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HOW DOES AUTOMATION AFFECT FOREIGN WORKERS IN ESTONIA?

Master Thesis

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I have written this Master Thesis independently. Any ideas or data taken from other authors or other sources have been fully referenced.

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Abstract

This paper investigates the effect of automation on foreign-born and native-born workers in Estonia for the period 2006-2017 and aims to uncover how the adoption of automation goods is associated with the employment of Estonian- and foreign-born workers in total and disaggregated by skill level. The paper relies on Estonian matched firm-individual registry data and utilises the Poisson Pseudo Maximum Likelihood (PPML) estimation method to investigate an association between the import of automation goods and firm-level employment. The results identify that automation good imports are associated with an increase in the number of foreign-born workers in the short-to-medium term. In contrast, the number of native-born workers declines in the year following the import and is insignificant beyond that. Decomposing each group by skill level shows that middle-skilled foreign-born and native-born workers appear most affected by automation. While automation has a complementary effect on middle-skilled foreign-born workers, and their number increases, the number of middle-skilled native-born workers decreases when firms adopt automation. Our findings show that automation is not associated with middle-skilled job disappearance for foreign-born workers, thus providing no evidence of job polarisation, which native-born workers experienced. In addition, contrary to the literature, we do not observe foreign-born workers facing worse employment outcomes; in fact, they experience higher employment. From a policy perspective, this paper highlights the importance of ensuring wage parity between foreign-born and native-born workers, upgrading vocational education to train and domestically fill shortage jobs, and creating an official shortage occupations list to align labour migration with business needs.

Keywords: automation, technology, foreign labour, immigrants, skill level, labour market segmentation.

CERCS: S180 Economics, econometrics, economic theory, economic systems, economic policy

JEL Classification: O33, J23, J24, J61.

1. Introduction

Understanding the impact of automation on the labour market has been an area of interest for researchers for decades (Acemoglu & Restrepo, 2016; Arntz et al., 2017; Autor & Salomons, 2018; Borjas & Freeman, 2019; Gregory et al., 2022; Koch et al., 2021). While the direct impact of automation is estimated to be negative on wages and employment of automated tasks due to the labour replacement effect, indirectly, it may increase demand for non-automated tasks through productivity increase and resulting capital accumulation (Acemoglu & Restrepo, 2018a). Automation of routine tasks is believed to play an instrumental role in wage and employment polarisation in the United States, where high- and low-skilled workers experienced an increase in both employment and wages, while middle-skilled workers faced a decline in these areas (Autor & Dorn, 2013).

In the context of disentangling native-immigrant workers' adjustment to labour demand shocks, the findings suggest these two groups may have different outcomes, with immigrants having adverse effects more often than natives (Dustmann et al., 2010). Moreover, a clear understanding of the effects of automation on native and foreign workers is of utmost importance for policymakers, as natives may demand restrictive immigration policies to cushion the negative impact of automation and robotisation on them (Im et al., 2019; Kurer, 2020; Pardos-Prado & Xena, 2019; Wu, 2023). Determining the impact of automation on labour market outcomes, particularly contrasting native and foreign workers, is quite complex, depending on many factors such as skills, occupation type, education level, and industry (Autor, 2015; Peri & Sparber, 2011). Therefore, research in this domain continues to provide a clearer understanding of causal relationships.

In Estonia, the share of companies utilising robots has been less than 5% of all companies (Azzopardi et al., 2020). The adoption in small and medium enterprises has been even lower than the national average, and large companies have automated less than 20% of their activities. These figures put the country's private sector among the least automated within the European Union. A study done by McGuinness et al. (2023) on European Skills and Jobs Survey data identified that skill-replacing technology impacts 28% of Estonian workers. In a similar paper based on the

Programme for International Assessment of Adult Competencies (PIAAC) data, it was found that 12% of Estonians identify their jobs as highly automatable, while another 31% find their jobs at risk of automation (Azzopardi et al., 2020). In terms of preparedness for automation, Estonia was ranked sixth in the Automation Readiness Index report prepared by the Economist Intelligence Unit in 2018 and demonstrated particularly high performance in skill readiness (Estonia 6th in the Automation Readiness Index, 2018).

Existing literature focused on Estonia shows that technological adoption leads to productivity gains (Mosiashvili & Pareliussen, 2020), and unlike other developed countries, automation increases the labour share of value added as a result of productivity increase (Tiwari, 2023). There is, however, a gap in understanding how automation and technological advancements affect different labour market groups in Estonia. Pavlenkova et al. (2024) investigated this relationship regarding the gender pay gap and found that automation deepens the gender wage gap, as women benefit relatively less from automation than men. Further empirical evidence on the disproportional effects of automation on different socio-demographic groups of workers in Estonia is very limited.

By carrying out this research, we aim to uncover the impact automation has on foreign-born workers' total employment over time and whether automation has substitution or complementarity effects on these workers. Additionally, we disaggregate foreign-born workers by their skill levels (low-/middle-/high-skilled) to examine which skill levels are the main drivers of employment changes. To better understand the overall impact, we then contrast foreign-born workers' employment outcomes with native-born workers to identify if foreign-born workers are disproportionately affected. Thus, we plan to determine whether automation solves labour shortages experienced in Estonia or boosts employment, particularly in the demand for foreign-born workers. While the goal is to identify the effects of automation on the labour market, focusing specifically on Estonia, findings and policy implications may apply to other countries sharing the same economic and technological transformation path. Therefore, this paper intends to close the gap in the literature and answer the following two questions:

RQ1. How does automation affect the number of foreign-born workers in Estonian firms, and how does this differ from the impact on native-born workers?

RQ2. How does automation affect each skill group of foreign-born workers (low-/middle-/high-skilled), and how does this differ from the impact on native-born workers?

The literature review in this paper will be based on two theoretical concepts and summarise relevant empirical evidence. First, the Routine Biased Technological Change (RBTC) hypothesis, introduced by Autor et al. (2003), provides a task-based framework to understand how automation affects demand for skills. Their findings suggest that technological change reduced the demand for manual and cognitive routine tasks while complementing non-routine tasks, such as problem-solving, communication and creativity. Second, Dual Labour Market theory (Doeringer & Piore, 1970) contributes to understanding possible differences in labour market outcomes of native-born and foreign-born workers. As per this theory, the labour market is divided into primary and secondary markets with different employment conditions, benefits, opportunities, wages, and responsibilities. Certain groups of workers, such as women, racial minorities, and migrants, could face poor labour market outcomes and be trapped in a secondary market due to institutional factors.

The empirical analysis in this paper is carried out using several Estonian register-based data. Namely, the analysis draws on firm-level data from the Estonian matched employer-employee, augmented with automation goods import statistics from the Internation Goods Trade data, wage information from Estonian Customs and Tax Office data, as well as migration background and skill-level inference from Statistical Registry of Population dataset. Panel data covers the period of 2006-2017. Only a small share of active firms imported automation goods during this period – around 2% per annum (Pavlenkova et al., 2024). At the same time, many firms have zero foreign-born workers, which may further affect estimation results. The Poisson Pseudo Maximum Likelihood (PPML) estimator, proposed by Silva and Tenreyro (2006) and extensively applied in previous studies, is a gravity estimation method found to perform well under such scenarios. Therefore, the empirical strategy is carried out using a PPML estimator with fixed effects for regression analysis.

This paper finds that importing automation goods is associated with employment growth for foreign-born workers in the short and medium run. Native-born workers, on the other hand, experienced a decrease in their number the year after automation. The medium-term effect on native-born workers is unclear due to the statistical insignificance of the models with 2- and 3-year lags. Disaggregating each segment of workers by their skill levels mainly demonstrates the association between automation and middle-skilled workers, although the direction of change differs for foreign-born and native-born workers. While foreign-born employees experience increases in numbers in the short- and medium-term, middle-skilled native-born workers experience a decrease, observed only in the medium-term – with 2- and 3-year lags. These effects can be attributed to skill shortages exacerbated by automation, which leads to increased reliance on foreign-born workers.

The rest of this paper is structured as follows: literature review findings are presented in Section 2; the data used in the analysis, as well as empirical methodology, are discussed in Section 3; Section 4 covers results, and their interpretation; concluding remarks and research limitations are presented in Section 5.

2. Literature Review

Technological change is considered to have played an important role in replacing labour in routine tasks, as well as affecting job and wage polarisation (Acemoglu et al., 2023; Acemoglu & Restrepo, 2017; Aghion, Antonin, & Bunel, 2020; Dawid & Neugart, 2023). Moreover, foreign-born and native-born workers may experience different outcomes when affected by labour market shocks, such as labour replacing automation (Barišić et al., 2024; Giesing & Rude, 2022; Jaimovich & Siu, 2017).

We will further discuss two pivotal theories, which help to shed light on the potentially disproportional effects of automation on foreign-born workers in Estonia, namely the Routine Biased Technological Change (RBTC) Hypothesis is complemented by the Dual Labour Market Theory to explain the differential impacts of automation on foreign-born and native-born workers.

These two theoretical concepts, as well as supporting empirical papers and case studies on Estonia, shape a theoretical foundation for this research.

2.1 Routine Biased Technological Change (RBTC) Hypothesis

The Routine Biased Technological Change (RBTC) hypothesis was formulated by Autor et al. (2003) as an alternative to Griliches' Skill-Biased Technological Change (SBTC) hypothesis (1969). The SBTC hypothesis suggests that technological development is skill-biased, and it has led to increased demand and increased wages for high-skilled labour, whose skills complement new technologies. This hypothesis was criticised as it cannot explain how technological change leads to such outcomes, requiring further research to identify underlying mechanisms. To fill the gap in the literature, Autor et al. (2003) developed a task-based framework, also referred to as AML, to explain how technological advancements affect demand for labour.

