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Robots and the Gender Pay Gap in Europe

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Abstract

Could robotization make the gender pay gap worse? We provide the first large-scale evidence on the impact of industrial robots on the gender pay gap using data from 20 European countries. We show that robot adoption increases both male and female earnings but also increases the gender pay gap. Using an instrumental variable strategy, we find that a ten percent increase in robotization leads to a 1.8 percent increase in the gender pay gap. These results are mainly driven by countries with high levels of gender inequality and outsourcing destination countries. We then explore the mechanisms behind this effect and find that our results can be explained by the fact that men at medium- and high-skill occupations disproportionately benefit from robotization (through a productivity effect). We rule out the possibility that our results are driven by mechanical changes in the gender composition of the workforce nor by inflows or outflows from the manufacturing sector.

Keywords: industrial robots, gender pay gap, automation, Europe JEL Codes: J00, J31, J71

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1 Introduction

Technological innovations are quickly shifting the frontier between activities performed by humans and those performed by machines, transforming the world of work. Recent advances in automation and their implications for the economy and society are central issues in the global policy and academic debate. However, despite the comprehensive examination of the impact of automation on overall employment and labor force participation (see Grigoli et al. 2020 for a review), there has been little empirical research on how automation might affect gender equality.

The impact of automation is likely to be different for men and women because women and men perform different job tasks and are differentially represented in the occupational hierarchy in most industries. Brussevich et al. (2019) construct a gender-specific routine task intensity (RTI) index, which quantifies the extent of codifiability of tasks performed on the job. Its higher values indicate that a worker engages in more routine activities and is thus at a higher risk of substitution with machines. Brussevich et al. (2019) find that the RTI index, on average, is 13 percent higher for female workers across the sample of 30 countries. They find that female workers perform fewer tasks requiring analytical and interpersonal skills or physical labor, and more tasks that are characterized by lack of job flexibility, little learning on the job, and greater repetitiveness. This suggests that female workers are more exposed to automation risk than male workers, on average. Moreover, in many countries, women are underrepresented in higher-level occupations that command higher wages. This implies that men are more likely to benefit from the large productivity gains that are produced by automation.

In this paper, we focus on one specific type of automation, adoption of industrial robots, which may have differentially gendered effects on labor markets, too. We provide the first large-scale evidence on the impact of robot adoption between 2006 and 2014 on the gender pay gap, by studying 20 European countries. Specifically, we examine how changes in the number of robots per worker between survey years (henceforth, 'robotization') affect the gender gap in the monthly earnings of workers in manufacturing and a few other sectors that employ robots.[1] We refer to the number of robots per 10,000 workers as 'robot density'.

We find that robotization increases the gender pay gap: a ten percent increase in robotization leads to a 1.8 percent increase in the (conditional) gender pay gap.[2] Given that in many countries and industries, we have seen increases in robotization of more than 10 percent, this effect is sizable. To put it in perspective, the introduction of the national minimum wage led to a fall in the raw gender pay gap of about 2 percent (see, for example, Robinson 2002 for evidence from the UK; Boll et al. 2015 for evidence from Germany). In addition, the effect we identified is larger than that of many family-friendly policies in European countries, where the evidence on their effectiveness for reducing the pay gap is mixed (see review in Olivetti and Petrongolo 2017).

The results are mostly driven by countries with high initial gender inequality that also experienced high robotization. These countries also tend to be outsourcing destination countries. We also explore potential underlying mechanisms and find that our results are likely to be explained by a larger increase in male earnings than female earnings, especially within medium and high-skilled occupations (through a productivity effect).[3] Put differently, the underrepresentation of women in medium and high-skill occupations in specific industries accompanied by robotization exacerbates the gender pay gap, especially in countries where gender inequality was already severe. Conversely, in countries where initial gender inequality has been low, robotization did not have any statistically significant effect on the gender pay gap, while it increased the earnings of all workers. We also show that our results cannot be explained by changes in the gender composition of the workforce nor by inflows or outflows from the manufacturing sector, which is in line

[1] Specifically, we have 12 industries: eight manufacturing (manufacturing of automotive/transport, plastic/chemicals, metal, food/beverages, electrical/electronics, wood/paper, textiles, and other manufacturing branches) and four non-manufacturing industries (mining/quarrying, education/research/development, construction, utilities).

[2] Conditional Gender Pay Gap (GPG) is defined in our paper as the difference between the earnings of men and women who work within the same occupational category, industry, are of similar age, live in the same country, measured in the same year and working in similar size of firms. Put differently, conditional pay gap is the pay gap after adjusting for a set of compositional factors that may account for differences between men's and women's earnings. Conditional GPG is more important than the unconditional (overall) pay gap, from the policy point of view, because it is related to 'equal pay' legislation in Europe.

[3] This is in line with Acemoglu et al. (2020), who show that firm-level adoption of robots coincides with increases in value added and productivity.

with the findings of Freeman et al. (2020).[4]

There is a risk of potential endogeneity of robotization to the gender pay gap. For example, a shock to relative female labor demand in an industry may affect a firm's decision to adopt robots. To identify a causal effect, we follow Graetz and Michaels (2018) and instrument robotization with an industry level replaceability index. In particular, our instrument specifies the fraction of each industry's hours worked in 1980 in the United States that was performed by occupations that became replaceable by robots by 2012 (Graetz and Michaels, 2018). The replaceability index strongly predicts the increase in robot intensity: as robot prices fell, industries with higher initial replaceability increased their use of robots.

We also show that our results are robust to different specifications (a different set of controls or using alternative measures of robotization or gender pay gap), and various alternative samples (for example, excluding Germany since it has the highest robotization rate in Europe or exclusion of automotive and transport industries).

Industrial robots are defined as 'automatically controlled, reprogrammable, multipurpose manipulator, programmable to perform tasks in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications' (International Federation of Robotics, 2017). Specific focus on robots and robotization is warranted for three critical reasons: First, rapid robotization continues in Europe. The annual sales volume of industrial robots increased by 114 percent in Europe since 2013 and is expected to continue double-digit growth (International Federation of Robotics, 2018). Second, unskilled male workers are more likely to be displaced by industrial robots. This is because the industrial robots, as opposed to many other forms of automation, replace workers with 'brawn' skills, who are more likely to be men (Rendall, 2017; Ngai and Petrongolo, 2017). Male-dominated occupations tend to be more manual and more easily replaced by robots (Muro et al., 2019). At the same time, skilled male workers are more likely to benefit from robot-driven productivity as they disproportionately occupy higher positions in the occupational hierarchy. Third, while some forms of AI and automation will be replacing repetitive tasks (Brynjolfsson et al., 2018) while requiring employees to work with the new technology, industrial robots often replace workers directly.

[4] Freeman et al. (2020) find that degrees of automation are only weakly related to subsequent changes in occupational employment. The authors claim: 'within-occupation impacts of technology may offer a better path to projecting the future of work than forecasts of changing employment levels or occupational shares.' (p.394).

Europe is an important setting because the exposure of its workers to industrial robots in 2016 was 19 percent higher compared with workers in the USA (Chiacchio et al., 2018). At the same time, the average gender pay gap is still around 15 percent (that is, women's gross hourly earnings are, on average, 14.8 percent below those of men) with some variation between countries (Eurostat, 2018). Therefore, studying the impact of robotization on the gender pay gap in Europe is fundamentally important. Hard-won gains from policies to increase the number of women in the paid workforce and to increase women's pay to equal that of men may be quickly eroded if women are disadvantaged by the process of automation (Brussevich et al., 2018).

Our paper contributes to several strands of the literature. First, there is a growing number of studies on the impact of robotization on labor market outcomes. Acemoglu and Restrepo (2020) show that industrial robot exposure reduces both employment and wages in the United States. This finding starkly contrasts with evidence from Europe. Graetz and Michaels (2018) show that robotization increases both labor productivity and wages and has no effect on employment in 14 European and three non-European countries. Dauth et al. (2018) focus on Germany and find no effects of automation on total employment. Our paper contributes to this growing literature by focusing on the gender pay gap – a crucial but neglected policy-relevant outcome.[5]

Second, our paper is also related to the literature on the determinants of the gender pay gap. While the gender wage gap in developed countries has narrowed considerably over the last half-century, a substantial gap remains (Kunze, 2018). An extensive literature has studied the factors that can explain this persistence of gender pay differences. However, most research focuses on supply-side explanations, such as gender differences in human capital factors, psychological attributes, or occupations (Blau and Kahn, 2017). There is much less evidence on how demand-side factors (such as automation) affect the pay gap (see reviews in Ngai and Petrongolo 2017; Petrongolo and Ronchi 2020). Among the literature studying demand-side factors, a few papers have analyzed the gendered effects of computerization. These papers find that the increased use of computers contributed to the narrowing of the gender pay gap (Weinberg, 2000; Black and Spitz-Oener, 2010; Yamaguchi, 2018). Differential changes in tasks can explain this finding: While women experienced a marked decline in routine tasks, men did not (Black and Spitz-Oener, 2010).

[5]Using a large-scale survey experiment, Jeffrey (2020) shows that automation-induced inequality increases preferences for redistributive policies.

We contribute to this literature by providing evidence on the impact of robotization, an important demand-side factor.

Only a few papers have explored the gendered labor market impact of recent waves of automation. Brussevich et al. (2019) relate data on task composition at work to occupation-level estimates of the probability of automation and find that female workers are at a significantly higher risk for displacement by automation than male workers, albeit with significant cross-country heterogeneity. They also show that the probability of automation is lower for younger cohorts of women, and those in managerial positions. Grigoli et al. (2020) examine the effects of automation (that is, routine-replacing technical change) on labor force participation rates and individuals' attachment to the workforce in 23 advanced economies over the period 1985-2016. They find that exposure to automation explains about half of the observed decline in labor force participation rates of prime-age men in the average advanced economy. While prime-age women joined the labor force in increasing numbers over the last three decades, automation subtracted from these gains. Recent evidence from the US indicates that robotization may have lowered the gender gap in labor force participation and pay (Anelli et al., 2019). The authors also show that regions affected by intense robot penetration experienced a decrease in the number of new marriages and an increase in both divorce and cohabitation rates.

Our data and setting provide some unique advantages that allow us to complement existing studies, as we directly examine the impact of robotization on earnings. Our analysis also offers the broadest cross-national evidence to date on the relationship between robotization and the gender pay gap. This allows greater confidence in the generality of the findings (28 million workers from 20 countries). It also makes it possible to investigate heterogeneity based on various country-level and individual-level characteristics. Furthermore, by instrumenting robotization, we address potential concerns related to endogeneity and omitted variables bias.

The rest of the paper is organized as follows: The next section provides background information on robotization trends in our sample of European countries. Section 3 describes the data, and Section 4 describes the empirical approach. Section 5 presents our results. Section 6 concludes.

2 Background

Europe has seen tremendous growth in robotization over the sample period, both in absolute terms and as a percentage of the number of workers employed. The number of robots per 10,000 workers increased, on average, by 47 percent in our sample of 20 European countries between 2006 and 2014. However, Figure 1 shows that the level and growth of robotization vary substantially across countries. With almost 50 robots per 10,000 employees in 2014, Germany shows the highest level. On the other hand, Bulgaria, Latvia, and Lithuania Bulgaria have the lowest robotization in our sample, with less than one robot per 10,000 workers. Furthermore, Figure 1 shows that many countries have seen high levels of growth in the number of robots per worker. For example, robotization in the Czech Republic grew from 6 per 10,000 workers in 2006 to 23 per 10,000 workers in 2014.

