher than in the other two models. There is approximately 0.03% growth in employment 3 years after the implementation of new technologies to companies according to the first two models, however this indicator is around 0.09% in the last one. Hence, it shows that the companies which implement innovations experience higher growth in workforce compared to non-innovating firms. According to the characteristics of the innovation variable used in our analysis, there are no direct estimations for short run innovation effects, thus it is impossible to forecast the exact long-run effects. One year lag of labour as explanatory variable may contain some short-run technological innovation effects on employment meaning that the overall impact can be larger.

According to the results of system GMM in Table 5.1, both the real capital stock and labour costs have a considerable effect on employment being significant at 5 percent level. Hence, there is around 0.16% growth in employment as a result of one percent increase in the real capital stock and 0.37% decline in employment stemming from one percent increase in the labour cost per employee. Thus, negative impact of the labour expenses per worker on labour demand is found as expected. The effect of lagged employment variable is significant with a coefficient of 0.887, hence it is positively related to the next year's labour demand. This result is consistent with the previous investigation by Piva and Vivarelli (2005). Moreover, Hansen test failed to reject the null hypothesis (p=0.437), so it means chosen instruments are valid.

Table 5.2 The impact of technological innovation on the young employees group (below 30)

	Pooled OLS		Within estimator		Two-step GMM-SYS	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Innovation *(t-3)*	0.055***	0.002	0.011	0.009	0.022	0.074
Young Employees *(t-1)*	0.336***	0.006	0.139***	0.104	0.399***	0.011
Labour cost per young employee	-0.684**	0.007	-0.789***	0.012	-0.651***	0.012
Labour cost per middle-aged employee	0.031***	0.007	0.050	0.145	0.069*	0.009
Labour cost per old employee	0.060***	0.004	0.035	0.051	0.075*	0.006
Real capital	0.041***	0.003	0.029***	0.006	0.044***	0.004
Hansen test					52.16	
Hansen p-value					**0.632**	
AR (1)					-1.22	
AR (1) p-value					0.222	
Number of observations	5,322		5,322		5,331	
Number of groups			2,066		2,070	

Table 5.3 The impact of technological innovation on the middle-aged employee group (between 31-50)

	Pooled OLS		Within estimator		Two-step GMM-SYS	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Innovation *(t-3)*	0.059***	0.007	0.009	0.007	0.091	0.081
Employment *(t-1) middle*	0.503***	0.007	0.167**	0.019	0.586***	0.028
Labour cost per young employee	-0.033***	0.004	-0.021**	0.006	-0.057*	0.009
Labour cost per middle-aged employee	-0.485***	0.008	-0.706***	0.020	-0.392***	0.025
Labour cost per old employee	0.073***	0.004	0.039*	0.009	0.095*	0.006
Real capital	0.034***	0.002	0.035***	0.005	0.037**	0.005
Hansen test					59.05	
Hansen p-value					**0.437**	
AR (1)					0.52	
AR (1) p-value					0.601	
Number of observations	5,460		5,460		5,469	
Number of groups			2,107		2,111	

Table 5.4 The impact of technological innovation impact on the old aged employee group (above 51)

	Pooled OLS		Within estimator		Two-step GMM-SYS	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Innovation *(t-3)*	0.029***	0.008	-0.001	0.007	-0.128**	0.055
Employment *(t-1) old*	0.455***	0.007	0.181***	0.017	0.516***	0.020
Labour cost per young employee	-0.008*	0.005	-0.008	0.023	-0.033*	0.007
Labour cost per middle-aged employee	-0.020**	0.006	-0.011	0.014	-0.004	0.008
Labour cost per old employee	-0.463***	0.007	-0.666***	0.017	-0.391***	0.018
Real capital	0.031***	0.002	0.023***	0.005***	0.037***	0.004

Hansen test					42.71	
Hansen p-value					**0.397**	
AR (1)					-1.64	
p-value					0.101	
Number of observations	5,378		5,378		5,386	
Number of groups			2,070		2,073	