In their paper, Autor et al. (2003) group tasks into four categories: routine, non-routine, manual, analytical and interactive. The main hypothesis of their task model is that computerisation can substitute humans in specific routine tasks and complement them in tasks that are not routine, ultimately increasing demand for labour for non-routine tasks. Their empirical analysis used job descriptions from the Dictionary of Occupational Titles of the US Department of Labour and the US Census and Current Population Survey datasets to aggregate panel data from 1960 to 1988. The authors tested the model on how job composition of tasks changed in light of computer price decrease. Their findings show that labour demand for routine manual and routine cognitive tasks decreased, while demand increased for non-routine tasks in industries with rapid computerisation in the US. Moreover, all education levels were impacted by this task demand shift. Occupations that experienced high computerisation decreased input for routine tasks and increased non-routine task input, thus leading to a task composition change.

Henceforth, many researchers have extensively used and empirically validated the task approach. In their task-based model, Acemoglu and Restrepo (2018b) find that labour-replacing technology negatively affects workers' wages whose task composition is directly affected by automation, which holds for both low- and high-skilled workers. When automation displaces low-skill labour, wage polarisation increases due to displacement and a decrease in the wages of low-skilled workers. Displacement due to high-skilled labour automation, on the other hand, decreases wage inequality due to decreasing wages of high-skilled workers, thus narrowing the overall wage gap. Employing a task-based model, Autor et al. (2006) also found that the US labour market experienced wage polarisation, where computerisation negatively affected middle-wage jobs and complemented high-wage jobs since 1980.

Goos and Manning (2007) identified similar polarisation effects due to computerisation in Britain since 1975. They showed that Britain experienced a decline in demand for middle-skilled occupations that were routine heavy and a growth of high and low-skilled jobs that were less routine. Using a task model, Spitz-Oener (2006) found that jobs have become more complex in task composition in West Germany compared to 1979. This effect was even more profound in jobs that underwent high computerisation, which led to a shift from routine to non-routine tasks within those jobs. Wage and occupation polarisation were also reported in numerous other papers (Acemoglu & Restrepo, 2022b; Autor, 2013; Cortes, 2016; Goos et al., 2014). However, the RBTC hypothesis cannot fully explain the changes in employment structure observed in European countries. Researchers argue that job complexity upgrading and institutional factors could be behind the observed dynamics (Breemersch et al., 2019; Fernández-Macías & Hurley, 2016; Hoftijzer & Gortazar, 2018).

At the same time, there is a stream of literature reporting a positive outlook of automation and technological change's impact on the labour market. For example, Autor (2015) predicts that occupational polarisation will not wipe out all middle-skill occupations. Many middle-skill jobs are not automatable as they require various skills to perform non-routine tasks. Similarly, using a task-based model, Arntz et al. (2016) concluded that potentially only around 9% of jobs can be fully automated in OECD countries and argued that most jobs have non-routine tasks. Moreover, automation is reported to have positively impacted aggregate employment in various papers (Aghion, Antonin, Bunel, et al., 2020; Koch et al., 2021). Graetz and Michaels (2018) found that an increase in robot adoption leads to productivity and wage increases while negatively impacting low-skilled workers in the analysis of 17 developed countries between 1993 and 2007. In another study, a cross-country analysis of seven advanced European economies and Japan demonstrated that adopting industrial robots increases productivity while employment was estimated to decrease in the short run and increase in the long run (Kromann et al., 2011).

In the context of Estonia, research on the effects of automation on employment and labour market outcomes is in its early stages and steadily growing. Using matched employee-employer data for 2016, Mosiashvili and Pareliussen (2020) analysed how technology adoption, defined with variables related to computer usage, digital tools, software, information and communication technology training and high-speed internet, impact firm productivity. The results show that technology adoption positively affects the productivity of the adopting firm. The adopter's positive spillover impact extends even to firms within the same sector, in the case of manufacturing field or other sectors where the stock of automatable tasks is high.

In another study, Tiwari (2023) researched labour market outcomes of automation in Estonia using OLS and Fixed Effects estimation methods on firm-level data from 1995 through 2018. The findings of the paper demonstrate that automating firms have a higher labour share of value-added and are more productive than non-adopters. Also, adopters have increased their market share, aggregate labour share of income and share of aggregate total factor productivity. Estimates also show that the share of labour-performed tasks decreases due to automation, particularly among serial adopters. Pavlenkova et al. (2024) researched the effects of automation on the labour market in terms of the gender pay gap in Estonia using Mincerian wage equations and propensity score matching on matched employer-employee data from 2006 to 2018. Although they identified that automation leads to an increase in the gender pay gap, overall results show that automation adoption leads to an increase in average wage and number of employees with a higher education two years post-automation.

The findings of Pustovalova and Vahter (2024) on the relationship between automation and various skills reveal important factors that can facilitate a firm's technology adoption while also benefitting its employees. Using the Estonian firm-individual matched panel dataset and skills defined as social, problem-solving, routine cognitive and manual, the authors identify that in the short-run, social skills are positively associated with wages in firms that automate. Problem-solving skills, on the other hand, positively impact wages in firms that are already adept at automation processes due to past automation experience and serial automation adoption patterns.

Furthermore, the positive impact of social skills was identified in workers across all skill levels (low-, middle- and high-skilled), with low-skilled employees getting the highest wage premium owing to social skills. This finding is crucial as low- and middle-skilled workers are often associated with the adverse impacts of technological adoption due to the high share of routine and manual tasks in their occupations. Therefore, possessing and acquiring social and problem-solving skills can shift the narrative and turn low- and middle-skill workers into gainers from technological change.

As per the study by Illéssy and Makó (2020) on the impact of automation on labour market outcomes using European Working Condition Surveys data for 2005 and 2015, Estonian labour market has an employment structure quite similar to those in Western European countries: a high share of jobs requiring a higher degree of cognitive abilities and autonomy of workers, which increased from 57% in 2005 to 62% in 2015, while having a low share of routine jobs - with low requirements of employees' cognitive input and autonomy – which declined from 19% to 18%. Considering the potential risk of a labour-displacing effect of automation, these figures make Estonia better-prepared compared to other similar countries, namely among Baltic and Eastern European states. Similar implications of automation on the Estonian labour market were identified in an OECD report published in 2018 (OECD, 2018). It shows that employment growth in Estonia in 2011-2016 was mainly driven by the creation of managerial and specialised jobs, which have a low risk of automation. During the same period, an employment decline in jobs at high risk of automation, such as mining, construction, manufacturing and transport labourers and plant and machine operators, was recorded. Overall, automation in Estonia has led to an employment structure change, making it more specialised and protected from automation.

RBTC hypothesis and its task framework are still in the process of development as there is no widely accepted framework to explain the effects of technological changes on the labour market, as well as lack of clear task categorisation and scarcity of data to perform more elaborate analyses (Acemoglu & Restrepo, 2018a; Biagi & Sebastian, 2018; Restrepo, 2024). Another issue with the task approach is that the task composition of jobs may change over time. Capturing this change is particularly challenging for data outside of the US due to limited information on the task contents of occupations.

2.2 Dual Labour Market Theory

This theory was developed at the end of the 1960s to explain labour market inequalities experienced by some groups in the United States. One of the most important studies in this domain was carried out by Doeringer and Piore in their book 'Internal Labor Markets and Manpower Analysis' (1970). They explain the labour market as a split between primary and secondary markets. Primary market workers enjoy job security, high wages, and career development chances, whereas secondary market is associated with job insecurity, low wages, lack of career progression, and high turnover. Racial minorities and migrants were among those who tend to be overrepresented in the secondary market and face high entry barriers to the primary market. The main emphasis of this theory is that there are demand-side institutional factors affecting poor outcomes for some groups beyond their skills and competencies.

A vast number of empirical papers provide evidence of segmentation in labour markets. Mandelman and Zlate (2022), analysing US data, show that a decline in middle-skilled occupations due to automation and offshoring does not lead to employment and wage polarisation for native workers. As low-skilled immigrant supply covers employment growth in low-skill jobs and depresses wages, natives reskill and move to high-skill jobs with higher employment and wage growth. Using US census data, Basso et al. (2020) came to the same conclusion – routine tasks replacing technological change attracted low-skill immigrants, who clustered in low-skilled jobs. This, in turn, acted as a catalyst for natives to upskill and move to jobs with tasks requiring a higher share of cognitive skills.

Different immigrant-native task specialisations occur for high-skilled workers also, as Peri and Sparber (2011) identified based on US data. They show that when faced with competition from immigrants, highly skilled natives move to jobs requiring communication and interactions with others. High-skill immigrants, on the other hand, tend to concentrate on analytical and quantitative jobs. In another study, Barth et al. (2002), using Current Population Census data from the US for 1979-2001, identified that economic shocks affect immigrants more severely. Their analysis showed that the wage gap between local and foreign workers increased during the high unemployment period and decreased during the low unemployment rate.

Native-foreign workers' labour market differences are also observed outside of the US. In a study using the European Social Survey, Bisin et al. (2011) found that first-generation immigrants were less likely to be in employment than natives, while employment of second-generation immigrants was similar to natives. However, both first- and second-generation immigrants with strong ethnic identity face lower employment. At the same time, the level of immigrants' integration plays an important role in achieving good employment outcomes. Analysing the relationship between migrants' assimilation and labour market outcomes in Australia, Piracha et al. (2023) found that assimilation – defined by measures of language ability, satisfaction with living in the host country and living in ethnically concentrated neighbourhoods – is positively associated with employment, wages and job satisfaction.