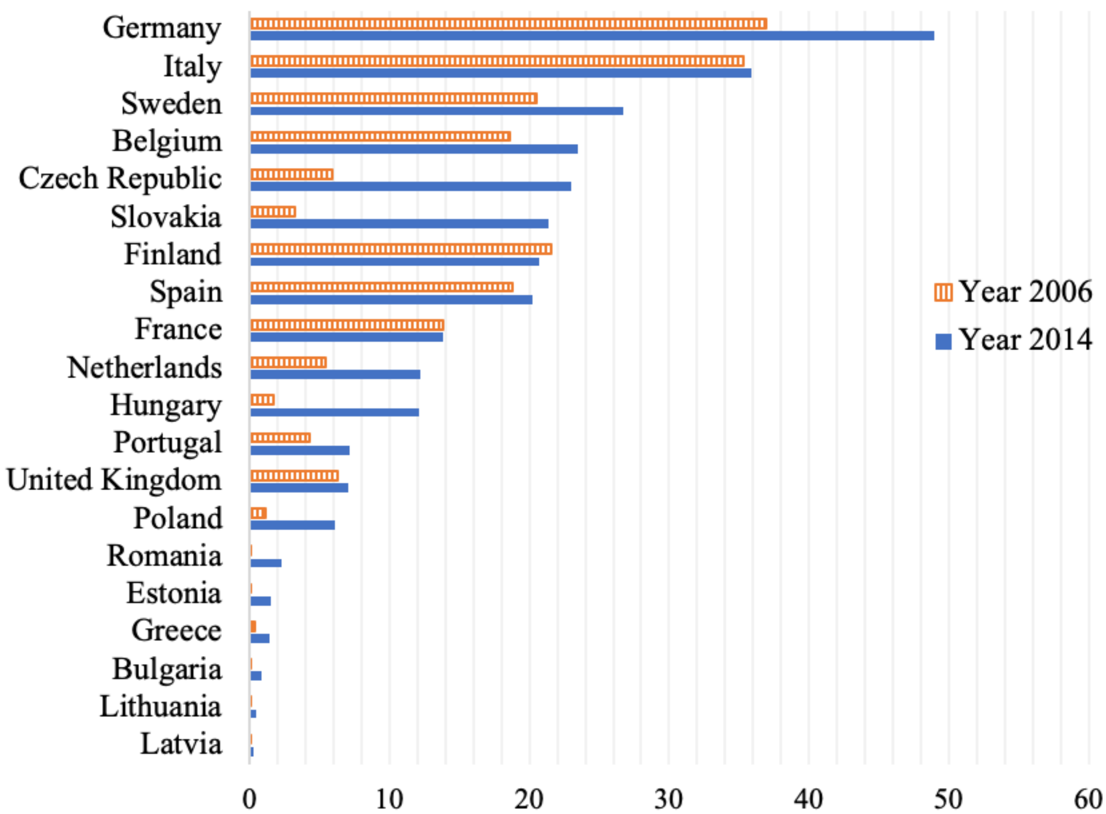

Figure 1: Industrial robots per 10,000 workers by country

Sources: IFR (2017), EU KLEMS, authors' calculations.

Figure 2A shows that industrial robots are mainly deployed in the automotive and

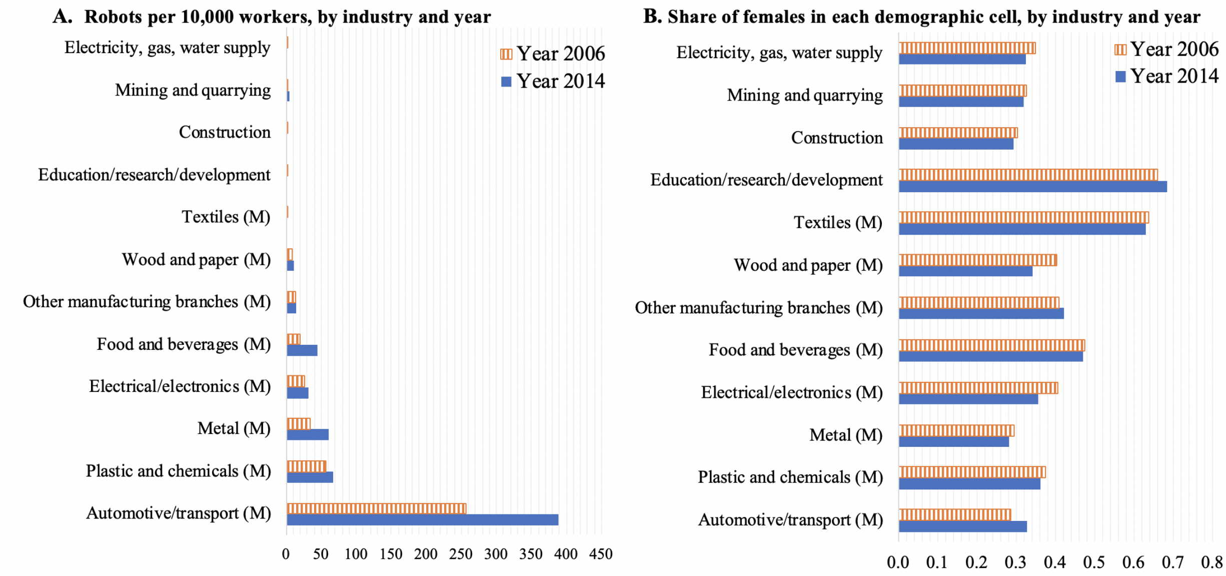

Figure 2: Robot density and share of females by industry

Sources: IFR, EU KLEMS, authors' calculations. (M) indicates manufacturing industry.

transport industry (about 390 robots per 10,000 workers in 2014), although they have also begun to be used more widely in the production of plastic, chemicals, and metals as well as food and beverages. Figure 2A suggests that the vast majority of industrial robots are employed in industries that are part of the manufacturing sector.

To understand whether there was a change in the gender composition of the workforce over the sample period, we present the share of female workers by industry and year in Figure 2B. The most common sectors of employment for women in Europe are education/research/ development (women accounted for 68 percent of all jobs in the sector in 2014), the textile (63 percent), and food and beverages (47 percent). Women are also less likely than men to be working in the automotive and transportation, metal, construction, and mining and quarrying industries. Overall, within-industry gender composition changes have been minimal (2 percentage points or less) between 2006 and 2014. Notable exceptions are wood and paper (7 percentage points), electrical/electronics (5 percentage points), and automotive/transport (4 percentage points).

Figure 3 shows the gender gap in median monthly earnings in 2010 for the 20 countries included in our sample. The size of the gender pay gap varies across economies: it ranges from 4 percent in Romania and Bulgaria to 18 percent in Germany and 19 percent in Estonia. To avoid the possibility that men and women's weekly earnings can be attributed to hours worked, we adjust the earnings of part-time workers to their full-time equivalents in Figure 3. However, the gender gap in median monthly earnings for all workers is larger than either the full-time or part-time pay gaps. This is because a much higher share of women than men are employed part-time, and part-time workers tend to earn less per hour than those working full-time. Additional analysis suggests that there has been a downward trend in the gender pay gap since 2006 and the average pay gap stood at 11 percent in the manufacturing sector in 2014.

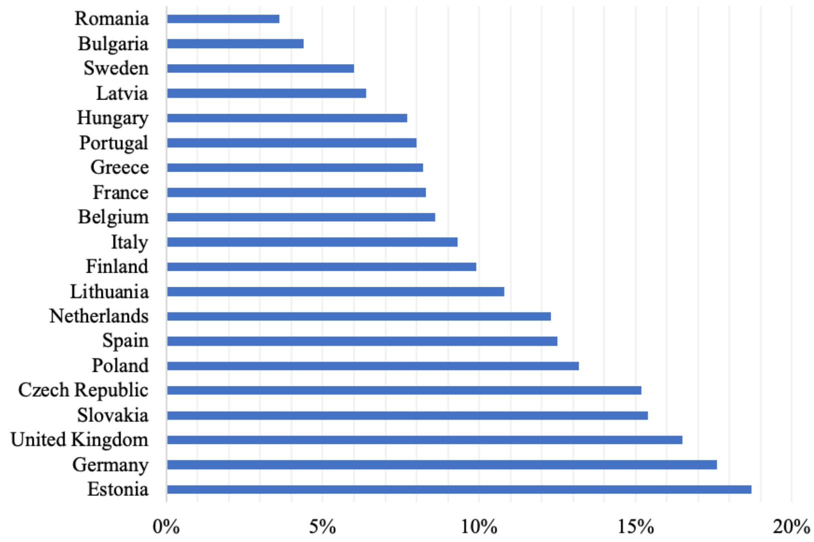

Figure 3: Gender gap in median monthly earnings 2010 by country

Source: EU-SES, authors' calculations. Notes: The gender gap in median monthly earnings is defined as in equation 2: the difference between median male earnings and median female earnings, divided by median male earnings. Earnings of part-time workers are adjusted to their full-time equivalents.

According to data from Eurostat, about two million enterprises were classified as working in manufacturing, and nearly 34 million people were employed in the manufacturing sector in the EU-28, representing 15.4 percent of total employment in 2014.[6] Although the role of the manufacturing industry in Europe has declined in recent years (a secular trend that is also observed in advanced economies) and the value of EU manufacturing production has increased from $1.835 trillion in 2004 to more than $2.229 trillion in 2014 in current prices (or 11.4 percent in constant prices).[7] By these

[6]For further details about the importance of manufacturing sector in Europe, see Veugelers (2013)

[7]Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs. It is calculated without making deductions for depreciation of fabricated assets or depletion and degradation of natural resources. The origin of value added is determined by the International Standard Industrial Classification (ISIC), revision 3. Data are available at: `https://data.worldbank.org/indicator/NV.IND.MANF.CD?locations=EU` (last accessed: 3/7/2020).

two measures, manufacturing has been the second largest economic activity within the EU-28's non-financial business economy in terms of its contribution to employment and the largest contributor to non-financial business economy value added.[8]

Collectively, these findings suggest that: (i) the extent to which robots are used in industries varies significantly from country to country; (ii) the vast majority of robots are used in manufacturing (particularly in the automotive sectors), and within-industry gender composition changes have been limited over the sample period; (iii) despite some convergence, the gender pay gap remains large; (iv) despite the decline in recent years, manufacturing still provides a large share of employment in Europe.

3 Data and Descriptive Statistics

3.1 Data

The data used in this paper come from four independent sources: the International Federation of Robotics (IFR), the EU Structure of Earnings Survey (EU SES), the EU KLEMS database, and the EU Labour Force Survey (EU LFS).

IFR provides information on the number of robots by country, industry, and year. It aims to capture the universe of industrial robots, and it is based on consolidated data provided by nearly all industrial robot suppliers worldwide. Typical tasks performed by robots include welding, assembly, packaging, and picking. Dedicated industrial robots that are designed to perform only a single task are not included in the dataset.

The IFR dataset is provided at the country-industry level, with broad industry categories outside of manufacturing, more detailed categories within manufacturing, and a residual category 'other non-manufacturing', which comprises a large part of the service sector. It also provides information on the operational stock of robots based on annual robot deliveries with the assumption of the average service life of 12 years and full depreciation thereafter.

The second and main source of data is the EU-Structure of Earnings Survey (EU-SES). It covers the universe of enterprises with at least ten employees in all sectors except public administration and aims to provide harmonized data on labor market earnings from the

[8]See `https://ec.europa.eu/eurostat/statistics-explained/pdfscache/10086.pdf`, last accessed 3/7/2020.

