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

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Akbar Mammadov, Polad Abdullayev

Automation Effects on Labor in Terms of Employment in Different Firm Groups in Estonia

Master's thesis

Supervisor: Junior Research Fellow Anastasiia Pustovalova

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Confidential

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ABSTRACT

The paper aims to analyze and identify how automation affected employment in different firm groups and compare those effects across different industrial sectors in Estonia.

So far, when it comes the effect of automation on employment in Estonia, previous studies examined effects of automation on gender pay gap, impact of digital technology on labor productivity and the impact of digitalization and artificial intelligence on labor relations in Estonia. However, our research has an extensive dataset with a whole universe of firms - not just a sample of them as it is often the case, and we observe them for a long period of time. Besides, in our paper, firms have been categorized in terms of both their size, sectoral identification, and experience of adopting automation tools, and unlike previous studies, our paper focused on micro and small sized-firm groups too.

Defining automation experience of firms, we used the data on the imported automation products by each firm accordingly, we have gathered the imports data of all firms in Estonia from 1995 to 2018. Additionally, as our study focuses on the effect of automation on employment, employment data for each firm has been collected and analyzed. To investigate this relationship, the fixed-effect linear regression model has been used, and our findings represent the new highlights of the automation effects in the labor market of Estonia.

The empirical part of the paper concentrated on more than 20,000 firms in various size groups in different industrial sectors (agriculture, manufacturing, construction, service and others) in Estonia from 1995 to 2021, with covering more than 175,000 observations. Based on our findings, results for the effect of automation on employment differ across sectors and different firm groups. However, there has been a statistically highly significant correlation between employment and automation for only manufacturing, mining and quarrying sectors and transportation, wholesale and retail trade sectors, our findings show that there has not been a statistically significant correlation in all other industries.

Keywords: automation, labor, employment, manufacturing, imports

JEL classification: C33, C35, C55, C88, J6, O14

1 Introduction

The impact of automation and digital technologies on our society has drawn increasingly more attention during the last half-century. Following their adoption, papers have investigated the impact of adoptions of new technologies on labor related outcomes. (G,Anzolin, 2021). As J. Bessen and M. Goos (2019) states that in the current technological era, a wide range of job tasks, including those that were previously thought of as non-routine, are increasingly being fully or partially automated by developing technologies. These tasks include reading X-rays to diagnose disease, selecting candidates for interviews, picking orders in a warehouse, and operating a vehicle. These technologies, which are used in a wide range of economic sectors, include robotics, voice recognition, and other uses of artificial intelligence. However, this paper will focus on tangible automation, analyzing different firm groups in various sectors of the industry in Estonia.

According to some academics, the speed of automation may be increasing and the spectrum of jobs affected is expanding, posing a concern of job displacement for significant portions of the workforce in the near future. The effects of such developments could be disastrous, according to a large body of research on worker displacement (Frey & Osborne 2016; Ford 2015): workers affected by plant closures and mass layoffs experience reduced employment prospects and wage damage, which results in long-term earnings losses, reductions in consumption, and worse health outcomes. As a result of these discussions, there is now a demand for new laws to assist those who are being displaced by automation, such as the universal basic income. Knowing that the automation itself has an increasingly large impact on different economic factors, such as productivity, lower costs, employment etc., we have decided to explore and learn the effects of automation on labor by narrowing the scope of the analysis to employment outcomes for better understanding of its consequences in Estonian firms' in terms of employment.

Several questions arise in the context of automation's impact on labor in different firm groups, such as how the average number of employees increases among the robot adopters, whereas the same for non-adopters decreases. (Koch, Manuylov & Smolka, 2021). For this purpose, a large amount of data on imports of automating equipment (industrial machines, apparatuses, various manufacturing devices etc.) has been explored and gathered by Business Register of Estonia to analyze the universe of firms, as well as the effects of these automating products which Estonian firms import. Moreover, this paper is composed to understand how this import policy of automation tools affects employees and other labor factors in terms of employment.

Being the pioneers of linking the gap in the literature about measuring the influence of the latest technological innovation on employment, Frey and Osborne (2013) notes in their studies that despite effective frameworks are existent for analyzing how computers affect the composition of the structure of occupational employment, they are insufficient for illuminating the effects of technological developments that go beyond the computerization of everyday jobs.

The research gap in this area is mainly due to the fact that the research papers in this area did not explore the effect of automation on employment in different firm-groups, and diversity among all main industrial sectors in Estonia. This regard, our paper is also linked to studies by Acemoglu & Restrepo (2018), which examined the link between two ways of employment displacement and automation.

This paper included the use of the fixed-effects linear regression method and correlation analysis of imports-trade and labor-employment data to determine the correlation and link between the automation process and employment, which is both methodologically and conceptually different from previous research papers as it focuses on the tangible automation process in different groups of firms in manufacturing areas.

As a result of empirical analysis, we found that as there was no statistically highly significance in the relationship between automation and employment in different firm groups, automation has not largely affected employment level in different firm groups in general, but only results differed across various sectors.

The thesis has the following structure. The first section covers the introductory part of the research while, the second one contains previous researches about automation and its effect on employment. In third and fourth parts, we have covered data, variables, methodology used in the analysis of the automation's effect on employment and demonstrated the empirical part of research along with its results gained through fixed-effects linear regression. In the end, we have made our conclusion about the study and depicted the possible implications in the discussion section.

CERCS research specifications: S180, S185

2 Literature Review

Trends in automation and mechanization are nothing new; they have been developing for years, particularly in advanced manufacturing industries. Mechanization, a process that began during the first and second industrial revolutions, is to be understood as the substitution of machine labor for human one. At that time, the electrification of the steam engine and other machines took the place of physical labor, frequently enhancing human labor (Landes, 2003). Automation, on the other hand, is a more advanced and intelligent form of mechanization where a machine takes the place of a person's brain processes. Within specific bounds, automation refers to a situation where the machine chooses its own program and has the ability to reprogram itself (Bliek, 1974). Yet, our research is concentrated on the replacement of human labor with the automation process and the logical economic consequences stemming from this substitution.

Selecting the automation as a measure of how technological progress affects the structure of employment and labor market is important since Autor and Dorn (2013), and Firpo et al. (2011) suggest that there is evidence that rising workplace automation has replaced employees from low and medium-skill occupations, “scooping out” the middle of the skill distribution. The future seems dismal for those with less specialized skills and abilities, says Brynjolfsson and McAfee (2014).

Schmidpeter and Winter-Ebmer (2021) note that variations in the labor market caused by automation and digitalization are one of the most debated policy matters, emphasizing the availability of a substantial number of researches on the effect of automation on the number of jobs; however, they add that there is negligible evidence about its consequence on individual level and policy choices. That is why our paper focused on the different economic sectors in order to understand how automation really leads to changes in employment.

