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Effects of Automation on the Gender Pay Gap: the case of Estonia

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Abstract

This paper investigates how investments in automation-intensive goods affects the gender pay gap. The evidence on the effects of automation on the labour market is growing; however, little is known about the implications of automation for the gender pay gap. The data used in the paper are from a matched employer-employee dataset incorporating detailed information on firms, their imports, and employee-level data for Estonian manufacturing and services employers for 2006–2018. We define automation using the imports of intermediates embedding automation technologies. The effect of automation is estimated using simple Mincerian wage equations and the causality of the effect is validated using propensity score matching. We find that introducing automation enlarges the gender pay gap. The negative effect of importing automation-intensive goods for female employees is about two to four percentage points larger than for male employees. The propensity score matching confirms that the introduction of automation has a higher causal effect on the wages of male employees than female employees.

Keywords: Automation, Technological change, Robotization, Gender pay gap.

JEL Classification: O33, J16, J31.

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1 Introduction

In recent decades, the respective inequality and evolution of wage polarization has received considerable attention (Milanovic, 2016; Piketty & Saez, 2003). At the same time, analyses on automation and its effects in terms of growth, unemployment and inequality are increasing. Nevertheless, in spite of the profound examination of the impact of automation on overall employment and labour force participation (Grigoli et al., 2020), there is very limited empirical research aimed at understanding the effect of automation on gender equality. Recent literature, such as Blanas et al. (2019) and Domini et al. (2020b), provides some insights into the issue but cannot be considered conclusive. Hence, the authors formulate the following research question: How does the increased tendency for automation and robotization determine the effect of technological development on the gender pay gap?

In particular, this paper aims to provide evidence of the relationship between the implementation of automation and the gender pay gap using Estonian data. Our work uses similar approaches and definitions of automation technologies as in Acemoglu and Restrepo (2018a) and Domini et al. (2019). Moreover, it moves a step further by focusing on the size of the gender pay gap and the effects on it of automation. To understand how the effects of automation work, it is critical to also study individual employee data. We link annual automation costs (using data from imports of automation-intensive goods) to Estonian employer-employee data. The data are provided by Statistics Estonia and covers the years 2006–2018. Finally, the work differentiates itself from the paper by Blanas et al. (2019) due to the use of firm-level data instead of industry level data, and from Masso and Vahter (2020), who underlined evidence of the increase in the gender pay gap in companies with technological and non-technological innovation, but did not specify respectively the introduction of automation and how that is connected.

The paper investigates and analyses the effects of technological change on labour dynamics and the gender pay gap, determines the interconnection between automation and the gender pay gap, taking into account contributing factors. The technological changes, automation and their effect on labour dynamics, being the research object of the given article, have been previously analysed by a number of studies (Aksoy, Özcan, & Philipp, 2020; Acemoglu & Restrepo, 2020; Graetz & Michaels, 2018; Domini et al., 2020b). The outcomes provide the following evidence – while a decrease in wages in the USA due to automation has been documented (Acemoglu & Restrepo, 2020), evidence of an increase in wages and labour productivity in European countries was also detected (Graetz & Michaels, 2018). At the same time, Domini et al. (2020b) report that in the French economy most of the wage dispersion exists due to differences among workers belonging to the same firm, rather than differences between sectors, firms and occupations, and that inequality is unaffected after an automation event. However, the research gap this article fills includes the evaluation of the gender pay gap with respect to automation technologies implemented in the Estonian market.

Estonia is a good example for investigating both the effects of technology adoption and automation and the gender pay gap. Estonia is one of the countries with the fastest growing IT sector among European countries (in 2020, the share of information and communication sector in GDP was the second highest in the EU after Ireland)[2], which develops the respective technological innovations. In recent decades, all industries in Estonia have been successful at modernizing companies and making them competitive, mainly by introducing automation and technology transfer from abroad (Kalvet et al., 2004). At the same time, Estonia is a country with the largest gender pay gap among

[2] See Eurostat (2019)

the EU countries (up to 30%, Vahter & Masso, 2019; Anspal, 2015a) and the research provides evidence that a large part of that gender pay gap is related to firm-level factors (Masso et al., 2020). The present study is based on matched employer-employee data from Statistics Estonia.

In order to analyse the effects of automation on the gender pay gap in Estonia, we based our methodology principally on recent papers on the subject in Estonia by Masso and Vahter (2020; 2019). Hence, we estimate the effects of automation on the gender pay gap through Mincerian equations and observe the possible variation of the results with the introduction of innovation variables as in Masso and Vahter (2020). Furthermore, we illustrate the variations of the effects on the gender pay gap in different occupations. Finally, we perform a standard Propensity Score Matching (PSM) analysis (Rosenbaum & Rubin, 1983) considering not only automation in general but the different kinds of automation (e.g. welding machines, industrial robots etc.).

Our findings show how firms investing in goods that are intensive in automation technologies affect the gender pay gap in Estonia. The results show a strong positive effect of imports of automation-intensive goods on the gender pay gap. However, the estimations show that the effect varies over years. In addition, the introduction of innovation variables does not substantially affect the results of the analysis. Furthermore, certain occupations, such as managers, technical professionals and support workers, show a greater increase in the gender pay gap due to automation. Finally, PSM confirms the results of the Mincerian equations and illustrates how different kinds of automation can lead to different levels of gender pay gap.

The paper contributes to the growing amount of literature on the effects of automation on inequality by focusing on the empirical information collected from Estonian databases and studying employer-employee matched data. Evidence on the direct effects on labour markets of the most recent wave of automation technologies is discussed by a number of researchers (Dauth et al., 2018; Acemoglu & Restrepo, 2018b), and some works specifically focus on the impact of automation at the worker level (Bessen et al., 2019). The effects of automation on wages and the evolution of wage inequality are analysed by Lankisch et al. (2017), Bessen (2016) and Domini et al. (2020b). This rise in wage inequality is characterized as one of the main reasons behind the rise in overall income inequality that has been observed since the 1980s (Milanovic, 2016; Piketty & Saez, 2003). The active development of international trade and outsourcing has also supplemented skill-biased technological change in its effect on the wage differential (Autor et al., 2016). As automation has received considerable attention in the current economic development and value chains, special focus is put on the discussion of R&D, new varieties of tasks and products (Acemoglu & Restrepo, 2018d). Steigum (2011) suggests to use of robots for sustaining long-run growth. Furthermore, the author underlines that the share of labour is set to fall or to be redistributed with the introduction of further automation and robotization.

Moreover, the paper contributes to the literature focusing on evaluating the various drivers of the male-female wage gap (Blau & Kahn, 2000; OECD, 2012). At the same time, the impact of automation presumably varies between men and women, as they conduct different tasks. We should also admit that the representation of men and women across various industries is different in terms of occupations and organizational social scales.

Finally, the paper adds insights to the recent contributions in the field of labour economics (Aksoy et al., 2020; Brussevich et al., 2018), where the analysis on variations of tasks show that female workers execute less assignments requiring interpersonal and analytical skills or physical labour, as well as perform tasks that are characterized by a lack of job variability, very limited opportunities for learning and development. In addition, the respective differences in wages may depend a lot on the following factor: in a number of countries women are underrepresented in the higher-level positions that influences the possibility to acquire higher wages. Taking into consideration the above-mentioned facts, analysing the relations between the tendency for automation and increases in the gender pay gap is a topical issue for further research. Despite the wide discussion about the automation and technologies' adoption, there is still limited evidence and explanations concerning the links between the implementation of automating technologies and the gender pay gap.

In the second section of the paper, we present the literature review related to the topic. In the third section, we illustrate the data and the models used. In the fourth section we show the results and their interpretation. The last section summarizes the author's conclusions.

2. Literature Review

The development of technologies and introduction of innovations bring automation to different jobs and areas of modern business processes. The implemented technologies may vary from robotics to different applications of artificial intelligence and find their use in a broad range of economic sectors. Research underlines that the current speed of automation and robotization might bring wide effects and changes in terms of job displacement, reallocation and polarization (Bessen et al., 2019; Frey & Osborne, 2017).

The possibility that automation will displace a number of jobs and workers and transform the labour market is being discussed in recent studies (Acemoglu & Restrepo, 2018a; Acemoglu & Restrepo, 2018c; Benzell et al., 2015; Acemoglu & Autor, 2011). Theories reflect evidence that automation can lead to the displacement of workers from jobs when newly implemented technologies demand a different set of skills from what was required before. At the same time, empirical literature states that large-scale automation should not cause the displacement of occupations, but rather a reallocation of labour to new emerging occupations and industries. In general, it is probable that automation causes an increase of employment in the respective industries if industry demand is sufficiently elastic (Acemoglu & Restrepo, 2018a; Bessen, 2018).