Going further from previous literature, we added different age structures of workforce to our analysis, so the dependent employment variable is categorized into the groups of young, middle-aged and older employees in this part. After the separation of the sample by the 3 different age groups, it seems that innovation has no significant impact on the demand for employees of the young and middle age groups according to the results of GMM-SYS estimation model (Tables 5.2 and 5.3). However, the negative relationship is found between innovation and older employees (Table 5.4), thus there is about 0.13% fall in the employment of older age group 3 years after the implementation of new technologies to companies. These results are consistent with the evidences from most of the studies in different countries (Beckman, 2007; Schubert and Andersson, 2013; Aubert et al., 2006). On the other hand, no age specific employment displacement due to technological innovation was founded in few researches (Norway (Rønningen, 2007). The impact of one year lagged employment variable of each age group has significant impact on the corresponding demand for each employee category at the 1 percent significance level.

Table 5.5. The impact of process and product innovation on young employee group (below 30)

	Pooled OLS		Within estimator		Two-step GMM-SYS	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Process innovation *(t-3)*	0.030**	0.012	-0.002	0.014	0.032	0.064
Product innovation*(t-3)*	0.03**	0.013	-0.010	0.015	0.016	0.067
Employment *(t-1) young*	0.337***	0.009	0.130***	0.016	0.347***	0.016
Labour cost per young employee	-0.689***	0.010	-0.556***	0.017	-0.671***	0.015
Labour cost per middle-aged employee	0.027**	0.009	0.055*	0.022	0.047*	0.011

Labour cost per old employee	0.066*	0.006	-0.013	0.015	0.081*	0.008
Real capital	0.038***	0.004	0.029**	0.012	0.040***	0.005
Hansen test					100.53	
Hansen p-value					**0.170**	
AR (1)					-1.97	
AR (1) p-value					0.049**	
AR (2)					-0.56	
AR (2) p-value					0.574	
Number of observations	2,870		2,870		2,875	
Number of groups			1,518		1,521	

We added the labour costs for all the 3 categories of workforce to the list of independent variables separately, since all of them affect hiring decisions of companies (Meschi et al., 2015). The relative labour costs have significant negative effects on the corresponding employee categories in the significance level of the 1%. This finding is in line with the result of Meschi et al. (2015). Additionally, each employee group is associated with the labour costs of alternative employee categories as well. (Table 5.2; 5.3; 5.4). For instance, there is approximately 0.08% growth in young-aged employee group as a result of one percent increase in the labour costs of older employees (Table 5.2). The effect of real capital stock is positive and around 0.04% for middle and old age groups being significant in 5 and 1 percent level, respectively (0.04% for young-aged workers in 1% significance). All in all, Hansen test failed to reject the null hypothesis in all estimation equations in this part (p=0.632, p=0.437; p=0.397, respectively for the equations of young, middle-aged and old employee groups) meaning that chosen instruments are valid.

Table 5.6. The impact of process and product innovation on middle aged employees (31-50)

	Pooled OLS		Within estimator		Two-step GMM-SYS	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Process innovation *(t-3)*	0.029**	0.010	-0.003	0.011	0.056	0.099
Product innovation*(t-3)*	0.034**	0.011	-0.005	0.012	0.011	0.053
Employment *(t-1) middle*	0.497***	0.009	0.151**	0.044	0.503***	0.036

Labour cost per young employee	-0.027*	0.006	-0.013	0.010	-0.035*	0.008
Labour cost per middle-aged employee	-0.512***	0.011	-0.732***	0.041	-0.492***	0.032
Labour cost per old employee	0.083**	0.005	0.004*	0.014	0.107**	0.007
Real capital	0.035***	0.003	0.036***	0.009	0.036***	0.005
Hansen test					59.05	
Hansen p-value					**0.437**	
AR (1)					-1.11	
AR (1) p-value					0.268	
AR (2)					-0.44	
AR (2) p-value					0.661	
Number of observations	2,950		2,950		2,956	
Number of groups			1,562		1,566	

Next, we decided to investigate separately the impact of product and process innovation on the different groups of employment. As can be seen from Table 5.5; 5.6; 5.7, the overall impact of product and process innovation is positive, but insignificant for all employee groups according to the SYS-GMM estimations (significant only in the results of OLS estimation method). In the case of within group estimator, the effect of process and product innovation on employment is negative, but not statistically significant. These results are quite surprising as lots of studies found positive and significant effect of product innovation. Additionally, direct effect of product innovation according to the theory should result in significantly positive impact on labour demand. It can be because of provided information by enterprises in CIS, so even new small technologies implemented in companies can be recorded as technological innovation by them.