Some researches (Merchant & Saridis, 2000) have concluded that advantages of automation are that it can boost the efficiency in production and diminish production costs, and Wei (1998) also state the benefit of automation in terms of enhancement of operational safety and productivity. The most important benefits of automation in manufacturing are to ensure opportunities for enhanced competitiveness by leading declines in production costs and extended efficiency and productivity (Frohm et al., 2006).

Technology will undoubtedly tend to replace labor in the deterministic perspective of the manufacturing process and technological advancements. While most studies use sectoral level data to measure the automation’s effect on employment, there aren't many research that demonstrate micro - or firm-level evidence. (Frey and Osborne, 2017; Arntz et al., 2016;

Brynjolfsson and McAfee, 2014; Sung, 2018; Manyika et al., 2017), frequently skipping over the critical organizational and technology analysis.During the second industrial revolution, mechanization processes gave birth to labor-saving automation, which has been slowly developing ever since (Staccioli and Virgillito, 2021). There has been intense focus on an apparent strong trend of automation, as though robots might soon replace human labor, despite the progressive nature of technological changes. A more thorough study would take into account that automation - and potential labor displacement - is only one component of what is happening in organizations, and it's not even the most recent or the most urgent one. Instead, firms are focusing on digitalization and connection concerns. (Cirillo et al., 2021).

Andreoni and Anzolin (2021) note that these trends are still demonstrating numerous hardships in regards to basic and intermediate capabilities, which are important in terms of structural changes implied by automation. They also add that due to the complexity of these trends, a large number of firms in both developing and developed countries cannot still be fully automated.

Both digitalization and automation are generating a lot of attention and contributions, but they overly emphasize the effects on worker displacement. The more modern forms of automation, particularly digitalization, still frequently focus more on connectivity, integration, and rearranging production processes than on automating manual jobs, with a number of other implications that exceed workforce substitution (Acemoglu and Restrepo, 2019; Autor et al., 2003).

New technologies are primarily concentrated in major multinational organizations or in niche enterprises that modified the policy to survive in the market, according to preliminary research at the firm level that adhere to the same line of thinking; Contrarily, SMEs struggle to adapt new technologies, especially in industrialized countries like South Korea and Germany (Sommer, 2015). (Yu, 2018). Thus, not only large-sized firms are examined by our paper, but also small and medium-sized firms are among firms from different economic sectors.

Regarding the effect of automation on employees, Schmidpeter and Winter-Ebmer (2021) highlight that employees, who obtain new occupations, in jobs where there is a high risk of automation have better salaries and higher stabilities in their new employment. The employees who obtain new jobs move from less routine intensive employment to higher-paying one (e.g. Cortes, 2016). Furthermore, Hershbein and Kahn (2018) state that a quality–quantity balance where the quantity of jobs in some professions decreased while the others have turned to be more productive might also be a factor.

Robotics is a further development in automation-related technological progress that brought a level of complexity to the execution of jobs as robots became adaptable enough to carry out many activities: After being programmed, it is able to alter the kind and degree of the duties with increasing levels of self-control (Richard, 2005; Kamaruddin et al., 2013).

It's still challenging to estimate a large amount of the risk associated with using new technologies (Anzolin, 2021). Beyond the effects on the duties and activities that are covered here, factors like flexibility in working hours and locations, casual contracts, longer work shifts, low pay, and a lack of legal protection are all potential dangers that affect working relations (Balliester and Elsheikhi, 2018). Due to poor relationships with coworkers and the loss of a dedicated workspace, workers are also prone to lose their ability to arrange and get organized within these aspects (Tran and Sokas, 2017).

It is difficult to predict how these components will interact because it depends on a wide range of diverse factors, among which institutional factors play a significant role in determining how technologies are adopted and their potential effects on working conditions, employment, and the labor process. For instance, a high unionization rate could facilitate technological change decision-making and prevent worker resistance. Less unionization, on the other hand, would open the door to the use of technology meant to limit workers' freedom and opportunity to organize, according to Anzolin (2021).

One of the most prominent contributions came from Frey and Osborne (2013), who foresaw a sizable amount of employment losses. They assess the degree to which different professions are automated under the presumption that automation will happen and that, when it occurs, the associated job will be removed. The truth appears to be different despite the transformational ramifications of this contribution, at least in part since automation is typically focused on given duties and because occupations are frequently affected but seldom eliminated. Since technological feasibility does not immediately imply economic feasibility, which varies between industries and businesses (Acemolu and Restrepo, 2016; Staccioli and Virgillito, 2021), such an approach does not take into account the automation process' much more gradual nature.

Because the International Federation of Robotics (IFR) dataset has been compiling comprehensive data on robots at 4 digits (ISIC rev. 4) for more than two decades, industrial robots are the only technology for which data is available. The studies that make use of these data have produced conflicting findings; those that use microdata discover a positive association between technological change and employment, while those that concentrate on IFR data find a negative relationship.

In general, research that identifies a link between employment and robotics shows a tiny robotization effect, indicating that job differences depend on other factors (Anzolin, 2021).

The following table shows that results from researches which applied dataset of International Federation of Robots are varying, or in another word, studies concentrating on dataset of IFR conclude a negative link between employment and technological progress; however, others that apply microdata demonstrate a positive relationship. In general, although those studies that demonstrate a positive link between employment and robots, they provide a minor result of application of robots, meaning that variety of jobs is dependent on other aspects.

Table 1. The comparison of results from various studies on automation's effect on employment

Authors	**Type of effects on employment**
(Graetz and Michaels, 2018)	Negative. 1993–2007 in 14 sectors and 17 countries.
(Carbonero et al., 2018)	Negative. 2000 to 2014 in 15 sectors and 41 countries.
(De Backer et al., 2018)	Positive 2000- 2014 in developed countries (depending on the years analyzed) and no correlation for developing countries.
(Borjas and Freeman, 2019)	Negative in particular low-skill employment, in the US.
(Klenert et al., 2020)	Positive 1995-2015, EU countries.
(Antón et al., 2020)	First period (1995-2005), association between robots and employment negative; second period (2005-2015) the association is negative with a high increase in productivity
(Acemoglu and Restrepo, 2019)	Negative effect of robots on employment and wages
(Dauth et al., 2017)	Negative in Germany (each robot destroys two manufacturing jobs), but it is counterbalanced by the effect of robots on the rest of the economy. The overall effect is thus neutral.

(Chiacchio et al., 2018)	Negative impact of robotization on employment and wages in six European countries.
(Jäger et al., 2016)	Neutral effect on employment and positive effect on productivity. Data from the European Manufacturing Survey across 3000 firms in six EU countries and Switzerland for the year 2012.
(Koch et al., 2019)	Positive 1990-2016 on 1900 manufacturing firms in Spain.
(Domini et al., 2019)	Positive for the case of France.