Despite economic literature widely discussing the coming technological changes, very few studies discuss questions about automation while considering the various aspects and forms related to automation. While talking about automation the literature mainly focuses on the introduction of industrial robots and enlarging robotization, as well as the potential effect this may have on the labour market, which gives us limited evidence of the effects of other forms of automation at aggregated levels (Acemoglu and Restrepo, 2017; Bonfiglioli et al., 2020; Graetz & Michaels, 2018). Concurrently, the evidence received from studies is mixed. Acemoglu (2018b) detects the fact that wages and employment have decreased in US regions exposed to automation by robots. While taking the empirical design by Acemoglu and Restrepo (2018b)' and using it for the analysis of German regions, Dauth et al. (2018) find evidence of a positive effect on wages and the absence of changes on total employment. The same tendency is confirmed by Graetz and Michaels (2018) when analysing a panel of countries and the various industries affected. Using French firm-level data, Bonfiglioli et al. (2020) find that robot adoption and employment growth are positively correlated, and at the same time an increase in robot intensity is followed by job losses, especially for those who are involved in production. Other recent papers show that even when there is no obvious effect from robotization, this could hide employment losses in some sectors that are offset by employment gains in others (Bessen et al., 2019). The effects of newly introduced technologies and automation may vary, depending of the type of workers. This can cause, for example, some categories of workers (young professionals, women) to change specialization and start looking for other positions or in other industries in case employment is affected by the introduction of robots (Bessen et al., 2019).

The effects of automation on the wages of high-skilled and low-skilled workers and thereby on the evolution of wage inequality are analysed by Lankisch et al. (2017) and Bessen (2016). The following tendency is taken into account: despite economic growth in the developed countries over the past decades, the median real wage stagnated, and the real wages of low-skilled workers even decreased since the 1970s (Murray, 2016; Acemoglu et al., 2012). At the same time, the wages of high-skilled workers with a degree have grown, revealing a rise in the skill-premium and a higher dispersion of wages in general. This rise in wage-related inequality is characterized as one of the driving incentives behind the rise in overall income inequality that has been observed since the 1980s (Milanovic, 2016; Piketty & Saez, 2003). The active development of international trade and outsourcing has also supplemented skill-biased technological change in its effect on the wage differential (Autor et al., 2016).

It is important to consider the situation in Europe, as based on available evidence from research, the exposure of the workers in Europe to industrial robots in 2016 was 19 percentage points higher when compared with workers in the USA (Chiacchio et al., 2018). At the same time, such an important factor as the average gender pay gap is still around 14% with some variation between countries, and with Estonian figures at the top end at 21.7% (the percentage shows the fact that females receive respectively smaller salaries) (Eurostat, 2019). Estonia is a special case in terms of showing the largest gender pay gap in the European Union along with providing long-term dynamics of this fact (Meriküll and Tverdostup, 2020; Masso et al., 2020). Being a small and fast developing country, Estonia provides a high level of female employment compared to the average in other European countries (Tverdostup & Paas, 2017), and despite the issue of the high gender pay gap having been actively discussed by researchers (Vahter & Masso, 2019; Tverdostup & Paas, 2016), most of the gap remains unexplained.

The above-mentioned fact shows that analysing the impact of automation and robotization on the gender pay gap is fundamentally important. The gains women received due to the introduction of policies aiming to enlarge the amount of women present in the paid workforce, along with corresponding equal remuneration, can deteriorate if women are disadvantaged by the process of automation (Aksoy et al., 2020; Brussevich et al., 2018). This could be related to different aspects: a lack of specific knowledge needed for certain typologies of automation; the relative lower presence of women in occupations or sectors where automation have positive effects on salaries; and country-specific issues.

When discussing labour market dynamics, the issue of the gender pay gap requires special attention. Despite the considerable narrowing of the gender wage gap in developed countries within recent decades, a significant gap remains and is a relevant topic for analysis and has policy implications (Kunze, 2018; Goldin, 2014). Comprehensive research is conducted with the purpose of evaluating factors that explain the persistence of the gender pay gap. Nonetheless, it should be mentioned that a number of studies put attention to supply-side explanations, such as gender variances in human capital aspects, psychological characteristics, or occupations (Aksoy et al., 2020; Blau & Kahn, 2017; Blau & Kahn, 2000). At the same time, demand-side factors (such as automation) lack scientific discussion and the provision of evidence in terms of the effects on the pay gap (Ngai & Petrongolo, 2017). When discussing the respective demand-side factors, only a few papers mention the effects of computerization on gender, indicating that the increase in computer use contributes to a narrowing of the gender pay gap (Bessen et al., 2019; Weinberg, 2000). In terms of the impact of automation for the gendered labour market, Brussevich et al. (2018) explore the fact that female workers are at a significantly higher risk of displacement or biased attitudes induced by automation than male workers. There is also an indication that the probability of automation having consequences is lower for younger cohorts of women, and those in managerial positions. Furthermore, recent data from the US indicates that automation and robotization may have lowered the gender gap in labour force participation and pay (Anelli et al., 2019). Hence, the presented overview proves that automation and its effects on the gender pay gap should be a subject for scientific discussion. Nevertheless, direct empirical evidence on the impact of automation on workers at the firm level is still scarce, though growing.

3. Methodology

3.1. Data and Descriptive Statistics

In our analysis, we use company importing products related to automation as a proxy for the introduction of automation at firm level. Following Domini et al. (2019) and Acemoglu and Restrepo (2018b), we first define the harmonized system (HS) codes (Table 1) related to automation among the codes related to imports for Estonian firms using data from the firm-product-market level exports and imports dataset elaborated in Masso and Vahter (2019) and Masso et al. (2015). In particular, the data on firm-level imports are taken from the international goods trade dataset of Statistics Estonia and the services trade dataset of the Bank of Estonia (central bank of Estonia). These categories of automation-related goods include industrial robots, numerically controlled machines, automatic machine tools, and other automatic machines, therefore their purchase can be counted as an investment in tangible assets. With the aim of analysing the relevance of the different categories of automation goods for the digital economy, the sectorial distribution of imports is considered, with the use of the taxonomy of digitally intensive sectors, developed by the OECD (Calvino et al., 2018). The advantage of that approach for the study of automation is the availability of information on automation over a long period. The disadvantage of that approach may be that we miss cases of automation without imports of particular goods from abroad when these goods are purchased from some other company within Estonia. As mentioned earlier, introducing automation and technology transfer from abroad has been the main source of technological catch-up for Estonian companies (Kalvet et al., 2004). Other relevant firm-level variables not available in the goods and services exports datasets are taken from the Estonian Commercial Registry (*Äriregister*) data on annual financial reports.

Table 1. Product classes referring to automation, based on the taxonomy by Acemoglu and Restrepo (2018b)

Label	HS Codes
Industrial robots	847950
Dedicated machinery (including robots)	847989
Numerically controlled machines	84563011, 84563019, 84573010, 845811, 845891, 845921, 845931, 84594010, 845951, 845961, 846011, 846011, 846021, 846031, 84604010, 84613010, 84614011, 84614031, 84614071, 84621010, 846221,846231, 846241, 84629120, 84629920
Machine tools	845600-846699, 846820-846899, 851511-851519
Tools for industrial work	820200-821299
Welding machines	851521, 851531, 851580, 851590
Weaving and knitting machines	844600-844699 and 844770-844799
Other textile dedicated machinery	844400-845399
Conveyors	842831-842839
Regulating instruments	903200-903299

Source: Domini et al. (2019)

Afterwards, we connect these data with individual level wage information via the Estonian Tax and Customs Office dataset on individual monthly payroll tax payments. Social security tax in Estonia is applied to all employees at the rate of 33% of the gross wage. The tax payments allow us to identify an employee's gross wage and employment status for each firm in every year. In the database, information on the gender and age of workers is provided. Additional characteristics of individuals (e.g. education and occupation) are obtained from the Population and Housing Census 2011 data, Structure of Earnings Survey waves 2014 and 2018, and the Estonian Population Registry data for 2019–2020.

Previous studies on the gender wage gap in Estonia were conducted using the labour force survey (LFS) (Anspal, 2015 (a, b); Krillo et al., 2010), CV Keskus dataset (Meriküll & Mõtsmees, 2017), PIAAC data (Programme for the International Assessment of Adult Competencies) (Tverdostup & Paas, 2017; Tverdostup & Paas, 2016), and linked employer-employee data (Masso et al., 2020) to provide proof of consistently high gender wage gaps. So far, the principal identified reasons for the gender wage gap were occupied industry and employee position (occupation). To investigate the tendency that appeared in terms of the gender wage gap, we combine these firm and individual level datasets and create a matched employer-employee dataset. The merging is obtained through the company registration numbers and anonymized personal identification numbers. The wages are transformed into real wages and are converted from Estonian kroon to euro for the period before Estonia entered the Eurozone (before 2011). Wages are subsequently considered in their logarithmic transformation.