Based on the analysis of the EU Labour Force Survey and PIAAC survey responses, Biagi et al. (2018) identified that digital transformation could affect migrant workers more negatively, as they tend to hold highly routine jobs more often than natives. Non-EU migrants are at higher risk of being replaced than EU migrants and natives of a reporting country. In addition, both EU mobile migrants and non-EU migrants are less likely to receive training and more likely to be hired on short fixed-term contracts. These factors and lack of secure residence status reduce the chances of foreign workers to upskill and find other jobs during economic shocks or technological job displacement.

In the context of Estonia, previous empirical studies on the ethnic aspect of labour market segmentation have been mainly focused on Estonians and national minorities of Estonia, particularly Russians. During the Soviet occupation between 1944-1991, a large number of Russians immigrated to Estonia as a part of the central government's labour force redistribution policy. As a result, Russians clustered in factories and other industrial sector facilities working as skilled workers, specialists, and managers, whereas Estonians were mostly working in agriculture, as well as cultural and educational sectors (Luuk & Pavelson, 2002). Labour market segmentation between these two groups remained even after the collapse of the Soviet Union, albeit with worsened conditions for Russians as they experienced downward social mobility. Since the restoration of Estonian independence, Russians in Estonia have experienced higher unemployment rates, higher unemployment rate increase at times of economic crisis, higher risks of unemployment and lower chances of holding specialist or managerial roles compared to Estonians (Lindemann, 2011; Masso & Krillo, 2011; Saar et al., 2017). Moreover, these disadvantages persist even when accounting for Estonian language competence and education attainment (Leppik & Vihalemm, 2015; Lindemann, 2009). Their results imply that different factors could lead to ethnic segmentation in the Estonian labour market other than human capital or host country-specific capital.

Focusing on migrant arrivals to Estonia during 2015-2019, Kalm and Tammaru (2021) provide insights into immigrants' characteristics and labour market performance. The study shows that most of the newly arrived people were from other European Union (EU) countries. Nevertheless, many leave Estonia after staying for a short time, and only a small share of EU citizens settle long-term. Immigrants from third countries (countries not covered by EU's freedom of movement right) and former Soviet countries have seen significant growth during this period. The data shows that EU nationals had lower educational attainment compared to third-country nationals (TCNs) and former Soviet countries nationals. Despite this, EU citizens had better education and occupation matches, where most people with higher education held high-skilled jobs. Education and occupation mismatch was more common among immigrants from third countries and former Soviet countries. The academic and occupational mismatch was particularly pronounced among nationals of former Soviet states, where over half of highly educated people worked in low-skilled jobs.

A report by Masso et al. (2021) details the challenges faced by foreign workers compared to native workers in Estonia, especially concerning working conditions and wages. The report shows that migrant workers had been often employed on a temporary basis in Estonia. Due to challenges in monitoring working conditions in such short-term jobs, employers may exploit the situation by providing migrants with worse working conditions and wages than they would have offered to local workers, for example, in the construction, metal and platform economy sectors. Furthermore, many foreign workers are employed under civil law contracts, as opposed to employment contracts, which renders these workers' access to employment benefits, such as health insurance, paid leave, and other employment-related protections. Foreign workers may have to work longer hours for the same pay as local workers if employed through an intermediary agency.

This issue has been prevalent among foreign workers in the metal industry. Also, foreign workers may have to work in worksites and conditions with weak occupational safety protections, such as the construction and platform economy sectors. Overall, the evidence shows that foreign labour, especially those working in temporary and low-skilled jobs, may face poorer employment outcomes than their native counterparts.

However, further empirical evidence on the differential labour market impact of automation on Estonian and foreign-born workers is missing. This ample research gap motivates this paper and allows us to benchmark the results for Estonia against those for other EU countries.

3. Data and Methodology

3.1 Data and Terminology Description

In this study, we used a matched firm-individual dataset covering the period of 2006-2017. This dataset was constructed by merging several firm- and individual-level registry datasets and has been used to analyse gender pay gap-related questions in Estonia (Masso et al., 2022; Pavlenkova et al., 2024; Vahter & Masso, 2019).[1] The dataset was constructed using unique and anonymised firm and individual ID codes, which enabled matching records across several datasets and years.

This study adopted the approach of Pavlenkova et al. (2024) to investigate the effects of automation on foreign- and native-born workers. As in the mentioned paper, this thesis considers the import of automation-related goods as a measure of automation (see Table 1), which was reported in the Estonian import-export dataset based on items' Combined Nomenclature (CN) codes in customs declaration forms. Considering that acquiring these goods requires substantial investments, it is deemed that the effect of potential resellers – those who import to sell

[1] The author gratefully acknowledges the help he received from Jaan Masso, Associate Professor of the University of Tartu, who prepared the initial dataset and provided valuable guidance for utilising the data.

domestically – is unlikely to significantly affect the findings of this study. This is because investing in such equipment often involves comprehensive warranty policies, as well as installation and maintenance support agreements with vendors. Moreover, the definition of automation in this paper applies to a firm only for years when this import takes place. Hence, if a firm imported several years across the observed period, it is recorded as an automating firm in those specific years, whereas in the remaining years, it is considered as a non-automating firm (there are also other approaches in the literature, for instance, considering firm automation adopter for several years after the automation event). In this manner, we want to identify the association between the time of automation import and its impact on the number of foreign-born and native-born workers.

Table 1

Classification of automation goods as defined by Acemoglu and Restrepo (2022a)

Good type	CN 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, 844770–844799
Other textile-dedicated machinery	844400–845399
Conveyors	842831–842839
Regulating instruments	903200–903299

Source: Pavlenkova et al. (2024)

In the scope of this study, the distinction between foreign and native employees is made based on the country of birth of individuals, which was taken from the Estonian Population and Housing Census and Statistical Registry of Population of Estonia. As citizenship information is unavailable in these databases for seven out of twelve years in the panel data, birthplace was considered to differentiate foreign and native workers. An additional benefit of birthplace usage was the ability to fill in missing values for any individual based on records from preceding or succeeding years. This approach was also suitable to account for the fact that Estonia has a sizable permanent resident population born in Estonia but decided to obtain citizenship from former Soviet Union countries of their ethnic origin (mainly Russians but also from other post-Soviet countries). Considering the above and the time-invariant nature of a birth country, this definition of the foreign and native workforce was identified as a suitable approach to identify an association between automation and employment across time.

Skill levels – categorised as high-, middle- and low-skilled – were determined based on individuals' highest level of acquired education. Education level classification is done per the International Standard Classification of Education (ISCED 2011) levels. ISCED 0, ISCED 1, ISCED 24, and ISCED 25 levels corresponding to primary education are proxies for low-skill. ISCED 34, ISCED 35 and ISCED 4, corresponding to secondary education (including vocational schools), are used as proxies for middle-skill. ISCED 5, ISCED 6, ISCED 7 and ISCED 8 levels correspond to higher education and are used as high-skill proxies in this paper. Using education as a skill proxy is relevant from a theoretical perspective since education is positively correlated with skill level (Becker, 1964). Alternative proxies for skill levels could have been occupational data as per the International Standard Classification of Occupations (ISCO) or wages; however, both had major limitations in the context of this research. Occupational information is only partially available for 2011 and 2014, in addition to being an unreliable proxy for foreign-born workers, especially in Estonia, where foreigners are more likely to be overqualified (OECD & European Union, 2015). Thus, using occupation information would have reduced the scope significantly and diminished the validity of the results. Moreover, foreign-born employees may hold low-level and low-paying jobs – below their actual skill level – due to labour market segmentation, discrimination and limited transferability of skills and education credentials acquired abroad. Hence, using wage as a proxy for skill level may underestimate the number of medium- and high-skilled workers of foreign origin.

The remaining variables used in this study include firms' age, ownership type, and turnover, which are taken from the Estonian Business Registry based on firms' annual financial statements. Information on Estonian firms' Outward foreign direct investment was taken from the Bank of Estonia database. The import and export activities of firms, which are based on customs declarations, were obtained from the goods trade dataset to identify automation goods and exporting companies. Individual-level data, such as country of birth and education level, was taken from the Estonian Population Census data of the Statistical Registry of Population. Individuals' wages and firm average wages were pulled from and calculated based on Income and Social Taxes Declarations (TSD) from the Estonian Tax and Customs Board.

Due to the complexity of the merging process behind the matched dataset, missing values are observed in most variables used in the estimation process. Due to this factor, the panel data presents an unbalanced structure, where firms are unevenly represented across years. The further attempt to transform the panel data into a balanced one was unsuitable as, in this case, the number of observations dropped from 6020 to 583. Therefore, the final data frame used in the analysis is unbalanced, and no restrictions were set on the number of minimum observation periods for firms.

3.2 Descriptive Statistics

Table 2 provides general information on the trends of foreign-born population and foreign-born workers in Estonia. We observe a decreasing pattern in the foreign-born shares of the population and workforce over the years, demonstrating a demographic and labour market composition shift.

Table 2

Share of foreign-born population and foreign-born workers in Estonia (%)

Year	Foreign-born (general population)	Foreign-born workers (total)	Foreign-born workers (Soviet migration)	Foreign-born workers (Post-Soviet migration)	Foreign-born workers (Other migration)
2006	16.9	15.6	14.1	1.0	0.6
2007	16.9	15.4	13.7	1.0	0.6
2008	16.7	15.1	13.4	1.1	0.6
2009	16.6	15.0	13.2	1.2	0.6
2010	16.4	14.3	12.6	1.2	0.6
2011	16	14.4	12.6	1.3	0.6
2012	15.9	14.0	12.0	1.3	0.7
2013	15	13.7	11.5	1.2	1.0
2014	14.9	13.2	10.9	1.1	1.1
2015	14.8	13.2	10.4	1.1	1.6
2016	14.7	12.8	10.0	1.1	1.7
2017	14.6	12.5	9.4	1.1	1.9

Source: OECD Data Archive and author's calculations based on Statistics Estonia database

Further segregation of foreign-born workers into cohorts based on the migration year to Estonia illustrates that workers who migrated during the Soviet occupation (*Soviet migration* - internal migration within the Soviet Union in 1944-1991) had been the largest source of foreign-born workers. Notably, the share of Soviet-period migrant workers has decreased significantly, from 14.1% in 2006 to 9.4% in 2017. This decreasing pattern can be attributed to retirement from the workforce, emigration or passing away of the Soviet-period migrant population and workers. The share of foreign-born workers who migrated after Estonia regained its independence in 1991 (*Post-Soviet migration* – 1991-onwards) and those with undisclosed/other periods of migration (*Other migration* – before 1944 or missing year) have remained stable or slightly increased over the years.