Source: Anzolin (2021).

As seen from the table, there have been both positive and negative effects of automation on employment in different sectors of various countries. As a result, and as has already been said, how new technologies are implemented into the manufacturing process will determine their effect on workers.

For the redesign of productive processes and organizational renewal, the management and operational components of this trend of embracing new technology are essential. According to Zott et al. (2011) and Chesbrough (2010), business model transformation can spark organizational innovation at any level and predict the kinds of technological implications that will affect organizational structures. Researchers have been examining the significance of various managerial choices in the technical and organizational restructuring and have come to conclusion that the use of technology at work depends on the way that work is organized and the production structure that is in place (Bailey, 1993).

Numerous studies have sought to examine the relationship between increased automation technologies and employment consequences, both statistically (displacement effects) and qualitatively (skills effects) (Anzolin, 2021). The effect of automation on employment and work skills are dependent on the policy adopted in the workplace (Smith & Thompson, 1998). Jurgen et al. (1993) deny the link between automation and skills by stating that decision on automation is only indirectly linked to deskilling by adding that it is certainly less than mass production mechanization processes.

Despite the cost of labor being frequently cited as a factor in business automation, there is little proof of this. For instance, Krzywdzinski (2017) shows that there is no correlation between the level of automation in CEE (Central Eastern Europe) countries and the lower cost of labor in a comparison between German and CEE automotive industries. According to his observations, the shop floor is tightly split among staff only handle jobs connected to ingesting the device indirect workers, who undertake regulation tasks—when automation happens. Actually, polarization and the growing labor force's segmentation are two effects of automation processes that may manifest (Lüthje and Tian, 2015). This is consistent with the research by Cagliano et al. (2019), which found that task standardization and segmentation are increased by initial technology use and a low level of technological integration.

In addition, although they may eventually undertake other duties, workers exposed to robots are more likely to remain employed at their original place of employment, providing them with greater stability, because they undergo training to acquire new skills. (Dauth et al., 2017). In a similar vein, Drahokoupil (2020) concludes that there is little evidence of considerable employment losses in a book that examines the effects of automation on employment in a number of European nations. However, there are early signs that employees are being moved to new jobs to acquire new skills (Drahokoupil, 2020).

But it is still relatively soon to get a comprehensive picture of this scenario, there are reasons to think that the adverse effect of robots on the overall production employment is not attributable to direct displacement but rather to task modifications. For example, recent studies on Italian automakers have likewise revealed a lack of displacement impacts. Moro et al. (2019) looked into the use of MES (manufacturing execution systems) as well as computerized torque tools in the automobile industry with a focus on the degree and kind of control over personnel. They find that even though such technologies aid in the imposition of impersonal rules and constraints, they also facilitate workers' interactions with tools and machinery. In a similar vein, Gaddi (2020) and Virgillito and Moro (2021) pointed out that modern technology allowed for quicker reconfiguration of lines and machinery as well as a shorter interval to reset the organization of production, both of which contributed to intensifying working rhythms. According to research done by Carbonell (2020) on the French PSA instance, employees frequently lose discretionary authority autonomy. Using a more detailed framework, Cirillo et al. (2021) discovered that while there is no such pattern for autonomy, efforts in terms of digitalization improve workers' discretionary.

3 Study design

3.1 Methods

Categorizing the type of automation to be used, and following Domini et al. (2020), we have used Harmonized System Codes, in this case, to classify automation-related products such as machine tools, tools for industrial operations, numerically controlled machines and etc. (Acemoglu and Restrepo, 2018b). As they suggested that it is cost-minimizing to use capital in all tasks that can be automated and labor is more productive in newly created tasks, in our paper we take automation as a measure of technological progress and analyze its effect on employment. We take into account firms, which imported automation products (automation tools, robots, manufacturing devices and etc.), as automation adopters and firms, which did not imports those products, as non-adopters or not automated firms.

Table 2. Product classes referring to automation, based on the taxonomy by Acemoglu and Restrepo (2018b)

Label	**HS codes**
Industrial robots	847950
Dedicated machinery (including robots)	847989
Numerically controlled machines	84563011, 84563019, 84573010, 845811, 845891, 845921, 845931, 84594010, 845951, 845961, 846011, 846011, 846021, 846031, 84604010, 84613010, 84614011, 84614031, 84614071, 84621010, 846221,846231, 846241, 84629120, 84629920
Machine tools	845600-846699, 846820-846899, 851511-851519
Tools for industrial work	820200-821299
Welding machines	851521, 851531, 851580, 851590
Weaving and knitting machines	844600-844699 and 844770-844799

Other textile dedicated machinery	844400-845399
Conveyors	842831-842839
Regulating instruments	903200-903299

Source: Domini et al. (2019)

This classification will be applied to Estonian imported goods between 1995 and 2021 by Statistics Estonia as a data source. Other key firm-level variables that aren't included in the goods and services import dataset have been derived from the Estonian Commercial Registry's annual financial reports. As Davis and Haltiwanger (1992) suggested workers flows from t-1 to t as rates, in order to check employment rate, we have constructed the dependent variable the dependent variable that was used previously by Domini (2019).

$$\Delta Emp_{i,t} = Emp_{i,t} - Emp_{i,t-1}$$

i=firm

t=years

$Emp_{i,t}$ and $Emp_{i,t-1}$ in years t and t-1, refer to the total number of employees in firm i. In order to check automation related products on employment rate, we used fixed-effects regression, following Domini et al. (2020).

For all industries in 5 years window:

$$\Delta Emp_{i,t} = \boldsymbol{\alpha} \ + \sum_{k=-2}^{2} \quad \boldsymbol{\beta k} * \boldsymbol{At+k} \ + \boldsymbol{\delta i, t} \ + \boldsymbol{\mu i, t} + \boldsymbol{\varepsilon i, t}$$

For each industrial sector in 5 years window:

$$\Delta Emp_{i,t} = \boldsymbol{\alpha} \ + \sum_{k=-2}^{2} \quad \boldsymbol{\beta k} * \boldsymbol{At+k} + \boldsymbol{\mu i, t} + \boldsymbol{\varepsilon i, t}$$

$\Delta Emp_{i,t}$ =*Employment rate*

A_{t+k} = *Automation*

$\delta_{j,t}$ =*Industry-year fixed-effects*

$\mu_{i,t}$=*Firm fixed-effects*

$\varepsilon_{i,t}$= *error term*

The major goal of using 5 years frame is to examine how different years of automation correlate with employment rates in time t, as well as how findings change within different industries and firm groups. When computing regression for all industries and firm groups, we utilize industry-year and firm-fixed effects, however in industry-level data, we exclude industry-year fixed-effects.

