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The effect of technological innovation on age-specific labour demand

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ABSTRACT

This research examines the relationship between technological innovation and age-specific labour demand at firm level. The research supports the hypothesis of age-biased technological innovation. A combined panel data set of Estonian firms is used in the study that merges three different data sets – Community Innovation Survey, Business Registry data, Estonian Tax and Customs Office data – consisting of 5,785 unique firms over the period of 2006–2016. This paper uses a constant elasticity of substitution production function to derive a labour demand equation for perfectly competitive firms and the System GMM approach to analyse a panel data set. The results are in accordance with the theoretical expectations that there is a significant positive impact of technological innovation on total employment at firm level and a 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.

JEL Classification: J14, J23, O33

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I. Introduction

The growth of computerisation and artificial intelligence play an essential role in the effectiveness of production, followed by shifts in labour demand in competitive global markets. In theory, technology affects labour demand in two ways. First, there is the 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. It has been well documented that the demand for workforce is reduced due to the automation of activities. For instance, statistics in the US revealed that 1.63 million technological devices replaced humans in different industries in 2015 (Frey & Osborne, 2017). Second, there is the compensation effect that there are increased demand for skilled labour through creating new job opportunities. The decrease in the costs of the country's products because of efficient production leads to an increase in demand; consequently, new jobs are created in the labour market (Evangelista & Savona, 2003).

Studies on employment and innovation have covered several research questions, such as whether technological innovation is skill-biased, routine-biased or age-biased (Dachs, 2018; Blanas et al., 2019). 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 the workforce in Estonia. Previously, few authors (Beckmann & Schauenberg, 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 for a company can also function against them. According to Aubert et al. (2006), there can be two main reasons behind this consequence. First, the skills and experience of older workers might not be suitable for innovations. Second, the adaptation of older employees to mechanisation can be much slower in comparison to younger co-workers.

The findings mentioned 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 there being an ageing population. Statistics from the United Nations (2017) report that approximately one-quarter of the EU population was 60 years old or older in 2017. Estimations reveal that this number will increase by 10 percentage points by 2050, so about 35% of the population in Europe will consist of older people. Moreover, the employment rate of people between the age of 55 and 64 in the EU was 58.7% in 2018 (Eurostat, table *fsi_emp_a*). This indicator stood at 68.9 % in Estonia, one of the highest values in the EU. In summary, analysis of the employment of those age groups in an age of rapid technological change and finding solutions to these issues should be the focus of economic policy makers.

This research expands upon existing empirical literature by analysing the link between technological innovation and employees using different age structures in Estonian firms. A unique combined data set is used in this study, namely three different data sets are merged for the study consisting of 5,785 unique firms in total. These data sets are the Community Innovation Survey (CIS), Estonian Business Registry data and Estonian Tax and Customs Office data. As the Estonian Customs and Tax Office data on payroll taxes contains information about firms starting from 2006, we dropped the first three waves of the CIS (CIS3, CIS4, and CIS2006). Hence, this data set allowed us to apply a thorough and advanced estimation strategy. This paper uses a constant elasticity of substitution production function (CES) from Van Reenen (1997) to derive a labour demand equation for perfectly competitive firms. Age-specific labour demand was regressed on 3-year-lagged technological innovation, lagged employment variable, the labour costs for each employee category (young, middle-aged, old), real capital stock, and time and industry dummies for NACE 2-digit industries in the final estimation equations. OLS, within-group and system GMM (using Roodman (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 as well as the impact of innovation on the employment of different age categories, the latter being the research question of the study. Third, we included both types of technological innovation, product and process innovation, in the analysis to see the impact of these specific types of technological innovation separately. Next, we added organizational innovation as an indicator of non-technological innovation to our estimations as a robustness test. Finally, the companies were split into low, medium and high-tech sectors as a further robustness check.

The results are in accordance with the theoretical expectations that there is a significantly positive impact of technological innovation on the total employment at firm level and a negative relationship exists 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 showed 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 labour demand through different age structures.

The rest of the paper is organized as follows. The second section presents analysis of different theoretical and empirical literature comparing evidence of innovation effects on employment internationally. Section III presents the econometric model used in this paper covering the derivation of the labour demand equation (estimation strategies for the total number of workforce and employees from 3 different age groups) from the 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 the empirical results obtained from the analysis to show the linkage between technological change and labour demand in terms of employee age in Estonia. Finally, Section VI concludes with a summary of the results.

II. Literature review

The literature on employment and innovation has covered several research questions. The relationship between employment and innovation is a complex one that has been addressed by many schools of economic thought. Some of them have considered there is a positive effect on employment and economic growth but the overall effect remains ambiguous on the side of theoretical contributions.

