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 driven by countries with high initial levels of gender inequality and 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.

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 tasks performed by humans and those performed by machines, transforming the world of work. Advances in robot technologies and the increased adoption of industrial robots in production processes have augmented interest in the impacts of robots on labor markets.[1] Specific focus on robots is warranted because rapid robotization is ongoing: 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). However, despite recent examinations of the impact of robots on overall employment and earnings (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Grigoli et al., 2020), there has been little empirical research on how robot adoption might affect gender equality.

In this paper, we provide the first large-scale evidence on the impact of industrial robots on the gender pay gap using data from 28 million workers in 20 European countries. Specifically, we examine how changes in the number of robots per worker between 2006 and 2014 (henceforth, 'robotization') affect the gender gap in the monthly earnings of workers in manufacturing and a few other sectors that employ robots.[2] 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.[3] To put the effect size 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. Our analysis offers the broadest

[1]An industrial robot is defined as an '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). Industrial robots are mainly employed in the manufacturing sector to perform tasks such as assembling, painting and welding.

[2]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).

[3]The conditional pay gap is the pay gap after adjusting for a set of factors that may account for differences between men's and women's earnings. In our paper, these factors include occupational category, industry, age group, country, year and firm size. From a policy perspective, the conditional gender pay gap is more important than the unconditional (overall) pay gap because it is related to 'equal pay' legislation in Europe.

cross-national evidence to date, which allows greater confidence in the generality of the findings. We are also able to investigate the role of initial country conditions in terms of gender equality and test underlying mechanisms of our results.

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 proving rather immune to change and remains at 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 important as it has implications for the success of ongoing policy efforts to reduce the pay gap. 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).

There are several ways in which we may expect robotization to affect the gender pay gap. On the one hand, robots perform physical tasks and replace 'brawn' skills, weakening the comparative advantage of low-skilled men compared to women (Rendall, 2017). Similarly, low-skilled men are more likely to be employed in manual jobs with higher robotization risks, whereas women are thought to have a comparative advantage in services (Ngai and Petrongolo, 2017; Muro et al., 2019). In line with these arguments, we may therefore expect robotization to decrease the gender pay gap. On the other hand, skilled male workers are more likely to benefit from robot-driven productivity increases. This is not only because men disproportionately occupy higher positions in the occupational hierarchy but also they are overrepresented in relevant STEM (science, technology, engineering, maths) occupations. For these reasons, we expect the effect of robotization to differ across skill-based occupational groups.

The underlying mechanism for our finding is that skilled men disproportionately benefit from robotization, through a productivity effect. In particular, we find that the increase in the gender pay gap due to robotization is driven by those in medium- and high-skilled occupations. Put differently, the underrepresentation of women in medium- and high-skill occupations in specific industries accompanied by robotization exacerbates the gender pay gap. This is in line with recent research, which shows that firm-level adoption of robots coincides with increases in value added and productivity (Acemoglu et al., 2020) and increases wages of high-skilled workers relative to low-skilled workers while also increasing average wages of manufacturing workers (Barth et al., 2020). We further show that, in line with the findings of Freeman et al. (2020)[4], our results cannot be explained by changes in the gender composition of the workforce nor by inflows or outflows from the manufacturing sector.

We also find that our results are driven by countries in which initial overall gender inequality, measured by the Gender Gap Index (GGI) of the World Economic Forum, is high. Conversely, in countries where initial gender inequality is low, robotization does not have any statistically significant effect on the gender pay gap. Instead, it increases the earnings of all workers.

There is a risk of potential endogeneity of robotization to the gender pay gap. For example, some industries may be adopting robots in response to domestic shocks to industries, which may directly impact the gender pay gap (e.g. industry-specific minimum wage changes). To identify a causal effect, we therefore 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 a higher initial replaceability increased their use of robots.

Our paper makes three contributions. First, our paper contributes to the growing literature on the labour market impacts of industrial robots. Existing research points to mixed impacts of robot adoption on labour markets in Europe. For example, Graetz and Michaels (2018) find that robotization increases both labor productivity and wages and has no effect on employment in 14 European and three non-European countries. Evidence from Germany suggests that robot adoption has no effect on total employment and also does not increase the risk of displacement for incumbent manufacturing workers (Dauth et al., 2018). Using a local labor market approach, Acemoglu and Restrepo (2020) show that industrial robot exposure reduces both employment and wages. Existing evidence therefore varies across contexts, with generally more positive effects in Europe compared

[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).

to the United States.[5] Our paper contributes to this growing literature by focusing on the gender pay gap – a crucial but neglected policy-relevant outcome.