Table 5.7. The impact of process and product innovation on older employee group (above 51)

	Pooled OLS		Within estimator		Two-step GMM-SYS	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Process innovation *(t-3)*	0.036**	0.011	0.004	0.011	0.027	0.049
Product innovation*(t-3)*	0.009	0.012	-0.001	0.013	0.039	0.053
Employment *(t-1) old*	0.451***	0.009	0.161***	0.027	0.443***	0.023

Labour cost per young employee	-0.007	0.006	-0.016	0.010	-0.021*	0.008
Labour cost per middle-aged employee	-0.029**	0.008	-0.041*	0.023	0.005**	0.010
Labour cost per old employee	-0.458***	0.009	-0.689***	0.029	-0.458***	0.021
Real capital	0.031***	0.003	0.027**	0.009	0.035***	0.005
Hansen test					88.02	
Hansen p-value					**0.479**	
AR (1)					-1.31	
AR (1) p-value					0.191	
AR (2)					-0.47	
AR (2) p-value					0.637	
Number of observations	2,902		2,902		2,908	
Number of groups			1,535		1539	

The tables in Appendix B, C and D describe the impact of a new independent variable – organizational innovation. In other words, we added the third type of innovation which is not technological to check for the robustness. Additionally, adding this innovative activity outcome variable allows us to find out if the effect of technological changes on the labour demand of different age groups differs by including new variable. According to the results, organizational innovation has a positive impact on young employees and a negative effect on middle-aged and older ones, but all these effects are statistically insignificant. From the side of the effect of process innovation, there are no significant quantitative changes in these specifications. Hence, both estimations (with and without organizational innovation) gave the same result that the process innovation does not have an age-specific significant impact on labour demand in the long run (over 3 years). In the case of product innovation, adding organizational innovation to our estimation equations increased the coefficients of product innovation slightly, however these impacts are statistically insignificant. But, overall the organizational innovation itself is not associated with the labour demand through different age structures significantly.

We split the companies into low, medium and high-tech ones for more robustness. OECD and Eurostat classification of technology and knowledge-intensive sectors had been used (OECD, 2007; Eurostat, 2008c). Thus, the tables in Appendix E, F and G examine the impact of technological innovation on employment through different age categories in low, medium and high-tech firms. No-age specific employment displacement due to technological innovation was found in the case of young and middle-age groups. Additionally, our previous result that there is a significantly negative relationship between innovation and older employees is only applicable for low-tech firms according to Appendix G.

Conclusions

In this study, we empirically explored the interlinked relationship between technological innovation and the age of employees at the firm-level. A unique combined panel data set of Estonian firms is used in this study, namely merged version of 3 different data sets (CIS, Business Registry data, Estonian Tax and Customs Office data). The contribution of the paper is extending the existing empirical literature which investigated the innovation effect on employment. Hence, employee age and firm level innovation relationship has not been researched before by using data set on a sample of Estonian firms.

The main result of checking the effect of new technologies on the total of the companies' employment presents that there is a positive and significant impact of technological innovation on the whole employment at the firm level. Hence, the companies which implement innovations experience higher growth in workforce compared to non-innovating firms. Moreover, negative impact of the labour expenses per worker on labour demand is found as expected. Next, one year lagged employment is positively and significantly related to the next year's labour demand.

By adding different age structures of workforce to our analysis, no age specific employment displacement due to technological innovation was found in the case of young and middle-aged employees. However, the negative relationship is revealed between innovation and older employees, but it is the case only in low-tech firms according to our further analysis. Additionally, the relative labour costs have significant negative effects on the corresponding employee categories and each employee group is associated with the labour costs of alternative employee categories.

