UNIVERSITY OF TARTU

Faculty of Social Sciences

School of Economics and Business Administration

Gunay Hajizada Sona Pashayeva

HOW ADOPTION OF ROBOTICS AFFECTS FIRM PERFORMANCE BASED ON ESTONIAN FIRM-LEVEL DATA

Master's thesis

Supervisor**:** Jaan Masso
Associate Professor

Tartu 2023

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

Abstract

In our master's thesis, we aim to fill the research gap and contribute to the existing literature by investigating the impact of employed robotics on firm productivity by considering the inclusion of service robots, which has been overlooked in previous analyses. We investigated the impact of robotics adoption by focusing on Total Factor Productivity (TFP) and labor productivity measures based on Estonian firm-level data. The study utilized two datasets – Information Technology Survey and Estonian Business Registry data from Statistics Estonia. We use Ordinary Least Squares (OLS), Fixed Effects (FE), and Propensity Score Matching (PSM) analyses to assess the relationship between robotics adoption and various productivity measures. The results of analyses indicate that the integration of robotics into firms' operations, particularly manufacturing robots, can result in substantial improvements in labor productivity. Additionally, it is important to note that the full realization of the robot adoption on productivity may require a certain time lag and usually takes a longer time to materialize. Our findings highlight that the slow pace of robot adoption in Estonian firms underlines the need for government intervention to promote awareness and benefits of robots and for the implementation of collaborative space between human workers and robots that addresses concerns about job displacement.

Keywords: robotics adoption, service robots, manufacturing robots, labor productivity, TFP

CERCS classification: S180

Table of Contents

1. Introduction

In today's tech-driven world, Information Technology (IT) tools, such as robotics, machine learning, and artificial intelligence (AI), have revolutionized the businesses and economic landscape and reshaped industries by challenging their traditional productivity norms. With the widespread adoption of robotics, firms harness these technologies to boost their productivity and efficiency and be more responsive to market demands. As the importance of technological innovations is becoming more prevalent, a considerable number of studies have focused on the question of whether using robots and automating processes actually improves productivity. Some existing papers suggest that the adoption of robotics and other types of IT positively affects productivity on a firm level (Acemoglu et al., 2020; Dirican, 2015; Kromann et al., 2020). Despite the growing recognition of technological innovations, a phenomenon known as Solow's paradox (1987) persists - the new technologies are evident everywhere, yet their impact is seemingly absent in productivity statistics. Thus, the impact of robotics on productivity is a nuanced topic, with some studies indicating potential negative consequences by highlighting the challenges of observing significant improvements in aggregate productivity and technological-driven growth (Brynjolfsson et al., 2018; Nordhaus, 2015; Somohano-Rodríguez & Madrid-Guijarro, 2022).

The spread of robotic technology began in the 1970s, initially in Japan and then in Germany (Cette et al., 2021). While some challenges and unresolved issues exist in the adoption of robotics, its application has been a beneficial tool for organizational growth (Wamba-Taguimdje et al., 2020). In 2021, a worldwide 31% increase in the installation of industrial robots in factories was reported, meaning that the number of firms adopting robots is increasing (International Federation of Robotics, 2023). The upward tendency of robotics adoption is one of the key factors that motivated us to explore its effects on firm performance. Therefore, we aim to research how using robotics in service and industrial areas affects firm performance by focusing on Estonian firm-level data. Alguacil et al. (2022) state that the use of robots is more prevalent in manufacturing firms compared to service firms based on 1990-2014 data. Therefore, we want to contribute to the literature by providing new analysis covering more recent information in the market (2014 - 2021) and testing whether service firms continue to lag behind manufacturing companies in adopting robots.

In our paper, we are analyzing how robot adoption, specifically service and industrial robots affect Estonian firms' total factor productivity and labor productivity. The impact of employed robotics on productivity in CEE countries, particularly in Estonia, remains a research gap despite numerous studies examining this relationship. Although some studies have explored the impact of robotics on firm productivity in CEE countries, such as those conducted by Bachmann et al. (2022) and Cséfalvay (2020), none of them has specifically focused on service robotics. This highlights the need for further research on the effects of employed robotics on productivity in CEE countries, including Estonia, to gain a better understanding of the potential benefits and limitations of adopting this technology. As such, our research aims to fill this gap by including service robots in our analysis to provide a comprehensive understanding of the impact of both industrial and service robots on productivity.

The pattern of employment of IT technologies and robotics in Estonia significantly differs from other OECD countries, such that the Estonian market has its own differences and specificity to IT, automation, and robotics adoption. Several factors contribute to that difference. The unique context of Estonia and its experience with technology make it an interesting case study for us to explore the relationship between robotics and firm performance. For example, Estonia has been a leader in digital innovation, with a supportive regulatory environment for technology startups (Heller, 2017). Compared to the advanced economies, such as the US, EU countries, and old EU member states, Estonian firms have a comparably great productivity gap and potential that leads them to adopt different proposed IT technologies (Azzopardi et al., 2020). However, statistics about robot density reveal that, compared to other European countries, Estonia has a relatively low level of robot adoption. In the country rankings of EUROSTAT, Estonia has one of the lowest shares (3%) of industrial and service robot adoption rate (see Appendix A) (Industrial Analytics Platform, 2021).

In our analysis, we measured how the adoption of robots in Estonian firms impacts total factor productivity (TFP) and labor productivity. Productivity is typically defined as units of output divided by units of input, and it shows how efficiently a certain amount of output is generated from a specific set of inputs. We calculated TFP by using the Levinsohn and Petrin (2003) methodology and measured labor productivity as value added per employee. We applied Ordinary Least Squares (OLS), Fixed effects (FE), and Propensity Score Matching (PSM) methods to measure the relationship between robotics adoption and productivity.

This article is structured into six sections. The second section discusses and compares the evidence from the theoretical and empirical literature on how Information Technology, Artificial

Intelligence, and robotics affect productivity. The third section presents data sources and descriptive statistics of all variables used in our analyses. The fourth section explains the methodologies that are used to measure the relationship between productivity and robotics adoption. The fifth section presents the results from all three analyses namely, OLS, FE, and PSM. Finally, the last section provides a summary and interpretation of the findings and conclusions of the study.

2. Literature review

In our paper, we will refer to available literature focusing on Information technology (IT), Artificial Intelligence (AI), and robotics. Since these are interrelated concepts, analyzing them together will give us broader insights. AI is the field of computer science that focuses on creating intelligent machines and learning from the patterns of repetitive processes to replicate human intelligence, which can be referred to as machine learning (Murphy, 2019; Raj & Seamans, 2019). Robotics, on the other hand, is the field of engineering science that focuses on the operation and design, construction of robots (Rajan & Saffiotti, 2017). For the purposes of our analysis, we defined industrial robots as "*an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications*" as per the Questionnaire manual of the Information Technology Survey (Questionnaires | Statistikaamet). Hence, an automatically controlled machine tool is not an industrial robot. Service robots are referred to as "*a machine, mostly mobile, that has a degree of autonomy and is able to identify the environment to operate in a complex and dynamic environment*" (Questionnaires | Statistikaamet). The Questionnaire manual of the Information Technology Survey excludes software robots from the definition of both industrial and service robots and further clarifies that automatically controlled machine tools are not considered as industrial robots.

IT is a general concept and includes a variety of technologies. It is worth grasping the idea what is the contribution of IT investments on firm performance overall. Then, we will use a bottom-down approach and will consider separate effects of IT tools, such as AI and robotics, in the current literature. In our literature review, to understand the impact of robot adoption, along with focusing on productivity impact, we will try to break the "productivity" term into several factors and assess the overall effects of IT and robotics adoption on output, company size, labor productivity, employment, and wages as well.

As mentioned by Brynjolfsson and Yang (1996), measuring the effects of IT on productivity has some complexities, and several studies with different methods have come to different results. Therefore, comparing the methodologies used in different studies is essential. Most studies on IT's impact on firm performance use accounting-related variables that ignore the intangible value of IT. However, (Mithas & Rust (2016) and Bharadwaj et al. (1999) analyzed the firm performance using Tobin's q value, which can reflect the potential market measure of the effects of IT investments on a company's future performance. Both studies concluded that firms' IT investments have significant and positive relationships with firms' performance.

Studies tried to uncover the effects of IT investments on a firm's performance by comparing different country and firm-level factors. For instance, Dewan and Kraemer (2000) looked at the IT effect on productivity in both developed and developing countries and found a positive effect of IT investments on productivity only in developed countries analyzed in 1985-1993. However, a more recent study covering the years 1994 - 2007 by Dedrick et al. (2013) found statistically significant evidence that firm productivity in developing countries also started to benefit from the contribution of IT investments. Referring to the above studies concluded in different time periods, IT and digitization effects on firms are changing as the IT sector grows over time. Brynjolfsson and Yang (1996) also found a tendency of continuous changes and improvements in the IT sector that lead to a positive relationship between IT investment and productivity.

From the perspective of cost-revenue comparison, Mithas and Rust (2016) highlighted that high levels of IT investment lead to the implementation of both revenue-increasing and cost-reducing strategies that enhance productivity more compared to firms with a one-sided strategy. On the other hand, Mithas et al. (2012) found no evidence that cost-reduction-focused IT investment contributes to productivity and put emphasis that IT investments on revenue have a greater impact on productivity than cost-reduction IT investments.

Artificial Intelligence (AI) has been developed over the years and is considered an essential element of IT nowadays. AI is not separate from IT, but it combines various IT configurations and systems that work together to automate routine work processes and facilitate intelligent decision-making and problem-solving (Wamba-Taguimdje et al., 2020). By utilizing AI, companies can benefit significantly from their IT infrastructure, leading to improved business performance and competitive advantage. Over time, AI has evolved into many different subfields and research areas, including image processing, natural language processing, robotics, and machine learning (Lee et al., 2018). Therefore, by incorporating AI concepts into robots, businesses can improve their efficiency, accuracy, and responsiveness, which could, in turn, have a positive impact on their overall performance.

Several studies have evaluated how the implementation of AI influences the performance of companies. Wamba-Taguimdje et al. (2020) have concluded that AI offers various advantages for firms to improve their productivity of organizational aspects and work processes. On the other hand, Mishra et al. (2022) evaluate the AI effects from financial and efficiency perspectives, and their findings support that in the short term, it increases costs due to the high demand for skilled employees and the requirement of higher wages for those positions. However, AI also contributes to productivity by cutting costs and automating certain tasks. Despite the increase in labor costs, results show that, overall, focusing on AI has a positive impact on a firm's efficiency measures, such as net profit (Mishra et al., 2022). Firms operating in the manufacturing sector are adopting AI technologies to improve their productivity and to gain a competitive advantage. A study by Pillai et al. (2022) focusing on Indian manufacturing companies concluded that the adoption of AI-empowered industrial robots has positively affected the return on investment and increased productivity by automating various stages of the manufacturing process. Similarly, the study by Wang et al. (2022) also reveals that the adoption of AI by Chinese manufacturing companies has resulted in a significant increase in Total factor Productivity (TFP).