Second, we contribute to the literature on the gendered labor market impacts of recent waves of robotization. Exploiting variation in robot exposure across commuting zones, recent evidence from the US indicates that robotization decreases both male and female earnings and also decreases the gender pay gap (Anelli et al., 2019; Ge and Zhou, 2020). These findings contrast those from our paper, which is in line with the contrasting results across Europe and the US emerging from the research on the overall impact of robots on employment and wages (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). There are also attempts to identify the gendered impacts of automation through relating data on task composition at work to occupation-level estimates of the probability of automation. For example, Brussevich et al. (2019) find that female workers are at a significantly higher risk for displacement by automation than male workers, albeit with significant cross-country heterogeneity. This is because "female workers perform fewer tasks requiring analytical and interpersonal skills or physical labor, and more tasks that are routine, characterized by lack of job exibility, little learning on the job, and greater repetitiveness" (Brussevich et al., 2018, p.8). They also show that the probability of automation is lower for younger cohorts of women, and those in managerial positions.

Third, our paper also contributes to the broader literature on the determinants of the gender pay gap. An extensive literature has studied the factors that explain the gender pay differences (see (Kunze, 2018) for a recent review). 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). Studies that focus on computerization find that it narrows the gender pay gap (Weinberg, 2000; Black and Spitz-Oener, 2010; Yamaguchi, 2018), which can be explained by differential changes in tasks: while women experienced a marked decline in routine tasks, men did not (Black and Spitz-Oener, 2010). While white-collar workers directly work with computers, industrial robots are employed at the firm level. Therefore, the underlying mechanisms for the gendered impacts of robots are fundamentally different from those of computerization.

[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 studying an important demand-side factor.

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, and Section 6 discusses heterogeneity across countries and potential mechanisms. The final section 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 robot density vary substantially across countries. With almost 50 robots per 10,000 employees in 2014, Germany shows the highest robot density. On the other hand, Bulgaria, Latvia, and Lithuania Bulgaria have the lowest robot density in our sample, with less than one robot per 10,000 workers. Furthermore, Figure 1 shows that many countries have seen high growth in the number of robots per worker. For example, the Czech Republic saw rapid robotization, with robot density growing from 6 per 10,000 workers in 2006 to 23 per 10,000 workers in 2014.

Figure 2A shows that industrial robots are mainly deployed in the automotive and transport industry (about 390 robots per 10,000 workers in 2014), although they have also begun to be used more widely in the plastic, chemicals, metals as well as food and beverage sectors. Figure 2A highlights 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