Investigating the impact of product and process innovation on the different groups of employment, the overall impact of product and process innovation was found being positive, but insignificant. The reason behind this finding can be because of provided information by enterprises in CIS, so even new small technologies implemented in companies can be recorded as technological innovation by them. Furthermore, adding organizational innovation to our estimation equations increased the coefficients of product innovation slightly, however all estimations show that both product and process innovations do not have an age-specific impact on labour demand in the long run. Finally, robustness check with organizational innovation revealed that organizational innovation itself is not associated with the labour demand through different age structures.

In summary, our research is supportive for the hypothesis of 'Age-biased technological innovation' and it can be extended into interesting and useful directions. Firstly, the results can be validated in the context of other countries beyond Estonia and the framework used here can be tested on the other economic sectors. Secondly, we mainly focus on the impact of product and process innovation, but the effect of marketing, organizational innovation or the combination of innovation types on different age groups of labour demand can be examined in further investigations. Thirdly, as we did not find significant effect of technological innovation on different age groups of employment, looking at the impact of innovations on the labour costs of these employee groups can be interesting topic. Finally, from the perspective of policy side, extending the research to more aggregated levels beyond firm-level might be much more necessary, such as industry level or the whole Estonian economy. Analysing all these extensions would increase the understanding of the dynamics in labour demand arise from the implementation of different innovation types and would be helpful for the evolution of the firms, industries and total economy.

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Appendices.

Appendix A: Selection of empirical studies on technological change and employment.

Author(s)	Dependent variable	Data (country, period, sector)	Sample size/ Number of treatment observations	Methods	Main results
Jaanika Merikull (2009)	Employment	Estonia, 1.The Estonian Business Register data (1994-2006) 2 CIS3(1998-2002 3.CIS4(2002-2004), Firm and industry level	The number of observation for CIS3 and CIS4 (merging with register data) is 3161 and 1747, respectively.	Labour demand equation, regressors include the lagged innovation variables, two AR terms of labour, System GMM	The author found a positive relationship between process innovation and employment in Estonian firms. However, the employment-friendly impact of product innovation can be seen at the industry level.
Beckmann Michael (2007)	Age-specific labour demand	Germany, 1993-1995, firm level	A sample of 1634 establishments	Age-specific labour demand regressed on the technological and organizational innovations, ”output-input ratio, firms’ total investment, other control variables for the structure of the workforce. SOLS	Implementation of organizational and technological innovation considerably damage the perspective of older workers, because they will need new hard skills and firms have no interest in to give additional training opportunities to them.
Birgit	Innovation input	Germany,	22,600	Innovation input and	Authors did not find that older workers have a

Verworn, Christiane Hipp (2009)	and output	Community Innovation Survey 2001, firm level	enterprises	output regressed on the change of personal structure of enterprises, Probit models	negative impact on the innovativeness of enterprises. Nevertheless, they revealed that firms consist of older people have not an inclination to invest in retraining.
Torben Schubert, Martin Andersson (2013)	Product innovation	Sweden, CIS and FEK 2004,2006,2008, LISA 2002-2008, manufacturing and service firms	1543 observations	Impact on innovation, regressors are mean age of the employees in each firm and staying rate (employment turnover) differentiated by total employment and R&D-related employees. Panel probit and tobit model.	Age and reaction to the technological innovation of the employees are negatively related. Employment turnover can moderate this negative relationship. Companies try to hire young and skilled individuals instead of older ones in order to create an innovative environment. As a consequence, it is more likely to have a higher employee turnover in the firms consists of mostly older workers.
Dag Rønningen (2007)	Change in age specific wage bill share between 2001 and 2003	Norway, 1992-2003, manufacturing firms	1047 firms, including 753 single-plant firms	Age specific wage bill share regressed on organizational change, technology, capital, value added, firm-specific characteristics, industry and regional dummies.	No age-specific employment displacement due to organizational and technological changes. Negative impact of technological innovations on the wages of individuals between the age of 50-60, while it is positive when they are over sixty.
Lachenmaier & Rottmann (2010)	Employment	Germany, 1982-2002, Manufacturing	31885 observations, 6817 firms	Employment level of firm regressed on product innovation, process	Positive effect of innovation on employment was founded. The impact of process innovation is larger than product innovation.