However, the intention of companies to employ such AI-based robots is significantly affected by different factors. The list includes the expected benefits of the adoption of AI-based robots, and the level of vendor support is the influencing factor for the adoption of AI, but the level of government support and quality, and availability of IT infrastructure is a less essential factor in that regard (Pillai et al., 2022). In order to reap positive gains from the adoption of robots and AI, firms require high-quality human capital with advanced skills. Expertise of high-quality human capital can contribute to both technological progress and the optimization of factor allocation, leading to improvements in Total Factor Productivity (TFP) for firms. Furthermore, the advent of AI has led to attracting highly skilled workers and significantly improving the quality of human capital. Hence, alongside location-based and industry-based factors, digital and human capital development of firms is a crucial element that determines the effect of AI on productivity (Wang et al., 2022).

The concept of AI and robotics started to integrate as they advanced, and AI can be integrated into the development of the robotics field as an intelligent tool, and it is essential to integrate them to achieve a positive impact on society as well (Brady, 1985; Rajan & Saffiotti, 2017). Robots adopted by different firms can have different functionalities. Therefore, they can be classified into two distinct categories such as industrial and service robots, as they differ in their purpose and design. Other studies available in the literature review mainly define industrial robots as "an actuated mechanism, programmable in two or more axes, with a degree of autonomy" which aims to perform multiple tasks to increase efficiency by reducing human intervention (Cette et al., 2021; International Federation of Robotics, 2023; Raj & Seamans, 2019). On the other hand, service robots are mostly defined as interfaces or robots that can operate autonomously, adapt to different situations, and interact with customers in professional settings (International Federation of Robotics, 2023; Ivanov et al., 2017; Wirtz et al., 2018). However, the usage of service-focused robots does not necessarily lead to a better quality of service, and the impact of these automations depends on the level of the adopted technological advancement (Rust & Huang, 2012). In service companies, productivity and service quality are interrelated, and focusing on one may negatively impact another. Ivanov and Webster (2017) discover that the implementation of robots, artificial intelligence, and service automation (RAISA) in different service industries can lead to benefits in productivity as they can automate repetitive tasks and allow human employees to focus on more important tasks. Nonetheless, current technology doesn't permit the replacement of human employees with RAISA extensively as they are more of a technological aid to employees rather than their replacement. However, there is still a shortage of studies focusing on the effects of distinctively service robots. Therefore, without necessarily excluding the effect of service robots, in our literature review, we mainly interpret results based on the performance of industrial robots.

Koc and Bozdag (2009) researched how adopting different types of advanced manufacturing technologies (AMT) impacts small and medium-sized enterprises (SMEs) and how commonly SMEs adopt them. Results show that robotics is less commonly used AMT in SMEs compared to computer-aided design and manufacturing technologies. Chung (1996) research demonstrated that more than half of investments in AMT fail, mainly due to wrong AMT selection according to the firms' needs and poor infrastructures to support it. Koc and Bozdag (2009) and

Chung (1996) provided evidence for firms, especially for new firms, whether or not to employ AMTs for their different needs and which AMTs to employ.

There is a considerable number of studies measuring the relationship between digital technologies employed and the performance of the firms. However, the results highly depend on which methodology the authors used to assess the relationship (Cardona et al., 2013). Alguacil et al. (2022) investigated the effects of robot adoption and its effect on export activities using Propensity Score Matching (PSM) and Difference-in-Difference methods in their research. They concluded that employing robotics among manufacturing firms in Spain significantly increased the firms' export sales, firms' TFP, and introduction of new products into the market and also decreased the costs. Ballestar et al. (2020) also tested the link between the adoption of robotics and firms' productivity by focusing on Spanish SMEs during 2008-2015 by using the Structural Equations Model (SEM), a model that is largely used in measuring the productivity of SMEs. This study discovers that there is a 5% increase in these robotics SMEs' productivity compared to non-robotics SMEs. A study by Kromann et al. (2020) also measured the impact of automation on TFP by using Fixed effects (FE) and Ordinary Least Squares (OLS) methods. The study concludes that greater utilization of industrial robots has a positive effect and results in more than a 6% increase in TFP within a 3-year timeframe.

The results of studies show that using various methods and country-level data leads to different conclusions. (Somohano-Rodríguez and Madrid-Guijarro (2022) analyzed the 274 Spanish SME companies' data using the Generalized Method of Moments (GMM) and concluded that there is a negative relationship between investment in Advanced Robotics and sales revenue due to complicated human-robot relationships. In this context, Advanced Robotics is a tool that enhances digital transformation and is referred to as one of the digital enablers, as it is often integrated with other digital technologies such as AI and machine learning. Cette et al. (2021) used OLS regression focusing on a longer time span (1975-2019) and data from 30 OECD countries in their research to find the degree of the effects of robotics on firm productivity via TFP and capital deepening. Overall, the contribution of robotics is not a remarkable factor in increasing firm performance in all countries studied in this paper. They concluded that the highest contributions of robotics to productivity were in Japan and Germany during specific time periods only. Afterwards, this relatively high contribution rate also lost its importance. The decrease in the amount of robotics was caused by the crisis in the IT sector and the relocation of activities in the automobile, electrical, and electronic industries. As a result, the study concludes that the implementation of robots did not result in a notable improvement in productivity in these countries. Moreover, Cette et al. (2021) show that at the firm-level analysis, this impact is small and less significant compared to the country-level analyses.

A growing amount of literature shows that several studies based on the firm-level data of French, Italian, and Chinese firms reveal the importance and positive impact of robotics on the firm's productivity (Acemoglu et al., 2020; Bettiol et al., 2019; Bonfiglioli et al., 2020; Huang et al., 2022). While robot adoption has a significant positive effect on productivity in general, its impact on aggregate sales was not strong (Bonfiglioli et al., 2020). This may lead to the conclusion that the efficiency gains from robot adoption do not necessarily associate with output prices, rather, it increases markups which increases the market dominance of large-sized firms.

One factor that highlights the role of robotics on productivity is the firm's past growth performance. More specifically, firms that have a high level of initial productivity have more high-skilled workers, and are large get more benefits from adopting robots compared to firms with middle and lower-level initial productivity and size (Bonfiglioli et al., 2020; Koch et al., 2021; Stiebale et al., 2020). Contrarily, the same size firms that require more skilled workers are less likely to adopt robots (Koch et al., 2021). Another factor that influences the firm's financial performance is the number of robots adopted by firms. Findings by Graetz and Michaels (2018) imply that there are decreasing returns in productivity as robot usage increases. Moreover, the analysis of Italian firms' survey data by Bettiol et al. (2019) also revealed that the adoption of digital technologies could have both negative and positive impacts on performance depending on the number of different digital technologies adopted. Hence, employing more than three different technologies has no significant contribution to firm performance, and finding the technology that fits best to a firm's needs is the key factor to a positive impact on performance. According to Bettiol et al. (2019), considering all types of digital technologies, only the adoption of robotics and laser cutting positively contribute to the firms' performance due to firms having more expertise on how to integrate robotics and laser cutting into their operations compared to other relatively new AI-related technologies.

Robots are expected to become increasingly prevalent and replace tasks previously performed by human labor. Several papers focused on assessing the impacts of robotics on wages, employment, and labor productivity factors which are essential contributors to overall productivity. Graetz and Michaels (2018) find no negative evidence of robotics adoption on employment on the aggregate level. However, they conclude that it may affect low-skilled workers by reducing job opportunities for them. The adoption of robots may lead to increasing demand for a skilled workforce (Jung & Lim, 2020). According to Acemoglu et al. (2020) and Acemoglu and Restrepo (2020), robotics is increasing labor productivity, but employment rate and labor share are negatively affected as robot adoption is becoming more prevalent. Findings support that the adoption of robots may affect employment and wages in two ways: robots can increase productivity by adding efficiency to work processes; however, the replacement of workers results in a reduction in employment and salaries (Acemoglu & Restrepo, 2020; Jung & Lim, 2020). Despite the fact that robotics causes a decline in unit labor costs, at the same time, robotics has positive effects on employment as it leads to an increase in hourly compensation level, suggesting that the increase in productivity is more significant than the increase in wages (Jung & Lim, 2020). In this sense, robotization can be seen as a positive contribution, as it allows firms to increase profits and productivity without the need to hire more workers (Stiebale et al., 2020).

Although many studies measure the impacts of different types of ITs on firm performance, we identified that there is still a research gap in measuring how employed robotics affects productivity, especially in Estonia. Several studies focused on the impact of IT and information communication technology (ICT) tools on the productivity of Estonian firms. Azzopardi et al. (2020) have done research on the effect of IT technologies on productivity by focusing on the Estonian market and comparing it with other OECD countries. The study concludes that although positive effects of digital change have been observed, overall aggregate productivity has been impacted negatively in OECD countries, including Estonia. A variety of factors has contributed to that conclusion, and one of the main reasons is the increased productivity gap between best-performing and less digital-intensive firms (Andrews et al., 2016). Also, Dashdamirova and Nilufar (2021) assessed the relationship between the adoption of Enterprise Resource Planning (ERP) and Customer Relationship Management (CRM) and firms' productivity and concluded that, in general, firms that employed Information and Communication Technologies (ICT) have higher productivity. However, under the Fixed Effects (FE) model, the analysis showed no significant linkage to productivity, and analyzing from the Propensity Score Matching (PSM) perspective, the analysis showed that firms adopting ICT (ERP and CRM) demonstrated higher productivity in the next year of adaptation of that ICT.

(Azzopardi et al., 2020) conclude in their study that, compared to the other EU countries, only a minor percentage (approx. 5%) of Estonian firms have actually adopted service or manufacturing robots in their work processes, and the automation level of production is low (approx. 20%) at the country level. Given such low employment of automation and robotics in Estonia, we aim to research how using robotics in service and industrial areas affects firm performance by focusing on Estonian firm-level data.

(Alguacil et al., 2022) state that the use of robots is more prevalent in manufacturing firms compared to service firms based on 1990-2014 data. Therefore, we want to contribute to the literature by providing new analysis covering current information in the market (2014-2021) and testing whether service firms still lag behind manufacturing companies in adopting robots. Additionally, existing literature mainly focuses on the analysis of robot adoption on employment and labor productivity (Acemoglu et al., 2020; Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018; Jung & Lim, 2020), therefore our study will be helpful to contribute to literature analyzing the effects of robot adoption on both labor and total factor productivity based on firm-level data.

3. Data

Our research utilized two primary data sources: the Business Registry data spanning the period from 1995 to 2021 and the Information Technology Survey (IT Survey) conducted between 2014 and 2022. The former provided various financial information about Estonian firms, while the latter comprised a questionnaire aimed at capturing different types of IT tools employed by firms in Estonia. Given that the IT Survey has been administered annually since 2014, we restricted our analysis data for the period between 2018 and 2021 to ensure consistency across our databases since robotics-related data is present after 2018. Additionally, to calculate labor productivity for the year 2022, we used the firm-level open data from the Estonian Tax and Customs Board on companies' tax payments.