The analysis of innovation and employment presents a complex problem both from the theoretical and empirical perspective. In this, a general theoretical framework covers different schools of thought where the debate has already started. During the classical period with David Ricardo, the labour class already considered the possibility that technological advances was detrimental to their interests. Marxism also considers it a phenomenon that increases unemployment through the introduction of new machines leading to the displacement of workers in different fields. The contributions of Schumpeter and Keynes enriched the understanding of the 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, the Schumpeterian approach explains the first type as labour-friendly and the second as labour-displacing (Vivarelli, 2014; Calvino & Virgillito, 2018). Among the four types of innovation (product, process, organizational and marketing innovation), product and process innovation have become more important objects of study. According to the Oslo Manual, product innovation is characterised 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 (OECD/Eurostat, 2005).

According to the general equilibrium view, when the market clearing assumption holds there is no place for overproduction and unemployment. Consequently, technological innovations only lead to a temporary labour destruction. The main cause is not less available job opportunities, but not being able to find a suitable low equilibrium salary that matches the decrease in the demand for labour (Calvino & Virgillito, 2018). Calvino and Virgillito (2018) examine how employment dynamics are affected by the introduction of technical changes. The authors review 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 to the creation of this type of firm, and therefore the growth of employment.

At the micro level, 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 in terms of firm level evidence, and these findings should be treated with caution (Brouwer et al., 1993; Greenan & Guellec, 2000). Studies that include peculiar characteristics, such as firm age and firm size are relevant in offering a different perspective at the micro-economic level to understand employment dynamics with an emphasis on high technology sectors.

Pianta (2003) examines the types of innovation and identifies their effects on employment. He found that studies generally show positive effects on job creation at the firm level. However, he also highlighted the differences between the findings of studies using micro level data and data at higher levels of aggregation. On the basis of the review of past 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.

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

The study of innovation surveys has become important over time for the implementation of innovation policies, providing quantitative and qualitative information to monitor their performance and measure market impact. This is a widely used data source for econometric analysis based on 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 (structure, content, characteristic, indicators and determinants) included in the surveys to have an extended overview of innovation, selecting those based on the Oslo Manual recommendations, considered among economists to be the most regularly used innovation surveys and implemented in many countries. Large numbers of studies throughout the EU have been conducted using CIS data covering issues, such as the links between technological changes and productivity or labour demand. The innovation surveys in some other countries, such as in Latin America, follow a similar approach using CIS (Crespi & Peirano, 2007). This implies that analysis based on CIS data is important for the decision-making process in firms, industries, and so on, but it is difficult to apply this to 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 the main contributor to the adoption of new products in a company. When it comes to the analysis of age composition in the workforce, it can be hard to actually measure the performance of different workforce groups. Therefore, this study embraces empirical papers that established possible solutions to this issue. According to the authors, 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 other age groups. Consequently, it has been said that these capacities tend to decrease at older ages, although most of these studies focus only on samples from specific industries or firms; therefore, they cannot be generalised to all industries and companies. Likewise, the results of analyses where cross sectional data is used should be interpreted carefully, since unobserved heterogeneity and selectivity bias can lead to biased estimations having favourable results towards younger workers to the detriment of the older workers.

However, different results from Feyrer (2008) propose that the age profile of inventors (patent holders) is quite stable over time reaching a peak (i.e. the highest invention performance) between the late-30s till the mid-50s. 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. If this performance is decreasing over time, it might be caused by a reduction in the number of workers in the economy rather than a decline in performance at older ages.

There are different approaches used to analyse the performance of labour and workforce. Some might consider measuring the impact of individual inventors that still lack information about the knowledge transfers and the inventor, while others take into consideration how the workforce in companies contribute to the overall innovative performance of the firm, and the value added per worker on the firm's level of innovativeness. More aggregated approaches at firm level offer a solution to this deficiency in the existence of analysis at the individual level by adding the direct contribution of the employee 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 Appendix A for an overview of empirical studies on technological change and employment). For instance, Van Roy et al. (2018) present 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 that includes 20,000 patenting firms from 2003 to 2012 and found that new technologies had a positive impact on labour demand at the firm level. However, the positive effect can only be observed to any great extent in the high-tech manufacturing sector, not in low-tech manufacturing branches.

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 of German firms by Lachenmaier and Rottmann (2011) for 1982–2002 using panel data identifies the positive effect of both process and product innovation on employment. One of their contributions to existing literature revealed 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 a significant impact caused by process innovation in the investigation of data from Italy. Analysing a dataset of manufacturing firms in Italy in the period 1995–2003, they indicated employment growth as a result of both product innovation and expansion in the sales of old products.