3.2 Variables

We have employment rate as a dependent variable and automation as a dummy variable, which denotes whether enterprise i has experienced an automation in a five-year window centered around year t. As a condition, we have identified the condition of if a firm is automated or non-automated based on its imported products. Thus, if a firm has imported the automation products (robots, machineries, and other automation tools), then it has been considered an automated firm, or otherwise. Also, by this way, we could find the total number of automated and non-automated firms by their size and industrial sector, which also allowed us to come to conclusion on which size of firms and which industrial sector has adopted the automation more.

Information on number of employees is obtained from the Estonian Business Registry data, which has information on certain variables for the population of Estonian firms. We have aggregated and calculated the employment level for both firms experienced automation and did not experience in each industrial sector. Moreover, another aggregated variable which was total number of employees was also applied to compare the employment level in both firm and sector level, enabling us to examine which sector and which size-firm has been mostly affected or not affected at all by the adoption of automation from 1995 to 2021.

Table 3. Proportion of firms that experienced automation and their employees among importers (The year represents both import and automation dates).

Year	Total number of firms that imported products	% of firms imported automation-related products	Total number of employees of firms that imported products	% of employees of firms that imported automation-related products
1995	10848	15.00%	329800	23.00%
1996	10330	16.00%	334854	23.00%
1997	10358	16.00%	305048	19.00%
1998	10858	18.00%	318216	25.00%
1999	10556	18.00%	293034	28.00%

2000	10417	21.00%	285533	30.00%
2001	10584	22.00%	294506	29.00%
2002	11026	22.00%	307219	30.00%
2003	11295	23.00%	288100	33.00%
2004	10354	21.00%	283445	31.00%
2005	8082	20.00%	235178	37.00%
2006	10449	16.00%	243926	33.00%
2007	14466	13.00%	257539	38.00%
2008	17579	12.00%	264270	38.00%
2009	9465	17.00%	217844	40.00%
2010	11868	14.00%	198633	38.00%
2011	19435	11.00%	228216	43.00%
2012	22195	12.00%	241071	42.00%
2013	23397	12.00%	243613	40.00%
2014	22691	11.00%	251452	38.00%
2015	26213	10.00%	253561	38.00%
2016	26023	10.00%	243435	42.00%
2017	24231	12.00%	258339	43.00%
2018	22988	12.00%	247788	42.00%
2019	12489	10.00%	253976	38.00%
2020	12169	10.00%	250505	38.00%

2021	14058	9.00%	266702	37.00%

Source: Statistics Estonia

In table 3, we show the percentage of firms that import automation-related products as well as the percentage of their employees among importers. However, there has been no consistent increase or drop for more than five years in succession. The ratio of firms using automation over the total number of firms importing automation products peaked in 2000-2005, as seen above. Furthermore, the percentage of employees working in automation-experienced firms fluctuates with time, with the lowest being 19% in 1997 and the maximum being 42% in 2018.

3.3 Data

Because of a non-existent domestic market for capital goods for automation, automation in Estonia is primarily imports-led; for example, the market size of the General-Purpose Machinery Manufacturing in Estonia industry has only been €61.5m in 2022, measured by revenue, with 30 different businesses in the whole market (IBIS World, 2022). Therefore, imports data provide almost all information on automation adopted by Estonian firms.

Our data has been extracted from Estonian Business Registry by including three main datasets in itself:

1. Firm properties, which contains all the main data about number of employees, size and unique identification code of each firm;
2. Trade import data, which consists of all the main data about the value of imported automation products, amount of imported automation tools and robots, importer, import year and unique identification code of each firm;
3. Common dataset, which covers all the main data about firm size, number of automated firms and non-automated firms, number of employees in automated and non-automated firms, etc.

Thus, extracting the needed data and linking these datasets in our model, we have categorized firms into 4 types in terms of their size by taking the number of employees into account:

a) micro-sized firms (0-9 employees);
b) small-sized firms (10-49 employees);
c) medium-sized firms (50-250 employees);

d) large-sized firms (over 250 employees);

Furthermore, in order to make segmentation of the firms in the market, NACE codes have been used to distinguish their belonging to different industrial sectors in Estonia. For a classification of industries “high-level SNA/ISIC aggregation A*10/11” (Table 1) will be used based on Statistical classification of economic activities in the European Community (2008).

Table 4. High-level SNA/ISIC aggregation

	ISC Rev.4/NACE Rev. 2 sections	Description
1	A	Agriculture, forestry and fishing
2	B, C, D and E	Manufacturing, mining and quarrying and other industry
3	F	Construction
4	G, H and I	Wholesale and retail trade, transportation and storage, accommodation and food service activities
5	J	Information and communication
6	K	Financial and insurance activities
7	L	Real estate activities
8	M and N	Professional, scientific, technical, administration and support service activities
9	O, P and Q	Public administration, defense, education, human health and social work activities
10	R, S, T and U	Other services

Source: Statistical classification of economic activities in the European Community, 2008