The Information Technology Survey consists of different sections and mainly provides data about the use of the internet, e-commerce, ICT, and Artificial Intelligence technologies. We specifically extracted data from the IT Survey regarding the use of robotics by firms, including information on the type of robots employed (i.e., industrial or service). To evaluate the impact of robotics adoption on firm performance, we used variables related to firm performance from the Business Registry data to calculate Total Factor Productivity (TFP) and Labor Productivity (LPV) as value added per employee and turnover per employee (LPQ). Overall, our study sought to shed light on the relationship between robotics adoption and firm performance while providing insights into the drivers behind such adoption decisions.

We calculated labor productivity and TFP and included them in our analysis as dependent variables. Considering that several factors can also affect a firm's productivity level, we included them in our analysis as control variables. For instance, the size of the firm may affect the amount of resources invested in robotics technology, the type of industry influences the adoption of robotics, or the amount of R&D investment may result in productivity gains. Also, newer firms may be more agile and better able to adopt new technologies, while older firms may be more resistant to change. Therefore, we added firm age, firm size, research and development expenses per employee, export, foreign ownership and 2-digit industry dummies as control variables since we believe each of these factors can affect a firm's productivity level. By controlling for these variables, we aim to isolate the impact of robotics on productivity. The Table 1 summarizes the description of the variables we used in our analysis.

Table 1

Variables used in the analysis

Data source	Variable name	Description	Variable type
Business Registry Data	Labor Productivity	LPV- Labor productivity calculated as value added per employee LPQ - Labor productivity calculated as turnover per employee.	Dependent variable
	TFP	Calculated by using Levinsohn and Petrin methodology	Dependent variable
	Firm size	Log value of the number of employees	Control variable
	Firm age	Difference between the current year and the firm's registration year	Control variable
	Foreign ownership dummy	Firm is owned by individuals or entities from another country	Control variable
	Export dummy	Firm has exports	Control variable
	Research and development expenses	Firm's log value of R&D expenses per employee	Control variable
Information Technology Survey	Industry type	2-digit industry codes by EMTAK (Estonian Classification of Economic Activities)	Independent variable

	Robotics dummy	Firm uses robotics	Independent variable
	Industrial robotics dummy	Firm uses manufacturing robots	Independent variable

Source: Information Technology Survey (2014-2022) from Statistics Estonia, Estonian Business Registry data (1995-2021)

The IT survey provides data about robotics usage in 2018, 2020, and 2022, including whether the firms use service or manufacturing robotics and information about the main motivation of firms to employ robotics in their operations. Since IT survey data on robotics is limited to 3 years and Business registry data is provided until 2021, we have to restrict our analysis to 2018 and 2021 data. However, we will also display robotics data of 2022 in the descriptive analysis part for the purposes of additional clarification without including this year's data in our econometric analysis.

Table 2

Frequency table of robotics variables

Variables	*Year /Response*	***2018***		***2020***		***2022***		***Total***	
		Frequency	*%*	*Frequency*	*%*	*Frequency*	*%*	*Frequency*	*%*
Robotics dummy	No	2910	94.97%	2736	94.51%	2656	91.74%	8302	93.77%
	Yes	154	5.03%	159	5.49%	239	8.26%	552	6.23%
Manufacturing robots dummy	No	2929	95.59%	2761	95.37%	2703	93.37%	8393	94.79%
	Yes	135	4.41%	134	4.63%	192	6.63%	461	5.21%
Service robots dummy	No	3032	98.96%	2855	98.62%	2835	97.93%	8722	98.51%
	Yes	32	1.04%	40	1.38%	60	2.07%	132	1.49%

Source: Information Technology Survey (2014-2022) from Statistics Estonia

Table 2 summarizes the responses on whether Estonian firms adopted robotics, including industrial and service robotics dummies. The robotics dummy combines the users' responses on robotics usage. It indicates whether the firm employed any type of robots in its business activities. In contrast, other manufacturing robots and service robots' dummies specifically indicate whether the firm employed the mentioned type of robots or not. The table summarizes the responses by frequency of responses and their percentage distributions by 2018, 2020, and 2022, as we have available data for these mentioned years.

The frequency table shows that the adoption of robotics is not popular among the majority of firms. This observation is further strengthened by the figure presented in Appendix A, which indicates a comparatively lower level of robotics adoption in Estonia compared to other European countries. When looking at the totals, we can conclude that the number of firms using robotics is summed up to 154 firms, with only 32 of these firms using service robots for 2018. The adoption rate in the following years has relatively increased. From the data, 13 firms in 2018 and 2022, and 15 firms in 2020 reported using both types of robots. By percentage-wise, this sums up to only 6.23% of the firms that participated in the survey use either type of robotics. However, as we can observe, mainly used robotics are industrial robots, with a frequency of 5.21%, and service robots accounted for only 1.49%. On a biannual basis, we can observe an increase in the share of firms using robotics, including both industrial and service robots, an overall 64% positive change in the range of 4 years. Additionally, among the robotics-adopters, 64 firms have used manufacturing robots both in 2018 and 2020, while only eight firms adopted service robots for both years.

Table 3

Robotics usage fields

Robotics usage fields	**2018**		**2020**	
	Count	*%*	*Count*	*%*
Surveillance, security, or inspection tasks	9	18.75%	5	9.26%
Transportation of people or goods (autonomous vehicle)	4	8.33%	5	9.26%
Cleaning or waste disposal tasks	2	4.17%	10	18.52%
Warehouse management systems (e.g., palletizing handling, picking goods, etc.)	13	27.08%	18	33.33%
Assembly works performed by service robotics	9	18.75%	5	9.26%
Robotic store clerks	10	20.83%	9	16.67%
Construction works or damage repair tasks	1	2.08%	2	3.70%

Source: Information Technology Survey (2014-2022) from Statistics Estonia

Table 3 describes the main reasons for firms to employ robotics by year. Since we only have the same questionnaire across the 2018 and 2020 years, we include only these two years to calculate the distributions. Among the robotics-adopted firms in both years, the robotization of warehouse management systems is the most popular reason for employing robotics in Estonia. The other popular responses are the robotic store clerks, surveillance, security, and assembly works performed by service robotics. Since only a few of the robotics-adopted firms responded to the question regarding usage fields of robotics, the number of responses in the table is very low compared to Table 2.

Table 4

Descriptive Statistics

Type of variable	Variable name	Observation	Mean	Std. deviation	Min.	Max.
Independent variables	Robotics (dummy)	5959	0.05	0.22	0	1
	Service robots (dummy)	5959	0.01	0.11	0	1
	Manufacturing robots (dummy)	5959	0.05	0.21	0	1
Dependent variables	Labor productivity(loglpv)	4638	10.33	0.73	3.84	13.58
	Labor productivity(loglpq)	5820	11.23	1.09	-0.19	16.34
	TFP (log)	3720	9.66	1.14	3.44	14.94
Control variables	Export (dummy)	4930	0.68	0.47	0	1
	Foreign ownership (dummy)	6119	0.17	0.37	0	1
	R&D expenses(log)	5467	0.17	1.01	-1.45	10.7
	Firm age	6707	18.28	8.4	1	31
	Firm size (log)	5927	3.48	1.15	0	8.25

Source: Information Technology Survey (2014-2022) from Statistics Estonia, Estonian Business Registry data (1995-2021)

The descriptive statistics table also shows that among the survey participants, only 5% and 1% of firms use industrial and service robots, respectively. Additionally, it is noteworthy to mention that small and medium-sized firms are the primary adopters of robotics, as illustrated in Figure 1. According to the OECD definition of firm-size categorization, among the robotics adopters, 54% of the firms in our sample are medium-sized, 26% are small-sized, and only 18% are large-sized. The adoption of robotics is less popular among micro-sized firms, as micro-firms constitute a mere 2% of the adopters of robots. Based on the results presented above, it can be implied that while the majority of firms adopting robotics are small and medium-sized, the adoption rate is slowly increasing on a bi-yearly basis. Thus, we can conclude that it is the prospective field that firms are slowly integrating. However, large-sized firms account for a relatively smaller proportion of the firms adopting robotics. The economy could experience a more substantial impact if larger firms were to increase their rate of robotics adoption.

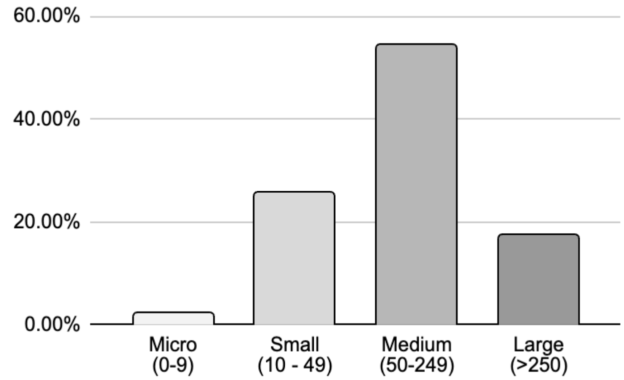
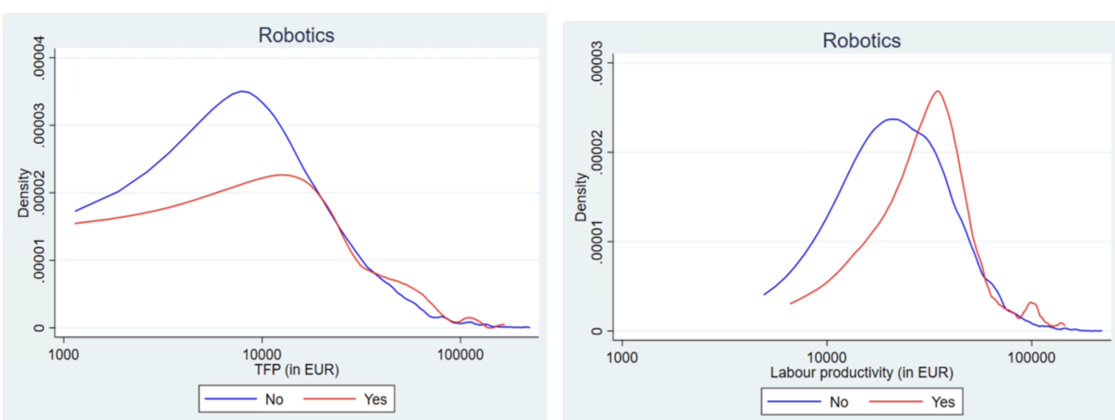


Figure 1. Robotics adopted firms specified by firm size

Source: Information Technology Survey (2014-2022) from Statistics Estonia

We compared the distributions of productivity variables, namely, the TFP and labor productivity, by visualizing the relationship between two groups (adopters and non-adopters). Kernel density graphs help to illustrate differences between the distributions of these two groups by visually comparing the shapes of the two density curves. In Figure 2, we plotted the Kernel density graph to demonstrate the relationship of robotics adopted and non-adopted firms by their TFP and labor productivity distributions. As can be observed from the density graphs, the productivity of robotics-adopted firms is slightly different, which means that the two groups have different patterns of productivity. Due to the limited number of responses, the sample size for service robots is relatively small. Therefore, the graph of service robots may not provide a reliable representation for productivity and should be interpreted with caution.