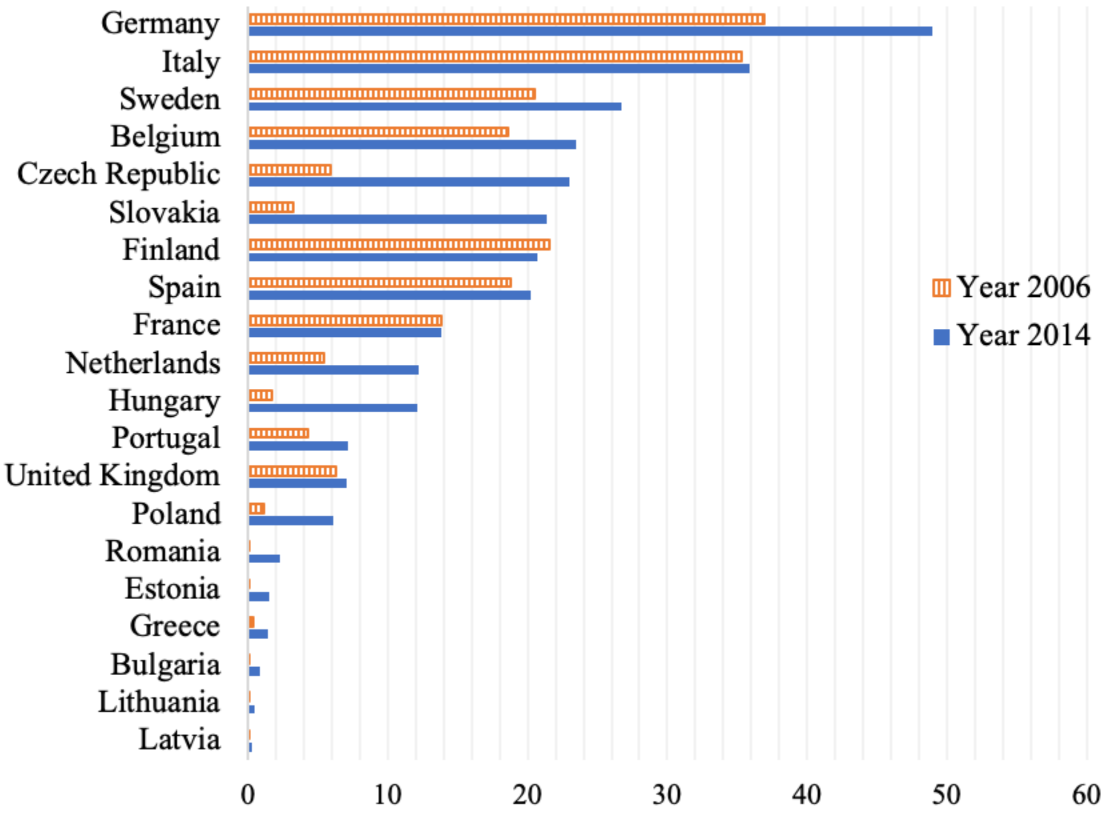

Figure 1: Industrial robots per 10,000 workers by country

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

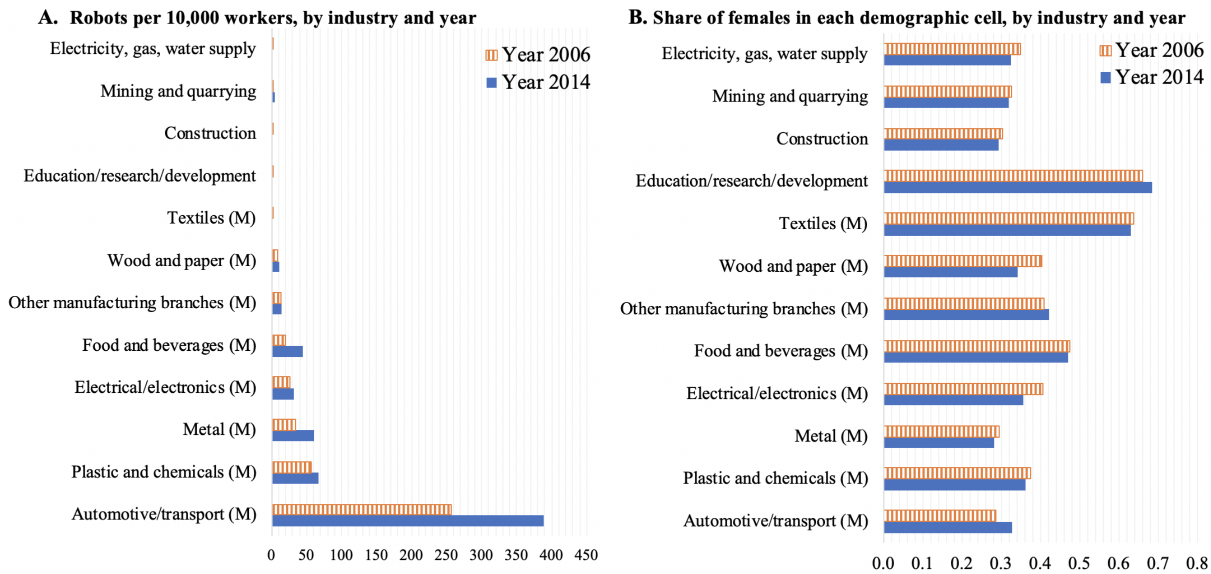

Figure 2: Robot density and share of females by industry

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

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. For part-time workers, the equivalent full-time earnings are used. 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. 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.