Taking a similar perspective, Meriküll (2009) used Community Innovation Survey (CIS3 and CIS4) and Business Register data for 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 could be seen at 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 of Estonia being a catching-up country.

In the next strand of literature, researchers added different aspects to employee diversity, such as skills, in order to see the extent to which technological and organizational innovations are skill-biased. The paper by Crespi et al. (2019) researched manufacturing firms using innovation surveys from Argentina, Chile, Costa Rica and Uruguay, and the authors identified a positive effect from product innovation in all countries except Costa Rica. In the case of process innovation, there is a negative relationship only in Chile and no evidence in Costa Rica. Additionally, they focused on the relationship 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 the demand for a skilled workforce, at least in the adoption phase of the new technologies. Similarly, Rønningen (2007) differentiated workers in terms of their education level, and by analysing Norwegian manufacturing firms based on data from 1992–2003 using OLS method, wage bill shares were not associated with low-medium level educated people; however, organizational changes were associated with a high-level educational background for people in their 30s (age group 30–40). In terms of methodology, all the papers discussed above used either a GMM approach or OLS estimation method.

Several studies have examined the impact of new technologies on the demand for employees through different age structures to see the extent to which technological changes are age-biased. 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 from 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 chances of elderly people being hired stem from the introduction of new technologies to the firms, specifically in 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 hand, technological innovations were found to result in a decrease in the wages of individuals aged 50–60, while an increase when they are over sixty.

A group of authors explored the effect of workforces with different age structures on firm innovativeness and productivity. Generally, recent analyses reveal a negative relationship between employee age and indicators of innovation. Bertschek and Meyer (2010) analysed German manufacturing firms and service sectors for 2004–2007 using nonlinear and linear probability models; they presented a positive interaction between IT innovation and process innovation, whereas a negative relationship between technological changes and the demand for older workers, particularly those who lack proper IT skills. Therefore, the occurrence of IT-enabled process innovation is rare at companies with a 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 perspective of workforce experience, namely managers and workers, in Italy for 2001–2003, Daveri and Parisi (2015) indicated that inexperienced workers could hinder the growth of both innovative and non-innovative firms. If the company consists of mostly elderly managers, they will be a disincentive for implementing innovation only in highly innovative firms, not in non-innovative ones. In summary, the direction of this particular effect depends on the innovation level of firms.

In contrast to these papers, Verworn and Hipp (2009) using 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. In general, no harmful effect from old people was found, despite a shortage of retraining. However, the findings in this paper do not mean the age structure of the workforce should be ignored. As their investigation was only based on 2001 data (i.e. they lacked longitudinal data), they could not analyse time lag effects of specific variables such as employment and innovation.

Some 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 between employees in terms of age but the most important criterion is whether the individuals have the skills at the required level for the particular position. More specifically, looking at employment data between 1993 and 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 and Schauenberg (2007) found that the implementation of both 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 providing additional training opportunities for them.

The impact of innovation in the 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 government organizations in the USA. 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 from ZEW in Germany and compared older workers to younger counterparts under 30. Adapting 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) comes in line with Meyer. They analysed manufacturing and service firms based on CIS data for Sweden in 2004, 2006 and 2008, and confirmed the conventional view that age and reaction to technological innovation among 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. Consequently, higher employee turnover is more likely in 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 a Linked IAB Establishment Panel dataset showing that the employment share of older workers is positively related to the introduction of organizational and product innovation to the firm.

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

III. Data and descriptive statistics

The paper employs data from three different sources: Estonian Community Innovation Surveys (the waves used cover the periods 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 data on employees' payroll taxes (2006–2017).

The study of innovations surveys has become important over time for the implementation of innovation policies, providing quantitative and qualitative information to monitor innovation performance of firms and measure the impact of innovations on markets, this being a widely used data source for econometric analysis based on 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, and including several EFTA countries and EU candidate countries. Estonia has had one of the highest response rates in CIS surveys among European countries – a response that is directed by Statistics Estonia. For instance, response rates were 74% and 78% in CIS3 and CIS4, respectively, while the 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; for example, 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 & Vahter, 2012). This paper uses product and process innovation indicators across five waves of CIS surveys.