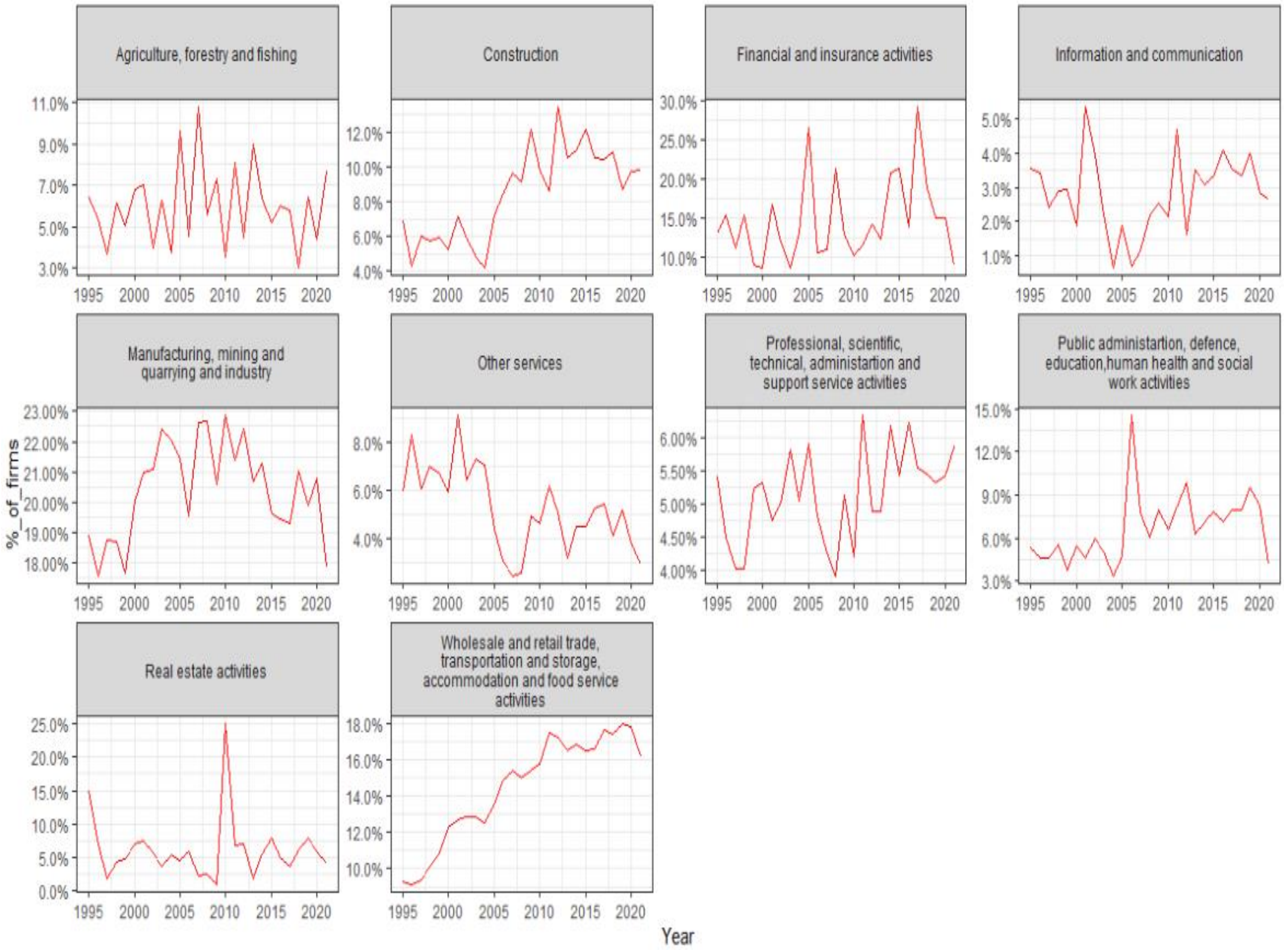
Figure 1. The percentage of the firms that imported automation products among all importing firms from 1995 to 2021 by firm size

Source: Statistics Estonia.

Figure 1 depicts table 3 in-depth and groups the data by firm size. It shows that the percentage of large firms that implemented automation-related goods increased until 2003, then fluctuated between 2005 and increased till 2020. Furthermore, the percentage of medium-sized and in, micro firms we see mainly fluctuation around 8 % until 2020. Except medium-sized firms, all company categories experienced a similar reduction after 2020.

In figure 2, we interpret the same data by industry and show that the percentage of firms that experienced automation overall fluctuated in almost all industries except construction, wholesale, and retail trade, which steadily increased by more than 20% and 50%, respectively. Furthermore, we can see a decreasing tendency in manufacturing, finance, information and communication, public administration, real estate, wholesale trade activities, and other services starting from 2018 and 2020, respectively.

Figure 2. The percentage of the firms that imported automation products among all importing firms from 1995 to 2021 by industrial sectors



Source: Statistics Estonia.

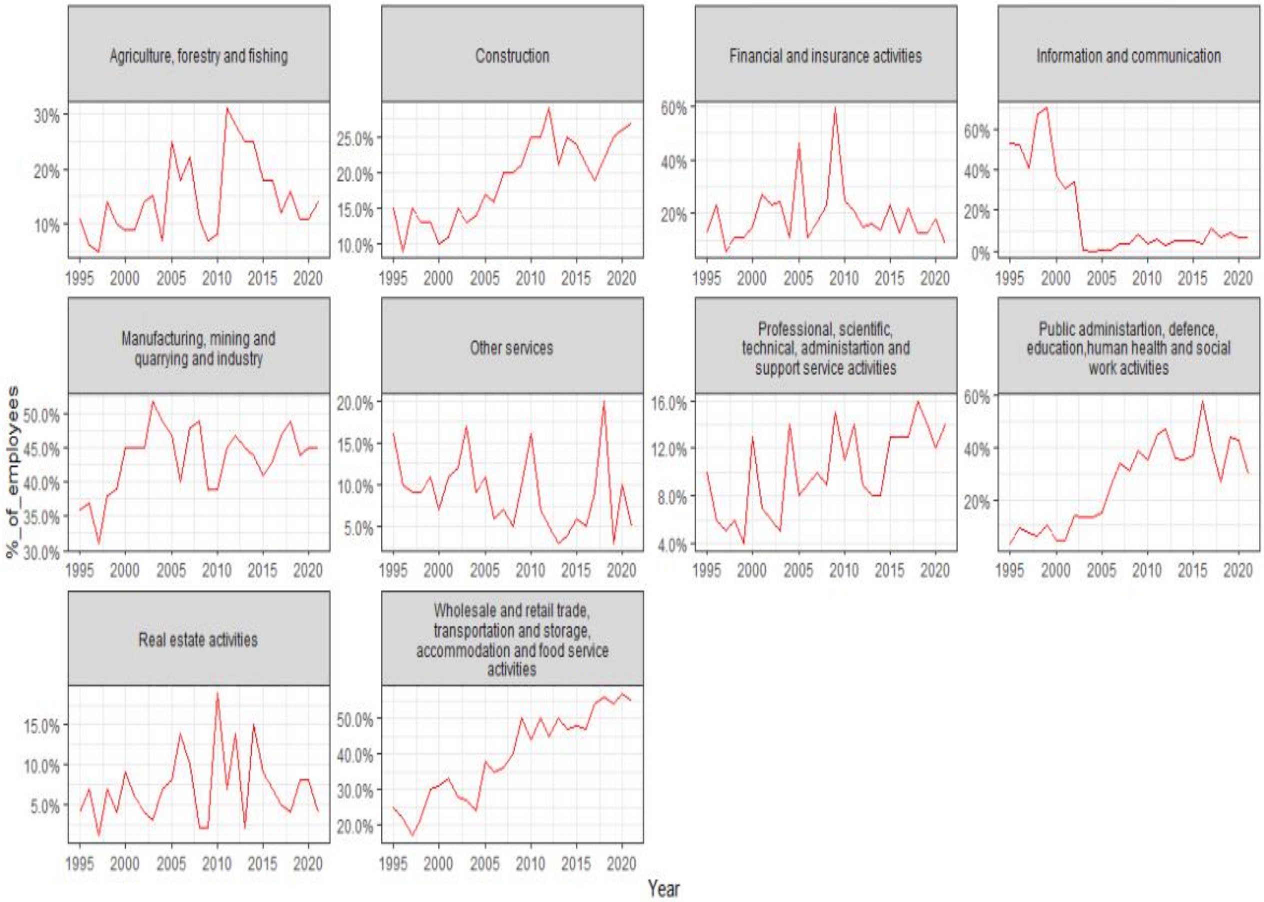
Figures 3 and Figures 4 illustrates the percentage change of employees in automation adopter firms among all firms' employees at the firm size and industry levels, respectively. As shown in Figure 3, the figures for the proportion of employment in automation adopters has increased since 1995 by fluctuating over time, especially after 2008. The main reason for this trend is that the number of automation adopters among all importer-firms has also increased in the same period (see figure 2), which eventually depicts itself in the proportion of employees. Besides, fluctuations after 2008 might also be a consequence of 2008's world financial crisis.