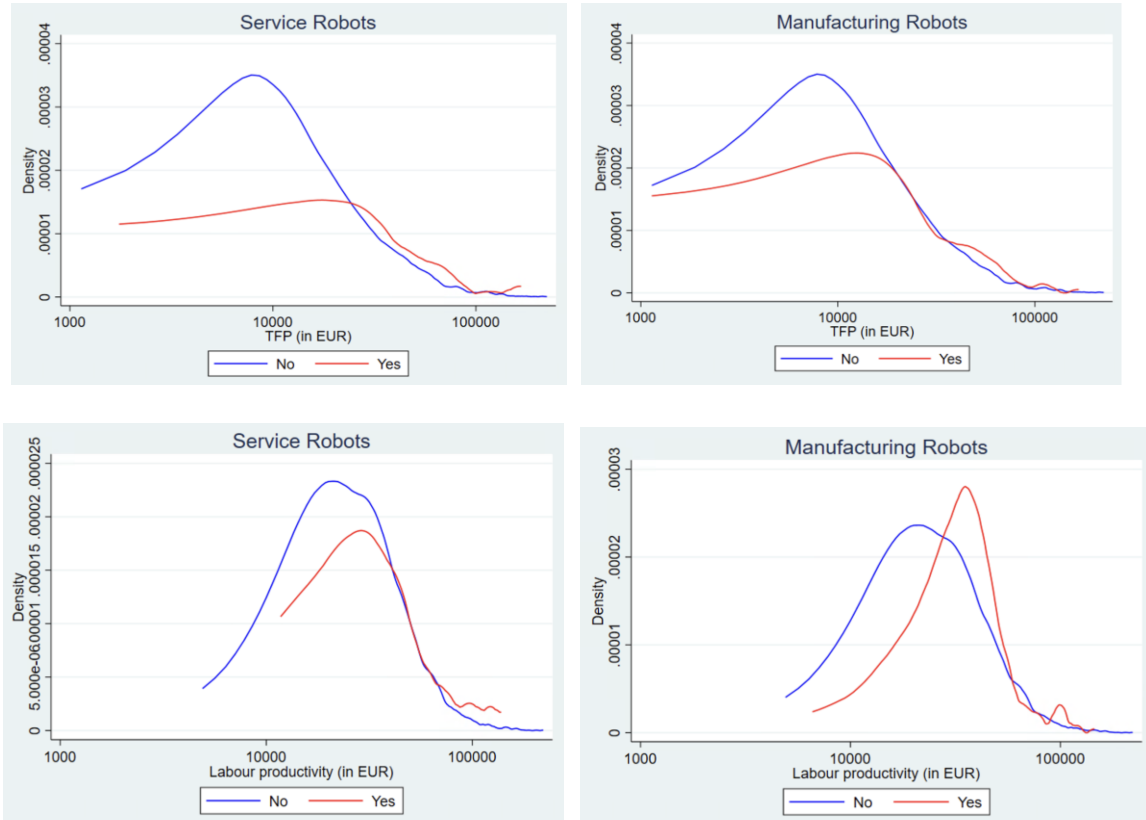


Figure 2. Kernel density graph for TFP and labor productivity

Source: Information Technology Survey (2014-2022) from Statistics Estonia, Estonian Business Registry data (1995-2021)

Overall, Kernel density graphs show that firms employing robots have slightly different productivity levels. This difference may suggest that there is a relationship between robot adoption and productivity, and it can be due to productive firms being more likely to introduce robots. Also, we ran the Kolmogorov-Smirnov (KS) test that compared the cumulative distribution functions (CDF) of the two groups, and there was no significant difference between the adopters and non-adopters in terms of their TFP distributions. However, the difference was significant in the labor productivity distributions of these two groups.

4. Methodology

Based on the questionnaire data, we classified firms that have adopted robotics as a treatment group, while firms that have not employed robots will be regarded as a control group. Through a comprehensive review of the literature, we have determined that Ordinary Least

Squares (OLS), Fixed Effects (FE), and Propensity Score Matching (PSM) are the most widely utilized methods to examine the association between technology adoption and firm performance, as indicated in recent studies (Alguacil et al., 2022; Dashdamirova & Nilufar, 2021; Huang et al., 2022).

Several methods also can be used to calculate our productivity variables, labor productivity, and TFP, with each method having its own assumptions and applicability. One of the most common methods for TFP calculation is Olley-Pakes (1996) method which assumes that firms have the same production function but vary in their level of efficiency. Ackerberg et al. (2007) method estimates TFP by using a semiparametric estimator and calculates TFP based on the differences in firms' efficiency. Blundell and Bond (2000) assumes that TFP evolves over time, and it is affected by both observed and unobserved factors. Considering our data specifics and analysis methods, we used Levinsohn and Petrin (2003) method to calculate TFP. Levinsohn-Petrin method estimates the magnitude of unobservable productivity shocks, which is then used as a measure of TFP. To calculate this variable, we utilized the costs of raw materials, goods, and services as substitute variables in the production function and adjusted all variables based on price deflators.

In our analysis, we calculated labor productivity (hereinafter, LPV) by using the value added per employee method, whereby labor productivity is determined by dividing the total value added (total output minus the cost of the materials and service used) by the number of employees. LPV indicates each employee's contribution to the overall output value and is an important metric of firm efficiency.

To investigate the relationship between productivity and robotics, we first use OLS regression analysis, and then to gain confidence in our results, we run Fixed Effects (FE) and Propensity Score Matching (PSM) analyses to measure changes more accurately. OLS is one of the most commonly used statistical methods that allow us to evaluate the statistical significance of the relationship between our variables by obtaining accurate and efficient estimates of coefficients. To ensure the reliability of our results, we consider other firm-level factors that may impact the relationship between robotics adoption and productivity, such as the log values of the firm's size, research and development expenses per employee, export, foreign ownership, industry dummies and the firm's age. We included these variables as control variables in our regression analysis to distinguish the specific effect of our independent variable. To measure the distinct effect and combined contribution of each variable on our outcome, we analyzed the adoption of service and manufacturing robots both separately and together. In our OLS regression equation below, the left-hand side denotes a firm's productivity at a particular time, and the right-hand side represents our independent and control variables. In the equation below, the variable *Robotics* refers to three types of adoption (adoption of service, manufacturing, and either type of robots):

$$Y_{it} = \alpha_0 + \alpha_1 Robotics_{it} + \alpha_2 Firm\_ageit + \alpha_3 Export\_dummy_{it} + \alpha_4 Industry\_dummies_{it} + \alpha_5 Firm\_size_{it} + \alpha_6 R\&D\_expense_{it} + \alpha_7 FDI\_dummy_{it} + \varepsilon_{it}$$

Moreover, to extend the scope of our analysis, we assessed the effects of robotics on firm performance across manufacturing and service sectors. This approach enabled us to develop a more comprehensive understanding of the relationship between our dependent and independent variables within these industries.

We used the FE model on panel data covering 2018 and 2020 years to estimate the coefficients of our independent and control variables and assess their impacts on firm productivity. The firm's age, log value of firm size, research and development expenses per employee, export and foreign ownership dummies were included as control variables to obtain more reliable estimates. The results of FE and OLS regressions were reported in terms of estimates of coefficients, their statistical significance, and R-squared values.

While OLS and FE methods control for observable variables, they may not fully account for unobservable variables that affect both the treatment and the control groups. Therefore, in addition to OLS and Fixed Effects analyses, we run the PSM analysis to address the potential selection bias that may be present in our data. PSM can mitigate this bias by matching treated and untreated observations based on their propensity scores. By matching observations with similar propensity scores, we can reduce selection bias and provide more accurate estimates of treatment effects. The PSM method is specifically advantageous in comparing two groups of data as treatment and control groups. Considering that our independent variable has two groups, firms that use robotics and firms that do not, using PSM will give us more precise estimations.

In our PSM model, we took 2020 as the base year. The firms that did not use robotics (either service or manufacturing robots) are included in the control group, and firms that did not adopt robotics in period t-2 (2018) but adopted it in period t (2020) are included in the treatment group. We run two different analyses to compare the firms' TFP and labor productivity. In the first model, we analyzed the productivity of firms in the previous period (at *t-2*) and after one year (at *t+1*) adoption of robotics (both either service or manufacturing robots). In the second model, we compared the firm's productivity levels before (at *t-2*), and after two years (at *t+2*) adopting robotics. We used the second model only in measuring labor productivity since 2022 data is missing for TFP.

To calculate propensity scores, we estimated a regression model where the dependent variable is a binary treatment indicator, and the independent variables are likely to influence the firm's decision to adopt robotics and productivity outcomes. Thus, the estimated regression model provides a propensity score of a firm adopting robotics at period *t* based on its observed characteristics at period *t-2*. The propensity score is essentially the probability of being treated given the observed covariates at period *t-2*. The probit regression equation for estimating propensity scores can be written as follows:

$$probit\ (P(R = 1)) = \beta_0 + \beta_1 Firm\_age + \beta_2 Firm\_size + \beta_3 R\&D\_expense + \beta_4 FDI\_dummy + \beta_5 Export\_dummy + \beta_6 Industry\_dummy$$

where R is the robotics dummy (1 if the firm adopted robotics at period t, 0 otherwise), β is a vector of coefficients, and probit (P(R = 1)) is the natural logarithm of the odds of adopting robotics at period *t* given the observed covariates at period *t-2*, i.e. all explanatory variables in the equation are measured at *t-2*.

After estimating the propensity scores, we matched treated and control firms based on their propensity scores using a nearest neighbor matching method. It is a common method that selects and matches control units based on the most similar and closest to treated units in terms of their propensity scores. The matching process involves selecting one or more control firms that are similar in terms of their propensity scores to each treated firm, and then comparing the productivity outcomes between the matched treated and untreated firms. The ATT (Average Treatment Effect on the Treated) is a statistical measure to estimate the impact of a particular change on the outcome variable, in our case, the impact of the adoption of robotics on outcome variables, the firm's labor productivity, and TFP. In our analysis, the ATT represents the gap between productivity variables of a firm that has transitioned from not using robotics to using one at period *t* against the hypothetical scenario in which the same firm will not adopt any type of robotics. The equation of ATT is given below:

$$ATT = E(Y_{it}(1) - Y_{it}(0)|R_i=1) = E(Y_{it}(1)|R_i=1) - E(Y_{it}(0)|R_i=1)$$

Here, ATT is calculated as the difference between the actual productivity outcomes of a firm that adopted robotics ($Y_{it}(1)|R_i=1$), and the productivity outcomes of the same firm if it had not adopted robotics ($Y_{it}(0)|R_i=1$). This difference represents the impact of robotics adoption on the firm's productivity, and is expressed as the expected value of the difference between the two productivity measures, $E(Y_{it}(1) - Y_{it}(0)|R_i=1)$.

We have included our productivity variables by controlling for different firm-specific variables, such as number of employees, firm age, R&D expenses per employee, year, export and foreign ownership that may influence the outcome. We run the analysis for each productivity variable separately, which allows us to estimate the treatment effect of robotics adoption on each productivity measure.