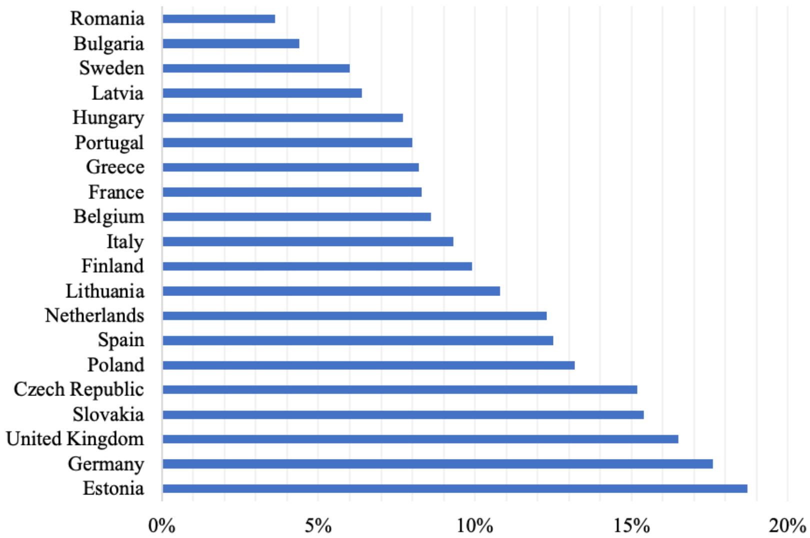

Figure 3: Gender gap in median monthly earnings 2010 by country

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. Although the role of manufacturing in Europe has declined in recent years (a secular trend observed across advanced economies), 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 by 11.4 percent in constant prices).[6] This means manufacturing is 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.[7]

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. These findings provide additional motivation for our analysis, validating our predominant focus on manufacturing industries and highlighting the importance of studying heterogeneous effects across countries.

3 Data and Descriptive Statistics

3.1 Data

We use data from five independent sources: the International Federation of Robotics (IFR), the EU Structure of Earnings Survey (EU SES), the EU KLEMS database, the EU Labour Force Survey (EU LFS), and Graetz and Michaels (2018).

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

[6] 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).

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

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 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 EU Member States and Candidate Countries. EU-SES provides 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 who may be directly affected by robotization. Another advantage of the dataset is that the information collected relates to the wages paid to each job, ensuring that wages of the same person from additional jobs do not confound the analysis. 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. It is important to note that for 13 out of the 20 European countries we have in the sample, the IFR data are disaggregated by industry only from the early 2000s. Therefore, we cannot compute robotization rates for the survey year 2002 (which would require robots data by industry for 1998) and restrict our analysis in EU-SES to years 2006, 2010, and 2014. In other words, our treatment is 4-year lagged robotization variable — for example, we regress gender pay gap in 2006 (calculated in EU-SES) on change in robot density (calculated in the IFR) between 2002 and 2006.

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 service sectors. The 20 countries comprise 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.[8]

The level of analysis is at the 'demographic cell'.[9] 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, (iii) year, (iv) age group (20 to 29, 30 to 39, 40 to 49, 50 to 59); (v) broad occupational group (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. We drop demographic cells with fewer than ten respondents so that the smallest cell contains at least ten respondents, of which at least five are female and at least five are male.[10] We use survey weights when collapsing the data to ensure averages are representative of the underlying target population.

Additional industry-level data on employment counts and information and communication technology (ICT) capital come from the EU KLEMS database.[11] 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 to minimise omitted variables bias as computer technology is an important source of recent technological change. 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. We use EU-

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

[9]In Robustness Section, we also directly show that our results are robust to using individual level EU-SES data.

[10]The number of observations (i.e. demographic cells) that are dropped due to this restriction is 279, or approximately 1.1 percent of observations.

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

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 2002, 2006, 2010, and 2014. Data for our instrumental variables come from Graetz and Michaels (2018), and more details are provided in subsection 4.2.

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':

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

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 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. In some countries such as Germany and the Netherlands, it is very common for women to work part-time, and therefore including full-time workers only would lead to a very selective sample. To avoid the possibility that the difference in men and women's monthly earnings can be attributed to the fact that women are more likely to work part-time, we adjust the earnings of part-time workers to their pro-rata full-time equivalents. 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. However, our results are robust to using alternative measures, namely (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 (see Table A.10 in Appendix A).

To understand why robotization may affect the gender pay gap, in a first step we also study whether robotization increases or decreases 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.[12]

3.2 Descriptive Statistics

Table 1 presents summary statistics of the variables used in the analysis, according to the skill-level of the occupation. Column 1 is high-skilled occupations; medium-skilled occupations are in Column 2; low-skilled occupations 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 gross 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 share of women employed across the industries studied is 44 percent, which is consistent with the predominant focus 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. Both men and women also earn substantially more in high-skilled occupations (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 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).

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

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 gross earnings (EUR)	2,049	19	1,265	13	1,087	13	1,559	11
Male median monthly gross 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:

$$\mathrm{GPG}_{cidt} = \beta_0 + \beta_1 \mathrm{robotization}_{ci(t-4)} + \beta_2 \mathrm{controls}_{cidt} + \delta_c + \theta_t + u_{cidt} \tag{3}$$

where GPG_{cidt} is the gender pay gap in country c, industry i, demographic cell d, and year t as defined in equation 2. $\mathrm{Robotization}_{ci(t-4)}$ (that is, the change in the number of robots per 10,000 workers — it is calculated with a lag of 4 years as SES data are available on a 4 yearly basis) is our main parameter of interest as defined in equation 1 and captures the effect of 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 our measure of changes in information and communication technology (ICT) capital (to minimize omitted variables bias as computer technology is an important source of recent technological change).