The relationship between export orientation, and innovation inputs and outputs can be estimated using CIS surveys. However, measuring innovation based on CIS surveys can lead to some errors during investigations. First, the type of business in terms of innovativeness, namely innovative or non-innovative, is a binary variable. The problem here is that the company is considered innovative regardless of the number of innovation activities implemented within a specific time. On the other hand, there are also available non-binary measures of innovation, 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. Second, as every company reports the innovation variable themselves, it may end up being misreported. Although the businesses are expected to have no interest in providing incorrect 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; therefore, theoretically, this could lead to better quality data. Moreover, each enterprise reports its innovation activity in the last year of the CIS survey period. It means the indicator will be reported in CIS2014 for the years 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 of the study

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. The Business Registry gives information about 20 – 50,000 firms each year in Estonia. The financial data based on profit and loss statements, cash-flow statements and balance sheets is included in the dataset. Additionally, it provides information about enterprise size (number of workers), firm entry and exit over the years, and economic activity codes of companies. We merged the Business Registry data with CIS to obtain the number of employees, employment costs, and capital stock variables for each firm and year, as CIS data does not cover these variables. To be precise, both data sets include employment variables, but the registry data is preferred as a source of observations on employment.

The total number of observations (firm-years) after merging the Estonian Business Registry and Estonian Community Innovation Survey data sets is 15,902, covering information on about 5,785 enterprises. The share of innovative firms regardless of 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 some form of innovative activity have higher employment, labour cost, and capital stock levels compared to non-innovative companies. Labour cost and real capital stock shows a deflated (by GDP deflator) yearly average wage cost per employee in thousands of euros in the company and a deflated (by GDP deflator) average capital stock per company in millions of euros, respectively. Both of these are higher for innovative companies 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[2]	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.

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 gender and date of birth. In addition, the dataset covers information about the social tax payments for employees by employers. The date of birth was used to calculate the age of individuals. The paper uses the records of employee age for each year in

[2] The indicator variable for the firm with organizational innovation was used at the later stage of the analysis in our robustness check.

January (but data for other months are also available). We categorised employees in three different age groups: 1) young (employees less than 30 years old), 2) middle-aged (employees between 31–50 years old), and 3) old (employees between 51–100 years old). This classification coincides with that of Beckmann and Schauenberg (2007) and enables us 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 summarising the observations for specific variables (employment, labour cost, and 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 the Estonian companies covered by the CIS survey is 14 as presented in Table 3. However, we can observe that this number for innovative firms is higher (22) than average and for non-innovators lower (8). 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, Table 3 indicates that the share of older employees is higher in non-innovative companies (32%) compared to innovative ones (28%).

Table 4 presents the shares of different age groups in Estonian companies by field of activity. We can see here that the statistics are consistent with Table 3, hence the share of young employees is higher in innovative compared to non-innovative companies. For instance, the largest group of firms are manufacturing firms (NACE code - D) and the average share of young employees in technologically innovative manufacturing firms (22%) is higher than those without having implemented technological innovation (18%).

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

NACE [a]	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) 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 Organizations and Bodies.

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

c) Non-innovators means firms without any product or process innovations.