In Table 2, we illustrate the share of companies that import automation-related goods compared to the total number of companies that import. It can be noticed here that the percentage of companies introducing automation over the total number of firms that import goods reached a peak in the period 2000–2003 and subsequently decreased. This cannot be described as a constant decrease in the total number of companies importing automation but it depends on the increase of the total number of firms that import.

Table 2. Companies importing automation over total import companies

Year	Total number of companies that imported goods	Number of companies that imported automation-related goods	% of total companies
1995	10848	1610	15%
1996	10330	1624	16%
1997	10358	1747	17%
1998	10858	1924	18%
1999	10556	1949	18%
2000	10417	2194	21%
2001	10584	2286	22%
2002	11026	2413	22%
2003	11295	2508	22%
2004	10354	2192	21%
2005	8082	1653	20%
2006	10449	1643	16%
2007	14466	1924	13%
2008	17579	2029	12%
2009	9465	1583	17%
2010	11868	1664	14%
2011	19435	2182	11%
2012	22195	2394	11%
2013	23397	2467	11%
2014	22691	2599	11%
2015	26213	2744	10%
2016	26023	2703	10%
2017	24230	2848	12%
2018	22987	2799	12%
Average	15238	2153	14%

Source: Statistics Estonia.

Table 3 shows the percentage of importing firms, firms employing automation and firms employing different types of automation. The percentages are observed for the total economy, three different years (2006, 2012, 2017), the manufacturing sector and the services sector. Moreover, the manufacturing sector is further analysed dividing it into four different levels (high, medium-high, medium-low, low) of technology implemented, and the services sector into knowledge intensive and less knowledge intensive services. We can observe that 9.1% of Estonian enterprises are importers and 57.5% are high-tech manufacturing companies.

Table 3: Automation companies in percentage grouped

Grouping variable name	Importer	Automation	Regulating instrument	Conveyors	Other dedicated machines	Weaving & knitting machines	Welding machines	Tools for industrial work	Machine tools	Numerically controlled machines	Dedicated machinery incl. robots	Industrial robots
Whole sample	9.1%	1.8%	0.5%	0.1%	0.2%	0.0%	0.2%	1.2%	0.6%	0.1%	0.4%	0.0%
Year 2006	10.9%	2.3%	0.5%	0.1%	0.3%	0.0%	0.2%	1.5%	0.9%	0.1%	0.4%	0.0%
Year 2012	8.9%	1.8%	0.5%	0.1%	0.2%	0.0%	0.2%	1.2%	0.6%	0.1%	0.3%	0.0%
Year 2017	8.2%	1.7%	0.4%	0.1%	0.2%	0.0%	0.2%	1.1%	0.6%	0.0%	0.4%	0.0%
Manufacturing sector	23.4%	6.9%	1.3%	0.3%	1.0%	0.1%	0.8%	4.1%	3.4%	0.3%	1.0%	0.1%
Services sector	9.9%	1.9%	0.5%	0.1%	0.2%	0.0%	0.2%	1.3%	0.5%	0.1%	0.4%	0.0%
High-tech manufacturing firms	57.5%	16.5%	5.6%	0.5%	0.4%		4.3%	9.4%	7.2%	0.4%	4.5%	0.5%
Medium-high-tech manufacturing firms.	41.0%	15.0%	5.3%	1.3%	1.1%		2.4%	8.9%	7.1%	1.0%	2.6%	0.7%
Medium-low-tech manufacturing firms.	26.0%	9.7%	2.1%	0.4%	0.6%		1.4%	5.8%	4.0%	0.4%	1.8%	0.2%
Low-tech manufacturing firms.	20.9%	4.6%	0.4%	0.2%	1.5%	0.2%	0.2%	2.7%	2.3%	0.0%	0.5%	0.0%
Knowledge intensive services firms	4.6%	0.4%	0.1%	0.0%	0.0%	0.0%	0.0%	0.2%	0.1%	0.0%	0.1%	0.0%
Less knowledge – intensive services firms	12.6%	2.6%	0.8%	0.1%	0.3%	0.0%	0.2%	1.9%	0.7%	0.1%	0.6%	0.0%

Source: Statistics Estonia

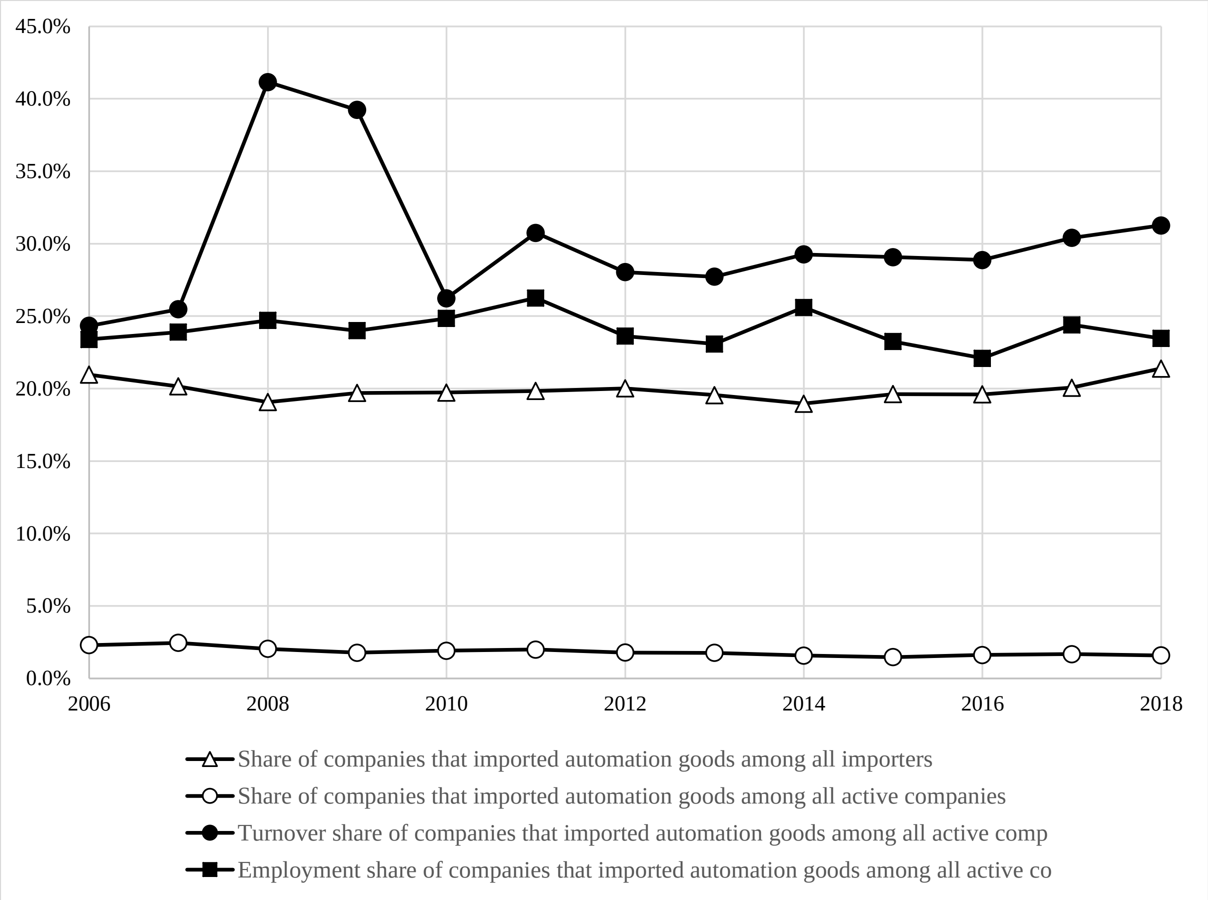

Figure 1. Shares of companies that have introduced automation

Data source: Statistics Estonia

Figure 1 illustrates that even if the number of companies that import automation goods is relatively small, 1.8% of all the economically active companies, the turnover and employment shares in active companies in Estonia is relevant. In particular, the firms' imported automation-related goods represent a stable 25% share of employment across the total number of active companies. The share of companies that imported automation goods is much higher in manufacturing (6.9%), especially for high and medium high-tech manufacturing (respectively 16.5% and 15%). In the services sector, the share of companies who have imported automation goods is higher in less knowledge intensive services compared to knowledge intensive services (respectively 0.5 and 2.6%). Figure 2 shows the top automation-related products to be imported to Estonia in the period under consideration. Electronic integrated circuits and hand tools of base metals[3] are the most common automation goods to be imported into Estonia. Processors and controllers, parts and accessories for machine tools, machines, apparatus and mechanical appliances are also relevant. However, the dynamics have changed in recent years. Hand tools are no longer important in recent years, and now electronic integrated circuits and machines, apparatus and mechanical appliances are gaining relevance.

[3] Those should be some hand tools containing automated parts.