		firms		innovation (including 2 lags of innovations), two lags of employment, real hourly wage rate, gross value added time and industry dummies. GMM system	
Van Roy, Versety, Vivarelli (2018)	Employment	Europe, 2003-2012, patenting firms (manufacturing and service firms)	20,000 firms	Firm specific labour demand regressed on output proxied by value added, wage, investments, 3 years lagged innovation, GMM system	Labour-friendly nature of innovation was found at the firm level. But it is applicable only for high tech manufacturing firms.
Hall, Lotti, and Mairesse (2007)	Employment growth	Italy, 1995-2003, Manufacturing firms	12,948 observations, 9,462 firms	Employment growth regressed on product innovation, process innovation, real sales growth and whole innovation activities. OLS and IV estimates	No significant employment displacement effects as a result of process innovation. Positive impact of product innovation and sales growth on employment growth was found.
Aubert, Caroli, & Roger (2006)	The shares of workers entering and leaving the firm among the total number of employment in	France, 1998-2000, Manufacturing firms	9573 firms	Employment inflow and outflow by age groups regressed on computer use, Internet, organizational innovations, physical	New technologies affect older employees through reduced hiring chances. However, organizational innovations affect their probability of leave, which decreases much less than for younger workers following reorganization.

	each age group			capital. JGLS method	
Jenny Meyer (2009)	Dummy for adoption of new technologies	Germany, 2005	356 firms	Technological innovation adoption regressed on the share of employment through different age groups, firm size, firm age, product innovation, exporter, foreign competitors, enhancement of team work, change in customer requirements. Probit model and LPM.	Negative relationship between older employees and probability of technology adoption. On the contrary, the dispersion of the employees' age within the workforce is not connected with the probability of technology adoption. There is positive link between employees of the same age and the probability of adopting new technologies in firms with intensified teamwork.
Gustavo Crespi and Ezequiel Tacsir (2013)	Employment growth	Latin American countries. Argentina (1998-2001), Uruguay (1998–2000, 2001–2003, 2004–2006, 2007–2009), Costa Rica (2006-2007), Chile (1995, 1998, 2001, 2005, 2007). Manufacturing firms	Number of observations: Argentina – 1415, Chile – 2049, Costa Rica – 208, Uruguay – 2532.	Employment growth regressed on product innovation, process innovation, real sales growth, time and industry dummies. OLS estimation.	Positive relationship between employment growth and new products. No displacement effects were found as a result of product innovation. Skill biased innovation effect was found on employment.
Irene	Process innovation	Germany, 2004-	1251 firms	The process innovation	The firms with higher share of older workers

Bertschek, Jenny Meyer (2010)	activity	2007, Manufacturing and service fims		activity regressed on the use of information technologies, employment, firm age and size, product and lagged process innovation. Probit model and LPM.	are less likely to be innovative. Older workers (older than 49 years) have negative impact on IT-enabled process innovations. Not participating in IT-specific trainings leads to the lack of the appropriate skills and qualifications, hence the findings is consistent with this group of older workers.
Reinhard Hujer and Dubravko Radic (2005)	Employment	Germany, 1993-1997,	2,429 establishments	Total employment regressed on product, process and organizational innovation.	Skill and age biased technological innovation is found. Organizational innovation and combination of it with product innovation is positively related to older employees. Regardless of the age, high skilled workers are positively connected to technological changes.
Tracey E. Rizzuto (2011)	Implementation satisfaction of technological innovation	North-eastern US state,	286 purchasing agents and directors from 25 departments across 18 government agencies	Satisfaction level of the implementation of new technologies regressed on employment with different age structures. HLM model.	More positive correlation between older employees and technological innovation compared to younger employees. Greater IT implementation satisfaction by the older workers if they are working in younger departments, while it is vice versa for younger workers.
Francesco Daveri & Maria Laura Parisi (2015)	Innovation	Italy, 2001-2003, Manufacturing firms	4177 firms	Innovation variable regressed on the share of R&D employees, the firm's propensity to undertake R&D, the firm's age, cash flow,	Older board members and managers has a negative impact on productivity and innovation in innovative firms, however it is not the case for non- innovative ones. There is correlation between unskilled workforce and lower level of productivity and innovativeness.