5. Results

5.1 Ordinary Least Squares

In this section, we present the results of analysis we performed to measure the relationship between the adoption of robotics and total factor and labor productivity in Estonia. Initially, we run OLS regression to analyze the association of service and manufacturing robotics with productivity and examine the relationship between these variables in a quantitative manner. The study examined the relationship of employing robotics and either manufacturing or service robots on labor productivity and TFP.

Table 5.

OLS results for TFP

	Robotics	**Manufacturing robots**	**Service Robots**
Robotics (dummy)	0.083* (0.05)		
Manufacturing robots (dummy)		0.067 (0.04)	
Service robots (dummy)			0.129 (0.16)

Firm size (log)	0.259*** (0.01)	0.260*** (0.01)	0.260*** (0.01)
Export (dummy)	0.225*** (0.03)	0.225*** (0.03)	0.226*** (0.03)
Foreign ownership (dummy)	0.158*** (0.03)	0.158*** (0.03)	0.158*** (0.03)
R&D expense (log)	0.012 (0.01)	0.012 (0.01)	0.012 (0.01)
Firm age	-0.006*** (0.00)	-0.006*** (0.00)	-0.006*** (0.00)
Constant	8.058*** (0.08)	8.056*** (0.08)	8.060*** (0.08)
Observations	2796	2796	2796
R-squared	0.751	0.751	0.751

Note: Standard errors are presented below the coefficients in parentheses. In the regression, industry and year dummies have also been used, but for illustrative purposes, they are excluded from the table. P-values: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Source: Compiled by authors

The results presented in Table 5 demonstrate the relationship between the overall robot adoption, and separately for manufacturing and service robots and TFP. Upon analyzing the adoption of robotics in its entirety, it is significant at a 10% level, and the findings show that firms that adopt one or both types of robotics, on average, have 9% higher productivity compared to non-adopters. Our findings do not provide sufficient evidence to support the claim that the adoption of manufacturing or service robots separately can significantly have an association with TFP.

Table 6

OLS Results for Labor Productivity

	Robotics	**Manufacturing robots**	**Service Robots**
Robotics (dummy)	0.182*** (0.04)		
Manufacturing robots (dummy)		0.182*** (0.04)	
Service robots (dummy)			0.124 (0.10)
Firm size (log)	0.006 (0.01)	0.007 (0.01)	0.010 (0.01)

Export (dummy)	0.280*** (0.03)	0.280*** (0.03)	0.281*** (0.03)
Foreign ownership (dummy)	0.167*** (0.03)	0.166*** (0.03)	0.168*** (0.03)
R&D expense (log)	0.032*** (0.01)	0.032*** (0.01)	0.032*** (0.01)
Firm age	-0.001 (0.00)	-0.001 (0.00)	-0.001 (0.00)
Constant	10.022*** (0.08)	10.020*** (0.08)	10.019*** (0.08)
Observations	3308	3308	3308
R-squared	0.234	0.234	0.231

Note: Standard errors are presented below the coefficients in parentheses. In the regression, industry and year dummies have also been used, but for illustrative purposes, they are excluded from the table. P-values: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Source: Compiled by authors

Table 6 presents the results of the OLS regression analysis that aimed to investigate how robotics adoption is linked with labor productivity. The results demonstrate that there is a strong association with the adoption of either type of robots and the adoption of manufacturing robots with firm's labor productivity at a 1% level of significance. The findings suggest that the adoption of manufacturing robotics is associated with a 20% higher labor productivity than firms that do not use robotics, while holding other independent variables constant. In contrast, the service robots are not linked with higher levels of productivity as the variable does not show significant results. This may be due to the smaller adoption rate and small sample size of service robots compared to manufacturing robots' data. Overall, the results show that employing robotics, particularly manufacturing robots, can improve labor productivity.

Our results are also supported by Jung & Lim (2020) that looked at the effect of industrial robots on labor productivity and found positive relationships. Several other studies also found that the adoption of robotics has a positive impact on labor productivity (Acemoglu et al., 2020; Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018).

In order to obtain a more comprehensive understanding of the relationship between robotics adoption and productivity, we run the OLS regressions separately for firms operating in the service and manufacturing sectors. The aim was to determine the impact of robotics on TFP and labor productivity in specific industries. Table 7 demonstrates the regression analysis results for both labor productivity and TFP of firms in the manufacturing and service sectors.

Table 7

OLS Results for TFP and Labor Productivity for sectors

	TFP	
	Manufacturing sector	Service sector
Robotics (dummy)	0.082* (0.05)	0.164 (0.12)
Manufacturing robots (dummy)	0.072 (0.05)	0.119 (0.10)
Service robots (dummy)	0.099 (0.13)	0.203 (0.25)
	Labor productivity	
	Manufacturing sector	Service sector
Robotics (dummy)	0.212*** (0.05)	0.194** (0.09)
Manufacturing robots (dummy)	0.203*** (0.05)	0.198** (0.10)
Service robots (dummy)	0.179 (0.13)	0.159 (0.15)

Note: Standard errors are presented below the coefficients in parentheses. In the regression, explanatory variables have also been used, but for illustrative purposes they are excluded from the table. P-values: *** p<0.01, ** p<0.05, * p<0.1.

Source: Compiled by authors

Upon analyzing the results for the service sector, again, we found that the adoption of robotics does not have a significant linkage with TFP, as presented in Table 7. However, the results explain that manufacturing sector firms that employed one or both types of robotics in their operations may achieve an 8.6% increase in TFP by utilizing robots. In contrast, when looking at the adoption of service and industrial robots separately, results do not support that there is a significant linkage.

When looking at the association of robots with labor productivity, only service robots do not have significant results in either sector. On the other hand, the adoption of only manufacturing robots is associated with approximately 22% higher labor productivity in both sectors. The results of the robotics dummy indicate that employing one or both types of robotics can increase the labor productivity on average 24% and 21% in manufacturing and service sectors, respectively. Compared to the service sector, these results suggest that the benefits of adopting robotics are more pronounced for firms in the manufacturing sector.

Overall, the results of OLS analysis show that the adoption of robotics has more significant effects on labor productivity compared to TFP, and we could not find any indicator that service robots have relationships with productivity variables.

5.2 Fixed Effects

To better understand the impact of robotics adoption on firm productivity by controlling for unobserved heterogeneity at the firm level, we also employed Fixed Effects analysis. We can isolate the within-firm variation in robotics adoption and productivity by including firm-specific fixed effects in the model, which provides a more accurate estimate of the relationship. Specifically, we investigated whether firms were able to enhance their productivity levels by adopting either or both types of robotics.

Table 8

Fixed Effect Results for TFP

	Robotics	**Manufacturing robots**	**Service Robots**
Robotics (dummy)	0.001 (0.05)		
Manufacturing robots (dummy)		0.014 (0.06)	
Service robots (dummy)			-0.008 (0.13)
Firm size (log)	0.330*** (0.05)	0.330*** (0.05)	0.330*** (0.05)
Export (dummy)	0.022 (0.06)	0.022 (0.06)	0.022 (0.06)
R&D (log)	-0.017 (0.02)	-0.017 (0.02)	-0.017 (0.02)
Foreign ownership	0.076 (0.06)	0.076 (0.06)	0.075 (0.06)
Firm age	-0.022*** (0.01)	-0.022*** (0.01)	-0.022*** (0.01)
Constant	8.937*** (0.25)	8.935*** (0.25)	8.937*** (0.25)
Observations	2796	2796	2796
R-squared	0.067	0.067	0.067

Note: Standard errors are presented below the coefficients in parentheses. In the regression, year dummies have also been used, but for illustrative purposes they are excluded from the table. P-values: *** p<0.01, ** p<0.05, * p<0.1.

Source: Compiled by authors

Table 9

Fixed Effect Results for Labor productivity

	Robotics	**Manufacturing robots**	**Service Robots**
Robotics (dummy)	-0.015 (0.06)		
Manufacturing robots (dummy)		-0.006 (0.06)	
Service robots (dummy)			-0.056 (0.12)
Firm size (log)	-0.085* (0.05)	-0.085* (0.05)	-0.083* (0.05)
Export (dummy)	0.024 (0.06)	0.024 (0.06)	0.023 (0.06)
R&D (log)	-0.025 (0.02)	-0.025 (0.02)	-0.025 (0.02)
Foreign ownership	0.086 (0.06)	0.086 (0.06)	0.085 (0.06)
Firm age	-0.015** (0.01)	-0.015** (0.01)	-0.015** (0.01)
Constant	10.919*** (0.23)	10.918*** (0.23)	10.914*** (0.23)
Observations	3308	3308	3308
R-squared	0.011	0.011	0.011

Note: Standard errors are presented below the coefficients in parentheses. In the regression, year dummies have also been used, but for illustrative purposes they are excluded from the table. P-values: *** p<0.01, ** p<0.05, * p<0.1.

Source: Compiled by authors

The results of FE analysis in Table 8 and Table 9 indicate that the adoption of robots, either or both types, does not have a statistically significant effect on TFP and labor productivity. That is, we were unable to find any evidence that the adoption of robotics affects TFP during the period of treatment. These insignificant results obtained from fixed effects analysis might be caused by multiple factors. One of the reasons for such results can be the short timeframe which covers only biannual data over two years, and this limits our ability to observe longer-term effects. Since the adoption of robotics is a more recent phenomenon compared to the other technological advancements, the time to adapt and develop important skills to achieve significant effects should be taken into consideration. Moreover, productivity is influenced by multiple factors such as organizational cultures, skill levels, management practices and other company-related factors besides robotics adoption. Including all these factors as control variables and accurately capturing their combined effects is challenging. Additionally, as the sample size in our study is relatively small, the analysis may not capture the true relationship between robotics adoption and productivity by reducing the ability to identify significant effects. Therefore, further investigation with a larger sample size and longer time horizon may be required to understand the relationship between robotics adoption and productivity fully.

5.3 Propensity Score Matching

Lastly, we conducted PSM analysis to take a step closer to the detection of the causal effects. In the PSM models, we looked at how the adoption of either or both types of robotics has a treatment effect on firms' TFP and labor productivity. In particular, we built two PSM analyses to observe the effect of robotics in the following periods, at *t+1* and at *t+2*.

We could not observe that the adoption of service robotics at period *t-2* has any significant positive effect either in TFP or labor productivity of firms in the following years (at *t+1* and *t+2*) as outlined in Table 10 and Table 11. Also, we could not find any significant evidence that the adoption of either type of robots affects a firm's TFP. However, only the adoption of manufacturing robots will increase their labor productivity by 27% at *t+1*, and this result is significant at 10%. Moreover, the effect becomes even more pronounced over time, and we are observing an increase in labor productivity in the size of 38% (at a 5% significance level) at *t+2*. Results summarize that, different from service robots, the adoption of manufacturing robots have affected labor productivity positively, with the magnitude of the effect increasing as more years pass.