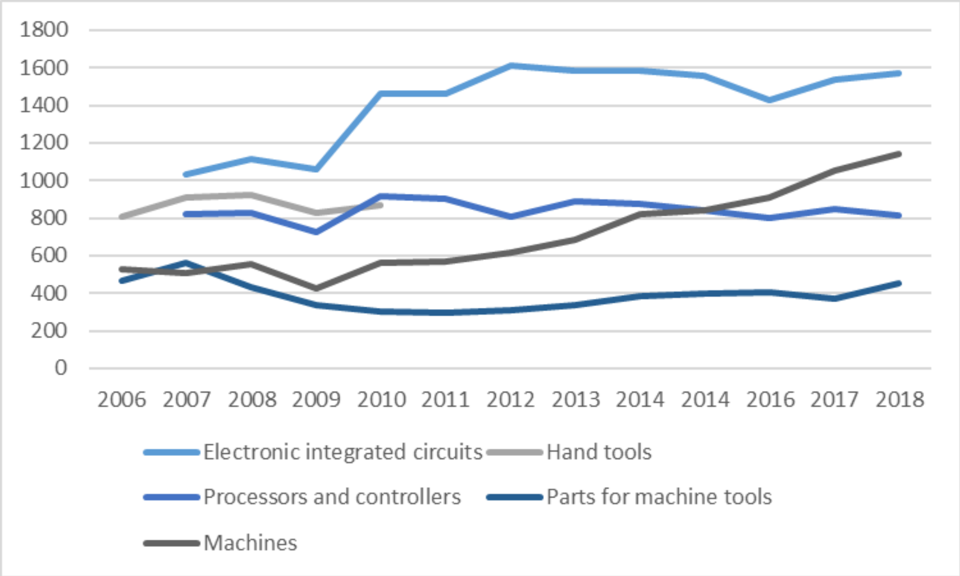

Figure 2. Dynamics of TOP imported automation products in Estonia
Data source: Statistics Estonia

Figure 3 shows the kernel density distributions of the average wages in companies in different firms with and without an automation variable for females and males. We can see that the lower level of the wages for females compared to males can be observed more or less throughout the wage distribution (upper left graph), and is not only about the differences in average or median wages. Our proxy for company automation is at the same time clearly associated with higher level of wages among males and females. When looking the data for all sectors (upper-left graph), the higher wages in automated companies can be observed especially among males, while among females the differences between companies with and without imports of automation goods are fairly small. The latter findings seem to indicate a higher gender pay gap in companies introducing automation, and that we can indeed also see in the bottom right graph that among companies importing automation goods the gender pay gap is larger. When looking at manufacturing industries only (bottom left), instead of the total economy, the positive association between wage level and automation is even more clearly visible, and in manufacturing the averages wages for females are clearly positively associated with automation. The graph in the upper-right shows that the previously described wage differences are also visible (albeit smaller) when the variable studied is instead the companies' average wages minus the 2-digit industry average wage level. These findings suggest we should look into the issue of wage gaps and automation in the econometric analysis.

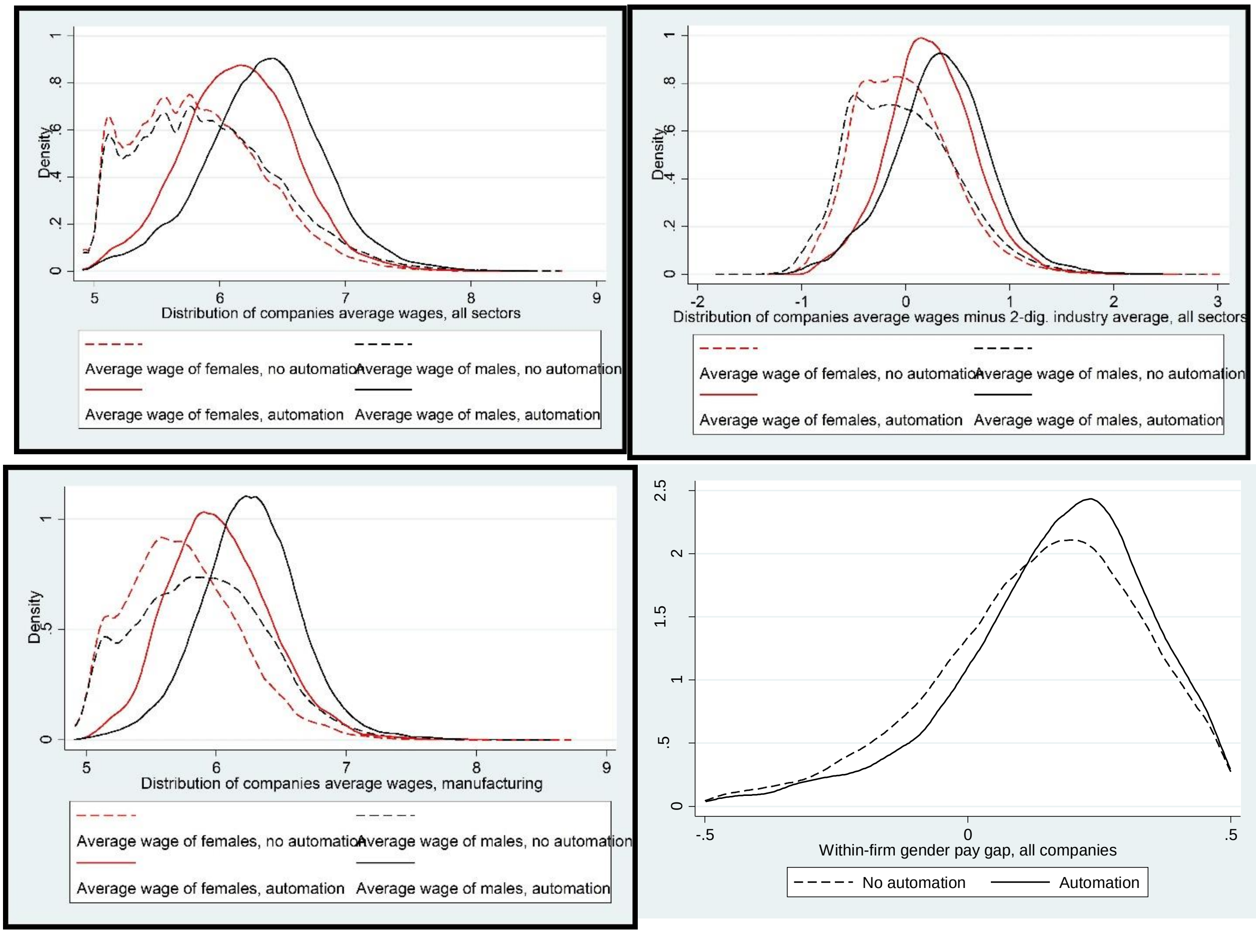

Figure 3. Kernel density distributions of company average wages with and without automation
Notes. Firms who imported automation goods compared to firms that did not import automation goods. Kernel density of wages is reported. Firms that imported automation goods are compared against the firms that did not import automation goods over the period of 2006–2018.

3.2. Methodology

The methodology of this paper follows the logic discussed in Masso and Vahter (2020), and Vahter and Masso (2019). First, we estimate the Mincerian equation taking into account a female dummy, an import dummy, an automation dummy, the iteration of female dummy with imports and automation as well as other regressors of potential changes in the wages (first column of Table 4). In this way, we aim to check the effects of the automation goods. The Mincerian equation can be described as follows:

$$\begin{aligned} \ln W_{i,j,t} &= \alpha + \beta_1 Female_{i,t} + \beta_2 Imp_{i,t} + \beta_3 \text{AutoIm}p_{i,t} + \\ &\beta_4 \text{Im}p_{i,t} \times Female_{i,t} + \beta_5 \text{AutoIm}p_{i,t} \times Female_{i,t} + \\ &+ \beta_6 Age_{i,t} + \beta_7 Age^2_{i,t} + \beta_8 R_{i,t} + \beta_9 Z_{j,t} + v_i + \lambda_t + e_{i,j.t} \end{aligned} \tag{1}$$

where $\ln W_{i,j,t}$ is the logarithm of the real wage of employee *i* in firm *j* at time *t*. $Female_{i,t}$ identifies if individual *i* in firm *j* is a female. $Imp_{i,t}$ is the dummy that describes whether firm *j* at time *t* is importing capital goods while $\beta_3 \text{AutoIm}p_{i,t}$ signals whether firm *j* at time *t* is importing automation capital goods. $Age_{i,t}$ is the age of the different individuals, $R_{i,t}$ represents a vector of other time-variant individual-level control variables and $Z_{j,t}$ is a vector of firm-level control variables[4]. λ_t is the vector of dummies for different years of the sample and v_i are firm-fixed effects. $e_{i,j,t}$ is the error term with zero mean and constant variance assumed to be normally distributed.