				regional, size, and industry dummies. OLS 2OLS GMM, LIML	
Elena Meschi, Erol Taymaz, Marco Vivarelli (2015)	Blue and white collar employees	Turkey, 1992-2001, Manufacturing firms	17462 firms	Blue and white collar employees regressed on the wages of each category, firm's value added, technology, investments firm's exporter, international involvement and capital dummies. OLS, FE, GMM-SYS.	Positive correlation between technology and employment. FDI and technological innovation lead to skill biasedness in employment.
Evangelista, Savona (2003)	Total employment, high and low skilled employment	Italy, 1993-1995, Service firms	943 firms	Total employment, high and low skilled employment regressed on process and service innovation, firm size, innovation expenses per employee. Not structural and logit models.	Innovation expenses and product innovation have a positive impact on total and highly-skilled employment. However, process innovation has no impact on employment 3 years after the implementation.
Piva, Vivarelli (2005)	Employment	Italy, 1992-1997, Manufacturing firms	575 firms	Employment regressed on innovation, wage, output and time dummies. GMM-SYS	Positive correlation between innovativeness and employment was found.

Greenan, Guellec (2000)	Employment growth	France, 1986-1990, Manufacturing firms	15186 firms	Employment growth regressed on product and process innovation. 2SLS	Positive impact of product and process innovation on employment was found. The effect of process innovation is higher.

Appendix B: The impact of technological and organizational innovation on young employees.

	Pooled OLS		Within estimator		Two-step GMM-SYS	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Process innovation *(t-3)*	0.024**	0.012	-0.002	0.014	0.067	0.044
Product innovation*(t-3)*	0.039**	0.013	-0.008	0.015	0.033	0.063
Organizational innovation *(t-3)*	0.017	0.017	-0.038*	0.017	0.023	0.047
Employment *(t-1) young*	0.351***	0.010	0.134***	0.016	0.354***	0.017
Labour cost per young employee	-0.685***	0.009	-0.542***	0.017	-0.659***	0.016
Labour cost per middle-aged employee	0.033**	0.009	0.063*	0.023	0.051*	0.011
Labour cost per old employee	0.064**	0.006	-0.015	0.016	0.081*	0.007
Real capital	0.039***	0.003	0.038**	0.012	0.040***	0.004
Hansen test					15.18	
Hansen p-value					**0.719**	
AR (1)					-2.92	
AR (1) p-value					0.004**	
AR (2)					-0.63	
AR (2) p-value					0.521	
Number of observations	2,780		2,780		2,785	
Number of groups			1,476		1,479	

Appendix C: The impact of technological and organizational innovation on middle-aged employee group.

	Pooled OLS		Within estimator		Two-step GMM-SYS	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Process innovation *(t-3)*	0.024*	0.010	-0.004	0.010	0.067	0.099
Product innovation*(t-3)*	0.034**	0.011	-0.005	0.011	0.006	0.059
Organizational innovation *(t-3)*	-0.005	0.014	-0.035**	0.015	-0.014	0.042
Employment *(t-1) middle*	0.518***	0.009	0.161**	0.052	0.514***	0.040
Labour cost per young employee	-0.026*	0.006	- 0.013	0.011	-0.032*	0.008
Labour cost per middle-aged employee	-0.493***	0.011	-0.725***	0.043	-0.462***	0.038
Labour cost per old employee	0.082**	0.005	-0.031**	0.015	0.104**	0.077
Real capital	0.035***	0.003	0.042***	0.009	0.033***	0.004
Hansen test					117.49	
Hansen p-value					**0.125**	
AR (1)					-1.10	
AR (1) p-value					0.269	
AR (2)					-0.42	
AR (2) p-value					0.676	
Number of observations	2,855		2,855		2,861	
Number of groups			1,518		1,522	

Appendix D: The impact of technological and organizational innovation on old employees.