EU Member States and Candidate Countries. EU-SES allows us to have harmonized data on earnings, demographic and firm characteristics, and detailed industry classifications for 28 million individuals. The surveys have been collected every four years since 2002 and are based on a two-stage sample. In the first stage, a stratified random sample of local units is drawn, and in the second stage, a random sample of employees is taken within each of the selected local units.

EU-SES is well-suited for our purposes because it covers the workers that can be directly affected by robotization. Another advantage of the dataset is that the information collected relates to the wages paid to each job (that is, it does not cover earnings by the same person from a different job). Finally, it is the only dataset that provides harmonized information on labor market earnings and an industry classification at the 2-digit level of NACE (Statistical Classification of Economic Activities in the European Community) for a large sample of European countries. This feature is particularly important as it allows us to combine the dataset with the industrial robot data at the country and industry level.

We match EU-SES and IFR data for 20 countries, 12 industries, and the years 2006, 2010, and 2014. The 12 industries comprise eight manufacturing (automotive/transport, plastic/chemicals, metal, food/beverages, electrical/electronics, wood/paper, textiles, and other manufacturing branches) and four non-manufacturing industries (mining/quarrying, education/research/development, construction, and utilities). Following prior research (Graetz and Michaels, 2018), we exclude the residual category, other non-manufacturing, which comprises the majority of services sectors. The 20 countries included are Belgium, Bulgaria, the Czech Republic, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, the Netherlands, Poland, Portugal, Romania, Slovakia, Spain, Sweden, and the United Kingdom.[9]

The level of analysis is at the 'demographic cell'. More specifically, we restrict our sample to those aged 20 to 59 with positive earnings information and a positive number of work hours. We then collapse the data at (i) country; (ii) industry (the four broad categories are mining and quarrying, education and research/development, construction, and utilities, and the eight within-manufacturing sectors automotive/transport, plastic/chemicals, metals, food/beverages, electronics, wood/paper, textiles, and other

[9]In 2006, information for Germany, Romania, and Slovakia is not available and in 2014 information for Greece is missing.

manufacturing); (iii) year (2006, 2010, and 2014); (iv) age groups (20 to 29, 30 to 39, 40 to 49, 50 to 59); (v) broad occupational groups (managers, professionals, associate professionals, clerical support workers, sales and service workers, craft and related trade workers, plant/machine operators and assemblers, and elementary occupations); and (vi) firm size (smaller and larger than 250 employees) level. We exclude the 'armed forces' and 'agricultural workers' occupational groups and any cells with missing values for any of the variables used in the analysis.

Our main sample consists of 24,215 demographic cells. On average, a demographic cell contains 342 observations. The smallest cell contains at least ten respondents, of which at least five are female, and at least five are male. We use survey weights when collapsing the data to ensure all groups are represented.

Additional industry-level data on employment counts and information and communication technology (ICT) capital come from the EU KLEMS database.[10] We use data on total employment counts by country and industry to calculate the number of robots per worker. Data on ICT capital are used as a control variable. Data on the instrumental variables come from Graetz and Michaels (2018), and more details are provided in section 4.2. We use EU-LFS to understand compositional changes in the manufacturing sector. More specifically, we investigate movements into and out of manufacturing by demographic cells (such as age, gender, educational attainment, and skill level) using EU-LFS data from 2006, 2010, and 2014.

Our key variable of interest is the inverse hyperbolic sine transformation (IHS) of the change in the number of robots per 10,000 workers between the current and last survey year, which we refer to simply as 'robotization':

$$\text{robotization} = IHS\left[\frac{\text{number of robots}_t}{\text{10,000 employees}_{2000}} - \frac{\text{number of robots}_{t-4}}{\text{10,000 employees}_{2000}}\right] \quad (1)$$

where t refers to a year. We use four-year changes as the EU-SES is a four-yearly survey. Robotization is calculated based on a constant base year, so that changes in robotization do not arise because of changes in the number of workers employed in an industry. Since the distribution of the change in robotization is highly skewed with a few large outliers, but also a substantial number of zeros and some negative values, the natural logarithm is an unsuitable transformation. We, therefore, follow common practice

[10]Downloaded from `http://www.euklems.net` (last accessed: 3/7/2020).

and apply the inverse hyperbolic sine transformation (Bellemare and Wichman, 2020).

The main dependent variable is the gender gap in median monthly earnings in each cell, which we refer to as the gender pay gap. It is calculated as:

$$\text{Gender Pay Gap} = \frac{\text{median male earnings} - \text{median female earnings}}{\text{median male earnings}} \tag{2}$$

Median earnings are based on the gross earnings in the reference month. We further adjust the earnings of part-time employees pro-rata to their full-time equivalent. This is because, in some countries, it is very common for women to work part-time, and including full-time workers only would lead to a very selective sample.

We also study the effect of robotization on male and female earnings. In line with the transformation of the robotization variable, we use the IHS transformation of male and female median monthly earnings in the analyses. Robustness checks using a logarithmic transformation of earnings return qualitatively similar results. All earnings are given in Euros and in constant 2015 prices.[11]

3.2 Descriptive Statistics

Table 1 presents summary statistics. The columns are structured as follows: high-skilled occupation in Column 1; medium-skilled occupation in Column 2; low-skilled occupation in Column 3; and the full sample in Column 4. The gender gap in median monthly earnings in the full sample is 11 percent. The median monthly male earnings are EUR 1,781, and female earnings are EUR 1,559. The mean robotization (that is, the change in robots per 10,000 employees between survey years) is 9.6. The proportion of women in the sample is 44 percent, which is not surprising, given that we focus mainly on manufacturing industries in our paper.

The gender pay gap is 10 percent among individuals who work in high-skilled occupations, and 11 (13) percent among individuals who work in the medium (low)-skilled occupations respectively. Both men and women also earn substantially more in high-skilled occupations group (relative to medium- and low-skilled occupation groups). There are other notable differences: workers in high-skilled occupations are less likely to be exposed to robotization, more likely to be men, more likely to be in full-time work, and

[11] We use exchange rates and CPI information from the Eurostat database (last accessed: 3/7/2020).

more likely to work in education, research and development, and construction sectors. There are no large differences when it comes to working for a large firm (that is, 250 workers or above) or working in different sectors.

Table 1: Summary Statistics

	High-skilled occupations		Medium-skilled occupations		Low-skilled occupations		Total	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Gender pay gap (monthly median earnings)	0.1	0	0.11	0	0.13	0	0.11	0
IHS male median monthly earnings	8.13	0.01	7.65	0.01	7.52	0.01	7.83	0.01
IHS female median monthly earnings	8.01	0.01	7.52	0.01	7.37	0.01	7.69	0.01
Female median monthly earnings (EUR)	2,049	19	1,265	13	1,087	13	1,559	11
Male median monthly earnings (EUR)	2,312	22	1,453	15	1,281	15	1,781	12
Overall median monthly earnings (EUR)	2,211	21	1,358	14	1,212	15	1,689	11
IHS of change in robotization	0.97	0.02	1.1	0.02	1.25	0.03	1.08	0.01
Change in robotization (per 10,000 workers)	8.5	0.47	9.87	0.57	11.19	0.71	9.6	0.32
Share of females	0.41	0	0.51	0	0.4	0.01	0.44	0
Change in share of females	0.01	0	-0.01	0	0	0	0	0
Gender gap in monthly hours paid	0.03	0	0.04	0	0.06	0	0.04	0
Share of full-time workers	0.9	0	0.87	0	0.88	0	0.88	0
IHS of change in ICT density	0.9	0.02	0.94	0.02	0.97	0.03	0.93	0.01
Dummy firm size > 250	0.48		0.47		0.46		0.47	
Age 20 to 29	0.2		0.22		0.21		0.21	
Age 30 to 39	0.27		0.26		0.24		0.26	
Age 40 to 49	0.27		0.27		0.28		0.27	
Age 50 to 59	0.25		0.26		0.28		0.26	
Industry: food and beverages (manufacturing)	0.08		0.11		0.12		0.1	
Industry: textiles (manufacturing)	0.04		0.06		0.07		0.05	
Industry: wood and paper (manufacturing)	0.04		0.04		0.05		0.04	
Industry: plastic and chemicals (manufacturing)	0.1		0.1		0.12		0.1	
Industry: metal (manufacturing)	0.12		0.14		0.15		0.13	
Industry: electrical/electronics (manufacturing)	0.06		0.06		0.08		0.07	
Industry: automotive/transport (manufacturing)	0.04		0.05		0.05		0.05	
Industry: other manufacturing branches (manufacturing)	0.02		0.03		0.04		0.03	
Industry: mining and quarrying	0.01		0.01		0.01		0.01	
Industry: electricity, gas, water supply	0.05		0.04		0.05		0.05	
Industry: construction	0.16		0.14		0.1		0.14	
Industry: education, research, development	0.27		0.23		0.17		0.23	
Elementary occupations	0		0		0.57		0.14	
Managers	0.27		0		0		0.11	
Professionals	0.35		0		0		0.15	
Technicians & associate professionals	0.38		0		0		0.16	
Clerical support workers	0		0.44		0		0.15	
Service & sales workers	0		0.24		0		0.08	
Craft & related trade workers	0		0.32		0		0.11	
Plant & machine operators, assemblers	0		0		0.43		0.1	

Notes: Within-country industry employment shares used as survey weights. Sample size is 24,215 and average number of observations within a demographic cell is 342.

4 Empirical Strategy

4.1 OLS Estimation

To assess the relationship between robotization and the gender pay gap, we start by estimating a series of OLS models which take the form:

$$\mathrm{GPG}_{cid} = \beta_0 + \beta_1 \mathrm{robotization}_{ci} + \beta_2 \mathrm{controls}_{cid} + \delta + \theta + u_{cid} \tag{3}$$

where GPG_{cid} is the gender pay gap in country c, industry i, and demographic cell d, as defined in equation 2. Robotization_{ci} (that is, the change in the number of robots per 10,000 workers) is our main parameter of interest as defined in equation 1 and captures the effect robotization on our gender pay gap measure.

In our fully saturated specification, we control for three age groups, seven occupational groups, sex composition (the share of females and the change in share of females between last and current survey year), labor market factors (share of full-time workers and a dummy variable for a firm size greater than 250 employees), as well as a measure of changes in information and communication technology (ICT) capital. ICT capital is measured by the real fixed capital stock in computing, communications, and computer software and databases equipment in 2010 prices, per 1,000 workers.[12]

To account for other unobservable characteristics, we include a full set of country and year fixed effects.[13] The country dummies, δ, control for any time-invariant difference in unobserved factors that vary cross-nationally. Year dummies, θ, capture the impact of shocks that affect all countries simultaneously. Robust standard errors, two-way clustered by country and industry, and adjusted for cases with few clusters are used. All regressions are weighted by within-country industry employment shares, as in Graetz and Michaels (2018).

We report elasticities for the models using the inverse hyperbolic sine transformation on the dependent variable to ease interpretation. They are calculated following Bellemare and Wichman (2020): the formula used for regressions with the gender pay gap as a dependent variable is $\hat{\xi}_{yx} = \frac{\hat{\beta}}{y}\frac{x}{\sqrt{x^2+1}}$. The formula used for regressions with the IHS of median earnings as dependent variable is $\hat{\xi}_{yx} = \hat{\beta} \cdot \frac{\sqrt{y^2+1}}{y} \cdot \frac{x}{\sqrt{x^2+1}}$. Given the skewness in the distribution of median earnings across all demographic cells, in addition to applying an IHS transformation in the dependent variable we also estimate a version of our main specification 3 using quantile regression (estimated at different percentiles including median). The results for the quantile regression are described in the robustness checks section.