The decreasing dynamics of foreign-born worker share are also observed when analysing foreign-born workers' sectoral representation, as shown in Table 3. Across all illustrated industries, shares had declined, but with varying sizes of decreases. The construction sector experienced the highest decline in foreign-born worker share, from 15.7% in 2006 to 9.8% in 2017, which makes the industry with a lower representation of foreign-born workers compared to the total foreign-born worker shares in the country (presented in Table 1). Manufacturing and Hospitality industries demonstrate proportions of foreign-born workers that closely follow the average in the total workforce. Metal, Services and Health sectors, on the other hand, were more reliant on foreign-born workers, with higher shares of foreign-born workers than the total foreign-born worker share in the workforce.

Table 3

Share of foreign-born workers in main industries (%)

Year	Manufacturing	Metal	Construction	Services	HoReCa	Health
2006	15.4	19.2	15.7	17.6	15.2	16.8
2007	15.5	20.0	14.2	17.2	15.1	16.9
2008	15.5	19.7	13.4	17.0	14.9	16.4
2009	15.3	20.1	13.0	17.1	15.3	16.7
2010	14.9	20.2	12.5	17.4	14.8	16.4
2011	14.8	19.6	12.2	17.6	14.6	15.6
2012	14.5	18.8	12.1	17.2	14.6	15.9
2013	14.2	17.7	11.7	16.9	13.4	15.7
2014	13.5	17.1	11.2	16.4	13.0	15.9
2015	13.6	17.3	10.8	16.0	13.0	15.3
2016	13.1	17.1	10.0	15.6	12.8	15.4
2017	12.9	17.0	9.8	15.3	12.6	15.1

Note: HoReCa stands for Hotel, Restaurant, Catering, a term used for the hospitality sector.

Source: Author’s calculations based on Statistics Estonia database

In Table 4, the unemployment rates of foreign-born and native-born people are illustrated to provide general information about the labour market situation in Estonia. The data shows that the unemployment rate had been consistently higher in the foreign-born population compared to the native-born. The difference in unemployment rates between these two segments was even more pronounced in the aftermath of the Great Recession, 2010-2012. This trend shows that, compared to native-born workers, foreign-born workers experience more difficulties in job search and integration into the workforce and are more negatively impacted by economic shocks. If automation has a job-displacement effect on foreign-born workers, their labour market indicators may further deteriorate without necessary policy intervention. With a job-creation possibility of automation, however, a higher rate of unemployed foreign-born workers can be an opportunity to mobilise this pool of workers to meet the growing demand.

Table 4

Foreign-born and native-born unemployment rates in Estonia (%)

Year	Foreign-born unemployment	Native-born unemployment	Gap with native-born
2006	7.8	5.7	2.1
2007	5.7	4.6	1.1
2008	6.0	5.6	0.4
2009	14.8	14.0	0.8
2010	22.8	16.4	6.4
2011	16.9	12.1	4.8
2012	12.9	9.9	3.0
2013	11.0	8.6	2.4
2014	9.3	7.3	2.0
2015	7.8	6.1	1.7
2016	9.0	6.7	2.3
2017	6.4	5.9	0.5

Source: OECD Data Archive

Table 5 presents the average gross wages of foreign-born and native-born workers in Estonia from 2006 to 2017, disaggregated by skill level. The overall trend shows that across years and skill groups, native-born workers earn more than foreign-born workers. While wages had increased for all workers across skill levels, high-skilled foreign-born and native-born workers experienced higher increases compared to their middle- and low-skilled counterparts. Moreover, the data shows that the wage gap[2] between foreign-born and native-born workers had been particularly high between high-skilled foreign-born and high-skilled native-born workers. Wage

[2] Wage gap for each skill group is calculated as below and rounded to the first decimal place: ((Native-born worker wage - Foreign-born worker wage)/Native-born worker wage) * 100

structure trends provide evidence of income inequality between foreign-born and native-born workers in the labour market. The data also suggests that compared to native-born workers, foreign-born workers, especially low- and middle-skilled, may be hit the hardest by economic shocks that could lead to labour displacement and depressed wages.

Table 5

Average gross wages in Euro of foreign-born and native-born workers disaggregated by skill levels

Year	Foreign-born wages (EUR)			Native-born wages (EUR)			Gap with native-born (%)		
	High-skilled	Middle-skilled	Low-skilled	High-skilled	Middle-skilled	Low-skilled	High-skilled	Middle-skilled	Low-skilled
2006	484.62	383.66	325.55	669.84	458.38	370.47	27.7	16.3	12.1
2007	579.50	461.69	391.59	778.23	550.29	452.83	25.5	16.1	13.5
2008	683.12	553.89	459.27	922.56	651.73	535.49	26.0	15.0	14.2
2009	737.37	581.66	471.81	991.77	680.71	555.72	25.7	14.6	15.1
2010	695.20	534.85	427.34	920.30	620.70	503.71	24.5	13.8	15.2
2011	702.36	544.54	425.13	933.17	634.07	515.43	24.7	14.1	17.5
2012	757.87	586.68	485.26	998.85	686.02	556.47	24.1	14.5	12.8
2013	803.80	611.14	499.68	1046.66	716.17	578.71	23.2	14.7	13.7
2014	857.46	660.36	540.35	1111.55	766.92	621.75	22.9	13.9	13.1
2015	914.37	696.65	568.22	1199.65	825.71	674.51	23.8	15.6	15.8
2016	961.98	729.20	610.74	1266.94	876.59	718.96	24.1	16.8	15.1
2017	1033.61	780.03	653.31	1335.54	932.71	767.77	22.6	16.4	14.9

Note: Average wages show the gross salary paid to workers in January each year per Income and Social Taxes Declarations (TSD). Figures also include workers with reduced working time (FTE below 1.0).

Source: Author’s calculations based on Statistics Estonia database

Furthermore, the comparison of some characteristics of automating and non-automating firms is presented in Table 6. The firm’s age shows that an average automating firm is more mature compared to an average non-automating firm. Similarly, from the productivity perspective, firms that automate stand out with their consistently and significantly higher turnover per worker than firms that do not automate over the years. When it comes to foreign-born workers' share, however, the data shows firms that import automation goods had a lower share of total foreign-born workers in their workforce, with this difference being, on average, 4% lower compared to non-importing firms across years. This disparity in the share of foreign-born workers was mainly driven by Soviet-period migrant workers, which can be noticed when total foreign-born workers are disaggregated by migration period. While the share of foreign-born workers in other cohorts has slightly increased in automating firms over the year, the trends show that these firms are less reliant on foreign-born workers.

Table 6

Comparative view of automating and non-automating firms

	Firms importing automation goods						Firms not importing automation goods					
Year	Firm age	Turnover per worker (EUR)	Foreign-born workers (total %)	Foreign-born workers (Soviet migration %)	Foreign-born workers (Post-Soviet migration %)	Foreign-born workers (Other migration %)	Firm age	Turnover per worker (EUR)	Foreign-born workers (total %)	Foreign-born workers (Soviet migration %)	Foreign-born workers (Post-Soviet migration %)	Foreign-born workers (Other migration %)
2006	11	331,954	12.2	10.7	1.0	0.5	6	225,640	16.2	14.2	1.2	0.7
2007	12	265,288	11.4	10.0	0.9	0.5	6	142,517	15.8	13.7	1.4	0.7
2008	12	358,589	11.4	9.6	1.2	0.6	7	117,441	15.5	13.3	1.5	0.7
2009	13	222,582	11.2	9.5	1.2	0.6	7	91,011	15.5	13.2	1.6	0.7
2010	13	231,664	10.3	8.5	1.3	0.5	8	96,255	15.6	13.2	1.6	0.7
2011	14	256,528	10.6	8.8	1.3	0.5	8	103,518	15.6	13.0	1.8	0.8
2012	14	246,242	10.9	9.1	1.4	0.5	9	108,702	15.2	12.3	1.8	1.1
2013	15	252,808	10.5	8.5	1.1	1.0	9	108,517	14.7	11.6	1.6	1.5
2014	15	254,035	10.1	7.8	1.4	0.9	9	89,449	14.3	11.0	1.6	1.8
2015	16	261,559	10.3	7.7	1.1	1.6	9	90,784	14.2	10.3	1.5	2.5
2016	16	232,828	10	7.4	1.0	1.6	9	102,571	13.7	9.8	1.3	2.6
2017	17	254,058	9.4	6.6	1.2	1.6	10	109,513	13.3	9.3	1.3	2.7

Source: Author's calculations based on Statistics Estonia database

Further analysis of foreign-born workers focusing on automating firms provides a breakdown by skill composition of these workers. A decreasing pattern observed in the total share of foreign-born employees (in Table 6) can also be seen in Figure 1 in companies adopting automation. Overall, most foreign-born workers in automating firms are highly skilled across the observed period. While their share was 6.7% of the total workforce in 2006, this figure dropped to 5.3% in 2017. Similarly, middle-skilled foreign-born labour experienced a decline in their share of the total employees – from 4.8% in 2006 to 3.6% in 2017. Low-skilled workers were the smallest skill group of foreign-born workers and constituted 0.5% of the total in 2006, and they experienced a slight decline to 0.2% in 2017. Thus, the data shows that automating companies are not reliant on low-skilled foreign-born workers. These companies tend to employ mainly high- and middle-skilled workers.