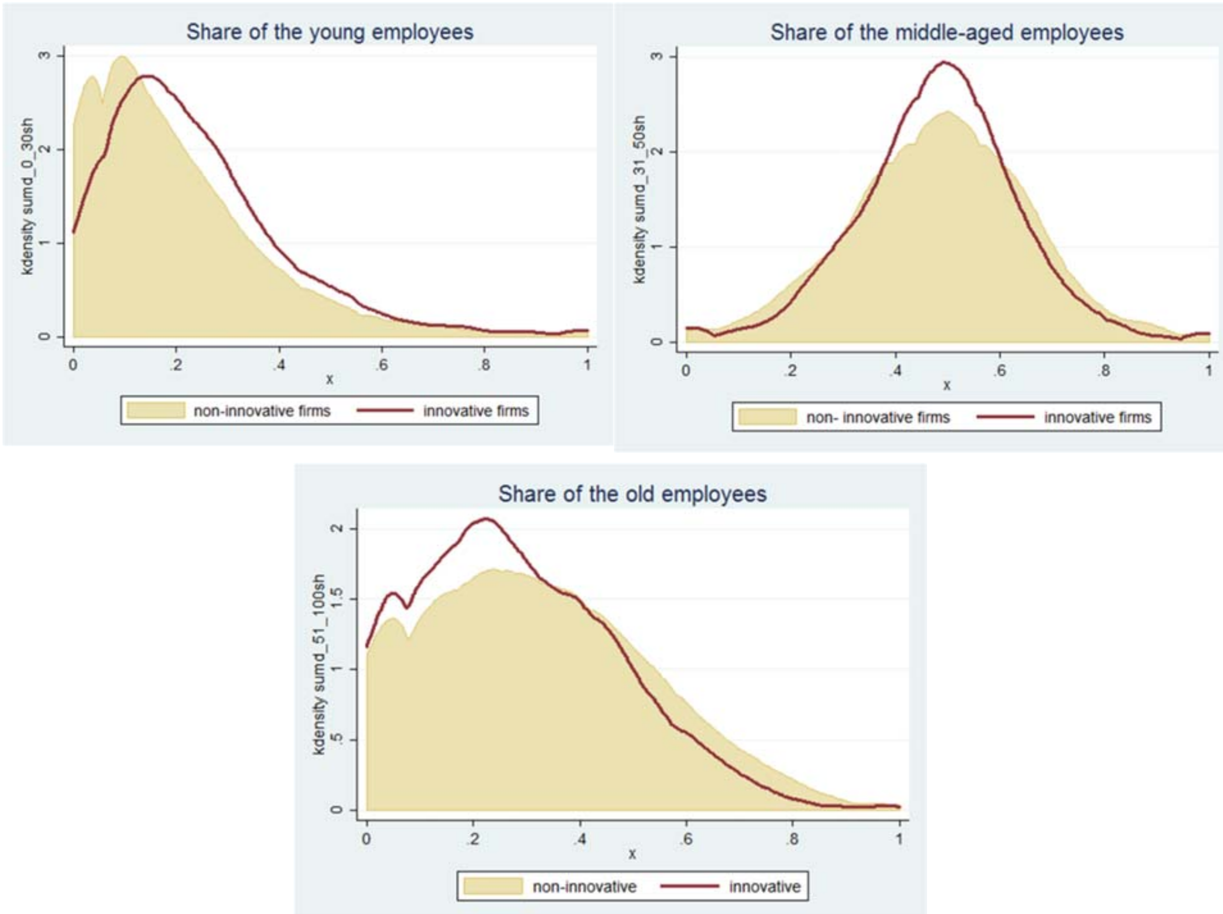

Figure 1. Kernel density plots of the distribution of young, middle-aged and old employees in innovative and non-innovative firms

Figure 1 above provides the Kernel density plots of the distribution of employees by different age structures in innovative and non-innovative firms. Hence, we can see the higher share of younger employees in innovative companies throughout the distribution. In other words, the share of young workers in innovative companies is higher compared to non-innovative firms. 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. In addition, we employed the two-sample Kolmogorov-Smirnov (KS) tests to compare the distribution of three different age groups in innovative and non-innovative firms, where the difference was statistically significant for all three 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.

IV. Econometric strategy

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

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

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 the elasticity of substitution between employment L and capital K. Substituting the marginal product of labour with real wages (W/P), and taking the first-order condition with respect to labour, our equation will be as follows:

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

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

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

or

$$\eta_{NL} = \eta_P \Theta + (\sigma - 1). \quad (4)$$

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 fixed production. Hence, labour demand will increase when the elasticity of substitution σ is higher than one. If capital and output can be varied, the positive impact of labour demand can still be observed even in the case of low elasticity (σ - 1) since a decrease in prices will lead to a rise in demand for products. The greater η_P and the larger Θ make the positive labour demand effects more likely (Neary, 1981; Dowrick & Spencer, 1994; Van Reenen, 1997).

Substituting output with the marginal product of capital (equal to the cost of capital R), the simple labour demand relationship in formula 2 can be rewritten as follows:

$$\log L = (\sigma - 1)\log\left(\frac{A}{B}\right) - \sigma\log\frac{W}{P} + \log K + \sigma\log R \ . \qquad (5)$$

Next, innovation *(INNO)* replaces unobserved technology variables. Technological changes have led to a rise in labour demand, not in capital, in the last 150 years according to Acemoglu's argument (2002); that is, 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 the model through labour augmenting and not capital augmenting technology. Consequently, the labour demand function's stochastic form should be as below:

$$l_{it} = \alpha_1 INNO_{it} + \beta_4 w_{it} + \beta_5 k_{it} + \tau_t + u_{it} \ , \qquad (6)$$

where lower case letters represent the logarithms of the variables, *INNO* 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*' time. The cost of capital (*R*) is assumed to be constant across all the firms and only differs over time.