When estimating the effects of automation on the gender pay gap, it needs to be considered that automation is just a particular kind of process innovation. Masso and Vahter (2020) showed using data from the Community Innovation Survey that innovation is associated with a higher gender pay gap across various innovation output indicators (both technological and non-technological) as well as how the innovations are developed (via internal R&D or using cooperation with partners outside the company). Therefore, in order to check for the possible effects of innovation, such as in Masso and Vahter (2020), we introduce different kinds of innovation variables and their interactions with the female dummy (Table 5, all the models but model 1). In this, we check whether the significance of the automation dummy disappears or persists with the presence of the other innovation indicators in the wage equation. While the default dataset covers the whole population, the innovation variables are available for the companies that are included in the Community Innovation Survey, approximately 1,500 companies in each wave. These models with an extended set of explanatory variables can be described as an extension of equation 1 as follow:

$$
\begin{aligned}
&\ln W_{i,j,t} = \alpha + \beta_1 Female_{i,t} + \beta_2 Imp_{i,t} + \beta_3 \mathrm{AutoIm}p_{i,t} + \\
&+\beta_4 \mathrm{Im}p_{i,t} \times Female_{i,t} + \beta_5 \mathrm{AutoIm}p_{i,t} \times Female_{i,t} + \\
&+\beta_6 Innov_{j,t} + \beta_7 Innov_{j,t} \times Female_{i,t} + \\
&+\beta_8 Age_{i,t} + \beta_9 Age_{i,t}^2 + \beta_{10} R_{i,t} + \beta_{11} Z_{j,t} + v_i + \lambda_t + e_{i,j.t}
\end{aligned} \tag{2}
$$

where $Innov_{j,t}$ is the innovation variable considered in the different models. We repeat the estimations for three different cohorts (2006–2009, 2010–2013, 2014–2018) to observe the evolution of the effect of automation on the gender pay gap over time. Finally, we consider the wages for different occupations of employees in the firm. We make these latter estimations due to the findings of Aksoy et al. (2020) and we choose the typologies of occupations available in the dataset taking into account the study by Masso and Vahter (2020). The estimation is the same as in equation 1 with the average wages for all occupations replaced by the average wages in the different occupations.

Afterwards, we estimate propensity score matching (PSM) (Rosenbaum & Rubin, 1983). In this case, too, we follow the methodology of Vahter and Masso (2019). We analyse the effects of the introduction of automation in the different firms and its counterfactual, such as the non-acquisition of automation technologies on the part of the firms. In the first part of the PSM estimation, we check for the effect of the automation on employee wages in the different firms after the import of automation-related goods compared to the same in firms that did not acquire automation. The treatment variable "automation" is a dummy that assumes the value 1 after the "treatment" period and the unit of analysis is the firm. Subsequently, we aim to observe what

[4] The firm and individual controls include: firm age and its squared term; the share of the managers in the enterprise; share of females among employees; regressors on education levels of the employees; a variable to check a recent change of job among the employees; the set of 1-digit ISCO occupational dummies; dummies related to the different industries (2-digit NACE level); region dummies and a dummy for foreign ownership (to take into account the findings of Vahter and Masso (2019).

happens if an employee is working in a firm with automation compared to a firm without automation. In this kind of estimation, the unit of analysis is the employee.

In the first type of estimation, we use a probit model,[5] where the independent variables are measured one year before the acquisition of automation technologies. The list of control variables included in the estimation of the propensity score in the probit model for individuals includes mostly a similar set of variables as in the Mincerian wage regressions, and also two additional firm-level controls – company liquidity ratio and capital-labour ratio, considering the possible importance of the financial conditions of the firm and existing capital intensity regarding decisions on automation. The control variables also include the lagged values of the outcome variables, log real wages and log real wages squared. In the second type of estimation, we consider the individuals working in the companies where automation is introduced and where there is no introduction of automation technologies.

The probit models collect the information to derive the propensity score. Considering the propensity score, each firm *j* or individual *i* are matched with the 5 best counter-factual firms and individuals (nearest neighbour - NN - with 5 neighbours). Finally, we estimate the average treatment effect on treated (ATT) individuals/firms. We derive in this way the effects of automation related to total wages, females' wages and males' wages over the post-treatment phase. The ATT can be described as follows:

$$(3)\quad ATT^{s}_{PSM} = \Delta^{s}\pi^{treated}_{t+s} - \Delta^{s}\pi^{control}_{t+s}$$

where ATT^{s}_{PSM} is the average treatment effect on treated at period in years *s* considering the PSM. $\Delta^{s}\pi^{treated}_{t+s}$ is the mean growth of the average wage at the individual or firm level for the treated individuals or firms at time $t + s$. The second term concerns the control group.

The time of the actual change is defined with t. The probit model is executed with *t-1* variables, and later, we estimate the effects of the acquisition of automation technologies at time t, *t+1* and *t+2*. The outcome variables examined in the firm-level estimations are: firm's average wage, the average wage of male employees, and the average wage of female employees. In the case of the individual level analysis, we use individual male and female wages. We also examine the share of females as a supplementary outcome variable. This allows us to check the effects on the workforce structure after the acquisition of automation technologies and its eventual contribution to wages. In order to understand what automation technologies have more effect on wages, we repeat the estimations with all the subcategories of automation technologies we could derive from the datasets (see Tables A.1–15 in Appendix I).

4. Results and Discussion

4.1 Mincerian wage regressions

Table 4 presents the results from the estimation of the Mincerian wage regressions for the whole period of 2006 to 2018. The models in the table include in the wage equations, in addition to the automation variable, different innovation indicators from the community innovation survey. While the baseline model (model 1) includes just the automation in the company (import of

[5] The results of the probit models are available under request. The control variables used are the same as in Vahter and Masso (2019).

automation-intensive goods), the next models sequentially introduce process innovation (model 2), product innovation (model 3), organizational innovation (model 4), marketing innovation (model 5), and technological innovation (i.e. product or process innovation, model 6). As expected, in the specifications the female dummy has a strong negative association with wages that is statistically significant in all specifications at 1% level and range from -0.217 (model 1) to -0.292 (model 5), broadly corresponding to the size of the conditional gender pay gap estimated in earlier studies in Estonia using various datasets (Masso & Vahter 2020; Vahter & Masso, 2019). In all the estimated regressions, the female dummy variable is similar to the value observed in earlier Estonian datasets that employed matched employer-employee data (Masso & Vahter, 2019; Masso & Vahter, 2020). In particular, the baseline model (Model 1) reports a negative effect equal to 24.2%. The introduction of the innovation process variable increases the negative effect of the female dummy to 32.2% (model 2). The specification with product innovation has an even greater effect, 34.1% (model 3). The introduction of organizational innovation (model 4) and marketing innovation (model 5) has a similar effect, respectively 33.6% and 33.9%. Lastly, the specification for technological innovation (model 6) implies an effect of the female dummy equal to 32.8%. When calculating the gender pay gap as the wage level of females minus the wage level of males divided by the wage level of females, it varies from 19% (in the baseline model) to 34% in the model with the product innovation variable. The corresponding effects of the variables are calculated from log forms with the exponential transformation of the coefficients.

The dummy variable for firm-level imports shows a positive and statistically significant association with wages ranging from 6.8% (model 2) to 10.2% (model 1); while it is a natural control variable for wages in our model given the imports of particular goods being used as a proxy for automation, it also shows the generally observed positive effects of internationalization on wages. The interaction terms between the female dummy and the import dummy is statistically significant at the 1% level and also economically significant with an estimated size of -2.6% to -7.7%, indicating from another angle in addition to FDI (Vahter & Masso, 2019) and exports (Masso & Vahter ,2020) the importance of internationalization for the gender wage gap.