[12]These data are obtained from the EU KLEMS database.

[13]We cannot include industry fixed effects since our robotization variable is varying at the industry level.

4.2 Instrumental Variable Estimation

To identify the causal effects of robotization on the gender pay gap, we need to address the issues of omitted variables bias and reverse causality. For example, a shock to relative female labor demand in an industry may affect firms' decision making on whether to adopt robots. If some industries adopt robots in response to domestic shocks, this may also directly impact the gender pay gap. Potential measurement error in the robotization variable may cause an attenuation bias.

To account for these possibilities, we use an instrumental variables strategy following Graetz and Michaels (2018). The first instrument, which we call 'replaceable hours', measures the share of each industry's hours worked in 1980 (that is, before robotization takes place) that were performed by occupations that were later susceptible to replacement by robots. This industry-level measure takes advantage of two key facts. First, robots perform a specific and limited set of tasks, such as welding, painting, and assembling. Second, each industry differs in the extent to which these tasks are performed. The data on our instrumental variable comes from Graetz and Michaels (2018). It is constructed using data on robot applications from the IFR, and US Census occupational classifications and distribution of hours worked by occupation and industry. If an occupation's title from the 2000 Census three-digit occupational classification contains at least one of the IFR application categories such as welding, painting, etc., it is labeled as replaceable.

The rationale for using this instrument is based on the assumption that firms employ robots when it is more profitable than employing workers. This is the case when the share of tasks in an industry that can be performed by robots exceeds a certain threshold (Graetz and Michaels, 2018). Therefore, the instrument filters out robot adoption due to demand-side industry shocks. Instead, it only captures robot adoptions that are driven by technological advances in robots.

Within this context, identification is achieved by an exclusion restriction that robotization should affect gender pay gap only through supply-induced variation in robotization. The main justification for this exclusion restriction is that the 'replaceable hours' instrument allows us to filter out variation in robotization from domestic demand shocks and instead captures only the variation resulting from industries' suitability for the use of robots based on the tasks they can perform.

The validity of this instrument is strengthened by the findings in Freeman et al. (2020), who show that occupational attributes, such as 'replaceable tasks' have little predictive power for employment changes. In other words, our assumption that robotization due to replaceable tasks would affect the gender pay gap within occupations, but not affect compositional changes, is plausible. In sum, the instrumental variable analyses provide us with an additional check and help us triangulate our findings from our reduced-form OLS and Quantile regression estimations.

We also combine our 'replaceable hours' instrument with a second instrument, following Graetz and Michaels (2018), called 'robotic arms'. It measures the extent to which industries employed occupations that were required to carry out. reaching and handling tasks, compared to other tasks, in 1980. This instrument takes advantage of technological advances made in robotic arms, which are supply-side characteristics of robots. We use this instrument together with replaceable hours and also separately as an additional check. The results using this instrument point in the same direction as the findings from the OLS estimation and 'replaceable hours' instrument.

5 Results

5.1 Main Findings from OLS and IV Estimations

Table 2 presents the main results on the relationship between the gender pay gap and the robotization from OLS regressions. We report five model specifications: Column 1 reports the baseline specification with no controls; Column 2 adds country and year fixed effects, Column 3 adds demographic (three age group and seven occupational group dummies) and job controls (share of full-time workers and a dummy indicating firm size larger than 250), Column 4 adds sex composition controls (share of females and change in share of females), and, finally, Column 5 adds control variable for changes in ICT capital to ensure that changes in other technologies are not driving our results.

In Column 1, with no controls, we find that higher robotization is associated with a higher gender pay gap: our elasticity estimate suggests that a one percent increase in robotization is associated with a 0.007 percent increase in the gender pay gap. After adding various controls (Columns 2 to 5), the coefficient size decreases to 0.004 with the elasticity of 0.035.

These results suggest that robotization and the gender pay gap are positively associated. However, there may be endogeneity concerns. Therefore, we instrument our robotization measure with the instrumental variables (that is, replaceable hours and robotic arms) as described in Section 4.

Table 2: Effect of robotization on gender gap in monthly earnings, OLS

Dependent variable	Gender pay gap				
	(1)	(2)	(3)	(4)	(5)
Robotization	0.007***	0.006*	0.004*	0.004**	0.004**
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Elasticity	0.068	0.054	0.035	0.035	0.035
Observations	24,215	24,215	24,215	24,215	24,215
Country fixed effects	No	Yes	Yes	Yes	Yes
Year fixed effects	No	Yes	Yes	Yes	Yes
Demographic controls	No	No	Yes	Yes	Yes
Job controls	No	No	Yes	Yes	Yes
Sex composition	No	No	No	Yes	Yes
ICT capital	No	No	No	No	Yes

Notes: The table reports results from OLS regressions of the gender gap in median monthly earnings on the robotization (that is, inverse hyperbolic sine transformation of changes in number of robots per 10,000 workers). All regressions include a constant. Demographic controls include three age group dummies and seven occupational group dummies. Job controls include the share of full-time workers and a dummy variable indicating firm size is larger than 250 employees. Sex composition controls include the share of females and the change in share of females in a cell. ICT capital is the IHS of changes in ICT capital. The elasticity estimate is calculated following Bellemare and Wichman (2020). Robust standard errors in parentheses, clustered two-way by country and industry, and adjusted for small number of clusters. Within-country industry employment shares used as survey weights. * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, own calculations.

We report the IV results in Table 3. Panels A and B report first- and second-stage results from the replaceable hours instrument, respectively, and Panels C and D show results from the combined instrument of replaceable hours and robotic arms. The coefficients from the first stage regressions of the replaceable hours instrument in Panel A show that replaceable hours strongly predict robotization. In Panel B, we find that the first-stage F-statistic is between 16 and 20 in all specifications, indicating that the replaceability measure is a strong instrument. Our fully saturated specification in column 5 suggests that a 10 percent increase in robotization leads to a 1.8 percent increase in the gender pay gap. The magnitude is sizable, given that the average gender pay gap in our sample is 11 percent.

Panel C shows the estimates with two instrumental variables. We find that that robotic arms do not predict robotization. The first-stage F-statistic is around 7 in all models and the second-stage coefficients are very similar to those using the replaceable hours instrument only (Panel D): a ten percent increase in robotization leads to a 1.9 percent increase in the gender pay gap.

We also estimate results using the robotic arms instrument only, which are reported in the Appendix in Table A.1. The coefficients are slightly smaller with larger standard errors but remain positive in sign. This is consistent both with our reduced form OLS estimations and with our replaceable hours instrument. Given the lack of predictive power of the robotic arms instrument, we use the replaceable hours instrument for the rest of the paper.

Our estimates for IV are larger than the OLS ones. There are two potential explanations: First, it is likely that there is a negative correlation between the errors in the gender pay gap and robotization. That is, the IV specification accounts for the initial selection of female workers into different manufacturing industries. Second, in the presence of omitted variables, there would be a tendency to underestimate the impact of robotization on the gender pay gap.

While these results indicate that women lose out compared to men due to the adoption of robots, it is still important to understand whether this is driven by rising or falling male and female earnings. Therefore, in Table 4, we present the effect of robotization on median male earnings (columns 1 and 2) and median female earnings (columns 3 and 4). In line with the robotization measure, we use the inverse hyperbolic sine transformation (IHS) of earnings as a dependent variable. Panel A shows OLS estimates and Panel B coefficients from the IV model, using the replaceability measure as an instrument for robotization.

When controlling for country and year fixed effects in column 1, we see a positive association between changes in robotization and male earnings. The coefficients remain similar when adding the full set of controls in column 2. Turning to female earnings, we can see that they are also positively associated with robotization. However, the size of coefficients is slightly smaller compared to those from the male earnings regressions and they become insignificant in the instrumental variable specification. These results suggest that robotization positively impacts both male and female earnings and the increase in the gender pay gap seems to be driven by the larger positive effect on male earnings.

Table 3: Effect of robotization on gender gap in monthly earnings, IV

	(1)	(2)	(3)	(4)	(5)
Panel A: IV replaceable hours 1st stage – outcome: robotization					
Replaceable hours	5.879***	5.601***	5.522***	5.389***	5.363***
	(1.391)	(1.260)	(1.287)	(1.336)	(1.326)
Panel B: IV replaceable hours 2nd stage – outcome: gender pay gap					
Robotization	0.023***	0.026**	0.018*	0.019*	0.019*
	(0.007)	(0.010)	(0.010)	(0.011)	(0.011)
Elasticity	0.208	0.238	0.169	0.175	0.177
First stage F-stat	17.87	19.75	18.41	16.27	16.37
Panel C: IV replaceable hours and robotic arms 1st stage – outcome: robotization					
Robotic arms	-6.884	-5.791	-5.898	-5.909	-6.100
	(6.510)	(5.537)	(5.478)	(5.673)	(5.616)
Replaceable hours	7.754***	7.215***	7.285***	7.291***	7.315***
	(2.190)	(1.853)	(1.907)	(2.020)	(1.997)
Panel D: IV replaceable hours and robotic arms 2nd stage – outcome: gender pay gap					
Robotization	0.023***	0.026***	0.019**	0.021*	0.021*
	(0.007)	(0.010)	(0.010)	(0.011)	(0.011)
Elasticity	0.213	0.240	0.177	0.189	0.191
First stage F-stat	9.147	10.73	9.869	9.189	9.352
Observations	24,215	24,215	24,215	24,215	24,215
Country fixed effects	No	Yes	Yes	Yes	Yes
Year fixed effect	No	Yes	Yes	Yes	Yes
Demographic controls	No	No	Yes	Yes	Yes
Job controls	No	No	Yes	Yes	Yes
Sex composition	No	No	No	Yes	Yes
ICT capital	No	No	No	No	Yes

Notes: The table reports results from IV regressions of the gender gap in median monthly earnings on the robotization (that is, inverse hyperbolic sine transformation of changes in number of robots per 10,000 workers). The instrumental variable is a measure of the share of hours in an industry performed by occupations prone to be replaced by robots. All regressions include a constant. Demographic controls include three age group dummies and seven occupational group dummies. Job controls include the share of full-time workers and a dummy indicating firm size is larger than 250 employees. Sex composition controls include the share of females and the change in share of females in a cell. ICT capital denotes the IHS of changes in ICT capital. The elasticity estimate is calculated following Bellemare and Wichman (2020). Robust standard errors in parentheses, clustered two-way by country and industry, and adjusted for small number of clusters. Within-country industry employment shares used as survey weights. * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, own calculations.

Table 4: Effect of robotization on male and female earnings, OLS and IV

Outcome	Male earnings		Female earnings	
	(1)	(2)	(3)	(4)
	Panel A: OLS			
Robotization	0.019**	0.015***	0.012**	0.011**
	(0.008)	(0.005)	(0.006)	(0.004)
Elasticity	0.019	0.015	0.012	0.011
	Panel B. IV replaceable hours			
Robotization	0.046	0.047*	0.015	0.023
	(0.034)	(0.028)	(0.026)	(0.021)
Elasticity	0.046	0.046	0.015	0.023
First stage F-stat	19.75	16.37	19.75	16.37
Observations	24,215	24,215	24,215	24,215
Country fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Demographic controls	No	Yes	No	Yes
Job controls	No	Yes	No	Yes
Sex composition	No	Yes	No	Yes
ICT capital	No	Yes	No	Yes

Notes: The table reports results from OLS and IV regressions of the IHS (inverse hyperbolic sine transformation) of male (columns 1 and 2) and female (columns 3 and 4) earnings on the robotization (that is, IHS transformation of changes in number of robots per 10,000 workers). All regressions include a constant. Demographic controls include three age group dummies and seven occupational group dummies. Job controls include the share of full-time workers and a dummy variable indicating firm size is larger than 250 employees. Sex composition controls include the share of females and the change in share of females in a cell. ICT capital denotes the IHS of changes in ICT capital. The elasticity estimate is calculated following Bellemare and Wichman (2020). Robust standard errors in parentheses, clustered two-way by country and industry, and adjusted for small number of clusters. Within-country industry employment shares used as survey weights. * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, own calculations.