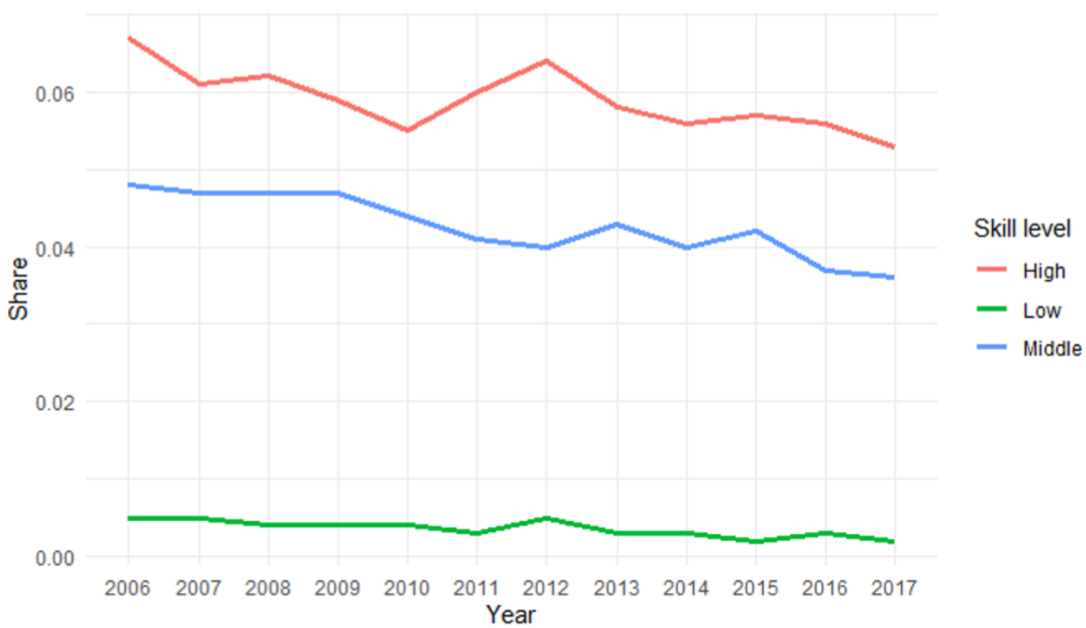

Figure 1. Time dynamics of skill-level composition of foreign-born workers in automating firms
Source: Author’s calculations based on Statistics Estonia database

Table 7 illustrates the frequency of firms importing automation goods disaggregated by good types. The data shows fluctuating figures across all goods with overall increasing and decreasing trends depending on the type of goods over the years, which can be attributed to changing demand and technological penetration. For example, the import of Industrial robots, Dedicated machinery and Conveyors increased in 2017 compared to 2006 figures, showing an increased demand for more advanced types of automation goods in firms. Other goods, such as Tools for industrial work and Regulating instruments, demonstrate a relatively consistent increase in demand. Numerically controlled machines, Machine tools, and Welding machines exhibited fluctuating demand, which slightly increased over time. The import of Weaving and knitting machines was relatively stable over the years, whereas Other textile-dedicated machinery is the only type of automation goods that show decreased demand. Overall, the total number of firms that imported automation goods increased from 1318 in 2006 to 1583 in 2017. This increasing trend shows that automation adoption has intensified over time, which may amplify its impact on the employment outcomes of foreign-born workers in Estonia. The import values of these goods are presented in a separate table in Appendix B.

Table 7

Number of automation importing firms by goods category

Year	Industrial robots	Dedicated machinery	Numerically controlled machines	Machine tools	Tools for industrial work	Welding machines	Weaving and knitting machines	Other textile-dedicated machinery	Conveyors	Regulating instruments	Total automation
2006	7	234	45	502	890	139	15	187	53	289	1318
2007	12	239	46	514	904	124	12	178	44	333	1349
2008	11	227	38	469	913	127	8	154	44	314	1325
2009	5	202	39	359	799	112	11	136	39	313	1198
2010	5	247	27	351	801	114	11	135	38	333	1171
2011	11	258	44	417	901	143	13	143	42	345	1289
2012	8	286	51	439	948	135	13	156	41	404	1379
2013	10	300	51	470	985	144	16	146	42	374	1400
2014	9	344	64	496	993	146	14	151	52	387	1467
2015	9	325	42	479	1011	161	14	153	66	411	1464
2016	15	375	45	491	1008	164	13	143	68	417	1507
2017	19	385	50	550	1107	146	15	166	68	425	1583

Note: Some firms imported more than one type of good in some years.

Source: Author's calculations based on Statistics Estonia database

3.3 Methodology

The methodology employed in this paper is tailored to identify how the import of automation goods affects the number of foreign-born and native-born workers in Estonia in total and across skill groups, accounting for several technical aspects of the data described below. Namely, the following regression specification is employed:

$$Y_{it+1} = exp(\beta_1 Aut_{it} + \beta_2 lnLPV_{it} + \beta_3 For_{it} + \beta_4 Age_{it} + \beta_5 AvW_{it} + \beta_6 ExpSh_{it} + \beta_7 inFDI_{it} + \beta_8 outFDI_{it} + \beta_9 lnTotEmp_{it+1} + \gamma_i + \delta_t) \quad (1)$$

where Y_{it+1} stands for the number of foreign-born or native-born workers of high-, middle- or low-skill level in firm i in year $t+1$. Aut_{it} is a proxy for total automation (includes all goods) and a dummy variable that takes the value of 1 if a firm imports any automation goods in year t and 0 otherwise. In addition, a set of control variables that can impact firms' decision to employ foreign-born workers is considered. The following variables are measured in year t: $lnLPV_{it}$is the logarithm of value added per employee; For_{it} is a dummy variable for firm's ownership type and takes the value of 1 if a firm is foreign-owned; Age_{it} represents firm's age; AvW_{it} stands for an average gross wage; $ExpSh_{it}$is export share of a firm's turnover; $inFDI_{it}$ and $outFDI_{it}$ are dummies for inward and outward foreign direct investments of a firm, respectively. Additionally, $lnTotEmp_{it+1}$ is a logarithm of the total number of employees in the year succeeding automation. γ_i and δ_t stand for firm- and year-fixed effects, respectively.

The models are estimated using firm- and year-fixed effects to account for unobserved and inherent characteristics that affect firms' ability to innovate and automate and to account for the demand shocks due to the global financial crisis of 2008-2009. Standard errors are clustered on a firm level to address potential firm-level correlation, thus increasing the robustness of the model.

The dependent variables for the total number of foreign-born workers and the number of foreign-born workers by skill level include a large proportion of zeros, ranging from approximately 37% to 83%, depending on the variable in question. In addition, all these variables have high skewness and high kurtosis values; for example, these values for the total number of foreign-born workers are 12.9 and 202.5, respectively. Also, these variables have variance much higher than their means. These dataset characteristics do not allow using common count data models, such as

Poisson or Negative Binomial. Two-part model versions of count data models, for instance, Zero-Inflated and Hurdle, were also ruled out as viable empirical approaches since the data generation process behind zero and non-zero values in this study is the same, unlike some other fields or scopes where these two values may have different explanations.

Considering all the above, the most suitable approach was identified as the Poisson Pseudo Maximum Likelihood (PPML) estimator for regression analysis due to its ability to handle a large proportion of zeros and overdispersion. This approach is an extension of the standard Poisson model and relaxes the assumption of variance and mean equality. The use of the PPML regression estimation technique under such circumstances was suggested and empirically validated by Silva and Tenreyro (2006) for the model's ability to handle non-negative data with many zeros and perform well in the presence of heteroskedasticity. Since then, this approach has been widely accepted and used in many research areas, such as gravity models for trade, healthcare, energy, and labour economics (Fabbri & Robone, 2010; Ghodsi et al., 2024; Yotov et al., 2016; Zhao et al., 2013).

It must be noted that there is a risk of simultaneity bias between independent and dependent variables, as there are papers that identified how labour supply affects firms' automation decisions (Danzer et al., 2024; Mann & Pozzoli, 2022), which is the opposite formulation of current paper's research questions. Therefore, to mitigate this risk, the dependent variables are estimated in the year following the import of automation goods.

4. Results

4.1.1 Effects of automation on the number of foreign-born and native-born workers

Regression outputs for baseline models for the total number of foreign-born and native-born workers, following specification (1), are presented in Table 8. Since the Poisson Pseudo Maximum Likelihood estimation method is of an exponential model family, the coefficients only allow a clear interpretation of the direction of a change, whether positive or negative. For interpretability, these coefficients are exponentiated and normalised to obtain semi-elasticities[3] for non-logged variables, all except for the logarithm of labour productivity (logLPV) and the logarithm of total number of workers. Henceforth, the interpretation of changes in all models is made by transforming coefficient values presented in tables. Moreover, all models are constructed by including firm-level and year-level fixed effects. This decision involved running various forms of random and fixed effects baseline models and selection based on the ability of two-way fixed effects models to capture the data better (see Appendix A for side-by-side comparison). Pseudo R squared[4], Pseudo Log Likelihood[5] and Root Mean Square Error (RMSE) statistics provided supporting evidence for this selection.

In Table 8, the automation dummy shows statistically significant effects in both models, albeit the direction of the change is opposite. In model 1, automation import is associated with a 5.7% increase in the number of foreign-born labour at a 1% significance level, whereas model 2 shows a 2.4% decrease in the number of native-born workers at a 5% significance. These percentages represent changes in conditional means of respective dependent variables after automation, all else being equal. Automation coefficients indicate that importing automation goods is associated with job creation for foreign-born workers, while native-born workers experience declining employment.