Table 10

PSM analysis for Labor productivity

ATT	*Robotics*	*Manufacturing robots*	*Service robots*
	t+1	*t+1*	*t+1*
Treated	9.875	9.806	10.299
Control	9.919	9.567	1.101
Difference	-0.044	0.239	0.198
Std. error	0.249	0.297	0.368
T-stat	-0.18	0.81	0.54

Source: Compiled by authors

Table 11

PSM analysis for Labor productivity

ATT	*Robotics*		*Manufacturing robots*		*Service robots*	
	t+1	*t+2*	*t+1*	*t+2*	*t+1*	*t+2*
Treated	11.656	11.788	11.618	11.777	12.060	12.247
Control	11.470	11.911	11.349	11.397	11.798	12.299
Difference	0.186	-0.122	0.269	0.380	0.261	-0.053
Std. error	0.208	0.176	0.210	0.210	0.249	0.335
T-stat	0.90	-0.69	1.28*	1.81**	1.05	-0.16

Source: Compiled by authors

The PSM results presented in Appendix B – Appendix J indicate matched observations are successful since the t-test of mean differences for each variable is insignificant after matching. These results support that our treated and control groups are well-matched. In Appendix K and Appendix L, we can see the number of observations for both treated and untreated groups. All observations are referred to as "on support" observations except one observation for manufacturing robots in terms of labor productivity. Considering that we have a small sample size for the adoption of robotics, we have a relatively small number of observations in the treatment groups.

The implications of our PSM results suggest that integrating manufacturing robots into the production processes can lead to significant improvements in the efficiency and labor productivity of the firm and highlights the long-term benefits of incorporating this technology. The adoption of robotics may lead to improvements in labor productivity, and the lack of significant effects on TFP raises some interesting points for further investigation. One possible explanation could be that the adoption of robotics primarily affects the firm's production process and resource allocation, leading to improvements in labor productivity but not necessarily in the overall TFP. It is also possible that the time frame of the analysis may not capture the full impact of robotics adoption on TFP, as the technology may require more time to fully integrate and generate substantial changes at the firm level. Additionally, TFP captures a broader range of factors, including technology, innovation, and other unobserved variables, which may not be fully captured or immediately influenced by the adoption of robotics (Abramovitz, 1956). Considering all the above factors, it is likely to observe an increase in labor productivity while TFP remains unaffected.

Additionally, the effects of robotics adoption on productivity may take time to materialize and does not lead to productivity gains immediately, as it can take time to build up the stock of new technology and discover complementary investments (Brynjolfsson et al., 2018; Jovanovic & Rousseau, 2005). This is further supported by the findings of Brynjolfsson and Hitt (2003), which suggest that the productivity benefits of firms' IT-related investments increase steadily over time, peaking after approximately seven years. Productivity benefits resulting from firms' IT investments increase significantly over an extended period. Therefore, considering the time lag in realizing the effects of technological adoption, the impacts of robotics adoption on productivity may take time to materialize fully. Moreover, the contribution of complementarities such as workforce skill (Cohen & Levinthal, 1989; Grossman & Oberfield, 2022), management innovations and adoption of complementary technologies (Tiwari, 2023) are influencing factors to discover the relationship between technological tools on productivity and these factors can be included in further studies.

6. Conclusion

The aim of this study is to investigate how robot adoption, specifically service and industrial robotics affects a firm's total factor productivity and labor productivity by using firm-level data of Estonian enterprises. To conduct this analysis, we used data from the Information Technology Survey (2014-2022) and Estonian Business Registry data (1995-2021). In our analysis, we used data from 2018 to 2022 due to the inclusion of robotics-related data starting from 2018. Our aim is to contribute to the existing literature by analyzing the effect of robotics in the context of Estonian firms since we identified the research gap, particularly for the service robots in the available literature.

We run three different analyses to examine the impact of robotics to ensure the accuracy and completeness of our results. Based on the OLS results, our study found that the adoption of robotics, particularly manufacturing robots, has a positive relationship with labor productivity. The results of this analysis demonstrate that the association with the adoption of robotics and labor productivity is positive, especially for manufacturing robots. However, the relationship between the usage of robots and TFP is significant only when firms adopt either one or both types of robotics. No evidence was found to show any linkage between service robots and productivity variables.

On the other hand, the FE analysis did not yield significant effects of robotics adoption on both TFP and labor productivity. The short panel data in our analysis limits our ability to observe the longer-term effects of adoption. Also, the unmeasured factors such as managerial abilities, education, and skill level of employees may have an impact on both robotics adoption and productivity outcomes that could affect the significance of results. Since measuring these indicators is challenging for our analysis, we could not assess the effects of these factors on our productivity variables.

Overall, our results suggest that integrating robotics, particularly manufacturing robots into the production processes can lead to significant long-term improvements in labor productivity of the firms. The results suggest that the impact of robotics adoption on productivity may vary across sectors, and it impacts labor productivity more than TFP in Estonian firms. Brynjolfsson et al. (2018) have concluded that an increase in the use of AI positively impacts labor productivity, and this does not depend on the measurement of AI capital. On the contrary, the precision of measurement is a necessary factor in terms of TFP. Therefore, the insignificance of TFP results in our analysis may not fully depict the real effect of robotics on productivity to some extent. Additionally, considering the time lag in realizing the effects of technological adoption, the impacts of robotics adoption on productivity may take time to materialize fully.

Several limitations can be listed as potential reasons for insignificant results. Firstly, to see more precise findings, it's crucial to take a longer time period into account. As we have only two years of bi-annual data, the analysis results for the treatment year show insignificant outcomes. Since the technology may require more time to fully integrate and generate substantial changes at the firm level, the time frame of our analysis may not capture the full impact of robotics adoption on TFP. Therefore, it might be the reason we could not observe any significant results on TFP.

Moreover, the relatively low adoption rate of robotics in Estonia, which leads to the limited sample size, hinders the capacity to achieve more precise results. Moreover, as stated in the study by Tiwari (2023) investment in complementary technologies, as well as enhancements for skill improvements, can affect the overall increase in productivity, which are difficult to measure and add to our analysis. For further investigation on this topic, more explanatory variables, a longer time horizon and larger sample size should be utilized to see the effects of robotics on firm performance more accurately. Workforce education level, the indicators measuring employees' skills might also be useful to include as a control variable since the adoption of robots highly requires skilled employees to manage and adjust them to the firm's operations.

The slow pace of robotics adoption in Estonian firms further highlights the need for governmental actions that increase public knowledge of the benefits of robots. The policy measures can be implemented to incentivize especially larger businesses to use robots in order to have more spillover effects in the economy and increase the potential economic advantages. Since various studies have indicated the threat of job loss associated with the adoption of robotics (Acemoglu et al., 2020; Acemoglu & Restrepo, 2020; Jung & Lim, 2020)), finding strategies to reduce this concern is necessary. For instance, demonstrating how robotics should be utilized as a supportive technology rather than a replacement of employees and emphasizing collaboration between humans and robots might be another legislative goal (Bachmann et al., 2022).

Acknowledgment

We would like to express our sincere gratitude and appreciation to our supervisor, Jaan Masso for his invaluable guidance and support throughout the completion of this master's thesis. His insightful feedback and constructive criticism have played an important role in shaping this research project. We are truly grateful for his mentorship and dedication to our academic growth. We are thankful to our reviewer Priit Vahter for his thorough review and constructive suggestions that greatly contributed to improving the quality of this research.

7. References

1. Abramovitz, M. (1956). Resource and Output Trends in the United States since 1870. In *Resource and Output Trends in the United States since 1870* (pp. 1–23). NBER. https://www.nber.org/books-and-chapters/resource-and-output-trends-united-states-1870/resource-and-output-trends-united-states-1870
2. Acemoglu, D., Lelarge, C., & Restrepo, P. (2020). Competing with Robots: Firm-Level Evidence from France. *AEA Papers and Proceedings*, *110*, 383–388. https://doi.org/10.1257/pandp.20201003
3. Acemoglu, D., & Restrepo, P. (2020). Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy*, *128*(6), 2188–2244. https://doi.org/10.1086/705716
4. Ackerberg, D., Lanier Benkard, C., Berry, S., & Pakes, A. (2007). Chapter 63 Econometric Tools for Analyzing Market Outcomes. In J. J. Heckman & E. E. Leamer (Eds.), *Handbook of Econometrics* (Vol. 6, pp. 4171–4276). Elsevier. https://doi.org/10.1016/S1573-4412(07)06063-1
5. Alguacil, M., Lo Turco, A., & Martínez-Zarzoso, I. (2022). Robot adoption and export performance: Firm-level evidence from Spain. *Economic Modelling*, *114*, 105912. https://doi.org/10.1016/j.econmod.2022.105912
6. Andrews, D., Criscuolo, C., & Gal, P. N. (2016). *The Best versus the Rest: The Global Productivity Slowdown, Divergence across Firms and the Role of Public Policy*. OECD. https://doi.org/10.1787/63629cc9-en
7. Azzopardi, D., Lenain, P., Molnar, M., Mosiashvili, N., & Pareliussen, J. (2020). *Seizing the productive potential of digital change in Estonia. Economics department working papers No. 1639*.
8. Bachmann, R., Gonschor, M., Lewandowski, P., & Madoń, K. (2022). *The Impact of Robots on Labour Market Transitions in Europe* (SSRN Scholarly Paper No. 4114890). https://doi.org/10.2139/ssrn.4114890
9. Ballestar, M. T., Díaz-Chao, Á., Sainz, J., & Torrent-Sellens, J. (2020). Knowledge, robots and productivity in SMEs: Explaining the second digital wave. *Journal of Business Research*, *108*, 119–131. https://doi.org/10.1016/j.jbusres.2019.11.017

10. Bettiol, M., Capestro, M., Maria, E. D., & Furlan, A. (2019). Impacts of industry 4.0 investments on firm performance: Evidence from Italy. *"Marco Fanno" Working Papers*, Article 0233. https://ideas.repec.org//p/pad/wpaper/0233.html
11. Bharadwaj, A. S., Bharadwaj, S. G., & Konsynski, B. R. (1999). Information Technology Effects on Firm Performance as Measured by Tobin's q. *Management Science*, *45*(7), 1008–1024. https://doi.org/10.1287/mnsc.45.7.1008
12. Blundell, R., & Bond, S. (2000). GMM Estimation with persistent panel data: An application to production functions. *Econometric Reviews*, *19*(3), 321–340. https://doi.org/10.1080/07474930008800475
13. Bonfiglioli, A., Crinò, R., Fadinger, H., & Gancia, G. (2020). Robot Imports and Firm-Level Outcomes. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3744604
14. Brady, M. (1985). Artificial intelligence and robotics. *Artificial Intelligence*, *26*(1), 79–121. https://doi.org/10.1016/0004-3702(85)90013-X
15. Brynjolfsson, E., & Hitt, L. M. (2003). Computing Productivity: Firm-Level Evidence. *The Review of Economics and Statistics*, *85*(4), 793–808. https://doi.org/10.1162/003465303772815736
16. Brynjolfsson, E., Rock, D., & Syverson, C. (2018). Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics. In *The Economics of Artificial Intelligence: An Agenda* (pp. 23–57). University of Chicago Press. https://www.nber.org/books-and-chapters/economics-artificial-intelligence-agenda/artificial-intelligence-and-modern-productivity-paradox-clash-expectations-and-statistics
17. Brynjolfsson, E., & Yang, S. (1996). Information Technology and Productivity: A Review of the Literature. In M. V. Zelkowitz (Ed.), *Advances in Computers* (Vol. 43, pp. 179–214). Elsevier. https://doi.org/10.1016/S0065-2458(08)60644-0
18. Cardona, M., Kretschmer, T., & Strobel, T. (2013). ICT and productivity: Conclusions from the empirical literature. *Information Economics and Policy*, *25*(3), 109–125. https://doi.org/10.1016/j.infoecopol.2012.12.002
19. Cette, G., Devillard, A., & Spiezia, V. (2021). The contribution of robots to productivity growth in 30 OECD countries over 1975–2019. *Economics Letters*, *200*, 109762. https://doi.org/10.1016/j.econlet.2021.109762