5.2 Heterogeneity of the Effects

The effect of robotization is likely to vary by country and population subgroups. To explore such heterogeneity, we consider running our preferred model specifications (OLS and IV) on various subsamples of countries and groups.

First, we explore whether results differ in countries that are major recipients of offshoring business. Several studies suggest that the estimated wage cuts in the destination country due to outsourcing appear to be small in economic terms (Geishecker et al., 2010; Wolszczak-Derlacz and Parteka, 2018). For example, in their industry-level study performed for a wide sample of EU-27 countries, Parteka and Wolszczak-Derlacz (2015) conclude that offshoring reduces the wage growth of domestic medium- and low-skilled workers. However, they also show that this negative effect is economically small. Brussevich et al. (2018) also show that since manufacturing is male labor-intensive and men face higher exit costs from manufacturing, wage and welfare gains from trade are higher for women than men. Therefore, the impact of robotization on the gender pay gap may be different in outsourcing destination countries.

We use the AT Kearney Global Services Location Index (2017) to determine the top 10 outsourcing destination countries.[14] The results are shown in Table 5. The first column of Table 5 shows that the coefficients for the subsample of outsourcing destination countries are large and statistically significant. This is consistent with the view that receiving outsourced manufacturing jobs and its interaction with robotization can worsen the gender pay gap.

Second, our sample of countries also differs in terms of broad gender equality. Therefore, we use the Gender Gap Index (GGI) of the World Economic Forum, which ranks countries' performance in economic, educational, health, and political dimensions of gender equality (see Hausmann et al. (2006)). In the first instance, we partition our sample into two groups: the top ten countries with a high GGI score, hence higher levels of gender equality, and the bottom ten countries with a low GGI score, that is, lower levels of gender equality. Results presented in Table 6 indicate that our results are mostly driven by countries with low levels of initial gender equality. This suggests that robotization

[14] See A.T. Kearney Global Services Location Index – The Widening Impact of Automation, available at `https://www.kearney.com/digital-transformation/article?/a/the-widening-impact-of-automation-article` (last accessed 3/7/2020).

Table 5: Heterogeneity by outsourcing destination countries

Subsample	Top 10 outsourcing destination countries	Remaining 10 countries
	(1)	(2)
Panel A1: OLS – outcome: gender pay gap		
Robotization	0.008**	0.001
	(0.004)	(0.002)
Panel A2: IV replaceable hours – outcome: gender pay gap		
Robotization	0.025**	0.008
	(0.012)	(0.008)
Panel B1: OLS – outcome: male earnings		
Robotization	0.023***	0.004
	(0.008)	(0.003)
Panel B2: IV replaceable hours – outcome: male earnings		
Robotization	0.044	0.031
	(0.030)	(0.019)
Panel C1: OLS – outcome: female earnings		
Robotization	0.014	0.003
	(0.008)	(0.003)
Panel C2: IV replaceable hours – outcome: female earnings		
Robotization	0.012	0.022
	(0.026)	(0.015)
First stage F-stat	11.50	9.40
Observations	14,043	10,172
Country fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Demographic controls	Yes	Yes
Job controls	Yes	Yes
Sex composition	Yes	Yes
ICT capital	Yes	Yes

Notes: The outsourcing destination country classification is based on the AT Kearney Index (2017). Top 10 outsourcing destination countries include Poland, Bulgaria, the Czech Republic, Romania, Estonia, Hungary, Latvia, Lithuania, Portugal, and Slovakia. The table reports results from OLS and IV regressions of the gender gap in median monthly earnings in Panels A1 and A2, median male earnings in Panels B1 and B2, and median female earnings in Panels C1 and C2 on the robotization (that is, inverse hyperbolic sine transformation of changes in number of robots per 10,000 workers). The instrumental variable is a measure of the share of hours in an industry performed by occupations prone to be replaced by robots. All regressions include a constant. Demographic characteristics include three age group dummies and seven occupational group dummies. Job controls include the share of full-time workers and a dummy indicating firm size is larger than 250 employees. Sex composition controls include the share of females and the change in share of females in a cell. ICT capital denotes the IHS of changes in ICT capital. Robust standard errors in parentheses, clustered two-way by country and industry, and adjusted for small number of clusters. Within-country industry employment shares used as survey weights. * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, AT Kearney Index (2017), own calculations.

could exacerbate existing inequalities in these countries.

Table 6: Heterogeneity by gender equality index scores

Subsample	High GGI score (Higher gender equality)	Low GGI score (Lower gender equality)
	(1)	(2)
	Panel A: OLS – outcome: gender pay gap	
Robotization	0.001	0.006**
	(0.001)	(0.003)
	Panel B: IV replaceable hours – outcome: gender pay gap	
Robotization	0.006	0.027**
	(0.010)	(0.012)
First stage F-stat	8.57	16.62
Observations	10,401	13,814
Country fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Demographic controls	Yes	Yes
Job controls	Yes	Yes
Sex composition	Yes	Yes
ICT capital	Yes	Yes

Notes: The World Economic Forum (WEF) Gender Gap Index (by Hausmann et al., 2006) ranks countries' performance in economic, educational, health, and political dimensions of gender equality. High GGI countries include Belgium, Germany, Estonia, Spain, Finland, Lithuania, Latvia, the Netherlands, Sweden, UK. Low GGI countries include Bulgaria, Czech Republic, France, Greece, Hungary, Italy, Poland, Portugal, Romania, and Slovakia. The table reports results from OLS and IV regressions of the gender gap in median monthly earnings in Panels A1 and A2, median male earnings in Panels B1 and B2, and median female earnings in Panels C1 and C2 on the robotization (that is, inverse hyperbolic sine transformation of changes in number of robots per 10,000 workers). The instrumental variable is a measure of the share of hours in an industry performed by occupations prone to be replaced by robots. All regressions include a constant. Demographic characteristics include three age group dummies and seven occupational group dummies. Job controls include the share of full-time workers and a dummy indicating firm size is larger than 250 employees. Sex composition controls include the share of females and the change in share of females in a cell. ICT capital denotes the IHS of changes in ICT capital. Robust standard errors in parentheses, clustered two-way by country and industry, and adjusted for small number of clusters. Within-country industry employment shares used as survey weights. * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, World Economic Forum Gender Gap Index by Hausmann et al. (2006), own calculations.

Third, we explore heterogeneity by skill-based occupational groups since within-occupation differences in earnings are more important than between-occupation differences (Goldin, 2014). The results presented in Table 7 show that robotization leads to an increase in the gender pay gap for medium- and high-skilled occupations.

Finally, we check whether the robotization effect is larger for countries with low levels of gender equality. To do so, we focus only on countries that experience high robotization over the sample period and present these results in Table 8. Countries that have experienced high levels of robotization are not the same countries that have always enjoyed a high robot density. We find that our main results are driven by countries with low overall gender equality that have experienced high robotization (Columns 4 and 6), such as the Czech Republic, Hungary, Italy, Poland, and Slovakia. In fact, the size of the coefficient for this group of countries is almost identical to the effect we found for all

Table 7: Gender pay gap by skill-based occupational groups

Subsample	Low-skilled	Medium-skilled	High-skilled
	(1)	(2)	(3)
Panel A1: OLS – outcome: gender pay gap			
Robotization	0.001	0.008**	0.002**
	(0.003)	(0.003)	(0.001)
Panel A2: IV replaceable hours – outcome: gender pay gap			
Robotization	-0.001	0.037***	0.014*
	(0.013)	(0.013)	(0.008)
First stage F-stat	14.77	19.15	16.09
Observations	6,399	7,991	9,825
Country fixed effects	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes
Job controls	Yes	Yes	Yes
Sex composition	Yes	Yes	Yes
ICT capital	Yes	Yes	Yes

Notes: The table reports results from OLS and IV regressions of the gender gap in median monthly earnings on the robotization (that is, inverse hyperbolic sine transformation of changes in number of robots per 10,000 workers). The instrumental variable is a measure of the share of hours in an industry performed by occupations prone to be replaced by robots. All regressions include a constant. Demographic characteristics include three age group dummies and seven occupational group dummies. Job controls include the share of full-time workers and a dummy indicating firm size is larger than 250 employees. Sex composition controls include the share of females and the change in share of females in a cell. ICT capital denotes the IHS of changes in ICT capital. Robust standard errors in parentheses, clustered two-way by country and industry, and adjusted for small number of clusters. Within-country industry employment shares used as survey weights. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Sources: EU-SES, IFR, EU KLEMS, own calculations.

countries (Table 3, Column 5). In contrast, robotization has had no effect on the gender pay gap in countries with high overall gender equality, such as Belgium, Germany, the Netherlands, Spain, and Sweden.

Table 8: Heterogeneity by Gender Gap Index for high robotization countries

Sample	High robotization and high gender gap equality			High robotization and low gender equality		
Outcomes	Gender gap in earnings	IHS male earnings	IHS female earnings	Gender gap in earnings	IHS male earnings	IHS female earnings
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: OLS			
IHS Robotization	0.002	0.008**	0.006*	0.005*	0.021***	0.015**
	(0.002)	(0.004)	(0.004)	(0.003)	(0.008)	(0.006)
			Panel B: IV replaceable hours			
IHS Robotization	0.005	0.023	0.018*	0.019**	0.040*	0.017
	(0.005)	(0.014)	(0.011)	(0.009)	(0.023)	(0.019)
1st stage F-stat	21.07	21.07	21.07	18.57	18.57	18.57
Observations	5,428	5,428	5,428	8,219	8,219	8,219
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Job controls	Yes	Yes	Yes	Yes	Yes	Yes
Sex composition	Yes	Yes	Yes	Yes	Yes	Yes
ICT capital	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Countries with high robotization and high GGI include Belgium, Germany, Spain, the Netherlands, and Sweden. Countries with high robotization and low GGI include the Czech Republic, Hungary, Italy, Poland, and Slovakia. The instrumental variable is a measure of the share of hours in an industry performed by occupations prone to be replaced by robots. All regressions include a constant. Demographic characteristics include three age group dummies and seven occupational group dummies. Job controls include the share of full-time workers and a dummy indicating firm size is larger than 250 employees. Sex composition controls include the share of females and the change in share of females in a cell. ICT capital denotes the IHS of changes in ICT capital. Robust standard errors in parentheses, clustered two-way by country and industry, and adjusted for small number of clusters. Within-country industry employment shares used as survey weights. * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, own calculations.

Germany is particularly worth mentioning. It is an exceptional country because it is the front runner in both robot density levels and robotization. It is also a large country with a dominant automotive/transport industry, as well as relatively high gender equality. Since Dauth et al. (2018) have already analyzed German data to investigate how robotization affected the outcomes of individual workers (that is, excluding the gender-pay gap or any gender differences), we only ran our models on the Germany sample to check the consistency of our results with theirs. Our findings are compatible with the findings of Dauth et al. (2018): We find both male and female earnings in Germany modestly increased due to robotization in comparable amounts, keeping the gender pay gap relatively unchanged (not shown but available upon request). In our robustness checks section below, we investigate the sensitivity of our results to the exclusion or inclusion of Germany and the automotive industry – and show that our results are not affected by exclusion or inclusion of either Germany or the automotive industry.