Table 4. Effects of import automation and gender dummy on real wages from 2006 to 2018 – baseline estimations and estimations with innovation variables

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Female (dummy)	-0.217***	-0.280***	-0.295***	-0.290***	-0.292***	-0.284***
	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Automation (dummy)	0.028***	0.016***	0.018***	0.017***	0.018***	0.016***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female × Automation	-0.012***	-0.017***	-0.021***	-0.019***	-0.021***	-0.020***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Importing (dummy)	0.102***	0.068***	0.070***	0.070***	0.069***	0.067***
	(0.012)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Female × Importing (dummy)	-0.077***	-0.025***	-0.031***	-0.028***	-0.030***	-0.026***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Process innovation		0.037***				
		(0.003)				
Female × Process innovation		-0.037***				
		(0.002)				

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Product innovation			0.006***			
			(0.002)			
Female × Product innovation			0.000			
			(0.002)			
Organizational innovation				0.028***		
				(0.002)		
Female × Organizational innov.				-0.021***		
				(0.002)		
Marketing innovation					0.027***	
					(0.002)	
Female × Marketing innovation					-0.012***	
					(0.002)	
Technological innovation						0.035***
						(0.002)
Female × Technological innov.						0.023***
						(0.002)
Number of obs.	3,703,715	1,186,766	1,186,766	1,186,766	1,186,766	1,186,766
R^2	0.350	0.400	0.399	0.400	0.400	0.400

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Standard errors are reported in parentheses. Coefficients approximated to the third decimal.
Control variables not included to save space. Estimations available upon request.
Data source: Statistics Estonia

Based on the respective coefficients and interactions presented, men earn 2.8% more when working in companies that introduce automation in their operations, compared to companies which do not introduce automation. At the same time, female employees who are working in companies that import automation-intensive goods, earn just 1.6% more; that is, their gain is less by 1.2 percentage points. It can be noticed that the introduction of innovation variables form the CIS into the model decreases the magnitude of the variables' coefficients of interest in comparison with the baseline model, yet it always remains there. For example, in the model with technological innovation, automation is associated with 1.6% higher wages for males, yet no gain for females due to the interaction term being at -2%. In Model 2, the specification with the process innovation, men's wages increase by 1.6% and the female wages decrease by -0.1%. In the model with product innovation (Model 3), the increase in the men's wages is equal to 1.8% and the decrease in women's wages is equal to -0.3%, the difference in this case being equal to 2.1%. In Model 4, with organizational innovation, male workers gain 1.7% more and female workers -0.18% (the difference being 1.9%), while in Model 5, with marketing innovation, males wages increase by 1.8% and female wages -0.3% (the difference is equal to 2.1%). Finally, the last specification, with technological innovation, shows an increase in men's wages equal to 1.6% and for women -0.4%, bringing the difference between the two genders' salaries to 2 %.

With the aim to observe the effects of automation on the gender pay gap throughout the period of analysis, we have conducted additional estimations for different sub-periods: from 2006 to 2009, from 2010 to 2013, and from 2014 to 2018 using the same set of control variables (Table 5). In the period of 2006–2009, the size of the female dummy varies from 29% (in the baseline model) to 37% (in the model with marketing innovation included). The estimated coefficients show that during 2006–2009 men gain 4.2% more when working in companies that introduce automation while females gain 0.8%, amounting to a difference in wages between men and women of 3.4%. From 2010 to 2013 the regressions show that the gender pay gap varies from 23% (in the baseline model) to 34.7% (in the model with product innovation) and men gain 3.6% when working in companies introducing automation, females 2.6% and difference being 1%. The results for 2014–2018 show the gender pay gap at the level from 20% (in the baseline model) to 31% (in the model with product innovation included). During this later period the evidence shows men and women as having approximately equal increases in wages of 1.7% when working in companies that import automation-intensive goods. Therefore, in summary, the results of Table 5 indicate how the negative effects of automation decreases over time. That finding is somewhat surprising given the evidence generally, or from Estonia in particular, on the increasing importance of firm-level factors for the gender pay gap (Masso et al. 2020); on the other hand, that is in line with the long-term downward trend over the last 30 years of the pay gap in Estonia (Meriküll & Tverdostup 2020).

Table 5. Effects of import automation and gender dummy on real wages in different sub-periods – baseline estimations

	2006-2009	**2010-2013**	**2014-2018**
Female (dummy)	-0.259***	-0.207***	-0.187***
	(0.002)	(0.002)	(0.002)
Automation (dummy)	0.042***	0.036***	0.017***
	(0.003)	(0.002)	(0.002)
Female × Automation	-0.034***	-0.010***	0.001
	(0.003)	(0.003)	(0.003)
Importing (dummy)	0.095***	0.111***	0.093***
	(0.002)	(0.002)	(0.002)
Female × Importing	-0.053***	-0.093***	-0.087***
(dummy)	(0.003)	(0.002)	(0.002)
Number of obs.	1,122,650	1,176,030	1,405,035
R^2	0.339	0.343	0.344

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are reported in parentheses. Coefficients approximated to the third decimal. Control variables not included to save space. Estimations available under request.
Data source: Estonia Statistics

Following equation (1), we also undertake estimations for wages across various occupation groups as defined at the ISCO 1-digit level from managerial positions to elementary occupations (Table 6). The average gender wage gap across occupations varies from 31% in craft and related trade workers to 14% in the skilled agricultural workers (but the latter group is often excluded from estimations given its smaller size and nonstandard coefficient estimates). The estimations indicate the importance of considering the heterogeneity of the effects of the broad occupational groups, as the automation dummy that was previously found to be positive in all of the estimations is now only in some broad groups (most significantly clerical support workers, +4.7%), but negative in some, like managers (-3.1%), and elementary occupations (-6.8%). The interaction terms between females and automation is also in most cases statistically significant and negative. Figure 4 on the association of automation with the wages of males and females indicates that wage loss due to automation is largest among female managers and clerical support workers, while only for males in elementary occupations.

Table 6. Effects of import automation and gender dummy on real wages in different occupations (2006–2018)

	Managers	**Professionals**	**Technicians and associated professionals**	**Clerical support workers**	**Service and sales work.**
Female (dummy)	-0.228***	-0.231***	-0.239***	-0.108**	-0.231***
	(0.373)	(0.030)	(0.021)	(0.030)	(0.029)
Automation (dummy)	-0.031***	-0.034***	0.016***	0.047***	-0.048***
	(0.025)	(0.026)	(0.018)	(0.025)	(0.028)
Female × Automation	-0.027***	0.036***	-0.044***	-0.102***	0.058***
	(0.039)	(0.032)	(0.022)	(0.031)	(0.030)
R^2 Adj.	0.393	0.354	0.383	0.504	0.397
	Skilled agricultural workers	**Craft and rel. trade work.**	**Plant & machine operators**	**Elementary occupations**	**All occupations**
Female (dummy)	-0.14***	-0.309***	-0.244***	-0.247***	-0.277***
	(0.095)	(0.025)	(0.020)	(0.031)	(0.010)
Automation (dummy)	-0.466	0.008***	0.004***	-0.068***	-0.008***
	(0.245)	(0.015)	(0.018)	(0.023)	(0.008)
Female × Automation	-0.029	-0.004***	-0.018***	0.044***	-0.01***
	(0.142)	(0.025)	(0.020)	(0.032)	(0.010)
R^2 Adj.	0.447	0.404	0.441	0.385	0.444

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are reported in parentheses. Coefficients approximated at the third decimal. Control variables not included to save space but full set of estimations are available under request.
Data source: Statistics Estonia

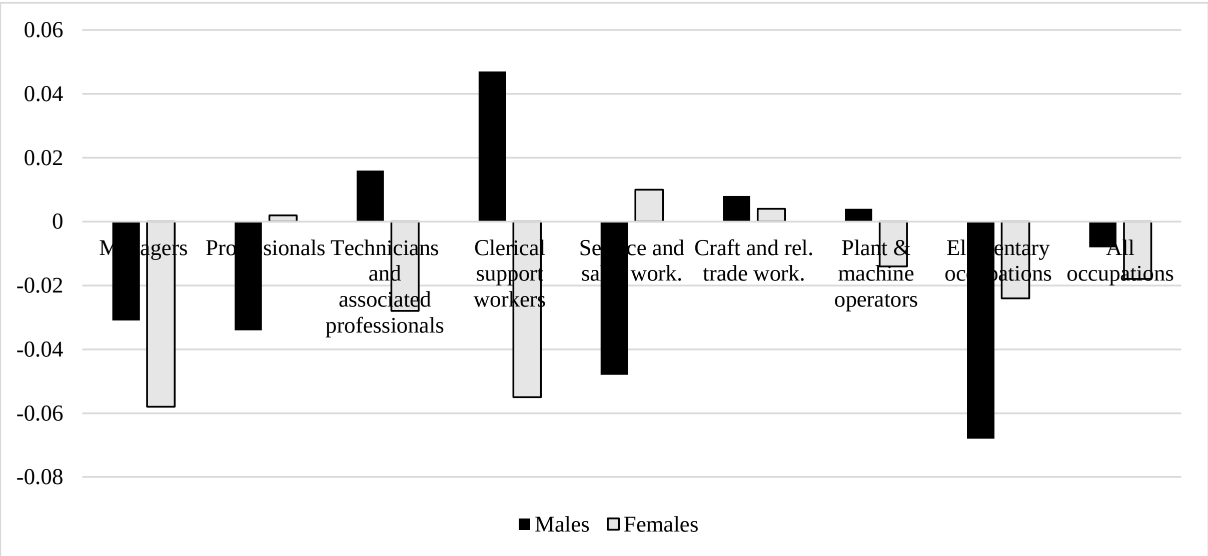

Figure 4. Effects on wages of imported automation products in Estonia per occupation – 2006–2018

4.2 Propensity Score Matching Results

In the following step, we use the propensity score matching (PSM) method to view the possible effects on the wages of men and women from companies that introduced automation to explore the gender pay gap, using companies that did not introduce automation as the control group. In order to account for the heterogeneity of the effects of automation given the very large and diverse sample of companies, the analysis is also conducted separately for manufacturing and services enterprises. Second, in addition to performing the impact evaluation for the general automation variable (i.e. imports of any automation goods), it is also performed for companies with various types of introduced automation (e.g. introduction of industrial robots, welding machines and others). Given that automation may be regarded as one particular kind of process innovation, we also run the estimations for the effects of process innovation from the CIS survey for comparison purposes. In the 1st step for estimating the propensity score for introducing various kinds of automations, probit models were evaluated, the dependent variable (treatment variable) being equal to 1 if the company without automation at t-1 introduced automation at time t. Following the literature, in particular the logic of Masso and Vahter (2020), the list of control variables included in the analysis include firm size, firm size squared, firm age, firm age squared, liquidity ratio, log of capital intensity, and location of the company in northern Estonia (the capital region). All of the mentioned controls are calculated from one year before the treatment (introduction of automation). After composing the propensity score, the control group for both males and females is compiled separately. In the following step, the ATT is estimated based on equation 3 presented above.