20. Chung, C. A. (1996). Human issues influencing the successful implementation of advanced manufacturing technology. *Journal of Engineering and Technology Management*, *13*(3), 283–299. https://doi.org/10.1016/S0923-4748(96)01010-7
21. Cohen, W. M., & Levinthal, D. A. (1989). Innovation and Learning: The Two Faces of R & D. *The Economic Journal*, *99*(397), 569–596. https://doi.org/10.2307/2233763
22. Cséfalvay, Z. (2020). Robotization in Central and Eastern Europe: Catching up or dependence? *European Planning Studies*, *28*(8), 1534–1553. https://doi.org/10.1080/09654313.2019.1694647
23. Dashdamirova, L. & Nilufar. (2021). *Assessing the importance of ICT adoption for productivity in Estonia* [Master thesis, Tartu Ülikool]. https://dspace.ut.ee/handle/10062/72463
24. Dedrick, J., Kraemer, K. L., & Shih, E. (2013). Information Technology and Productivity in Developed and Developing Countries. *Journal of Management Information Systems, 30*(1), 97–122. https://doi.org/10.2753/MIS0742-1222300103
25. Dewan, S., & Kraemer, K. L. (2000). Information Technology and Productivity: Evidence from Country-Level Data. *Management Science*, *46*(4), 548–562. https://doi.org/10.1287/mnsc.46.4.548.12057
26. Dirican, C. (2015). The Impacts of Robotics, Artificial Intelligence On Business and Economics. *Procedia - Social and Behavioral Sciences*, *195*, 564–573. https://doi.org/10.1016/j.sbspro.2015.06.134
27. Graetz, G., & Michaels, G. (2018). Robots at Work. *The Review of Economics and Statistics*, *100*(5), 753–768. https://doi.org/10.1162/rest_a_00754
28. Grossman, G. M., & Oberfield, E. (2022). The Elusive Explanation for the Declining Labor Share. *Annual Review of Economics*, *14*(1), 93–124. https://doi.org/10.1146/annurev-economics-080921-103046
29. Heller, N. (2017, December 11). Estonia, the Digital Republic. *The New Yorker*. https://www.newyorker.com/magazine/2017/12/18/estonia-the-digital-republic
30. Huang, G., He, L.-Y., & Lin, X. (2022). Robot adoption and energy performance: Evidence from Chinese industrial firms. *Energy Economics*, *107*, 105837. https://doi.org/10.1016/j.eneco.2022.105837
31. International Federation of Robotics, I. I. F. of. (2023). *International Federation of*

Robotics. IFR International Federation of Robotics. https://ifr.org

32. Ivanov, S. H., & Webster, C. (2017). *Adoption of Robots, Artificial Intelligence and Service Automation by Travel, Tourism and Hospitality Companies – A Cost-Benefit Analysis* (SSRN Scholarly Paper No. 3007577). https://papers.ssrn.com/abstract=3007577
33. Ivanov, S. H., Webster, C., & Berezina, K. (2017). *Adoption of Robots and Service Automation by Tourism and Hospitality Companies* (SSRN Scholarly Paper No. 2964308). https://papers.ssrn.com/abstract=2964308
34. Jovanovic, B., & Rousseau, P. L. (2005). Chapter 18—General Purpose Technologies. In P. Aghion & S. N. Durlauf (Eds.), *Handbook of Economic Growth* (Vol. 1, pp. 1181–1224). Elsevier. https://doi.org/10.1016/S1574-0684(05)01018-X
35. Jung, J. H., & Lim, D.-G. (2020). Industrial robots, employment growth, and labor cost: A simultaneous equation analysis. *Technological Forecasting and Social Change*, *159*, 120202. https://doi.org/10.1016/j.techfore.2020.120202
36. Koc, T., & Bozdag, E. (2009). The impact of AMT practices on firm performance in manufacturing SMEs. *Robotics and Computer-Integrated Manufacturing*, *25*(2), 303–313. https://doi.org/10.1016/j.rcim.2007.12.004
37. Koch, M., Manuylov, I., & Smolka, M. (2021). Robots and Firms. *The Economic Journal*, *131*(638), 2553–2584. https://doi.org/10.1093/ej/ueab009
38. Kromann, L., Malchow-Møller, N., Skaksen, J. R., & Sørensen, A. (2020). Automation and productivity—A cross-country, cross-industry comparison. *Industrial and Corporate Change*, *29*(2), 265–287. https://doi.org/10.1093/icc/dtz039
39. *Leaders and Laggards in the Diffusion of Industrial Robots | Industrial Analytics Platform*. (2021, July 9). Industrial Analytics Platform. https://iap.unido.org/articles/leaders-and-laggards-diffusion-industrial-robots
40. Lee, J., Davari, H., Singh, J., & Pandhare, V. (2018). Industrial Artificial Intelligence for industry 4.0-based manufacturing systems. *Manufacturing Letters*, *18*, 20–23. https://doi.org/10.1016/j.mfglet.2018.09.002
41. Levinsohn, J., & Petrin, A. (2003). Estimating Production Functions Using Inputs to Control for Unobservables. *The Review of Economic Studies*, *70*(2), 317–341. https://doi.org/10.1111/1467-937X.00246

42. Mishra, S., Ewing, M. T., & Cooper, H. B. (2022). Artificial intelligence focus and firm performance. *Journal of the Academy of Marketing Science*, *50*(6), 1176–1197. https://doi.org/10.1007/s11747-022-00876-5
43. Mithas, S., & Rust, R. T. (2016). How Information Technology Strategy and Investments Influence Firm Performance: Conjecture and Empirical Evidence. *MIS Quarterly*, *40*(1), 223–246.
44. Mithas, S., Tafti, A., Bardhan, I., & Goh, J. M. (2012). Information Technology and Firm Profitability: Mechanisms and Empirical Evidence. *MIS Quarterly*, *36*(1), 205–224. https://doi.org/10.2307/41410414
45. Murphy, R. R. (2019). *Introduction to AI Robotics, second edition*. MIT Press.
46. Nordhaus, W. D. (2015). *Are We Approaching an Economic Singularity? Information Technology and the Future of Economic Growth*.
47. OECD (2023), Enterprises by business size (indicator). *doi: 10.1787/31d5eeaf-en (Accessed on 14 May 2023)*
48. OpenAI. (2022). ChatGPT (Dec 20 version), large language model, https://chat.openai.com/
49. Pillai, R., Sivathanu, B., Mariani, M., Rana, N. P., Yang, B., & Dwivedi, Y. K. (2022). Adoption of AI-empowered industrial robots in auto component manufacturing companies. *Production Planning & Control*, *33*(16), 1517–1533. https://doi.org/10.1080/09537287.2021.1882689
50. Questionnaires | Statistikaamet. *(n.d.-b)*. https://www.stat.ee/en/questionnaires?combine=information+technology
51. Raj, M., & Seamans, R. (2019). Primer on artificial intelligence and robotics. *Journal of Organization Design*, *8*(1), 11. https://doi.org/10.1186/s41469-019-0050-0
52. Rajan, K., & Saffiotti, A. (2017). Towards a science of integrated AI and Robotics. *Artificial Intelligence*, *247*, 1–9. https://doi.org/10.1016/j.artint.2017.03.003
53. Rust, R. T., & Huang, M.-H. (2012). Optimizing Service Productivity. *Journal of Marketing*, *76*(2), 47–66. https://doi.org/10.1509/jm.10.0441
54. Somohano-Rodríguez, F. M., & Madrid-Guijarro, A. (2022). Do industry 4.0 technologies improve Cantabrian manufacturing smes performance? The role played by industry competition. *Technology in Society*, *70*, 102019.

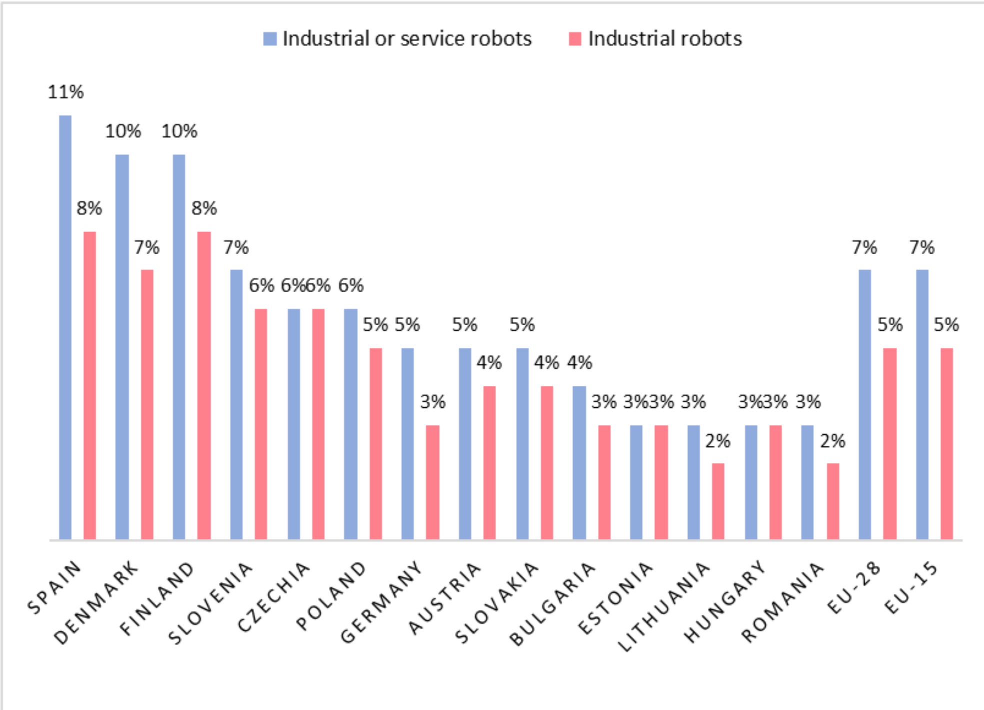
https://doi.org/10.1016/j.techsoc.2022.102019

55. Stiebale, J., Suedekum, J., & Woessner, N. (2020). *Robots and the Rise of European Superstar Firms* (SSRN Scholarly Paper No. 3661423). https://papers.ssrn.com/abstract=3661423
56. Tiwari, A. K. (2023). Automation in an Open, Catching-up Economy: Aggregate and Microeconometric Evidence. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4376874
57. Wamba-Taguimdje, S.-L., Fosso, W. S., Kala, K. J. R., & Tchatchouang, W. C. E. (2020). Influence of artificial intelligence (AI) on firm performance: The business value of AI-based transformation projects. *Business Process Management Journal*, *26*(7), 1893–1924. https://doi.org/10.1108/BPMJ-10-2019-0411
58. Wang, K.-L., Sun, T.-T., & Xu, R.-Y. (2022). The impact of artificial intelligence on total factor productivity: Empirical evidence from China's manufacturing enterprises. *Economic Change and Restructuring*. https://doi.org/10.1007/s10644-022-09467-4
59. Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: Service robots in the frontline. *Journal of Service Management*, *29*(5), 907–931. https://doi.org/10.1108/JOSM-04-2018-0119

Appendices

Appendix A

Comparison between Estonia and other European countries based on industrial and service robot adoption



Source : EUROSTAT, ICT usage in entreprises.