In sum, robotization particularly exacerbated the gender pay gap in outsourcing destination countries (which tend to be predominantly eastern European countries); especially those in which overall gender inequality was already high. In contrast, in outsourcing origin countries (predominantly western European countries) where initial gender inequality was low, robotization did not increase the gender pay gap.

5.3 Mechanisms

Why would robotization increase the gender pay gap in the first place? In this section, we analyze two potential mechanisms underlying the observed relationship between robotization and the gender pay gap. First, robotization may lead to earnings increases and spillovers at different parts of occupational ranking, where men and women are disproportionately present (or they benefit differentially from earnings increases). Second, robotization may lead to compositional changes at the industry level, and employment levels of men and women are affected differentially leading to an increase in the gender pay gap.

The results presented in Tables 6 to 8 indicate the importance of the initial gender inequality situation of the country and occupational ranking. Therefore, we explore whether our results can be explained by the fact that men higher in the occupational hierarchy disproportionately benefit from robotization (through productivity effects).

Previous research shows that the gender gap in earnings rises or falls with progression up the hierarchy and highly skilled occupations are strongly positively related to earnings (Aksoy et al., 2019). This suggests that medium- and high-skilled occupations such as associates, professionals, and managers, where men are generally more highly represented, are also typically better paid. To test this, we estimate our models relating robotization to the gender pay gap by skill-based occupational groups and in high robotization countries.

The results in Table 9 confirm that the robotization is associated with sizable and statistically significant earnings premia for male workers in medium- and high-skilled occupations, while there is no such effect for women. This is in line with the observation that women are under-represented in high-paying occupations and with Goldin (2014), who shows that within-occupation wage differentials actually account for a larger proportion of the gender wage gap than between-occupation wage differentials.

Table 9: Heterogeneity by skill-based occupational groups for countries with high robotization and low levels of gender equality

Occupational group	Low-skilled			Medium-skilled			High-skilled		
Outcomes	Gender gap in earnings	IHS male earnings	IHS female earnings	Gender gap in earnings	IHS male earnings	IHS female earnings	Gender gap in earnings	IHS male earnings	IHS female earnings
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Panel A: OLS					
IHS Robotization	0.002	0.017***	0.016***	0.011*	0.025***	0.012**	0.005***	0.016*	0.011
	(0.002)	(0.006)	(0.006)	(0.006)	(0.010)	(0.006)	(0.001)	(0.009)	(0.009)
				Panel B: IV replaceable hours					
IHS Robotization	-0.002	0.033*	0.037**	0.037***	0.052*	0.009	0.022**	0.024	-0.005
	(0.009)	(0.018)	(0.014)	(0.011)	(0.028)	(0.022)	(0.010)	(0.021)	(0.025)
1st stage F-stat	23.47	23.47	23.47	22.20	22.20	22.20	17.60	17.60	17.60
Observations	2,139	2,139	2,139	2,914	2,914	2,914	3,166	3,166	3,166
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sex composition	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ICT capital	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample consists of high robotization and low GGI countries, which are the Czech Republic, Hungary, Italy, Poland, and Slovakia. The instrumental variable is a measure of the share of hours in an industry performed by occupations prone to be replaced by robots. All regressions include a constant. Demographic characteristics include three age group dummies and seven occupational group dummies. Job controls include the share of full-time workers and a dummy indicating firm size is larger than 250 employees. Sex composition controls include the share of females and the change in share of females in a cell. ICT capital denotes the IHS of changes in ICT capital. Robust standard errors in parentheses, clustered two-way by country and industry, and adjusted for small number of clusters. Within-country industry employment shares used as survey weights. * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, own calculations.

We also examine to what extent our results can be explained by compositional changes (in terms of gender, gender-age, gender-education, and gender-occupation) in the manufacturing industry as well as movements in and out of the labor force. Ideally, one would need a very large panel of data that follow individuals for a long period to obtain job-cycle profiles of workers. Since such data are not available in a cross-country setting, we examine to what extent workers whose previous job was in manufacturing are still employed in the manufacturing industry. To do so, we turn to the EU-LFS and restrict our attention to workers who are between 20 and 59 years of age for the 20 countries included in our sample.

We present the share of workers in manufacturing (that is, current job in manufacturing industry) whose previous job was also in manufacturing by gender and skill level for all countries included in our sample in Table 10.[15] We present outflows from manufacturing (that is, the previous job in manufacturing) to other industries (that is, current job in any other industry) by gender and skill level for all countries included in our sample in Table 11. These mobility tables provide descriptive evidence and an indication whether the movements in and out of a given industry due to robotization can drive up the gender pay gap.

The tables show that nearly all workers who used to work in manufacturing are still in the same sector. This is true for all survey years – 2006, 2010, and 2014 and when we construct similar shares by gender and age, gender, and education level nexus. Similarly, few workers whose previous job was in manufacturing moved to other industries, while most moved to another job in manufacturing. We also check this pattern for Germany as it has the highest robotization rate in our sample. The patterns we observe in Germany remain the same (see Appendix A Table A.2). Collectively, we conclude that compositional changes in the manufacturing sector are negligibly small.

[15] Overall, around 95 percent of workers whose previous job was in manufacturing stay in employment. Around 3 percent become inactive and around 2 percent become unemployed.

Table 10: Share of workers currently in manufacturing whose previous job was also in manufacturing, by gender and skill level

	2006						2014					
	Male			Female			Male			Female		
Manufacturing inflows	Low skilled	Medium skilled	High skilled	Low skilled	Medium skilled	High skilled	Low skilled	Medium skilled	High skilled	Low skilled	Medium skilled	High skilled
Belgium	96.2	97.4	98.0	95.8	95.2	95.6	97.8	97.9	97.5	95.5	96.5	96.3
Bulgaria	–	–	–	–	–	–	98.0	99.6	100.0	98.9	98.8	99.3
Czech Republic	96.4	97.3	97.9	96.8	97.2	97.0	98.0	98.3	99.0	97.2	97.3	96.3
Estonia	95.3	94.1	96.4	94.6	94.6	96.6	95.1	97.0	95.4	97.0	96.7	94.1
Finland	98.3	95.9	97.3	95.9	94.7	95.1	98.6	96.7	95.4	98.7	93.8	96.5
France	98.2	98.2	98.2	97.5	97.7	97.6	93.3	96.4	98.0	94.7	92.9	97.2
Germany	98.3	98.9	99.1	98.7	98.5	98.7	97.0	97.6	98.0	96.7	96.9	96.4
Greece	98.5	98.3	99.3	97.6	99.0	98.4	97.9	99.5	100.0	99.0	98.4	98.4
Hungary	95.6	96.6	98.1	97.3	97.5	98.7	96.3	97.1	97.8	97.2	96.1	97.9
Italy	96.6	96.0	95.7	96.8	95.2	94.8	99.0	99.2	99.1	98.5	98.7	98.7
Latvia	88.2	93.6	96.1	94.7	95.2	93.4	96.5	98.1	97.3	95.9	96.7	97.1
Lithuania	94.7	92.6	96.8	93.8	97.5	98.0	93.5	93.7	95.9	97.0	95.4	97.8
Netherlands	97.7	97.7	96.8	97.8	96.0	95.0	96.5	96.9	97.1	92.5	98.8	93.5
Poland	94.7	96.0	96.4	95.8	97.9	97.4	96.5	97.3	98.6	96.4	97.7	98.2
Portugal	96.9	98.0	98.3	98.3	98.9	99.0	98.3	99.1	98.3	99.2	98.2	97.0
Romania	97.4	98.7	98.9	98.5	98.6	98.4	99.1	99.1	99.3	99.4	99.1	99.6
Slovakia	96.3	97.3	97.9	97.6	99.3	97.6	97.8	99.3	99.1	98.9	99.8	98.6
Spain	95.1	96.1	97.4	95.2	91.9	95.4	95.8	97.2	96.2	96.2	94.6	95.4
Sweden	–	–	–	–	–	–	99.3	99.2	99.3	98.7	98.9	99.4
United Kingdom	92.8	93.5	92.9	92.1	92.9	90.6	93.2	96.2	96.0	95.7	87.6	93.9

Notes: This table shows the workers whose previous job was in manufacturing, as a percentage of the workers currently in manufacturing, by gender and skill level. The sample is restricted the employees in Belgium, Bulgaria, the Czech Republic, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, the Netherlands, Poland, Portugal, Romania, Slovakia, Spain, Sweden, and the United Kingdom who are between 20 and 59 years of age. The industry classification is NACE-1. Skill level is defined using the ISCO 1-digit level: the low-skilled category is comprised of elementary occupations and plant, machine operators and assemblers; the medium-skilled category is comprised of clerical workers, service and sales workers, skilled agricultural, forestry and fishing workers and craft and related trade workers; the high-skilled category is comprised of managers, professionals and technicians and associate professionals. Source: EU-LFS and own calculations.

Table 11: Outflows from manufacturing to other industries by gender and skill level

	2006						2014					
	Male			Female			Male			Female		
Manufacturing outflows	Low skilled	Medium skilled	High skilled	Low skilled	Medium skilled	High skilled	Low skilled	Medium skilled	High skilled	Low skilled	Medium skilled	High skilled
Belgium	2.3	3.4	2.5	3.5	4.2	2.1	1.8	2.8	1.5	1.4	3.2	3.0
Bulgaria	–	–	–	–	–	–	0.9	0.4	0.7	0.8	1.2	3.7
Czech Republic	2.1	2.0	2.1	1.1	4.5	2.3	1.5	1.1	1.0	0.4	2.7	0.7
Estonia	6.9	8.7	4.1	2.7	8.8	2.9	4.9	5.0	3.6	1.2	7.2	3.4
Finland	3.1	4.1	2.2	2.3	2.8	2.2	2.8	3.3	5.7	1.4	7.1	4.2
France	1.3	2.3	1.9	1.0	3.5	3.6	4.8	5.6	3.3	3.4	6.1	6.5
Germany	1.0	0.6	0.6	4.7	1.7	1.3	1.9	2.0	1.5	3.1	2.7	3.1
Greece	1.4	1.4	1.1	1.4	1.5	2.4	0.8	0.7	0.5	0.2	1.8	3.6
Hungary	3.7	3.0	2.3	1.6	3.8	3.7	2.9	2.6	1.8	1.8	4.0	4.1
Italy	3.2	4.5	5.1	2.8	6.2	8.5	0.6	0.4	0.3	0.8	1.1	0.7
Latvia	15.1	9.7	11.6	5.3	8.4	19.8	5.7	3.0	5.8	1.7	2.1	0.6
Lithuania	5.1	4.8	1.1	6.5	3.3	4.5	5.3	4.5	5.9	1.4	3.5	1.3
Netherlands	1.9	2.7	3.4	2.5	5.3	4.3	2.2	1.1	2.1	3.9	4.7	4.0
Poland	3.2	2.2	2.4	1.6	1.6	2.0	2.4	1.7	2.0	0.5	2.1	2.2
Portugal	1.6	2.0	1.7	2.5	1.3	2.9	1.3	0.9	1.3	0.5	2.3	1.9
Romania	4.3	1.1	1.1	3.7	1.3	2.7	0.7	0.7	1.2	0.1	0.5	2.1
Slovakia	2.3	1.6	1.3	1.0	2.1	0.8	1.2	1.0	1.1	0.7	2.0	2.3
Spain	3.6	4.0	3.1	3.6	8.5	5.8	3.2	3.0	3.7	4.1	4.5	3.8
Sweden	–	–	–	–	–	–	0.8	1.5	0.9	1.5	1.1	1.2
United Kingdom	1.7	1.5	1.0	0.5	3.1	1.5	3.5	3.4	2.2	3.3	7.4	4.7

Notes: This table shows the percentage of workers whose previous job was in manufacturing and who currently work in another industry by gender and skill level. The sample comprises those workers whose previous job was in manufacturing, and is restricted to employees in Belgium, Bulgaria, the Czech Republic, Estonia, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, the Netherlands, Poland, Portugal, Romania, Slovakia, Spain, Sweden, and the United Kingdom who are between 20 and 59 years of age. The industry classification is NACE-1. Skill level is defined using the ISCO 1-digit level: the low-skilled category is comprised of elementary occupations and plant, machine operators and assemblers; the medium-skilled category is comprised of clerical workers, service and sales workers, skilled agricultural, forestry and fishing workers and craft and related trade workers; the high-skilled category is comprised of managers, professionals and technicians and associate professionals. Source: EU-LFS and own calculations.