Figure 3. The percentage of employees in the firms that imported automation products among all importing firms from 1995 to 2021 by firm size

Source: Statistics Estonia.

From the Figure 4, we can see that only manufacturing, mining and quarrying sector has experienced the sharp increase in the percentage of employees starting from the end of 90's until 2005 by reaching to over 50% from 30%. However, the percentage of employees in service sector firms (ITC, professional, scientific, technical, administration and support service activities and other services) has started to decrease from the same period; particularly for ITC, which declined by over 50%. In general, manufacturing, mining, quarrying sector, construction sector, service activities sector and wholesale and retail trade, transportation, accommodation and food service activities sector has followed the increasing trend, whereas other sectors have reached a decline throughout the time period after 2008's financial crisis. Consequently, these trends are possible results of the changes in the number of total imported firms and automation adopters which were depicted in the figure 3 above.

Figure 4. The percentage of employees in the firms that imported automation products among all importing firms from 1995 to 2021 by industries



Source: Statistics Estonia.

4 Results

As previously indicated, we have decided to investigate how automation experience correlates with employment rate, and how these results fluctuate among industries and company groups. To start, we divided the years under examination into two groups: 1995-2021 and 2009-2021. The main aim for checking half of the data after 2009 is because combining all the 1995-2021 data could give us skewed results.

In table 5, we compute results for the entire economy and for individual industries. As we can see from the statistics for the entire economy, different conclusions are reached within the automation years. As an example: Automation two years before (t-2) has a statistically higher negative correlation with the employment level of the firms in all industries in general in the base year (t), more precisely (-5%). For example, the automation adopted by firms in 1998 has led about 5% decline in the employment level after 2 years in 2000. While moving to later years, we still see a significant drop (-3%), followed by unsignificant correlations in years t, (t+1), and (t+2). We found various results across industries since not all industries had significant conclusions. Areas with repetitive operations and a high degree of standardization are more affected by automation. For example, automation has had a significant impact on the manufacturing business, with many jobs being replaced by robots and other automated systems. Similarly, automation has reduced the need for human labor in the retail, transportation, and logistics sectors. Additional reason for this variation is the characteristic of automated-related products that we used. These products are primarily industrial robots and numerically machineries that are not applicable to all industries on the same level

In our situation, for instance, the only activities that show statistically significant results are those related to manufacturing, mining, quarrying, and other industries, construction and wholesale, and retail commerce, transportation and storage, accommodation, and food service. However, there is a statistically strong negative significance in the correlation between automation two years before (t-2) and employment level in the base year (t) in the manufacturing, mining and quarrying sector. Thus, it means that the automation products imported by firms in this sector has caused the considerable decrease (-6%) in the employment level two years later, and automation 1 year before (t-1) has a significant negative (-0.7%) correlation and automation in the same year (t) a weak significant (-0.5%) correlation with employment rate in the base year t, with automation having insignificant correlations in the year after the automation (t+1) and two years after automation (t+2). In the wholesale and retail trade sector, we also see statistically significant results for automation that occurred before year t, specifically (-5%) and (-1%) decline. Similarly, in construction there is a weak positive relationship (7.2%) but considerable (7.1%) increase in years (t-1) and (t-2). Furthermore, because the number of observations in the manufacturing, mining and quarrying sector and wholesale and retail trade, transportation and storage, accommodation and food service activities sector are considerably higher than that of other sectors, correlations between automation and employment rate in those mentioned sectors is the main reason of the similar result for the correlation between employment rate and automation in all industries.

Table 5. Regression results of the effect of import automation on employment rate from 1995 to 2021 (in different industries)

Dep var: Employment rate	**automation t-2**	**automation t-1**	**automation t**	**automation t+1**	**automation t+2**	**Nb. obs.**	**R^2 Adj**
All Industries	-0.0557*** (0.0133)	-0.0369** (0.0136)	0.0063 (0.206)	0.0191 (0.0226)	0.0438* (0.0204)	175,478	0.0021
Agriculture, forestry, and fishing	-0.3499* (0.0204)	-0.2875 * (0.0195)	0.0250 (0.0032)	-0.0060 (0.0317)	-0.0058 (0.0310)	2,742	0.0035
Manufacturing, mining, and quarrying and other industry	-0.0603*** (0.0204)	-0.0072 ** (0.0450)	-0.0054* (0.0748)	0.0265 (0.0556)	0.0529 (0.0602)	41,419	0.0036
Construction	0.0722* (0.0548)	0.0713** (0.0541)	-0.1462 (0.0123)	-0.1568 (0.0190)	-0.1601 (0.0198)	5,939	0.0010
Wholesale and Retail trade, transportation and storage, accommodation, and food service activities	-0.0507*** (0.0232)	-0.0150* (0.0201)	0.0111 (0.0104)	-0.0350 (0.0305)	-0.0020 (0.0110)	89,412	0.0073
Information and communication	-0.0502* (0.5286)	-0.0885 (0.5286)	-0.0402 (0.0960)	0.0690 (0.2163)	0.0672 (0.2245)	4,371	0.0014
Financial and insurance activities	-0.456 (0.0586)	-0.3896 (0.0985)	0.4435 (0.0629)	-0.4463 (0.2953)	-0.4775 (0.0994)	658	0.0186
Real estate activities	-0.1331 (0.1061)	-0.0225 (0.0061)	0.0769 (0.0142)	-0.0385 (0.0819)	-0.0355 (0.0828)	745	0.0003
Professional, scientific, technical, administration and support service activities	0.0397* (0.0644)	0.0351 (0.0636)	0.0713 (0.0575)	0.0052 (0.0684)	0.0051 (0.0679)	7561	0.0028
Public administration, defense, education, human health, and social work activities	-0.0594 (0.0582)	0.0184 (0.0227)	0.0626 (0.0427)	-0.0481 (0.0480)	-0.0495 (0.0502)	3,395	0.0097

Other services	0.0340 (0.0308)	0.0345 (0.0309)	-0.1085 (0.902)	0.0875 (0.0615)	0.0926 (0.0998)	4,402	0.0013

* p < 0.1, ** p < 0.05, *** p < 0.01
Standard errors are shown in parentheses. Coefficients rounded to the fourth decimal.
Source: Statistics Estonia.