	Pooled OLS		Within estimator		Two-step GMM-SYS	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Process innovation *(t-3)*	0.029*	0.011	0.002	0.011	0.044	0.035
Product innovation*(t-3)*	0.010	0.012	-0.001	0.013	0.061	0.049
Organizational innovation *(t-3)*	-0.002	0.015	-0.004	0.015	-0.013	0.032
Employment *(t-1) old*	0.469***	0.009	0.176***	0.028	0.472***	0.021
Labour cost per young employee	-0.007	0.006	-0.017*	0.010	-0.015*	0.008
Labour cost per middle-aged employee	-0.026**	0.008	-0.0438	0.024	0.011	0.010
Labour cost per old employee	-0.444***	0.010	-0.682***	0.040	-0.438***	0.021
Real capital	0.032***	0.003	0.029**	0.010	0.034***	0.005
Hansen test					94.06	
Hansen p-value					**0.675**	
AR (1)					-1.26	
AR (1) p-value					0.207	
AR (2)					-1.37	
AR (2) p-value					0.170	
Number of observations	2,812		2,812		2,818	
Number of groups			1,493		1,497	

Appendix E: The impact of technological innovation on young employee group, by sectors.

	High-tech sector		Medium-tech sector		Low-tech sector	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Innovation *(t-3)*	0.079	0.227	0.099	0.206	0.097	0.132
Employment *(t-1) old*	0.395***	0.039	0.411	0.023	0.351***	0.023
Labour cost per young employee	-0.675***	0.026	-0.638***	0.023	-0.686***	0.022
Labour cost per middle-aged employee	-0.047*	0.024	0.064*	0.026	0.033	0.020
Labour cost per old employee	0.077**	0.016	0.079**	0.013	0.089*	0.014
Real capital	0.038***	0.011	0.031***	0.007	0.052***	0.007
Hansen test	64.32		45.45		39.53	
Hansen p-value	0.215		0.134		**0.275**	
AR (1)	0.99		-1.01		-1.26	
AR (1) p-value	0.324		0.315		0.209	

Appendix F: The impact of technological innovation on middle-aged employee group, by sectors.

	High-tech sector		Medium-tech sector		Low-tech sector	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Innovation *(t-3)*	0.012	0.042	0.166	0.077	0.037	0.108
Employment *(t-1) old*	0.422**	0.199	0.344**	0.051	0.319***	0.201
Labour cost per young employee	0.076	0.124	0.003	0.098	0.111	0.098
Labour cost per middle-aged employee	-0.666**	0.281	-0.831**	0.110	0.617**	0.0737
Labour cost per old employee	0.069	0.099	0.177*	0.104	0.025	0.155
Real capital	0.021	0.019	0.023	0.014	0.058**	0.017
Hansen test	52.30		29.27		25.06	
Hansen p-value	0.611		0.741		0.838	
AR (1)	-1.20		0.83		-0.89	
AR (1) p-value	0.230		0.407		0.372	

Appendix G: The impact of technological innovation on older employee group, by sectors.

	High-tech sector		Medium-tech sector		Low-tech sector	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
Innovation *(t-3)*	0.013	0.090	0.089	0.146	-0.142**	0.07
Employment *(t-1) old*	0.565***	0.048	0.548***	0.043	0.498***	0.029
Labour cost per young employee	-0.019	0.023	-0.016	0.015	-0.023*	0.011
Labour cost per middle-aged employee	-0.021	0.025	0.011	0.014	-0.016	0.019
Labour cost per old employee	-0.344***	0.039	-0.366***	0.037	-0.408***	0.024
Real capital	0.021**	0.007	0.025***	0.006	0.039***	0.007
Hansen test	13.20		29.27	34.52	31.19	
Hansen p-value	0.355		0.741	0.674	0.697	
AR (1)	-1.24		-0.03		-1.65	
AR (1) p-value	0.216		0.973		0.098	

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