[3] Semi elasticities for logarithmically not transformed variables were derived using (exp(coefficients)-1) *100 formula and rounded to the first decimal place.

[4] Since the PPML estimation technique is nonlinear, Pseudo R squared is reported as standard practice.

[5] Pseudo Log-Likelihood statistics are presented since standard Log-Likelihood is not available in PPML.

Table 8

Effect of automation on the number of foreign-born and native-born workers

Dependant variable	*Model 1* No. of foreign-born workers (t+1)	*Model 2* No. of native-born workers (t+1)
Automation (t)	0.055***	-0.024**
	(0.021)	(0.012)
Log Value added per employee (t)	-0.015	0.004
	(0.020)	(0.004)
Foreign-owned firm (t)	-0.043	-0.004
	(0.049)	(0.007)
Firm age (t)	-0.005***	0.001***
	(0.001)	(0.000)
Firm average wage (t)	0.000**	0.000***
	(0.000)	(0.000)
Export share of turnover (t)	0.000	0.000
	(0.001)	(0.000)
Inwards FDI (t)	-0.064**	0.005
	(0.027)	(0.005)
Outwards FDI (t)	-0.070***	0.010**
	(0.021)	(0.004)
Log total N employees (t+1)	1.120***	0.978***
	(0.039)	(0.013)
Fixed Effects	Firm + Year	Firm + Year
Observations	4,364	5,992
Pseud. R2	0.93428	0.96280
Pseud. Log-Lik	-7,411.0	-14,730.7
RMSE	2.6642	2.9847
Wald test	300.10	1,037.6

Notes: Robust-clustered standard errors are reported in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Source: Author's calculations

These results can be explained by several labour market factors. In line with the Routine Biased Technological Change (RBTC) Hypothesis, firms that automate their production and operating processes do so to reduce their volume of routine tasks, increase productivity and profitability, and reduce operational costs. Once firms adopt the new technology and start operating in a streamlined manner, they may require fewer employees to be involved in routine tasks. At the same time, firms need skilled people to operate new equipment. From an employer perspective, training employees to work with new machines can be an expensive and lengthy process, which may not be a desirable path due to already incurred automation investment costs (Faia et al., 2020). In addition, Estonia experiences a shortage of skilled trade workers, which can inhibit firms' optimisation plans if only a domestic talent pool is considered. Therefore, a more cost-efficient approach may be to hire foreign workers with the necessary skill set to work with new equipment. An additional benefit of hiring foreign workers for firms could be that foreign-born labour is usually paid less than native-born workers in Estonia (as shown in Table 5), and firms may opt for hiring foreign workers to optimise labour costs. Native workers, who lack the skills to fulfil new technical requirements, may be displaced as a result of automation and seek other employment where they can benefit from their social skills and face less competition from foreign workers, as suggested in other papers (Basso et al., 2020; Peri, 2012).

Reviewing other control variables, we see that the logarithm of value added per employee and firm ownership type are not statistically significant in either model despite having relevance to employment structure as identified in the literature (Meriküll et al., 2014; Pyun & Sun, 2022). A one-year increase in the firm's age is associated with a 0.5% decrease in foreign-born workers' numbers while increasing native-born workers' numbers by 0.1%, both statistically significant. Coefficients of the firm average wage, which is an important factor in employers' attractiveness, are statistically significant and have a positive effect on the number of foreign-born and native-born workers, but the values are very close to zero. Thus, while the firm average wage is a statistically significant control variable and improves model performance, its effect on the employment outcomes of both groups is very small.

Exports' share in turnover is statistically insignificant in both models, although the empirical connection has been established in the literature, for example, by Peri and Requena (2009). Inward and Outward Foreign Direct Investments (FDI) are associated with a statistically significant reduction of foreign-born workers by 6.2% and 6.7%, respectively. For native-born workers, only Outward FDI is statically significant and shows a 1% increase in native-born worker numbers. As for total number of employees, the models show that a 1% increase in total employee number is linked to a 1.12% increase in foreign-born workers and about a 0.98% increase in native-born workers, both coefficients being statistically significant.

4.1.2 Robustness check

The next question arising from these baseline models is whether labour adjustments may take longer than one year to show the full impact of automation on job displacement/creation effect in either group. To investigate this, the number of foreign-born and native-born workers is additionally estimated with 2- and 3-year lags after the automation import takes place and is compared to their baseline versions at time $t + 1$. Table 9 presents the results for foreign-born and native-born employees with 1-3 years lags.

Table 9

Effect of automation on the number of foreign-born and native-born workers with 1-, 2- and 3-year lags

Dependant variable	*Model 1* No. of foreign-born workers (t+1)	*Model 3* No. of foreign-born workers (t+2)	*Model 4* No. of foreign-born workers (t+3)
Automation (t)	0.055***	0.053**	0.074**
	(0.021)	(0.025)	(0.036)
Fixed Effects	Firm + Year	Firm + Year	Firm + Year
Observations	4,364	4,280	3,771
Pseud. R2	0.93428	0.92706	0.92233
Pseud. Log-Lik	-7,411.0	-7,278.1	-6,359.0
RMSE	2.6642	2.8138	3.1185
Wald test	300.10	219.10	250.81
Dependant variable	*Model 2* No. of native-born workers (t+1)	*Model 5* No. of native-born workers (t+2)	*Model 6* No. of native-born workers (t+3)
Automation (t)	-0.024**	-0.019	-0.019
	(0.012)	(0.014)	(0.017)
Fixed Effects	Firm + Year	Firm + Year	Firm + Year
Observations	5,992	5,907	3,771
Pseud. R2	0.96280	0.96183	0.92233
Pseud. Log-Lik	-14,730.7	-14,534.5	-12,828.2
RMSE	2.9847	3.3154	3.4576
Wald test	1,037.6	766.80	833.24

Notes: Robust-clustered standard errors are reported in parentheses. Control variables are not presented to save space; full regression versions are available upon request.

* p<0.10, ** p<0.05, *** p<0.01

Source: Author’s calculations

In all three models, the automation dummy remains statistically significant and positive: 1 year after automation imports occur, a firm posts a 5.7% increase in the number of foreign-born employees, whereas, in lag 2 and lag 3, these values are 5.4% and 7.6%, respectively. Thus, a magnified effect of automation import is observed in these models over time, which is in line with similar findings of Aghion et al. (2020). Although automation dummy coefficients remain statistically significant across the models, the significance level weakens beyond 1-year lag. For native-born employees, the coefficients for the automation dummy become statistically insignificant after the first year, although they still show a negative effect. Due to this, the significant negative association between automation and the number of native-born employees is short-term and is mitigated after one year upon automation import, unlike that of foreign-born workers.

In addition to having prior knowledge and skills matching the automating firm's needs, foreign-born workers also hold a competitive advantage by acquiring firm-specific experience and knowledge of standard operating procedures (SOPs) once they join and start working in an automating firm. That may be the reason why we observe the persistent positive effect of automation on the number of foreign-born workers, which lasts up to three years after automation. When it comes to native-born workers, however, the negative effect is only temporary. Native-born employees unable to meet new skill requirements face job losses shortly after automation and do not experience statistically significant effects beyond 1-year lag. These results suggest that native-born labour who remain employed may either be unaffected by automation or possess skills complementing new technology.

4.2.1 Effects of automation on foreign-born and native-born workers by skill level

Table 10 presents models 7-12, where dependent variables are the number of foreign-born and native-born workers disaggregated by skill level in the year following the automation import. Of the three skill groups of foreign-born employees – high, middle and low – only the coefficient for the number of mid-skilled foreign-born employees is statistically significant, showing a 5.8% increase linked to automation import. Although automation dummy coefficients for high- and low-skilled foreign-born workers are also positive, they are not significant. The post-automation increase in the number of mid-skilled foreign-born labour suggests that firms need more workers who have some level of secondary or post-secondary education that enables them to operate machinery, robots or other imported equipment.

Table 10

Effect of automation on the number of foreign-born and native-born workers by skill level (1-year lag)

Dependant variable	*Model 7* No. of high-skilled foreign-born workers (t+1)	*Model 8* No. of mid-skilled foreign-born workers (t+1)	*Model 9* No. of low-skilled foreign-born workers (t+1)
Automation (t)	0.037	0.056***	0.173
	(0.030)	(0.021)	(0.111)
Fixed Effects	Firm + Year	Firm + Year	Firm + Year
Observations	3,680	3,548	1,525
Pseud. R2	0.89233	0.90047	0.58867
Pseud. Log-Lik	-5,384.1	-5,358.5	-1,625.3
RMSE	1.6358	1.8273	0.91227
Wald test	657.79	261.46	14.078
Dependant variable	*Model 10* No. of high-skilled native-born workers (t+1)	*Model 11* No. of mid-skilled native-born workers (t+1)	*Model 12* No. of low-skilled native-born workers (t+1)
Automation (t)	-0.027	-0.027	0.028
	(0.023)	(0.021)	(0.028)
Fixed Effects	Firm + Year	Firm + Year	Firm + Year
Observations	5,844	5,779	4,439
Pseud. R2	0.90302	0.94540	0.84856
Pseud. Log-Lik	-11,834.6	-13,001.8	-7,751.5
RMSE	3.3279	4.0080	2.8609
Wald test	122.80	256.74	144.89

Notes: Robust-clustered standard errors are reported in parentheses. Control variables are not presented to save space; full regression versions are available upon request.