In table 6, we perform the same study for the period of years 2009-2021. While we see similar tendencies for the same table for this period, we can state that across the entire economy, automation which occurred at t-2 has statistically significant negative correlations with employment rate almost -3.6% and weak significance in automation years t-1 and (t+1). Manufacturing, mining, and quarrying, as well as wholesale and retail trade, transportation and storage, lodging, and food service industries, show a significant negative significant relationship (2.5%) and (3%) with automation 2 years before. Unlike table 5, information and communication had a statistically significant positive correlation (9%) with automation 2 years before which matches with our results of descriptive statistics (see figure 5).

Table 6. Regression results of the effect of import automation on employment rate from 2009 to 2021 (in different industries)

Dep var: Employment rate	**automation t-2**	**automation t-1**	**automation t**	**automation t+1**	**automation t+2**	**Nb. obs.**	**R^2 Adj**
All Industries	-0.0369** (0.0091)	-0.0101* (0.0106)	-0.0038 (0.0085)	0.0179* (0.0088)	0.0137 (0.0092)	54469	0.0049
Agriculture, forestry, and fishing	-0.1173 (0.1227)	-0.1287 (0.1471)	-0.1299 (0.1465)	-0.0545 (0.1303)	-0.0922 (0.1638)	475	0.0118
Manufacturing, mining, and quarrying and other industry	-0.0257 ** (0.0119)	0.0036 (0.0159)	-0.0028 (0.0056)	0.0100 (0.0125)	0.0220 (0.0132)	14041	0.0024
Construction	-0.0487. (0.0275)	-0.0071 (0.0252)	-0.0288 (0.0570)	0.0948. (0.0532)	-0.0116 (0.0434)	1518	0.0050
Wholesale and Retail trade, transportation and storage, accommodation, and food service activities	-0.0302** (0.0106)	-0.0087 (0.0113)	0.0070 (0.0101)	0.0158 (0.0103)	0.0086 (0.0092)	28930	0.0058
Information and communication	0.0980** (0.0713)	0.0331 (0.1199)	-0.1576 (0.1077)	0.0935 (0.0889)	-0.0053 (0.1104)	168	0.0258
Financial and insurance activities	-0.1053 (0.1186)	-0.2856 (0.2628)	-0.3811 (0.2766)	-0.2188 (0.1956)	-0.3844 (0.2990)	130	0.1029
Real estate activities	-0.0554 (0.0414)	0.0433 (0.0791)	0.0522 (0.0423)	0.0058 (0.0588)	0.1281. (0.0654)	1864	0.0068
Professional, scientific, technical,	-0.2255 (0.2390)	-0.2005 (0.2557)	-0.3016 (0.2771)	0.1252 (0.1230)	-0.3493 (0.2654)	592	0.0403

administration and support service activities							
Public administration, defense, education, human health, and social work activities	0.0490 (0.0858)	-0.0462 (0.0825)	-0.0234 (0.0851)	0.0573 (0.1192)	-0.0632 (0.1285)	903	0.0011
Other services	-0.2255 (0.2390)	-0.2005 (0.2557)	-0.3016 (0.2771)	0.1252 (0.1230)	-0.3493 (0.2654)	592	0.0403

* p < 0.1, ** p < 0.05, *** p < 0.01
Standard errors are shown in parentheses. Coefficients rounded to the fourth decimal.
Source: Statistics Estonia.

Tables 7 and 8 continue our research with different firm group time periods ranging from 1995 to 2021 and 2009 to 2021, respectively When we look at the entire period, we can notice a substantial negative connection between automation two years before (t-2) (-4.5%) and (t-1) (-1.2%) and employment in the year t, and hardly significant positive outcomes (0.1%) in the same year-t. Meanwhile, medium-sized businesses follow similar patterns for automation before and during the year automation, (-0.13%), (-0.11%), and (1.2%). Furthermore, small businesses have a significantly positive relationship between years (t-2) and t, (0.71%), (0.7%), and (0.43%), respectively. Except for medium-sized firms, we do not see the same tendencies in table 8. While there are statistically significant decreases in employment rate in the year t (0.2%) 2 years after automation and a hardly significant decline in (0.5%) 1 year after automation, then the results are statistically insignificant. Additionally, micro firms are not affected by automation like other firm groups, depending on the industry and resources available to them. Because of their limited resources, they cannot import more automation products to increase productivity, they incline to increase the labor productivity by hiring more employees. Based on our data, we may conclude that automation has significant effect on employment rates two years and one year before but has little impact after 1 or 2 years. Furthermore, these coefficients are about the firms preparing for automation by reducing or increasing the number of employees. When split into firms of different sizes, there doesn't seem to be any preparation - the firms only hire more exactly when they automate. But when all industries and firms of all sizes are combined (tables 5 and 6) there is an increase in employment prior to automation. Also, when we compare the results to our descriptive statistics, we see that the trend with percentage changes in employment is not the same. For example, in the construction industry, automation has a positive influence on employment rate and increases in number of automating firms, whereas it has the opposite effect in wholesale and retail trade, transportation and storage, accommodation, and food service activities. One of the key reasons that changes in employment dynamics are not necessarily the product of automation is that an increase in the number of firms influences total employment dynamics.

Table 7. Regression results of the effect of import automation on employment rate from 1995 to 2021 (in different firm groups)

Dep var: Employment rate	**Large**	**Medium-sized**	**Small**	**Micro**
automation t-2	-0.0485** (0.0366)	-0.0013** (0.0046)	0.0071*** (0.0047)	0.0090 (0.0124)
automation t-1	-0.0128** (0.0351)	-0.0011 *** (0.0040)	0.0070*** (0.0044)	0.0088 (0.0121)
automation t	0.00112* (0.0042)	0.0127* (0.0049)	0.0043** (0.0049)	0.0279* (0.0126)
automation t+1	0.0677 (0.0704)	0.0070 (0.0047)	0.0058 (0.0048)	0.0085 (0.0115)
automation t+2	0.0653 (0.0711)	0.0071 (0.0047)	0.0062 (0.0055)	0.0087 (0.0119)
Nb. obs.	3,706	17,148	43,706	95,585
R^2 Adj	0.00156	0.00644	0.00465	0.00121

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are shown in parentheses. Coefficients rounded to the fourth decimal.
Source: Statistics Estonia.