In addition to the descriptive evidence we draw from the EU-LFS, we provide further evidence on the sex composition of our sample in Table 12. In particular, we analyze whether robotization impacts the sex composition in the demographic cells in our data. The outcome variable is the gender pay gap in the hours worked in the last month, which measures the intensive margin of labor supply of women relative to men. Column 1 reports the results for the full sample, columns 2 to 4 report the results for subsamples of the low-, medium-, and high-skilled occupational groups, respectively. The point estimates are small in magnitude and statistically insignificant, suggesting that robotization did not affect the sex composition in the sample.

In summary, our results are likely to be explained by an increase in male earnings in medium- and high-skilled occupations, which is primarily to do with the male predominance in the higher occupational hierarchy. In other words, women's underrepresentation in high(er)-skill occupations accompanied by robotization exacerbates the gender pay gap.

Table 12: Effect of robotization on the gender gap in hours worked last month

Sample	Full sample	Low-skilled	Medium-skilled	High-skilled
	(1)	(2)	(3)	(4)
Panel A: OLS – outcome: gender gap hours worked				
Robotization	0.000	-0.002	0.001	-0.000
	(0.001)	(0.002)	(0.001)	(0.000)
Panel B: IV replaceable hours – outcome: gender gap hours worked				
Robotization	0.006	-0.008	0.011	0.006
	(0.007)	(0.010)	(0.008)	(0.005)
First stage F-stat	16.37	14.77	19.15	16.09
Observations	24,215	6,399	7,991	9,825
Country fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes
Job controls	Yes	Yes	Yes	Yes
Sex composition	Yes	Yes	Yes	Yes
ICT capital	Yes	Yes	Yes	Yes

Notes: The table reports results from OLS and IV regressions of the gender gap in hours worked on the robotization (that is, inverse hyperbolic sine transformation of changes in number of robots per 10,000 workers). The instrumental variable is a measure of the share of hours in an industry performed by occupations prone to be replaced by robots. All regressions include a constant. Demographic characteristics include three age group dummies and seven occupational group dummies. Job controls include the share of full-time workers and a dummy indicating firm size is larger than 250 employees. Sex composition controls include the share of females and the change in share of females in a cell. ICT capital denotes the IHS of changes in ICT capital. The elasticity estimate is calculated following Bellemare and Wichman (2020). Robust standard errors in parentheses, clustered two-way by country and industry, and adjusted for small number of clusters. Within-country industry employment shares used as survey weights. * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, own calculations.

5.4 Robustness Checks and Alternative Specifications

Quantile regressions

We investigate whether the positive effect of robotization on earnings varies across the earnings distribution. In order to asses this, we run quantile regressions at different percentiles of the distribution of median earnings of each demographic cell. We present results from the quantile regressions in Table 13, which are based on unweighted data and standard errors clustered at the country level only. Notably, the point estimates in column 6 (full-sample) are similar to those from the weighted regressions in Panel A of Table 4. A comparison across columns 1 to 5 shows that quantile regression estimates are positive across all earnings quantiles for both men and women. The coefficients for male earnings are larger than the ones for female earnings at all quantiles. Moreover, for both male and female earnings, the coefficients become slightly smaller for higher quantiles. Hence, while robotization increases gender inequality, these results suggest that they may decrease overall earnings inequality.

Table 13: Quantile regressions

Quantile	0.1	0.3	0.5	0.7	0.9	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Quantile regressions – outcome: male earnings						
Robotization	0.015***	0.010***	0.008***	0.007***	0.004***	0.010***
	(0.005)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
R-squared	0.915	0.922	0.924	0.921	0.909	0.925
Panel B: Quantile regressions – outcome: female earnings						
Robotization	0.013***	0.008***	0.007***	0.006***	0.003*	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
R-squared	0.924	0.931	0.932	0.931	0.922	0.933
Observations	24,215	24,215	24,215	24,215	24,215	24,215
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Job controls	Yes	Yes	Yes	Yes	Yes	Yes
Sex composition	Yes	Yes	Yes	Yes	Yes	Yes
ICT capital	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports results from quantile regressions of the IHS (inverse hyperbolic sine transformation) of male (columns 1 and 2) and female (columns 3 and 4) earnings on the robotization (that is, inverse hyperbolic sine transformation of changes in number of robots per 10,000 workers). All regressions include a constant. Demographic controls include three age group dummies and seven occupational group dummies. Job controls include the share of full-time workers and a dummy indicating firm size is larger than 250 employees. Sex composition controls include the share of females and the change in share of females in a cell. ICT capital denotes the IHS of changes in ICT capital. Standard errors in parentheses, clustered at the country level. * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, own calculations.

Are the results driven by the demographic cell definition?

For our purposes, it is important to distinguish different skill-based occupational groups in the analysis. Nevertheless, we want to make sure this is not biasing our results and so we present results using an alternative unit of analysis. In Table 14, we define a demographic cell in the same way as in the main analysis except that we do not collapse by occupational skill group. Not collapsing by occupational skill groups results in much larger cell sizes while reducing the overall number of observations (that is, fewer but larger cells). This definition of demographic cells gives us a mean earnings measure that is more resistant to outliers. Additionally, movements between occupations due to robotization are not relevant. However, cells may be more heterogenous with respect to skill levels. The results of this new unit of analysis show that the positive relationship between robotization and the gender gap in earnings remains and if anything, the robotization effect becomes stronger. Despite a smaller sample size in these analyses, the larger effects are also statistically significant at the 1 percent level. It is reassuring that our results do not change when we use different definitions of demographic cells.

Table 14: Robustness to alternative demographic cell (not collapsed by skill groups)

	(1)	(2)	(3)	(4)	(5)
Panel A: OLS – outcome: gender pay gap					
Robotization	0.011**	0.010**	0.009**	0.009**	0.009**
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Panel B: IV replaceable hours – outcome: gender pay gap					
Robotization	0.057***	0.064***	0.072***	0.074***	0.074***
	(0.020)	(0.023)	(0.025)	(0.028)	(0.028)
First stage F-stat	15.37	15.98	13.22	11.76	11.87
Observations	4,927	4,927	4,927	4,927	4,927
Country fixed effects	No	Yes	Yes	Yes	Yes
Year fixed effect	No	Yes	Yes	Yes	Yes
Demographic controls	No	No	Yes	Yes	Yes
Job controls	No	No	Yes	Yes	Yes
Sex composition	No	No	No	Yes	Yes
ICT capital	No	No	No	No	Yes

Notes: The table reports results from OLS and IV regressions of the gender gap in median monthly earnings on the robotization (that is, inverse hyperbolic sine transformation of changes in number of robots per 10,000 workers). The instrumental variable is a measure of the share of hours in an industry performed by occupations prone to be replaced by robots. All regressions include a constant. Demographic characteristics include three age group dummies. Job controls include the share of full-time workers and a dummy indicating firm size is larger than 250 employees. Sex composition controls include the share of females and the change in share of females in a cell. ICT capital denotes the IHS of changes in ICT capital. Robust standard errors in parentheses, clustered two-way by country and industry, and adjusted for small number of clusters. Within-country industry employment shares used as survey weights. * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, own calculations.

Are the results driven by Germany and the automotive industry?

As discussed in Section 2, robotization is particularly high in Germany and the automotive industry. To alleviate the concern that our results are driven by a specific country or industry, we present the results of several estimations in Table 15. We show that our results are robust to: (i) excluding Germany; (ii) excluding the automotive and transport industry. In all subsamples, the size of the coefficient remains similar compared to the main results.

Table 15: Robustness to excluding Germany and automotive/transportation industry

Outcomes	Male earnings	Female earnings	Gender pay gap
	(1)	(2)	(3)
Panel A1: OLS, sample without Germany			
Robotization	0.015***	0.010**	0.004**
	(0.005)	(0.004)	(0.002)
Panel A2: IV replaceable hours, sample without Germany			
Robotization	0.046	0.021	0.021*
	(0.029)	(0.022)	(0.011)
First stage F-stat	15.99	15.99	15.99
Observations	23,031	23,031	23,031
Panel B1: OLS, sample without automotive/transportation industry			
Robotization	0.015***	0.010**	0.005**
	(0.006)	(0.005)	(0.002)
Panel B2: IV replaceable hours, sample without automotive/trans. industry			
Robotization	0.047	0.020	0.022*
	(0.031)	(0.023)	(0.013)
First stage F-stat	12.72	12.72	12.72
Observations	22,519	22,519	22,519
Country fixed effects	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes
Job controls	Yes	Yes	Yes
Sex composition	Yes	Yes	Yes
ICT capital	Yes	Yes	Yes

Notes: The table reports results from OLS and IV regressions of the gender gap in median monthly earnings on the robotization (that is, inverse hyperbolic sine transformation of changes in number of robots per 10,000 workers). The instrumental variable is a measure of the share of hours in an industry performed by occupations prone to be replaced by robots. All regressions include a constant. Demographic characteristics include three age group dummies and seven occupational group dummies. Job controls include the share of full-time workers and a dummy indicating firm size is larger than 250 employees. Sex composition controls include the share of females and the change in share of females in a cell. ICT capital denotes the IHS of changes in ICT capital. The elasticity estimate is calculated following Bellemare and Wichman (2020). Robust standard errors in parentheses, clustered two-way by country and industry, and adjusted for small number of clusters. Within-country industry employment shares used as survey weights. * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, own calculations.

Are the results driven by the definition of the gender pay gap variable?

Our main dependent variable is the gender gap in median monthly earnings. Since part-time work for women is common in a few European countries, we adjust part-time earnings to pro-rata full-time earnings. However, one might argue that part-time work results in less work experience, which accumulates less work experience than in a comparable full-time job (Kunze, 2018). Previous research also shows that part-time work leads to a downgrading of a career in terms of occupation (Manning and Petrongolo, 2008; Connolly and Gregory, 2008). In Table 16, we show that results do not substantively change when we use alternative earnings measures: (i) the gender gap in median monthly earnings without adjusting part-time earnings pro-rata; (ii) the gender gap in median hourly earnings. Again, we also find very similar point estimates.