* p<0.10, ** p<0.05, *** p<0.01

Source: Author's calculations

As for native-born workers, the automation dummy does not produce a statistically significant coefficient in either of the three models – the number of high-, mid- and low-skilled native-born workers. As observed in some of the previous models, the significance of coefficients can weaken when using fixed effects and robust standard errors, despite their role in addressing biases and data issues in this paper.

Based on these results, we do not observe a job polarisation effect of automation import on foreign-born workers. While there is no statistically significant effect for native-born middle-skilled workers in our models, foreign-born middle-skilled employees experience higher employment. Our findings could be understood through the arguments of Autor (2015) in his paper about the impact of automation on the workplace. He argues that although automation is mainly for task labour displacement, it also creates a higher demand for complementary skills for automation. Middle-skilled jobs are affected by job polarisation, but not all will disappear, as many middle-skilled jobs have a non-routine share of tasks. Therefore, firms that import automation goods may experience growth in demand for middle-skilled labour. Subsequently, if the native talent pool is not the right match, they may turn to foreign workers to fill vacancies. As for native-born workers, we do not observe significance in any coefficients across models. This result can be due to heterogeneity among workers of this segment, which results in a loss of statistical significance, as reported in aggregated models in section 4.1.1 (see Table 8).

4.2.2 Robustness Check

Table 11 compares foreign-born and native-born workers by skill groups two years after automation import. The first three models for foreign-born workers – model 13, model 14 and model 15 – show that automation only relates to a statically significant increase for mid- and low-skilled foreign-born employees by 7.9% and 23.4%, respectively. Models 16-18 for native-born workers, on the other hand, show that only the coefficient of the number of mid-skilled workers, model 17, is significant at 10% and shows a decline of 4.2% in the number of mid-skilled native-born employees two years after the automation import. These opposite effects for foreign-born and native-born workers suggest that while importing automation goods boosts the employment of low- and middle-skilled foreign-born workers, it decreases the number of mid-skilled native-born employees.

Table 11

Effect of automation on the number of foreign-born and native-born workers by skill level (2- and 3-year lag)

	Model 13	*Model 14*	*Model 15*	*Model 16*	*Model 17*	*Model 18*
Dependant variable	No. of high-skilled foreign-born (t+2)	No. of mid-skilled foreign-born (t+2)	No. of low-skilled foreign-born (t+2)	No. of high-skilled native-born (t+2)	No. of mid-skilled native-born (t+2)	No. of low-skilled native-born (t+2)
Automation (t)	0.014	0.076**	0.210**	0.010	-0.043*	0.023
	(0.028)	(0.031)	(0.090)	(0.013)	(0.025)	(0.025)
Fixed Effects	Firm + Year	Firm + Year	Firm + Year	Firm + Year	Firm + Year	Firm + Year
Observations	3,620	3,479	1,492	5,750	5,702	4,426
Pseud. R2	0.88221	0.88768	0.57840	0.89969	0.94396	0.85022
Pseud. Log-Lik	-5,274.2	-5,275.4	-1,558.0	-11,653.3	12,808.9	-7,727.0
RMSE	1.6550	1.8120	0.89510	3.1360	4.0682	2.6199
Wald test	650.11	169.60	21.117	110.70	264.74	312.91
	Model 19	*Model 20*	*Model 21*	*Model 22*	*Model 23*	*Model 24*
Dependant variable	No. of high-skilled foreign-born (t+3)	No. of mid-skilled foreign-born (t+3)	No. of low-skilled foreign-born (t+3)	No. of high-skilled native-born (t+3)	No. of mid-skilled native-born (t+3)	No. of low-skilled native-born (t+3)
Automation (t)	0.043	0.104**	0.117	0.024	-0.045*	-0.028
	(0.032)	(0.043)	(0.111)	(0.015)	(0.026)	(0.027)
Fixed Effects	Firm + Year	Firm + Year	Firm + Year	Firm + Year	Firm + Year	Firm + Year
Observations	3,202	3,007	1,296	5,060	5,038	3,845
Pseud. R2	0.87722	0.87662	0.57143	0.90029	0.94327	0.85274
Pseud. Log-Lik	-4,612.0	-4,600.3	-1,321.7	-10,242.2	-11,286.2	-6,755.2
RMSE	1.6823	2.0075	0.86521	2.7543	3.7892	2.5738
Wald test	492.79	84.764	13.949	318.73	305.91	313.77

Notes: Robust-clustered standard errors are reported in parentheses. Control variables are not presented to save space; full regression versions are available upon request.

* p<0.10, ** p<0.05, *** p<0.01

Source: Author’s calculations

Similarly, we estimated changes in the number of foreign-born and native-born workers three years after automation. Among all six models – models 19 through 24 – only the ones for mid-skilled foreign-born and mid-skilled native-born workers produce statically significant coefficients: at a 5% significance level for mid-skilled foreign-born workers and 10% significance for mid-skilled native-born employees. The results show that the import of automation goods is associated with an 11% increase in the number of mid-skilled foreign-born workers, whereas for mid-skilled native-born employees, it exhibits a 4.4% decrease. These values are similar to the models with a 2-year lag and demonstrate an amplification effect on the direction of the change in mid-skilled workers.

Middle-skilled foreign-born workers appear to be the most significant group driving their employment growth with 2- and 3-year lags. Similar results for foreign-born labour were identified with a 1-year lag as well. Low-skilled foreign-born employees only briefly observe a positive and statistically significant effect of automation - in the model with a 2-year lag. The results show that middle-skilled foreign-born labour is a labour force category with skills that align with the requirements of automating forms. Reviewing native-born workers, we observe weak statistical impact with 2- and 3-year lags, whereas no effect was identified with a 1-year lag. These findings indicate that foreign-born workers, especially middle-skilled, benefit from automation, whereas native-born workers (middle-skilled) face job losses. Overall, our results did not provide supporting evidence to suggest that foreign-born workers, a segment that is more likely to be unemployed, underpaid and overqualified than native-born workers in Estonia, are negatively and disproportionately affected because of automation.

5. Conclusion

The increasing adoption of automation raises concerns over its social welfare implications and labour market outcomes worldwide. Specifically, little research has been done focusing on foreign workers. Therefore, it is imperative to understand how this process takes place so that appropriate measures can be taken to facilitate the transition and dampen potential negative effects. The available studies in this area have predominantly focused on the US and other big, developed economies in Europe and Asia. However, the impact of automation on the foreign labour force as a workforce segment and foreign workers disaggregated by skill level is under-researched. In the context of Estonia and other similar economies within Europe, the lack of available studies on understanding how foreign and native employees experience this transformation motivated this study. Considering that this topic is relatively new, our research identified this distinct gap in the literature and aimed specifically at identifying the impact of automation on foreign-born workers across skill levels. As a result, we intend to understand how the technological adoption process affects foreign-born workers in Estonia. While the study focuses on Estonia, our results can be relevant to other countries, such as the Baltic and Eastern European states.

Proxying automation by the import of automation-associated goods, foreign-native belonging by birth country and skill level by acquired education level, this study carried out the empirical analysis on a matched employee-employer dataset from Statistics Estonia register-based database for the years 2006-2017. The results of two-way fixed effects Poisson Pseudo Maximum Likelihood (PPML) estimations show that total automation, as defined in this paper, is associated with an increase in the number of foreign-born workers in the year following the import while it lowers the number of native-born workers. Statistically significant, albeit diminishing, positive association for foreign-born workers continues up to the third year after automation, whereas for native-born employees, this significance disappears beyond 1-year lag. When looking into the skill levels of each of these two segments and based on the models' significance, it can be concluded that the impact of automation on foreign-born and native-born workers was mainly driven by middle-skilled workers – those holding secondary and post-secondary education, as per our definition. Middle-skilled foreign-born employees experience an increase in their numbers, whereas the number of native-born workers decreases.

Our findings show that automation is not associated with a job polarisation effect for foreign-born workers, while it decreased the employment of native-born workers. Thus, we cannot attribute the job polarisation that has been happening in Estonia for the past several decades to automation when it comes to foreign-born workers (OECD, 2019). Moreover, the results do not demonstrate that automation further exacerbates the employment outcomes of foreign-born workers. In fact, they appear to benefit from automation as it is associated with higher employment for this segment, which does not seem to be the case for native-born employees.

This paper makes two contributions to the existing body of studies on the effects of automation on foreign-born workers. Firstly, applying the PPML estimator in regressions with fixed effects in this context is a novel approach. To our knowledge, the PPML estimation method has been used only once (Ghodsi et al., 2024), but the data and empirical strategy between these papers are different. Thus, the current paper enriches the literature by providing evidence of the application of the PPML estimator in this topic. Secondly, the data and empirical findings are novel for investigating the labour outcomes of foreign-born workers. Previous research in this domain focused mainly on robots, patents, computer software, and hardware aspects of automation and how they impact the labour market. The current paper, on the other hand, studied the impact of automation – defined by a broader list of automation goods – and aimed at investigating specifically foreign-born labour employment. In doing so, we combined the novelty of the dataset with the novelty of research questions.

From a policymaking perspective, several measures can improve the social welfare of the labour force. Firstly, policy actions are needed to control and ensure firms pay fair wages to all employees, whether foreign-born or native-born. As descriptive statistics showed, foreign-born workers are consistently paid less in Estonia across all skill groups. Control mechanisms should be set so that firms do not exploit foreign-born labour with low salaries. For example, residents in Finland can request the salary information of any taxpayer in the country by contacting tax authorities (In Finland, all it takes is a phone call, 2017). A similar solution that enables transparency can mitigate downward pressure on wages, benefit all workers and create a fair labour market. Secondly, a shortage of skilled workforce, particularly for technical and industrial jobs, is an issue in Estonia (Raidla, 2024). This is partly due to the fact that the vocational education system and job placement of graduates are not at a level that can enable bridging this skill gap domestically at the moment, which makes hiring foreign workers imperative (Lumi, 2024). A proactive approach in promoting study programmes for shortage jobs and public-private sector collaboration on improving the school-to-workforce transition process can help people displaced by automation regain employment. As our findings show, native-born workers appear to be negatively affected by automation. Therefore, ensuring their well-being and return to the workforce must be emphasised. Thirdly, Estonia's population is projected to decline based on current fertility rate trends, which will result in a shrinking workforce without immigration (Kukk, 2024). This necessitates a carefully devised migration policy that aims to meet labour demand internally and only then the remaining gap by bringing foreign workers. Moreover, an official list of shortage jobs can be created and reviewed annually to determine the allocation of work permits and the basis for renewing expiring permits. These steps can facilitate smooth and sustainable technological development while mitigating its negative impacts on the labour market.