Appendix B

Comparison between treated and untreated groups of robotics for TFP (at t+1)

	Matched			*Unmatched*		
	Treated	*Control*	*T-test*	*Treated*	*Control*	*T-test*
TFP	*9.860*	*9.891*	*-0.11*	*9.860*	*9.865*	*-0.03*
Firm age	*19.370*	*19.352*	*0.01*	*19.370*	*19.773*	*-0.29*
Firm size	*4.420*	*4.406*	*0.05*	*4.420*	*3.861*	*2.79****
Export	*0.926*	*0.944*	*-0.27*	*0.926*	*0.770*	*1.90**
Foreign ownership	*0.333*	*0.315*	*0.14*	*0.333*	*0.179*	*2.03***

Source: Compiled by authors

Appendix C

Comparison between treated and untreated groups of manufacturing robots for TFP (at t+1)

	Matched			*Unmatched*		
	Treated	*Control*	*T-test*	*Treated*	*Control*	*T-test*
TFP	*9.792*	*9.553*	*0.66*	*9.792*	*9.874*	*-0.35*
Firm age	*20.000*	*20.290*	*-0.13*	*20.000*	*19.75*	*0.17*
Firm size	*4.471*	*4.334*	*0.54*	*4.471*	*3.874*	*2.77****
Export	*0.917*	*0.896*	*0.24*	*0.917*	*0.773*	*1.67**
Foreign ownership	*0.333*	*0.417*	*-0.59*	*0.333*	*0.180*	*1.90**

Source: Compiled by authors

Appendix D

Comparison between treated and untreated groups of service robots for TFP (at t+1)

	Matched			*Unmatched*		
	Treated	*Control*	*T-test*	*Treated*	*Control*	*T-test*
TFP	*10.305*	*10.108*	*0.45*	*10.305*	*9.960*	*0.64*
Firm age	*17.75*	*18.500*	*-0.11*	*17.750*	*20.341*	*-0.74*
Firm size	*4.255*	*3.690*	*0.94*	*4.255*	*4.031*	*0.45*
Foreign ownership	*0.500*	*0.625*	*-0.31*	*0.500*	*0.233*	*1.26*

Source: Compiled by authors

Appendix E

Comparison between treated and untreated groups of robotics for labor productivity (at t+1)

	Matched			*Unmatched*		
	Treated	*Control*	*T-test*	*Treated*	*Control*	*T-test*
TFP	*11.531*	*11.569*	*-0.20*	*11.531*	*11.384*	*1.02*
Firm age	*20.659*	*21.795*	*-0.79*	*20.659*	*19.760*	*0.82*
Firm size	*4.515*	*4.513*	*0.01*	*4.515*	*3.890*	*4.02****
Export	*0.841*	*0.818*	*0.28*	*0.841*	*0.752*	*1.35*
Foreign ownership	*0.295*	*0.250*	*0.47*	*0.295*	*0.180*	*1.93**

Source: Compiled by authors

Appendix F

Comparison between treated and untreated groups of robotics for labor productivity (at t+2)

	Matched			*Unmatched*		
	Treated	*Control*	*T-test*	*Treated*	*Control*	*T-test*
TFP	*11.549*	*11.711*	*-0.82*	*11.549*	*11.466*	*0.55*
Firm age	*20.738*	*20.607*	*0.08*	*20.738*	*19.586*	*1.01*
Firm size	*4.539*	*4.410*	*0.66*	*4.539*	*4.094*	*2.85****
Export	*0.881*	*0.917*	*-0.54*	*0.881*	*0.802*	*1.26*

Foreign ownership	*0.310*	*0.381*	*-0.68*	*0.310*	*0.211*	*1.51*

Source: Compiled by authors

Appendix G

Comparison between treated and untreated groups of manufacturing robots for labor productivity (at t+1)

	Matched			*Unmatched*		
	Treated	*Control*	*T-test*	*Treated*	*Control*	*T-test*
TFP	*11.482*	*11.433*	*0.21*	*11.482*	*11.392*	*0.58*
Firm age	*20.595*	*20.135*	*0.28*	*20.595*	*19.746*	*0.71*
Firm size	*4.568*	*4.486*	*0.40*	*4.568*	*3.890*	*3.91****
Export	*0.865*	*0.905*	*-0.54*	*0.865*	*0.753*	*1.56*
Foreign ownership	*0.297*	*0.258*	*0.38*	*0.297*	*0.181*	*1.79**

Source: Compiled by authors

Appendix H

Comparison between treated and untreated groups of manufacturing robots for labor productivity (at t+2)

	Matched			*Unmatched*		
	Treated	*Control*	*T-test*	*Treated*	*Control*	*T-test*
TFP	*11.501*	*11.409*	*0.40*	*11.501*	*11.472*	*0.18*
Firm age	*20.686*	*21.529*	*-0.50*	*20.686*	*19.602*	*0.87*
Firm size	*4.599*	*4.463*	*-0.15*	*4.599*	*4.103*	*2.88****
Export	*0.914*	*0.914*	*-0.00*	*0.914*	*0.802*	*1.65**
Foreign ownership	*0.314*	*0.286*	*0.26*	*0.314*	*0.211*	*1.46*

Source: Compiled by authors

Appendix I

Comparison between treated and untreated groups of service robots for labor productivity (at t+1)

	Matched			*Unmatched*		
	Treated	*Control*	*T-test*	*Treated*	*Control*	*T-test*
TFP	*11.938*	*11.915*	*0.08*	*12.062*	*11.397*	*2.76****
Firm age	*22.000*	*21.929*	*0.03*	*21.400*	*19.912*	*0.81*
Firm size	*4.685*	*4.505*	*0.52*	*4.644*	*3.960*	*2.57***
Export	*0.786*	*0.643*	*0.82*	*0.733*	*0.769*	*-0.33*
Foreign ownership	*0.429*	*0.321*	*0.57*	*0.400*	*0.192*	*2.03***

Source: Compiled by authors

Appendix J

Comparison between treated and untreated groups of service robots for labor productivity (at t+2)

	Matched			*Unmatched*		
	Treated	*Control*	*T-test*	*Treated*	*Control*	*T-test*
TFP	*12.032*	*12.092*	*-0.18*	*12.158*	*11.473*	*2.74****
Firm age	*21.692*	*19.846*	*0.61*	*21.071*	*19.782*	*0.66*
Firm size	*4.731*	*4.778*	*-0.13*	*4.685*	*4.165*	*1.95**
Export	*0.846*	*0.885*	*-0.28*	*0.786*	*0.819*	*-0.32*
Foreign ownership	*0.462*	*0.308*	*0.78*	*0.429*	*0.225*	*1.81**

Source: Compiled by authors

Appendix K

Number of observations for TFP

	Robotics		
	Untreated	*Treated*	*Total*
t+1	671	27	698
	Manufacturing robots		
	Untreated	*Treated*	*Total*
t+1	678	24	702
	Service robots		
	Untreated	*Treated*	*Total*
t+1	584	4	588

Source: Compiled by authors

Appendix L

Number of observations for labor productivity

	Robotics				
	Off-support		*On support*		
	Untreated	*Treated*	*Untreated*	*Treated*	*Total*
t+1	0	0	1065	37	1102
t+2	0	0	787	35	1346
	Manufacturing robots				
	Off-support		*On support*		
	Untreated	*Treated*	*Untreated*	*Treated*	*Total*
t+1	0	1	1157	14	1172
t+2	0	1	868	13	882
	Service robots				
	Off-support		*On support*		
	Untreated	*Treated*	*Untreated*	*Treated*	*Total*

t+1	0	0	1048	44	1092
t+*2*	0	0	773	42	815

Source: Compiled by authors

Resümee

Robotite kasutuselevõtmise mõju ettevõtete tulemuslikkusele Eesti ettevõttetasandi andmete põhjal

Sona Pashayeva Gunay Hajizada

Käesolev magistritöö panustab teaduskirjandusse robotite kasutamise mõjust ettevõtete tootlikkusele, püüdes seejuures täita uurimislünka teenindusrobotite kaasamise mõjudest, mis on varasemates analüüsides jäänud enamasti tähelepanuta. Uurisime robotite kasutuselevõtu mõju, kasutades Eesti ettevõttetasandi andmeid ja keskendudes kogutootlikkuse (TFP) ja tööjõu tootlikkuse näitajatele. Uuringus kasutati kahte andmekogumit, Statistikaamet uuringut infotehnoloogia kasutamisest ettevõtetes ja Eesti Äriregistri andmeid. Robotite kasutuselevõtu ja erinevate tootlikkuse näitajate vahelise seose hindamiseks kasutasime regressioonianalüüsi, sealhulgas tavalise vähimruutude meetodiga ja fikseeritud efektidega hinnatud regressioonimudeleid, ja tõenäosuslikku sobitamisanalüüsi (PSM). Analüüsi tulemused näitasid, et robotite, eelkõige tootmisrobotite integreerimine ettevõtte tegevusse võib kaasa tuua tööviljakuse olulise paranemise. Lisaks on oluline märkida, et robotite kasutuselevõtu täielik positiivne mõju tootlikkusele võib realiseeruda alles pikema aja jooksul. Meie tulemused rõhutavad, et robotite kasutuselevõtu aeglane tempo Eesti ettevõtetes tingib vajadust riigipoolse sekkumise järele, edendamaks ettevõtete teadlikkust robotite kasutamise eelistest ning arendamaks inimeste ja robotite vahelist koostööd, mis aitaks lahendada töökohtade kadumisega seonduvad probleeme.

Licence

Non-exclusive license to reproduce thesis and make thesis public

Sona Pashayeva and Gunay Hajizada

(authors' name)

herewith grant the University of Tartu a free permit (non-exclusive license) to:

reproduce, for the purpose of preservation and making available to the public, including for addition to the DSpace digital archives until expiry of the term of validity of the copyright,

How adoption of robotics affects firm performance based on Estonian firm-level data

supervised by Jaan Masso

(supervisor's name)

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

2. I am aware of the fact that the author retains these rights.

3. I certify that granting the non-exclusive license does not infringe the intellectual property rights or rights arising from the Personal Data Protection Act.

Tartu, 18.05.2023