To account for factors that vary systematically across countries or over time, such as macroeconomic conditions or gender equality policies, we include a full set of country and year fixed effects.[13] The country dummies, δc, control for any time-invariant difference in unobserved factors that vary cross-nationally. Year dummies, θt, capture the impact of shocks that affect all countries simultaneously. Given that the robotization measure is constructed off of three data points (that is, two changes between three specific years), our model is similar to a first-difference specification. We use robust standard errors, which are two-way clustered by country and industry. All regressions are weighted by within-country industry employment shares, as in Graetz and Michaels (2018), giving more weight to larger industries within each country while giving equal weight to each

[13]We cannot include industry fixed effects in our IV models since our robotization variable is only varying at the industry level. In robustness section, we directly show that our OLS results are robust to inclusion of industry fixed effects.

country independent of population size.

Alongside the regression coefficients, we report elasticities for the models using the inverse hyperbolic sine transformation on the dependent variable to ease interpretation. The elasticities are calculated from the regression coefficients following Bellemare and Wichman (2020). The formula used for regressions with the gender pay gap as a dependent variable is $\hat{\xi}_{yx} = \frac{\hat{\beta}}{y}\frac{x}{\sqrt{x^2+1}}$; and the formula used for regressions with the IHS of median earnings as dependent variable is $\hat{\xi}_{yx} = \hat{\beta} \cdot \frac{\sqrt{y^2+1}}{y} \cdot \frac{x}{\sqrt{x^2+1}}$.

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. Shocks to relative female labor demand in an industry, such as industry-specific policies on gender-equal pay, may affect firms' decision making on whether to adopt robots. Further, firms may adopt robots in response to larger shocks to specific industries, which may also directly impact the gender pay gap.[14]

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

[14]We acknowledge the possibility of other unobserved industry-level shocks. However, we are not aware of any shocks that took place during our sample period which could differentially affect the industries that experienced robotization (versus others).

(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 the replaceability measure should affect the gender pay gap only through robot adoption.

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. To the extent that robotization affects pay gaps, our instrument ensures that this is consequent on the automation itself rather than compositional changes also associated with differences in pay between men and women. While they do not fully address all possible endogeneity concerns, the instrumental variable analyses provide us with an additional check and help support our findings from our OLS 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 required reaching and handling tasks, compared to other tasks in 1980, prior to robot adoption. This instrument takes advantage of the fact that robotic arms are a widespread and supply-side characteristic 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. Finally, it is important to note that our instruments only vary at the industry level (that is, they are constant across countries and years) and, hence, we exploit cross-industry variation in our analysis.

5 Results

5.1 Main Findings from OLS and IV Estimations

Table 2 presents the main OLS results on the relationship between the gender pay gap and robotization. We report five model specifications: the baseline specification with no controls (column 1); 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 Column 5 adds a control variable for changes in ICT capital to ensure that changes in other technologies are not driving our results.

Without controls, we find that higher robotization is associated with a higher gender pay gap: our elasticity estimate suggests that a ten percent increase in robotization is associated with a 0.68 percent increase in the gender pay gap. After adding various controls (Columns 2 to 5), the coefficient size decreases to 0.004 with an elasticity of 0.035.

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 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.

These results suggest that robotization and the gender pay gap are positively associated. But to address potential endogeneity, we turn to our IV model (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.

Panels C and D show the first- and second-stage estimates with two instrumental variables, in which we find that robotic arms do not predict robotization. The first-stage F-statistic for both instruments range between 9.1 and 10.7 and the overidentification test suggests that the instruments are valid. In Panel D, we find that second-stage coefficients are very similar to those using the replaceable hours instrument only: 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 focus solely on the replaceable hours instrument for the rest of the paper.[15]

Our estimates for IV are larger than the OLS ones. A potential explanations for this is that in the presence of omitted variables there could be a tendency to underestimate the impact of robotization on the gender pay gap. For example, there could be a negative correlation between the errors in the gender pay gap and robotization due to an initial selection of female workers into different manufacturing industries.