The impact of technological innovation on labour demand reveals 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 the innovation variable by 3-year time periods. Additionally, considering that the previous year's employment has an effect on current labour demand, a one-year lag of labour is added to the model (Meriküll, 2009; Piva & Vivarelli, 2005). Longer time lags turned out to be statistically insignificant in the study by Meriküll (2009). Taking into account the adjustments, the above labour demand equation can be written as below:

$$l_{it} = f_i + \alpha_1 INNO_{it-3} + \beta_1 l_{it-1} + \beta_2 w_{it} + \beta_3 k_{it} + \tau_t + u_{it} \ . \ (7)$$

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):

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

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

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

$$o_{it} = f_i + \alpha_1 INNO_{it-3} + \beta_1 o_{it-1} + \beta_4 ow_{it} + \beta_2 yw_{it} + \beta_3 mw_{it} + \beta_5 k_{it} + \tau_t + u_{it} \;. \quad (10)$$

In these formulas, y, m and o describe workforce in three groups as young (below 30 years old), middle-aged (31–50 years old), and older (above 50 years old) respectively. This kind of employee classification has been used by several authors such as Mahlberg et al. (2013 a, b) and Vandenberghe (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 three categories of workforce, since all of them affect the hiring decisions of companies (Meschi et al., 2015).

In terms of the short and long-run impacts of new technologies, in the EU15 and in 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-year) impact of technological innovation on total employment and the employment of the different age groups.

Dynamic estimation models may lead to some problems. There may be a positive correlation between the lagged employment variable and the firm specific component of the error term (u_{it}). Hence, an estimation using a simple OLS will result in a biased coefficient. A within-group estimator or first-difference method can be used to solve this problem instead of using the OLS estimation method. However, analysis using a within-group estimator will be biased (negative correlation between transformed version of lagged employment and error terms) again because of the limited number of periods. The biasedness in the 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 the lagged difference employment variable and the error term. However, adding instrumental variables to lagged difference employment can solve this correlation issue. To apply this technique for dynamic panel data estimations, GMM estimation methods are mostly used (Difference GMM, System GMM) (Arellano & Bond, 1991; Arellano & Bover, 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 a GMM estimator will resolve the issue of the biased results arising from endogeneity or reverse causality (Leszczensky & Wolbring, 2019). It is also applicable for our analysis considering the large number of observations. In addition, Blundell and Bond (1998) revealed that the Difference GMM has weak predictive power in the finite sample, so the coefficient estimates will be biased. They found that 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.

V. Empirical results

This section discusses the empirical results obtained from the analysis to show the linkage between technological changes and labour demand in Estonia. First, we checked the effect of new technologies on total employment in companies in Estonia (Table 5.1). Second, 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). Third, different types of innovation, namely product and process, were included in the analysis to see the impacts of these different types of technological innovation separately (Table 5.5; 5.6.; 5.7). Next, we added organizational innovation to our estimations as a robustness test (see Appendix B, C, D). Finally, the companies were split into low, medium and high-tech as further robustness checks (See Appendix E, F, and G). Our analyses take into consideration the effects in questions only at firm level not the effects at industry level or on the whole Estonian economy.

The OLS and within-group estimation methods are expected to provide overestimated and downward biased results of the lagged variables, respectively (Baltagi, 2008). Moreover, the results of the System GMM model should be between the coefficients of the OLS and within-group estimator. Hence, we can consider the OLS as the upper boundary and the within-group estimator as a lower boundary of the coefficients.

We performed a number of tests to check for autocorrelation (Arellano–Bond autocorrelation test), the validity of the estimated models and 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 the instruments. It is preferred to the Sargan test in two-step estimations to prevent overidentification issues (Labra & Torrecillas, 2018). The number of groups (in our case firms) or observations should be higher than the number of instruments to avoid overidentification. Roodman's (2006) Xtabond2 command in Stata was used for our System GMM estimations. The Xtabond2 command provides more options in terms of the usage of instruments and enables us to investigate the 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. Therefore, since innovation is reported over 3-year periods in our data set, we lag innovation by 3 years to avoid a biased estimation, namely the impact of future new technologies on current labour demand. In addition, as wage and capital can have an impact on the 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 stock	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	
No. of obs.	10,526		10,526		10,519	
Number of groups			4,161		4,169	

As can be seen from Table 5.1, a positive and significant impact of technological innovation on overall employment was found from all the estimation methods used (OLS, WG, GMM-SYS). This result is consistent with the evidence from other countries, such as Germany, Italy and Turkey (Lachenmaier & Rottmann, 2011; Van Roy et al., 2018; Evangelista & 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 3% growth in employment 3 years after the implementation of new technologies in companies according to the first two models; however, this indicator is around 9% in the latter model. Hence, this shows that the companies that 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; therefore, it is impossible to forecast the exact long-run effects. One-year lag of labour as an 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 that is significant at the 5% level. Hence, there is around 0.16% growth in employment from a one per cent increase in real capital stock and 0.37% decline in employment from a one per cent increase in labour cost per employee. Therefore, the negative impact of labour expenses per worker on labour demand is found as expected. The effect of the 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, the Hansen test failed to reject the null hypothesis (p=0.437), so it means the chosen instruments are valid.