Table 8. Regression results of the effect of import automation on employment rate from 2009 to 2021 (in different firm groups)

Dep var: Employment rate	**Large**	**Medium-sized**	**Small**	**Micro**
automation t-2	0.0083 (0.0171)	-0.0020** (0.0066)	-0.0095 (0.0076)	-0.0100 (0.0127)
automation t-1	0.0081 (0.0141)	-0.0051 * (0.0058)	0.0030 (0.0064)	0.0051 (0.0149)
automation t	-0.0147 (0.0133)	0.0011 (0.0065)	0.0103 (0.0060)	-0.0042 (0.0128)
automation t+1	0.0090 (0.0153)	0.0058 (0.0061)	0.0019 (0.0057)	0.0110 (0.0123)
automation t+2	0.0202 (0.0170)	0.0103 (0.0069)	0.0128* (0.0059)	0.0010 (0.0140)
Nb. obs.	1,122	4,918	11,803	25,686
R^2 Adj	0.00218	0.00110	0.00120	0.00135

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are shown in parentheses. Coefficients rounded to the fourth decimal.
Source: Statistics Estonia.

Additionally, similar to studies done by Acemoglu and Restrepo (2018) and Dauth et al. (2017), we have identified negative effects in some sectors, but also different from their conclusion, we could learn that automation has also had positive effects in other sectors like manufacturing as Domini et al. (2019) and Koch et al (2019) proposed. We could agree that automation has had both negative and positive effects on employment because four industrial sector groups have experienced the positive influence thanks to the new jobs created by the adoption of automation and increased productivity, others have been negatively impacted due to low-skill employment and service-and-technology-related sectoral differences where automated products replaced the traditional jobs performed by employees and automated work process eliminated the manual work processes.

5 Conclusion

The main aim of the study was to analyze and understand the impact of automation practice implemented by different Estonian firm groups on their employment level by comparing their automation and employment level by their size and industrial variety. Using the data extracted from Statistics Estonia and Business Registry (more than 20,000 firms) 175,000 observations have been analyzed to demonstrate the differences between firms in terms of the effect of automation on the employment level.

First of all, our paper found that the effect of automation varied among different firm groups depending on their sectoral identification. It is a remarkable finding in acknowledgment of positive and negative effects of automation on employment in different firm-groups. As each industrial sector requires to have different job skills, the adoption of automation has been varied among various firm groups, as well as depending on their size. Thus, we could show that the influence of adopting automation and using it a measure to demonstrate the effect of technological progress on employment has not been the same for all the firms at all. Plus, there has been a statistically highly significant correlation between employment and automation for only manufacturing, mining and quarrying sectors and transportation, wholesale and retail trade sectors in the year t-2; however, our findings show that there has not been a statistically significant correlation in all other industries.

It may be speculated that this case is because of varying requirements and functions of different industries, more precisely, job skills; therefore, automation has boosted production and created new jobs in sectors like manufacturing, mining and quarrying industry and construction, thus also enabling firms to hire more employees. However, in other sectors such as agriculture, forestry and fishing, and service sectors, the automation has shown the considerably negative impact on the employment level that automation has affected to employment negatively in low-skill employment which is agriculture, forestry and fishing in our case. Yet completely contrary to the fact that the negative impact of automation on employment by stating that each robot destroys two manufacturing jobs, where our analysis of Estonian manufacturing firms highlighted the opposite effect showing that the employment level has increased around 15% from 1995 to 2018 in manufacturing, mining and quarrying firms that imported automation goods.

Furthermore, we found that the employment rate in different Estonian firms have been positive until 2010 for almost all firm groups, and this trend has changed differently after that year for each sector too. Thus, in this case, there may be some missing data or indicators that could reflect the effect of automation on employment better to understand this missing link and different trend.

Our study confirmed findings of neutral effects of automation on employment in different firm groups in Estonia depending on the job-skill levels or industrial sectors' employment differences. The implemented comparisons indicated that applying 20-years-period's data on employment level and imported automation goods by different firm groups contributed to understand how automation's effect varied among different industrial groups. However, according to our comparison, there is an important finding that until 2010, except ITC sector's firms, every other from agriculture, fishing and forestry to service, and manufacturing firms, automation boosted employment level, whereas after 2010, it has started to change for each sector differently to the fact that adoption of automation has changed between the first and second periods. Thus, we found that the first period of adopting of automation has been mostly positive from 1995 to 2010 in general, while it has started to yield negative effects on employment from 2010 to 2018.

Further examinations are surely important to verify the results obtained from this research. Future research could help to understand the effect of automation on employment level in different firm groups, if a study would have investigated this trend why there was a different trend in the employment level across sectors and firm groups and covered the analysis of job skills and productivity level of different firm groups. Also, it would be better to compare this case for Estonia with another country which itself produces automation products as our research identified the adoption of automation with imports of intermediate goods. Thus, there might be different consequences in case of buying the local automation goods in terms of their costs' impact on firms.

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„Automatiseerimise mõju tööjõule tööhõive osas aastal erinevatest firmagruppidest Eestis“

Magistritöö eesmärgiks on selgitada välja, kuidas automatiseerimine erinevates Eesti ettevõttete gruppide on mõjutanud ettevõtete tööhõivet, arutleda selle tagajärgede üle, ning võrrelda neid mõjusid erinevate Eesti majandusharude lõikes. Meie uuringus on ettevõtted kategoriseeritud nii nende suuruse kui ka kasutusele võetud automatiseerimistööriistade järgi. Selleks oleme kasutanud kõigi Eesti ettevõtete impordiandmeid aastatest 1995-2021, ning automatiseerimise lähendiks on analüüsis automatiseerimisega seotud kaupade import. Lisaks, kuna meie uuring keskendub automatiseerimise mõjule tööhõivele, on kogutud ja analüüsitud iga ettevõtte tööhõiveandmed. Varasemad uuringud on käsitlenud automatiseerimise mõju tööhõivele erinevates ettevõtte suurusrühmades läbi mõju soolise palgalõhe ja töösuhetele, või keskendunud digitaliseerimise ja tehisintellekti mõjule töölepingutele ja tööhõivele Eestis. Selle seose uurimiseks on kasutatud fikseeritud efektiga lineaarset regressioonimudelit, mida on hinnatud tavalise vähimruutude meetodiga. Töö empiiriline osa keskendus Eestis aastatel 1995-2021 enam kui 20 tuhandele ettevõttele erinevates suurusrühmades ja majandusharudes (põllumajandus, töötlev tööstus, ehitus, teenindus jm), hõlmates kokku üle 175 tuhande vaatluse (ettevõtte aasta). Erinevalt varasematest uuringutest keskendus meie artikkel ka mikro- ja väikeettevõtete rühmadele. Meie uurimistöö tulemute põhjal on automatiseerimine mõjutanud tööhõivet nii negatiivsel kui ka positiivsel viisil, olenevalt ettevõtete valdkondlikust kuuluvusest.

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