While these results indicate that women lose out compared to men due to the adoption of robots, it is also important to understand whether this is driven by rising male or falling 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

[15] We are aware of the fact that the robotic arms instrument does not perform as well as it does in Graetz and Michaels (2018). However, there are reasons for this discrepancy: (i) Graetz and Michaels (2018) predict robotization that took place between 1993-2007. The robotization trend during this period was much less steep than the trend in our period; (ii) the period differences is also important because the reaching and handling tasks (that is, robotic arms) were more crucial at the initial stages of robotization. As Graetz and Michaels (2018) predict, robot capabilities have developed over time, and early adapting industries intensified their use of robots later on. However, this made robotic arms' reaching and handling capabilities possibly less relevant than the earlier generation of robots. Indeed, evidence suggests that precision, added functionalities, and increased automatability, etc. have become more important for robots' capabilities in the last decade (IFR, 2017). Taken together, it makes sense and sort of expected that this instrument predicts better in earlier robotization than more recent robotization.

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
Overidentification test p-value	0.816	0.928	0.753	0.571	0.584
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 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.

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 impacts both male and female earnings positively, but the increase in the gender pay gap is driven by the larger positive effect on male earnings.

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 Robustness Checks and Alternative Specifications

We conducted a range of checks to ensure the robustness of our results, and the tables are included in Appendix A.

Individual level analysis

In addition to cell-level analysis, we also replicated our results at the individual-level to check the robustness of our results. In particular, to examine the relationship between robotization and the gender pay gap, we estimate the following model:

$$\text{(log)earnings}_{citw} = \beta_0 + \beta_1 \text{rob}_{ci(t-4)} * female_w + \beta_2 \text{rob}_{cit} + \beta_3 \text{female}_w + \beta_4 \text{X}_w + \delta_c + \theta_t + u_{citw} \tag{4}$$

where (log) earnings$_{citw}$ is the gross log monthly earnings in country c, industry i, year t and for worker w. $\text{rob}_{ci(t-4)} * female_w$ (that is, IHS transformation in the number of robots per 1,000 workers at t-4 interacted with a female worker dummy) is our main parameter of interest and captures the effect of robotization on the gender pay gap.

In the fully saturated specification, consistent with our cell-level analysis, we control for various individual (i.e. worker) and aggregate-level characteristics, X_w, which are: three age group dummies (30 to 39, 40 to 49, 50 to 59 with 20 to 29 being the excluded category), seven occupational group dummies (managers, professionals, associate professionals, clerical support workers, sales and service workers, craft and related trade workers, plant/machine operators and assemblers, with elementary occupations being the excluded category), a full-time worker dummy, a firm size dummy (greater than 250 employees) as well as our measure of changes in information and communication technology (ICT) capital. We also include a full set of country, δ_c, and year, θ_t, fixed effects.[16] We use robust standard errors, two-way clustered by country and industry.

We report the OLS estimates in Appendix Table A.2 and IV estimates in Appendix Table A.3. Consistent with our cell-level analysis, we find that robotization leads to an increase in the gender pay gap. These results hold for both OLS and IV.

Robustness to alternative demographic cell definition

Our definition of a demographic cell distinguishes by skill-based occupational groups. This is necessary to be able to test heterogeneous effects across occupational hierarchies.

[16] As mentioned above, we cannot include industry fixed effects in our IV models since our robotization variable is only varying at the industry level.

However, we show that the positive relationship between robotization and the gender gap in earnings remains (and even becomes stronger) when an alternative demographic cell definition that does not distinguish across occupational groups (Table A.4). This suggests that our findings are robust to a demographic cell definition in which movements between occupations due to robotization cease to be relevant and cells contain information from individuals with more heterogenous skill levels.

Quantile regressions

In Table 4, we showed that the increase in the gender pay gap due to robotization is driven by the fact that male earnings increase more strongly than female ones. We show that the positive association between robotization and (male and female) earnings holds across the earnings distribution by conducting quantile regressions at different percentiles of the distribution of median earnings of each demographic cell (Appendix Table A.5).

Robustness to inclusion of country*year fixed effects

Appendix Table A.6 shows that our results are robust to inclusion of country*year fixed effects, which controls for all potentially omitted variables that can vary across countries and years (such as trade shocks, outsourcing and so on).

Robustness to inclusion of industry dummies

Our OLS results are also robust to inclusion of broad-level industry fixed effects (see Appendix Table A.7). Note that since our instruments only vary at the industry level (that is, they do not vary across countries and years), we are unable to include industry fixed effects in IV models as they are perfectly collinear.