In Figure 5 we can observe the estimated ATT effects for males and females across various sectors of the economy (manufacturing, services, all sectors) two years after the actual introduction of automation in the company. Across the three studied sectoral groupings (total economy, manufacturing, services) and different kinds of automation, the positive effect on wages is in most cases larger in the case of males compared to females. In the analysis for the economy as a whole, the positive effect on the wages of males is 7.6 percentage points and for females 6.5 percentage points. These effects are slightly larger compared to the process innovation variable from the CIS, 4.1 and 4.8 percentage points respectively. Concerning the variation of effects across various automation goods, the largest positive effects can be seen from the introduction of conveyors, 19.4 percentage points for males and 16 for females. Rather large effects can also be seen from the introduction of dedicated machinery, +13.9% for males and 10.2% for females, and welding machines, 12.4% for males and 7.8% for males. Nevertheless, some of the effects are statistically insignificant because the number of treatments is quite small (e.g. for industrial robots there are only 40 treatments available for evaluation – generally around 50 can be considered as a minimum to have robust results). These results provide additional evidence of the existence and increase of the gender pay gap across various sectors of the economy for employees working in companies with introduced automation.

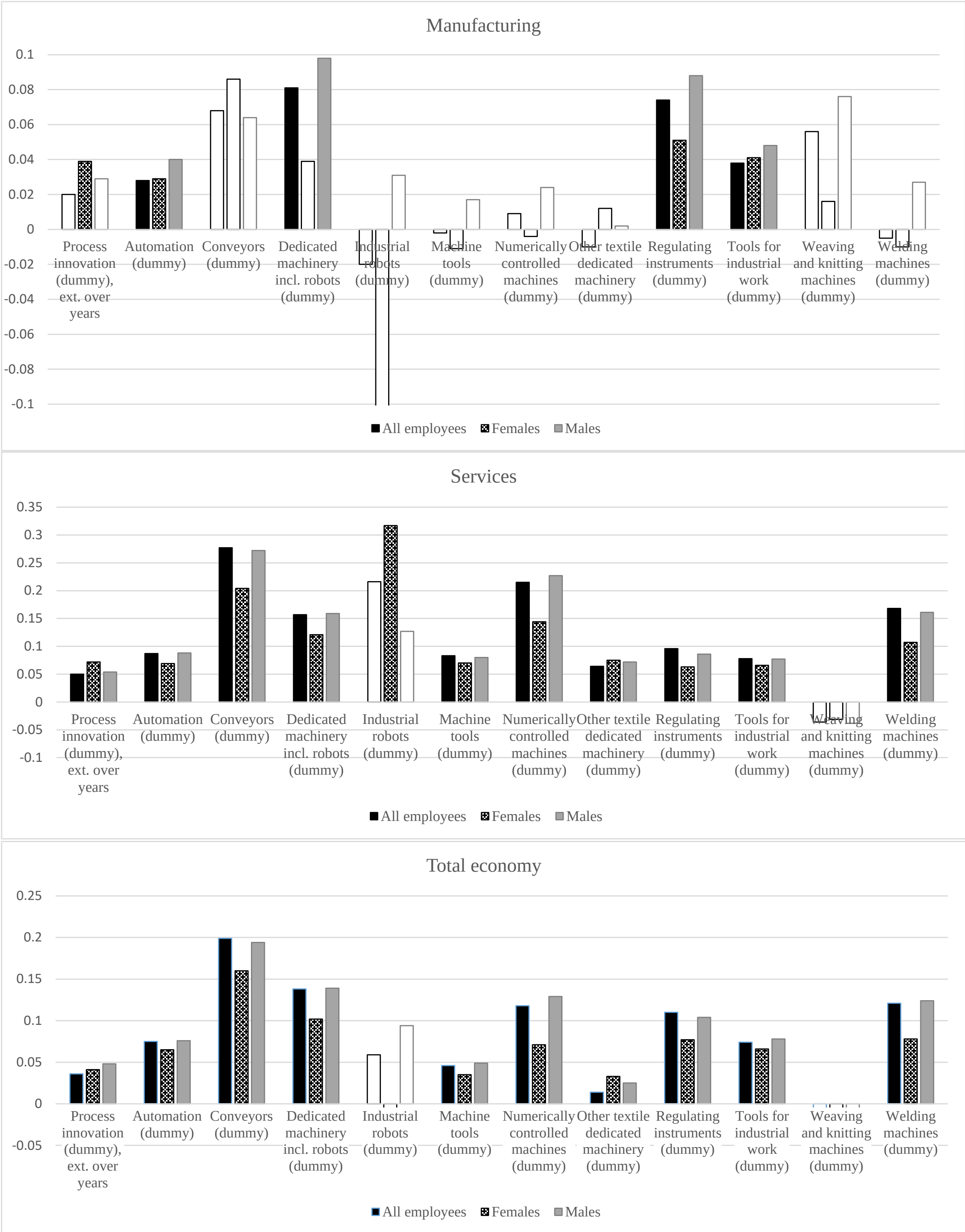

Figure 5. The effects of automatization and innovation according to propensity score matching over 2006–2018 (The blank bars indicate statistically insignificant estimates)
Data source: Statistics Estonia

Table 7. Effects of different automation tools on log real wages t+2 – manufacturing sector

Treatment	No. of Treated	No. of Untreated	All employees	Females	Males
Manufacturing					
Process innovation	1,687	1,550	0.02	0.039**	0.029
Automation	1,786	7,741	0.028**	0.029**	0.04***
Conveyors	61	5,240	0.068	0.086	0.064
Dedicated machinery incl. robots	254	7,640	0.081***	0.039	0.098***
Industrial robots	32	2,256	-0.02	-0.102	0.031
Mach tools	813	7,515	-0.002	-0.011	0.017
Numerically controlled machines	90	5,257	0.009	-0.004	0.024
Other text dedicated machinery	272	5,986	-0.01	0.012	0.002
Regulating instruments	289	7,587	0.074**	0.051*	0.088***
Tools for industrial work	1,081	7,627	0.038**	0.041**	0.048***
Weaving and knit machines	19	896	0.056	0.016	0.076
Welding machines	172	5,007	-0.005	-0.01	0.027
Services					
Process innovation	1,171	1,552	0.05**	0.072***	0.054**
Automation	4,319	27,369	0.087***	0.069***	0.088***
Conveyors	131	19,981	0.277***	0.204***	0.272***
Dedicated machinery incl. robots	1,101	24,616	0.157***	0.121***	0.159***
Industrial robots	6	2,835	0.216	0.317**	0.127
Mach tools	1,175	23,823	0.083***	0.07***	0.08***
Numerically controlled machines	93	18,319	0.215***	0.144***	0.227***
Other text dedicated machinery	473	19,090	0.064***	0.075***	0.072***
Regulating instruments	1,435	24,813	0.096***	0.063***	0.086***
Tools for industrial work	3,307	27,147	0.078***	0.066***	0.077***
Weaving and knit machines	33	17,232	-0.036	-0.031	-0.038
Welding machines	430	17,765	0.168***	0.107***	0.161***
Total economy					
Process innovation	3,233	3,565	0.036***	0.041***	0.048***
Automation	6,461	46,351	0.075***	0.065***	0.076***
Conveyors	204	28,599	0.199***	0.16***	0.194***
Dedicated machinery incl. robots	1,437	41,644	0.138***	0.102***	.139***
Industrial robots	40	8,513	0.059	-0.03	0.094
Mach tools	2,083	41,901	0.046***	0.035***	0.049***
Numerically controlled machines	197	31,579	0.118***	0.071**	0.129***
Other text dedicated machinery	796	33,208	0.014	0.033*	0.025
Regulating instruments	1,830	39,704	0.11***	0.077***	0.104***
Tools for industrial work	4,559	45,906	0.074***	0.066***	0.078***
Weaving and knit machines	52	18,357	-0.022	-0.024	-0.013
Welding machines	620	27,511	0.121***	0.078***	0.124***

Note. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Going further into the variation of these effects across sectors, the analysis in the manufacturing sector indicates an increase in salaries for males equal to 9.8% in industries using dedicated machinery, 8.8% in those with regulating instruments, and 4.8% in industries with tools for industrial work. At the same time, across the different automation variables, most estimated effects on the wages of females are statistically insignificant, except that female employees gain 5.1% in firms that introduced regulating instruments and 4.1% in enterprises with tools for industrial work. In the services sector, most of the effects are positive and statistically significant either for males or females (except for industrial robots and weaving and knitting machines), and this is also related to the larger number of the treated companies (firms introducing automation into their operations). As for any kind of automation, the positive effects on wages are somewhat larger compared to manufacturing, 6.9% for females and 8.8% for males. Across the different kinds of automation, the effects are the largest for conveyors (27.2% males, 20.4% females), numerically controlled machines (22.7% males, 14.4% females), and dedicated machinery (15.9% males, 12.1% females). As we can see, here the male-female difference is quite considerable – 6.8 percentage point greater positive effects on the wages of males due to the introduction of conveyors. While the difference in aggregate effect might have not seemed so huge (1.1 percentage point difference for automation effects between males and females), these estimates demonstrate that considerable effects can be observed for particular sub-samples.