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

	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 stock	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	
No. of obs.	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 (31–50 years) employee group

	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

	Pooled OLS		Within estimator		Two-step GMM-SYS	
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.
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 stock	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	
No. of obs.	5,460		5,460		5,469	
Number of groups			2,107		2,111	

Table 5.4 The impact of technological innovation impact on the older employee group (above 51 years)

	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 stock	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	
No. of obs.	5,378		5,378		5,386	
Number of groups			2,070		2,073	

Going beyond previous literature, we added different age structures of the workforce to our analysis, so the dependent employment variable is categorised into the groups of young, middle-aged and older employees in this part. After dividing the sample into 3 different age groups, it seems that innovation has no significant impact on the demand for employees in the young and middle-aged groups, according to the results of the GMM-SYS estimation model (Tables 5.2 and 5.3). However, a negative relationship is found between innovation and the employment of older employees (Table 5.4); therefore, there is about a 13% fall in the employment of older employees 3 years after the implementation of new technologies in companies. These results are consistent with the evidence from most of the studies in different countries (Beckmann & Schauenberg, 2007; Schubert & Andersson, 2013; Aubert et al., 2006). On the other hand, a few studies did not find any age specific employment displacement due to technological innovation (see e.g. Rønningen, 2007). A one-year lagged employment variable for each age group has a significant impact on the corresponding demand for each employee category at the 1% significance level.

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

	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	
No. of obs.	2,870		2,870		2,875	
Number of groups			1,518		1,521	

We added the labour costs for all 3 categories of workforce to the list of independent variables separately, since all of them affect hiring decisions in companies (Meschi et al., 2015). The relative labour costs have significant negative effects on the corresponding employee categories at the significance level of 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 a 0.08% growth in the young employee group as a result of a 1% 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 older groups, being significant at the 5% and 1% level, respectively (0.04% for young workers being significant at the 1% level). Overall, the 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 the chosen instruments are valid.

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

	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	
No. of obs.	2,950		2,950		2,956	
Number of groups			1,562		1,566	

Next, we decided to investigate the impact of product and process innovation separately on the different groups of employment. As can be seen from tables 5.5, 5.6, and 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 the OLS estimation method). In the case of the within-group estimator, the effect of process and product innovation on employment is negative but not statistically significant. These results are quite surprising, as many studies have found positive and significant effect of product innovation. Additionally, the direct effect of product innovation according to the theory should result in a significantly positive impact on labour demand. This can be because of the information provided by enterprises in the CIS, where even small new technologies implemented in companies can be recorded as technological innovation.

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

	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 stock	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	
No. of obs.	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 a third type of innovation that is not technological to check for 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 the 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. In terms 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. Nevertheless, overall, organizational innovation itself is not significantly associated with labour demand through the different age structures.

We divided companies into low, medium and high-tech for a further robustness check. The OECD and Eurostat classification of technology and knowledge-intensive sectors was used (OECD, 2007; Eurostat, 2020). Therefore, 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-aged 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.

VI. Conclusions

In this study, we empirically explored the interlinked relationship between technological innovation and the age of employees at firm level. A unique combined panel data set of Estonian firms is used in this study, where we have merged three different data sets: Community Innovation Survey, Business Registry data on company financial statements, and Estonian Tax and Customs Office data on employee payroll taxes. The contribution of the paper extends existing empirical literature investigating the innovation effect on employment by looking at how that relationship varies for employees of different age groups.

The main result of studying the effect of new technologies on total employment at firm level shows that there is a positive and significant impact of technological innovation on total employment at firm level. Hence, companies that implement innovations experience higher growth in workforce compared to non-innovating firms. By adding different age structures of workforce to our analysis, no age-specific employment displacement effect due to technological innovation was found in the case of young and middle-aged employees. However, a negative relationship is revealed between innovation and the employment of older employees but it is the case only in low-tech firms according to our further analysis. Additionally, the relative labour costs have a significant negative effect 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 to be positive, but insignificant. The reason behind this finding can be how the information on the innovative activities is collected in CIS, so companies can report even small new technologies implemented in companies as technological innovation. Furthermore, adding organizational innovation to our estimation equations increased the coefficients of product innovation slightly; however, all estimations showed that both product and process innovations do not have any age-specific impact on labour demand in the long run. Finally, a robustness check using organizational innovation revealed that organizational innovation itself is not associated with labour demand through different age structures.