Robustness to removing age restrictions

Appendix Table A.8 shows that our results are remain similar when we focus on the full-sample (that is, instead of the 20-59 age band). This adds age groups 14 to 19 and 60 or older.

Ruling out influential observations

Next, we show that our results are robust to the exclusion of Germany from the sample, as well as to the exclusion of the automotive and transport industry (Appendix Table A.9). This alleviates concerns that our results are driven by the country or industry with the highest robotization.

We also rule out the importance of influential observations by plotting the coefficients of our fully saturated IV specifications as one country is omitted at a time. Figures 4 and 5 in the Appendix show that our coefficient estimates are quite stable once a specific survey country is eliminated from our main sample in each iteration.

Robustness to alternative pay gap definitions

We adjust part-time earnings to pro-rata full-time earnings since part-time work for women is common in a few European countries. We show that our results are robust to gender pay gap definitions that are based on alternative earnings measures, (i) the gender gap in median monthly earnings without adjusting part-time earnings pro-rata, and (ii) the gender gap in median hourly earnings (Appendix Table A.10).

Robustness to alternative robotization definitions

In Appendix Table A.11, we show that our results are robust to using the natural logarithm of robotization, instead of using an IHS transformation.

Robustness to defining robotization in terms of a percentile of the change and the outcome as a change in GPG

We also execute a specification similar to Graetz and Michaels (2018) where robotization is defined as a percentile of the change in robot density and the dependent variable is defined as a change in gender pay gap. Our results remain robust (Appendix Table A.12).

Robustness to controlling for a capital/labor ratio

We also check the robustness of our results by including a capital/labor ratio as an additional control, with the capital variable adjusted for the stock of robots. Our findings do not change (Appendix Table A.13).

Robustness to bootstrapping standard errors

Appendix Table A.14 reports bootstrapped standard errors and we find that the results remain qualitatively identical.

6 Country heterogeneity and mechanisms

6.1 Heterogeneity across countries

The sample of countries included in our analysis differs in terms of levels of gender equality. It is therefore possible that the impact of robotization is stronger in countries with high initial levels of gender inequality. To test this, 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)). We split 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. The countries with high gender equality levels are 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. Results presented in Table 5 indicate that our main findings are mostly driven by countries with low levels of initial gender equality. This suggests that robotization exacerbates existing inequalities in these countries. On the other hand, robotization has no effect on the gender pay gap in countries with high initial gender equality.[17] We also performed additional analyses in which we split the countries into Eastern and Western European subsamples. We find that robotization increases the gender pay gap to a similar extent in both groups (see Appendix Table A.15. This suggests that initial gender equality per se, rather than regional grouping, mediates the impact of robotization on the gender pay gap.

Our sample of countries also varies in terms of the robotization experienced over the study period. Countries that have experienced high levels of robotization are not the same countries that have always enjoyed a high robot density. We therefore study results across levels of initial gender equality for the subsample of the ten countries that have had the highest changes in robots per worker over the study period (Table 6). We find that our main results are driven by countries with low overall gender equality but which experienced high robotization (Columns 4 and 6), such as the Czech Republic, Hungary, Italy, Poland, and Slovakia. With the exception of Italy, these are all Eastern European countries. The size of the coefficient for this group of countries is almost identical to the effect we found for the full sample of countries (Table 3, Column 5). In line with results presented in Table 5, robotization had no effect on the gender pay gap in countries with high overall gender equality (and high robotization), which includes Belgium, Germany, the Netherlands, Spain, and Sweden.

[17] We also tried to classify the 20 countries into 4 groups based on their GGI ranking, and the take-away remains the same. Robotization increases the gender pay gap among the two country groups with the lowest GGI rankings but have no effect on the two groups with higher GGI rankings.

Table 5: 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.

Table 6: 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			
Robotization	0.002	0.008**	0.006*	0.005* A	0.021***B	0.015**C
	(0.002)	(0.004)	(0.004)	(0.003)	(0.008)	(0.006)
			Panel B: IV replaceable hours			
Robotization	0.005	0.023	0.018*	0.019**A	0.040* B	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. A indicates statistically significant difference in each pair of means at $p<0.05$ between column 1 and column 4. B indicates statistically significant difference in each pair of means at $p<0.05$ between column 2 and column 5. C indicates statistically significant difference in each pair of means at $p<0.05$ between column 3 and column 6. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Sources: EU-SES, IFR, EU KLEMS, own calculations.