Table 16: Robustness to alternative outcome variable definitions

Outcomes	Gender gap monthly earnings (PT not adjusted)	Gender gap hourly earnings
	(1)	(2)
	Panel A: OLS	
Robotization	0.004*	0.004*
	(0.002)	(0.002)
	Panel B: IV replaceable hours	
Robotization	0.025*	0.018*
	(0.011)	(0.010)
First stage F-stat	16.37	16.92
Observations	24,215	23,719
Country fixed effects	Yes	Yes
Year fixed effect	Yes	Yes
Demographic controls	Yes	Yes
Job controls	Yes	Yes
Sex composition	Yes	Yes
ICT capital	Yes	Yes

Notes: The table reports results from OLS and IV regressions of the gender gap in median monthly earnings on the robotization (that is, inverse hyperbolic sine transformation of changes in number of robots per 10,000 workers). The instrumental variable is a measure of the share of hours in an industry performed by occupations prone to be replaced by robots. All regressions include a constant. Demographic characteristics include three age group dummies and seven occupational group dummies. Job controls include the share of full-time workers and a dummy indicating firm size is larger than 250 employees. Sex composition controls include the share of females and the change in share of females in a cell. ICT capital denotes the IHS of changes in ICT capital. The elasticity estimate is calculated following Bellemare and Wichman (2020). Robust standard errors in parentheses, clustered two-way by country and industry, and adjusted for small number of clusters. Within-country industry employment shares used as survey weights. Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, own calculations.

Additional robustness

In Table A.5 in Appendix A, we show that our results are robust to using the natural logarithm of robotization (instead of IHS transformation). In Table A.6 in the Appendix, we report bootstrapped standard errors and find that the results remain qualitatively identical.

6 Conclusions

Automation sets important challenges for labor market policy. While public attention has focused on the labor-replacing technological developments, we argue that the challenge of automation lies in its distributional impact. We provide the first large-scale evidence on the impact of industrial robots on the gender pay gap using data from 20 European countries and covering the period from 2006 to 2014. For identification, we follow prior research and instrument robot adoption with a measure of replaceability which specifies the fraction of each industry's hours worked in 1980 that was performed by occupations that became replaceable by robots by 2012 (Graetz and Michaels, 2018).

We find that robotization increases the gender pay gap. Our IV estimates suggest that a 10 percent increase in robotization leads to a 1.8 percent increase in the gender pay gap. We further present evidence that these results are mostly driven by countries with high gender inequality to start with, and outsourcing destination countries. Our results are likely to be explained by an increase in male earnings in medium- and high-skilled occupations.

At a time when policymakers are putting increased efforts into tackling gender gaps in the labor market, our evidence is important. Our results suggest that governments not only need to ensure that education and vocational training systems provide people with the right skills demanded in the future, but also need to pay attention to distributional issues. They need to increase efforts to make sure that women and men are equally equipped with the skills most relevant for future employability.

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A Appendix

Table A.1: Effect of robotization on gender gap in monthly earnings, IV robotic arms

	(1)	(2)	(3)	(4)	(5)
Panel A: IV robotic arms 1st stage – outcome: robotization					
Robotic arms	9.103**	8.725***	7.834***	9.099***	9.002***
	(3.787)	(3.300)	(2.933)	(2.830)	(2.786)
Panel B: IV robotic arms 2nd stage – outcome: gender pay gap					
Robotization	0.021*	0.025	0.015	0.014	0.014
	(0.012)	(0.017)	(0.016)	(0.014)	(0.015)
First stage F-stat	5.778	6.988	7.135	10.34	10.44
Observations	24,215	24,215	24,215	24,215	24,215
Country fixed effects	No	Yes	Yes	Yes	Yes
Year fixed effect	No	Yes	Yes	Yes	Yes
Demographic controls	No	No	Yes	Yes	Yes
Job controls	No	No	Yes	Yes	Yes
Sex composition	No	No	No	Yes	Yes
ICT capital	No	No	No	No	Yes

Notes: The table reports results from OLS and IV regressions of the gender gap in median monthly earnings on the robotization (that is, inverse hyperbolic sine transformation of changes in number of robots per 10,000 workers). All regressions include a constant. Demographic characteristics include three age group dummies and seven occupational group dummies. Job controls include the share of full-time workers and a dummy indicating firm size is larger than 250 employees. Sex composition controls include the share of females and the change in share of females in a cell. ICT capital denotes the IHS of changes in ICT capital. The elasticity estimate is calculated following Bellemare and Wichman (2020). Robust standard errors in parentheses, clustered two-way by country and industry, and adjusted for small number of clusters. Within-country industry employment shares used as survey weights. Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, own calculations.

Table A.2: Inflows to manufacturing by gender, age and education level

Year	Category	Previous job in manufacturing	Moved to another industry
2006	Male, 20-39 yrs., high school or less	98.23%	1.05%
2006	Male, 20-39 yrs., degree-level education	98.87%	0.75%
2006	Female, 20-39 yrs., high school or less	98.24%	1.26%
2006	Female, 20-39 yrs., degree-level education	100.00%	1.06%
2006	Male, 40-59 yrs., high school or less	98.73%	0.68%
2006	Male, 40-59 yrs., degree-level education	99.77%	0.68%
2006	Female, 40-59 yrs., high school or less	98.75%	1.1%
2006	Female, 40-59 yrs., degree-level education	98.73%	2.5%
2010	Male, 20-39 yrs., high school or less	98.27%	1.6%
2010	Male, 20-39 yrs., degree-level education	98.50%	1.5%
2010	Female, 20-39 yrs., high school or less	97.14%	2.55%
2010	Female, 20-39 yrs., degree-level education	98.36%	1.64%
2010	Male, 40-59 yrs., high school or less	98.98%	0.94%
2010	Male, 40-59 yrs., degree-level education	99.61%	0.39%
2010	Female, 40-59 yrs., high school or less	98.32%	1.49%
2010	Female, 40-59 yrs., degree-level education	100.00%	0%
2014	Male, 20-39 yrs., high school or less	96.17%	3.89%
2014	Male, 20-39 yrs., degree-level education	95.71%	1.47%
2014	Female, 20-39 yrs., high school or less	94.43%	4.37%
2014	Female, 20-39 yrs., degree-level education	87.80%	0%
2014	Male, 40-59 yrs., high school or less	97.97%	1.18%
2014	Male, 40-59 yrs., degree-level education	98.95%	0%
2014	Female, 40-59 yrs., high school or less	96.98%	1.91%
2014	Female, 40-59 yrs., degree-level education	91.18%	6.06%

Notes: The third column of the table shows workers whose previous job was also in manufacturing, as a share of the workers currently in manufacturing. The fourth column shows workers who moved out of manufacturing, that is, workers currently working in any other industry as a share of the workers whose previous job was in manufacturing. The sample is restricted the employees in Germany who are between 20 and 59 years of age. The industry classification is NACE 1-digit level. Source: EU-LFS.

Table A.3: Gender gap index scores

Country	GGI score 2006	Classification
Italy	0.65	0
France	0.65	0
Greece	0.65	0
Hungary	0.67	0
Czech Republic	0.67	0
Slovakia	0.68	0
Romania	0.68	0
Poland	0.68	0
Bulgaria	0.69	0
Portugal	0.69	0
Estonia	0.69	1
Lithuania	0.71	1
Belgium	0.71	1
Latvia	0.71	1
Netherlands	0.73	1
Spain	0.73	1
United Kingdom	0.74	1
Germany	0.75	1
Finland	0.8	1
Sweden	0.81	1

Source: World Economic Forum Gender Gap Index by Hausmann et al. (2006).

Table A.4: Heterogeneity by skill-based occupational groups for countries with high robotization and high gender equality

Occupational group	Low-skilled			Medium-skilled			High-skilled		
Outcomes	Gender gap in earnings	IHS male earnings	IHS female earnings	Gender gap in earnings	IHS male earnings	IHS female earnings	Gender gap in earnings	IHS male earnings	IHS female earnings
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: OLS									
IHS Robotization	0.002	0.011***	0.009**	0.005*	0.009*	0.003	-0.001	0.006	0.007
	(0.003)	(0.002)	(0.004)	(0.003)	(0.005)	(0.004)	(0.000)	(0.004)	(0.004)
Panel B: IV replaceable hours									
IHS Robotization	-0.005	0.015	0.026**	0.019***	0.023	-0.001	-0.001	0.024**	0.027***
	(0.008)	(0.020)	(0.012)	(0.007)	(0.018)	(0.013)	(0.000)	(0.012)	(0.010)
1st stage F-stat	21.44	21.44	21.44	18.99	18.99	18.99	23.68	23.68	23.68
Observations	1,341	1,341	1,341	1,861	1,861	1,861	2,226	2,226	2,226
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Job controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sex composition	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ICT capital	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Sample consists of high robotization and high GGI countries, which are Belgium, Germany, Spain, the Netherlands, and Sweden. The instrumental variable is a measure of the share of hours in an industry performed by occupations prone to be replaced by robots. All regressions include a constant. Demographic characteristics include three age group dummies and seven occupational group dummies. Job controls include the share of full-time workers and a dummy indicating firm size is larger than 250 employees. Sex composition controls include the share of females and the change in share of females in a cell. ICT capital denotes the IHS of changes in ICT capital. Robust standard errors in parentheses, clustered two-way by country and industry, and adjusted for small number of clusters. Within-country industry employment shares used as survey weights. * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, own calculations.

Table A.5: Alternative functional form: regressor ln + 1 in robotization

Outcome	ln (Male earnings) (1)	ln (Female earnings) (2)	ln (Gender pay gap) (3)
	Panel A: OLS		
ln (robotization + 1)	0.029***	0.022***	0.007*
	(0.008)	(0.007)	(0.003)
	Panel B: IV replaceable hours		
ln (robotization + 1)	0.046*	0.023	0.019*
	(0.027)	(0.021)	(0.011)
1st stage F-stat	21.97	21.97	21.97
Observations	22,458	22,458	22,458
Country fixed effects	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes
Job controls	Yes	Yes	Yes
Sex composition	Yes	Yes	Yes
ICT capital	Yes	Yes	Yes

Notes: The table reports results from OLS and IV regressions. The instrumental variable is a measure of the share of hours in an industry performed by occupations prone to be replaced by robots. All regressions include a constant. Demographic characteristics include three age group dummies and seven occupational group dummies. Job controls include the share of full-time workers and a dummy indicating firm size is larger than 250 employees. Sex composition controls include the share of females and the change in share of females in a cell. ICT capital denotes the IHS of changes in ICT capital. The elasticity estimate is calculated following Bellemare and Wichman (2020). Robust standard errors in parentheses, clustered two-way by country and industry, and adjusted for small number of clusters. Within-country industry employment shares used as survey weights. * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, own calculations.

Table A.6: Bootstrapped standard errors

Outcome	Male earnings	Female earnings	Gender pay gap
	(1)	(2)	(3)
Panel A: Standard errors two-way clustered			
Robotization	0.010***	0.008**	0.002*
	(0.004)	(0.003)	(0.001)
Panel B: Standard errors bootstrapped and two-way clustered (400 repetitions)			
Robotization	0.010***	0.008***	0.002**
	(0.002)	(0.002)	(0.001)
Observations	24,215	24,215	24,215
Country fixed effects	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes
Job controls	Yes	Yes	Yes
Sex composition	Yes	Yes	Yes
ICT capital	Yes	Yes	Yes

Notes: Comparison of results with bootstrapped standard errors (400 repetitions) vs standard errors clustered two-way (both unweighted). Demographic characteristics include three age group dummies and seven occupational group dummies. Job controls include the share of full-time workers and a dummy indicating firm size is larger than 250 employees. Sex composition controls include the share of females and the change in share of females in a cell. ICT capital denotes the IHS of changes in ICT capital. * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, own calculations.