In summary, our research supports the hypothesis of age-biased technological innovation and can be extended in interesting and useful directions. First, the results could be validated in the context of other countries beyond Estonia and the framework used here can be tested on other economic sectors. Second, we mainly focus on the impact of product and process innovation, but the effect of marketing and organizational innovation or a combination of innovation types on different age groups of labour demand could be examined in further investigations. Third, as we did not find any 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 could be an interesting topic. Finally, combining firm-level analysis with analysis at industry level might be deemed useful from the perspective of policy implications. Analysing all these extensions would increase our understanding of the dynamics in labour demand arising from the implementation of different innovation types and would be helpful in understanding the evolution of firms, industries and the economy as a whole.

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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	Methods	Main results
Meriküll (2009)	Employment	Estonia, Estonian Business Registry data (1994-2006), CIS3 (1998-2002), CIS4 (2002-2004), firm and industry level	The number of observation for CIS3 and CIS4 (merging with register data) is 3,161 and 1,747, 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, Schauenberg (2007)	Age-specific labour demand	Germany, 1993-1995, firm level	A sample of 1,634 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; system OLS	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 providing additional training opportunities to them.
Verworn, Hipp (2009)	Innovation input and output	Germany, Community Innovation Survey 2001, firm level	22,600 enterprises	Innovation input and output regressed on the change of personal structure of enterprises, Probit models	Authors did not find that older workers have a negative impact on the innovativeness of enterprises. Nevertheless, they revealed that firms consist of older people have not an inclination to invest in retraining.
Schubert, Andersson (2013)	Product innovation	Sweden, CIS and FEK 2004, 2006, 2008, LISA 2002-2008, manufacturing and service firms	1,543 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.	Mean age of the employees and the companies' reaction to the technological innovation 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 consisting of mostly older workers.
Rønningen (2007)	Change in age specific wage bill share between 2001 and 2003	Norway, 1992-2003, manufacturing firms	1,047 firms, including 753 single-plant firms	Age specific wage bill share regressed on organizational change, technology, capital, value added, other firm-specific	No age-specific employment displacement effect 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.

Author(s)	Dependent variable	Data (country, period, sector)	Sample size	Methods	Main results
				characteristics, industry and regional dummies.	
Lachenmaier, Rottmann (2011)	Employment	Germany, 1982-2002, manufacturing firms	31,885 observations, 6,817 firms	Employment level of firm regressed on product innovation, process innovation (including 2 lags of innovations), lagged employment, real hourly wage rate, gross value added time and industry dummies. GMM system	Positive effect of innovation on employment was found. The impact of process innovation is larger than the effect of product innovation.
Van Roy et al. (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 et al. (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 was found. Positive impact of product innovation and sales growth on employment growth was found.
Aubert et al. (2006)	The shares of workers entering and leaving the firm among the total number of employment in each age group	France, 1998-2000, manufacturing firms	9573 firms	Employment inflow and outflow by age groups regressed on computer use, Internet, organizational innovations, physical capital. JGLS method	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.
Meyer (2009)	Dummy for adoption of new technologies	Germany, 2005	356 firms	Technological innovation adoption regressed on the share of employment of different age groups, firm size, firm age, product innovation, exporter, foreign competitors, enhancement of team work, change in customer	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.

Author(s)	Dependent variable	Data (country, period, sector)	Sample size	Methods	Main results
				requirements. Probit model and linear probability model.	
Crespi et al. (2019)	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 – 1,415, Chile – 2,049, Costa Rica – 208, Uruguay – 2,532.	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 was found. No displacement effects were found as a result of product innovation. Skill biased innovation effect was found on employment.
Bertschek, Meyer (2010)	Process innovation activity	Germany, 2004-2007, manufacturing and service firms	1,251 firms	The process innovation activity regressed on the use of information technologies, employment, firm age and size, product and lagged process innovation. Probit model and linear probability model.	The firms with higher share of older workers 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.
Hujer and Radić (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.
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; hierarchical linear 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.
Daveri, Parisi (2015)	Innovation	Italy, 2001-2003, manufacturing firms	4,177 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, regional, size, and industry	Older board members and managers have a negative impact on productivity and innovation in innovative firms; however, that is not the case for non- innovative ones. There is correlation between unskilled workforce and lower level of productivity and innovativeness.

Author(s)	Dependent variable	Data (country, period, sector)	Sample size	Methods	Main results
				dummies; OLS, GMM, LIML methods	
Meschi et al. (2015)	Blue and white collar employees	Turkey, 1992-2001, manufacturing firms	17,462 firms	Blue and white collar employees regressed on the wages of each category, firm's value added, technology, investments, exports, international involvement and dummies; OLS, fixed-effects, GMM-SYS regressions.	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; 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	15,186 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 stock	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 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*	0.010	-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 stock	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 stock	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 employees, 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 stock	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 employees, 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 stock	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 employees, 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 stock	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	