These results are in line with some of the previous literature but, at the same time, add new insights on the effects of automation on the gender pay gap. For example, the increasing effect of automation on the gender pay gap could be related to the observations of Blanas et al., (2019). Female workers are developing skills more prone to automation than men. Anelli et al. (2019) confirm these dynamics studying US data. Indeed, our results confirm the importance of taking into account different sectors and typologies of workers as in Bessen et al. (2019). Moreover, we can observe that even in higher positions like managerial positions automation may positively affect the gender pay gap, suggesting that being employed in higher positions alone does not provide assurance of better salaries for women as Aksoy et al. (2020) suggest. Another novelty of our results is the strong evidence that the effect of automation on wages and the pay gap varies strongly across the different types of automation.

Conclusions

Estonia has had for many years the highest gender pay gap among the EU countries. However, in the past decade the gender pay gap has decreased similarly as in other developed countries. In the present paper, we analyse Estonian data from 2006 to 2018 to study the effects of company automation on the gender pay gap. The regression analysis showed a negative and significant association of automation with the gender pay gap. This implies that automation has an adverse effect on the current observed reduction of the gender pay gap in Estonia. These results were robust even after controlling for the more general technological and non-technological innovation variables in the wage regressions. However, dividing the timeframe into different intervals we can observe how the relation between automation and the gender pay gap is becoming weaker. This is in accordance with the dynamics observed by previous literature whereby women are acquiring new skills more compatible with automation faster than men (Blanas et al., 2019), as well as studies which illustrate how automation is decreasing the gender pay gap in other countries, such as the USA (Anelli et al., 2019). The robustness of these results and the correctness of these interpretations should nevertheless be checked in future studies.

In addition, based on the undertaken estimations, we show that imports of automation-intensive goods and the respective introduction of automation across companies correlates with the existence and increase of the gender pay gap across companies in different sectors of the economy. This confirms recent literature on the subject that the losses due to technological changes have to be analysed accounting for possible variations across sectors. Moreover, the authors suggest that the typology of workers could count in determining the individual losses or gains due to automation. Indeed, we observed that the introduction of automation in companies also provides variation among earnings for different occupational groups. For male employees, more positive effects and higher wages are observed in technical professionals and support worker occupations. Instead, female employees appear to observe an increase in real wages when they are professionals, service and sales workers, craft and related trade workers. These results add further insights into previous works on the effects of automation on the gender pay gap in different occupations (Aksoy et al., 2020; Bessen et al., 2019). Moreover, even if the women were more represented in managerial positions in comparison to the present situation, the effects of automation would still be associated with an inferior wage compared to men. When making estimations using the propensity score matching method, we observe that male employees receive higher gains and wages in the companies with various types of introduced automation than female employees and this holds across different categories of automation (albeit with insignificant estimates in some subcategories due to the small number of treatment units). These results allow us to observe not only the effects of automation on the gender pay gap in different occupations, sectors and firms, but also how different automations can affect the gender pay gap in employer-employee data. Indeed, the introduction of certain types of automation affect the gender pay gap differently even if they are consistent with the general results.

Our results lead to certain policy implications. For example, upgrading skills compatible with new technologies among workers is needed for both men and women. However, this should be tailored considering occupation, sector and the typology of automation employed by the different firms. A higher representation of women in higher paid positions does not guarantee a reduction in the gender pay gap in the presence of automation. Indeed, more appropriate education/training can be necessary for female workers in managerial positions where automation has significant effects. The effects of the different kinds of automation can indicate which competencies female workers can apply to overcome the gender pay gap. Firms aiming to close the gender pay gap should provide these specific forms of training based on the automations needed for their operations. Possible public subsidies can also be considered. Alternatively, enterprises importing automation-goods should take into account the effects on relative wages and the current education and skills of male and female workers and allocate them accordingly. Even if this could reduce the gender pay gap, there is a risk of the polarization of female workers.

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Appendix 1. Average treatment effect on the share of females and wages at t+2

Treatment variable	Treated	Untreated	Share of female employees	Share of female managers	Log average wage	Log average wage of females	Log average wage of males
			Total economy				
Process innovation	3,233	3,565	.03***	0.029	.036***	.041***	.048***
Automation	6,461	46,351	-.038***	-.034***	.075***	.065***	.076***
Conveyors	204	28,599	-.118***	-.178***	.199***	.16***	.194***
Dedicated machinery incl. robots	1,437	41,644	-.07***	-.082***	.138***	.102***	.139***
Industrial robots	40	8,513	.116**	-0.013	0.059	-0.03	0.094
Machine tools	2,083	41,901	-.059***	-.059***	.046***	.035***	.049***
Numerically controlled machines	197	31,579	-.088***	-0.007	.118***	.071**	.129***
Other textile dedicated machinery	796	33,208	.03***	.059**	0.014	.033*	0.025
Regulating instruments	1,830	39,704	-.09***	-.1***	.11***	.077***	.104***
Tools for industrial work	4,559	45,906	-.03***	-.03***	.074***	.066***	.078***
Weaving and knitting machines	52	18,357	0.048	-0.032	-0.022	-0.024	-0.013
Welding machines	620	27,511	-.086***	-.1***	.121***	.078***	.124***
			Manufacturing				
Process innovation	1,687	1,550	.029*	.055**	0.02	.039**	0.029
Automation	1,786	7,741	0.012	0.003	.028**	.029**	.04***
Conveyors	61	5,240	-0.022	-.11**	0.068	0.086	0.064
Dedicated machinery incl. robots	254	7,640	-0.021	-.107***	.081***	0.039	.098***
Industrial robots	32	2,256	.136**	-0.038	-0.02	-0.102	0.031
Machine tools	813	7,515	.02*	0.014	-0.002	-0.011	0.017
Numerically controlled machines	90	5,257	-0.002	0.045	0.009	-0.004	0.024
Other textile dedicated machinery	272	5,986	.049*	.094*	-0.01	0.012	0.002
Regulating instruments	289	7,587	0.019	-0.025	.074**	.051*	.088***
Tools for industrial work	1,081	7,627	.024**	0.026	.038**	.041**	.048***
Weaving and knitting machines	19	896	-0.016	-0.164	0.056	0.016	0.076
Welding machines	172	5,007	0.045	0.02	-0.005	-0.01	0.027

Treatment variable	Treated	Untreated	Share of female employees	Share of female managers	Log average wage	Log average wage of females	Log average wage of males
			Services				
Process innovation	1,171	1,552	0.018	-0.015	.05**	.072***	.054**
Automation	4,319	27,369	-.059***	-.056***	.087***	.069***	.088***
Conveyors	131	19,981	-.165***	-.223***	.277***	.204***	.272***
Dedicated machinery incl. robots	1,101	24,616	-.088***	-.097***	.157***	.121***	.159***
Industrial robots	6	2,835	-0.017	0.048	0.216	.317**	0.127
Machine tools	1,175	23,823	-.098***	-.068**	.083***	.07***	.08***
Numerically controlled machines	93	18,319	-.17***	-0.01	.215***	.144***	.227***
Other textile dedicated machinery	473	19,090	0.019	.081**	.064***	.075***	.072***
Regulating instruments	1,435	24,813	-.103***	-.119***	.096***	.063***	.086***
Tools for industrial work	3,307	27,147	-.049***	-.041***	.078***	.066***	.077***
Weaving and knitting machines	33	17,232	.12***	0.077	-0.036	-0.031	-0.038
Welding machines	430	17,765	-.129***	-.16***	.168***	.107***	.161***

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are reported in parentheses. Coefficients approximated at the third decimal.