While this paper plays an important role in enhancing our understanding of automation's impact on the labour market in Estonia, some limitations of the analysis must be taken into consideration. These are related to proxies used for automation, foreigner-native categorisation, and skill level, as was pointed out in the data description section. Depending on the available data, researchers have used various proxies for automation, which makes comparability of results across countries or even within the same country quite challenging. Findings based on one definition of automation may not hold when the definition is different. Similarly, using a birth country as a proxy for foreign-native identity has downsides. Firstly, we miss out on information about foreigners' level of integration without citizenship data. Foreigners who naturalised in Estonia may perform better in the labour market than those without Estonian citizenship due to secure legal status, language ability and social integration. Secondly, even native-born non-Estonians, regardless of citizenship status, may have worse employment outcomes compared to Estonians due to limited cultural and social integration (for example, it has been extensively studied in the context of integration and challenges of ethnic Russians in Estonia).

Despite this, the benefits of using birth country instead of citizenship as a proxy far outweigh the disadvantages since the dataset completely lacked citizenship information for nearly half of the panel data period and contained missing values in available years. It means that if some foreigners lived in Estonia for a short period (only in years when citizenship information was not recorded), their missing citizenship information cannot be filled with any value. Another disadvantage of citizenship as a proxy was the concern that citizenship status might change over time; thus, replacing missing values would not be a correct approach. Lastly, education level as a proxy for skill level is not the only way to infer skill-level information. One of the common alternatives is occupation type as per the International Standard Classification of Occupation (ISCO). However, foreigners may take up jobs below their actual skill level and competencies due to financial or residence permit circumstances. Therefore, taking occupation information as a basis for skill level may not be an appropriate proxy when the main research topic is foreigners' employment outcomes. Moreover, this information was available for only two years in the entire panel data in this study, further proving it unsuitable as a proxy.

Future research on this topic could try to focus on the theoretical and econometrical application of the Instrumental Variable approach with the PPML estimator with fixed effects and implement it to capture causal inference. As the PPML estimation method is nonlinear, currently, there is a lack of theoretical knowledge and practical tools to combine these approaches. Furthermore, additional studies using different skill proxies, such as Programme for the International Assessment of Adult Competencies (PIAAC) data or occupational data from the Employment registry once sufficient panel data is formed (available only from 2019), can elucidate how technological adoption impacts foreign workers and overall employment, thus creating a benchmark with the findings of this paper.

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Appendices

Appendix A

Selection between Fixed Effects and Random Effects models

Dep. variable	No. of foreign-born workers (t+1)			
Automation (t)	0.055***	0.053**	-0.142	-0.131
	(0.021)	(0.022)	(0.128)	(0.133)
Log Value added per employee (t)	-0.015	-0.027	-0.091	-0.108
	(0.020)	(0.020)	(0.111)	(0.115)
Foreign-owned firm (t)	-0.043	-0.040	-0.225*	-0.213*
	(0.049)	(0.048)	(0.117)	(0.129)
Firm age (t)	-0.005***	-0.016***	-0.018*	-0.028***
	(0.001)	(0.003)	(0.010)	(0.009)
Firm average wage (t)	0.000**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Export share of turnover (t)	0.000	0.000	0.005***	0.005***
	(0.001)	(0.001)	(0.002)	(0.002)
Inwards FDI (t)	-0.064**	-0.068**	-0.133	-0.200
	(0.027)	(0.027)	(0.222)	(0.219)
Outwards FDI (t)	-0.070***	-0.079***	-0.209	-0.189
	(0.021)	(0.021)	(0.139)	(0.165)
Log total N employees(t+1)	1.120***	1.112***	1.249***	1.252***
	(0.039)	(0.036)	(0.042)	(0.045)
Intercept				-1.500
				(1.131)
Fixed Effects	Firm + Year	Firm	Year	None
Observations	4,364	4,364	6,020	6,020
Pseud. R2	0.93428	0.93421	0.78699	0.78276
Pseud. Log-Lik	-7,411.0	-7,419.8	-28,353.1	-28,916.0
RMSE	2.6642	2.9869	23.089	25.489
Wald test	300.10	244.19	154.03	117.44

Notes: Robust-clustered standard errors are reported in parentheses.

* p<0.10, ** p<0.05, *** p<0.01

Source: Author's calculations

Appendix B

Average total value in Euro per import by product category

Year	Industrial robots	Dedicated machinery	Numerically controlled machines	Machine tools	Tools for industrial work	Welding machines	Weaving and knitting machines	Other textile-dedicated machinery	Conveyors	Regulating Instruments
2006	19,801	216,349	100,908	841,084	341,689	65,620	13,255	227,951	42,753	86,977
2007	3,819	185,193	95,261	637,900	365,899	79,046	9,672	245,824	31,358	86,340
2008	3,673	253,950	78,242	562,197	332,557	75,365	1,053	187,145	46,338	74,730
2009	5,195	78,305	101,516	361,951	211,963	32,294	2,504	136,233	19,039	68,383
2010	2,246	112,019	64,593	370,545	309,232	33,852	6,221	169,107	20,564	77,452
2011	5,712	156,077	177,168	657,481	351,185	57,471	5,549	160,966	85,357	77,534
2012	1,378	121,326	134,687	839,282	365,105	106,089	3,053	206,217	21,931	95,983
2013	15,187	139,767	105,630	605,148	401,025	42,577	5,642	151,733	20,031	91,076
2014	11,329	143,720	112,203	522,242	370,027	39,250	4,856	129,371	23,021	77,474
2015	6,323	163,961	103,874	639,554	404,457	52,206	3,507	155,588	98,097	67,219
2016	17,081	195,588	188,149	874,146	423,228	70,261	1,072	168,228	74,920	75,680
2017	14,187	194,048	92,855	685,625	400,219	61,347	2,940	185,297	88,337	75,402

Source: Author’s calculations based on Statistics Estonia database

Resümee

Käesolev magistritöö uurib automatiseerimise kui teatud tehnoloogia kasutusele võtmise mõjusid Eesti kohalikule ja võõrtööjõule perioodil 2006–2017. Uurimistöö eesmärgiks on selgitada, kuidas konkreetse ettevõtte poolt automatiseerimistoodete kasutuselevõtt, mille lähendiks on vastavate toodete import ettevõtte poolt, on seotud erinevate mõjudega kohalike töötajate ja välismaal sündinud töötajate tööhõivele ettevõttes nii agregeeritud tasandil kui erinevate oskuste gruppide lõikes. Töös kasutatakse ühendatud töötajate ja tööandjate andmeid, mis on saadud erinevate Eesti ettevõtete ja töötajate registriandmete ühendamisega, sealhulgas automatiseerimistoodete impordi andmed on võetud Eesti Statistikaameti detailsetest ettevõtte-turu-toote taseme väliskaubanduse andmetest. Ökonomeetrilises analüüsis rakendatakse selleks Poissoni pseudo maksimaalse tõepära (Poisson Pseudo Maximum Likelihood, PPML) hindamismeetodit, mis annab vastused automatiseerimistoodete impordi ja ettevõtte tasandi tööhõive vaheliste seoste kohta. Tulemused näitavad, et automatiseerimistoodete impordiga kaasneb lühikeses ja keskpikas perspektiivis võõrtöötajate arvu kasv ettevõttes, samas kui kohalike töötajate arv väheneb automatiseerimistoodete impordile järgneval aastal ning hiljem on selle muutus statistiliselt ebaoluline. Jagades tööjõu oskustaseme kaupa gruppideks, ilmneb, et keskmiste oskuste tasemega töötajad on automatiseerimisest kõige rohkem mõjutatud sõltumata nende päritolust. Samas on automatiseerimisel keskmiste oskustega võõrtöötajate arvule positiivne mõju, kuid keskmiste oskustega kohalike töötajate arvule negatiivne mõju. Siiski tuleb tõdeda, et antud töös ei leia kinnitust väide nagu automatiseerimine oleks seotud välismaalastele kättesaadavate keskmiste oskustega töökohtade kadumisega, küll aga leiab selline töökohtade kadumine kinnitust kohaliku tööjõu hulgas. Niisiis on meie tulemused vähemalt osaliselt vastuolus töökohtade polariseerumise teooriaga. Seega, vastupidiselt varasematele uurimistulemustele, ei leia magistritöös kinnitust, et välismaalased saaksid tööturul kohalikest kehvemini hakkama, ja nende hulgas on hoopiski automatiseerimise seos tööhõivega positiivsem. Poliitikasoovituste seisukohalt on oluline toonitada, et oluline on luua eeldused vältimaks palgalõhesid välistööjõu ja kohalike töötajate vahel, aga tuleks ka reformida kutseharidust ja panustada ümberõppesse tagamaks vajaliku tööjõu kättesaadavus kohapeal. Täiendavalt on oluline luua eraldi nimekiri ametikohtadest või valdkondadest, kus on tööjõupuudus kõige teravam, misläbi on võimalik paremini siduda tööjõurännet riigi ettevõtluse vajadustega.

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