Germany has a unique position, with high levels of robotization and robot density as well as a dominant automotive/transport industry. Dauth et al. (2018) analyzed German data to investigate how robotization affected the outcomes of individual workers, but did not examine the potential gendered impacts. We therefore reran our models just on the German sample to check the consistency of our results with theirs. Our findings are compatible: we find both male and female earnings in Germany modestly increased due to robotization in comparable amounts keeping gender pay gap relatively unchanged (not shown here but available upon request). As discussed in the robustness checks section, we also show that our results are not affected by exclusion or inclusion of Germany nor of automotive industry.

In sum, robotization exacerbated the gender pay gap in countries in which overall gender inequality was already high. These are predominantly Eastern European countries. In contrast, in countries where initial gender inequality was low, robotization did not increase the gender pay gap. These results also hold when focusing only on the countries that experienced higher increases in robotization.

6.2 Potential mechanisms

In this section, we analyze two potential mechanisms underlying the observed relationship between robotization and the gender pay gap. First, robotization may lead to differential earnings increases 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.

To test the first mechanism, we explore heterogeneity by skill-based occupational groups. The results presented in Table 7 show that robotization leads to an increase in the gender pay gap for medium- and high-skilled occupations. In contrast, there is no effect of robotization among those in low-skilled occupations.

Next, we explore whether the heterogeneous results across occupational ranking 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

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.

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.

Table 8: 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					
Robotization	0.002	0.017***	0.016***	0.011*A	0.025***	0.012**	0.005***	0.016*	0.011
	(0.002)	(0.006)	(0.006)	(0.006)	(0.010)	(0.006)		(0.009)	(0.009)
				Panel B: IV replaceable hours					
Robotization	-0.002	0.033*	0.037**	0.037***A	0.052*B	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. We tested for coefficient equality between the medium-skilled and the high-skilled sample: A indicates statistically significant difference in each pair of means at $p<0.05$ between column 4 and column 7. B indicates statistically significant difference in each pair of means at $p<0.05$ between column 5 and column 8. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Sources: EU-SES, IFR, EU KLEMS, own calculations.

Building on results from Table 6, which demonstrated the importance of the initial gender inequality situation of the country, we focus on the subsample of countries with high initial gender inequality and high robotization. The results in Table 8 confirm that robotization is associated with sizable and statistically significant earnings premia for male workers in medium- and high-skilled occupations. 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. On the other hand, the results also show that robotization positively impacts female earnings only for those in low-skilled occupations. Our results suggest that the underlying mechanism for the impact of robotization on an increased gender pay gap is that skilled men disproportionately benefit from robotization, through a productivity effect.

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 9.[18] 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 10. 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

[18]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.

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.16). Collectively, we conclude that compositional changes in the manufacturing sector are negligibly small.

Table 9: 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 10: 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 11. 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.

We further complement these findings by conducting additional analysis to check whether sex composition of workers have changed due to robotization. Table 12 reports these results and show that robotization did not have any statistically significant effect on the share of female workers.

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.

7 Conclusions

We provide the first large-scale evidence on the impact of industrial robots on the gender pay gap using data from 28 million individuals living in 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 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, overall, 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 driven by countries with high initial gender inequality. Moreover, our results appear to be explained by disproportionate increases in male earnings, compared to female earnings, in medium- and high-skilled occupations. This suggests that skilled men disproportionately benefit

Table 11: 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.

Table 12: Effect of robotization on share of females in a demographic cell

Outcome	Share of females			
	(1)	(2)	(3)	(4)
Panel A: OLS				
Robotization	-0.029*	-0.025	-0.013	-0.013
	(0.017)	(0.016)	(0.011)	(0.011)
Panel B: IV				
Robotization	-0.097	-0.094	-0.042	-0.043
	(0.062)	(0.064)	(0.057)	(0.057)
First stage F-stat	17.87	19.75	18.41	18.61
Observations	24,215	24,215	24,215	24,215
Country & year FE	no	yes	yes	yes
Demographic & job controls	no	no	yes	yes
Sex composition	no	no	no	no
ICT capital	no	no	no	yes

Notes: The table reports results from OLS and IV regressions of the share of females in a demographic cell on 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. 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.

from robotization, through a productivity effect.

Automation sets important challenges for labor market policy. While much attention has focused on the overall labor-replacing consequences of technological developments, our findings highlight that automation may have important distributional consequences, which depend on country context and occupational hierarchies. Specifically, our findings suggest that countries that have been less successful in promoting gender equality are also worse equipped to deal with technological developments that may exacerbate gender inequalities.

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 and that women are equally represented in positions across the skill-based occupational hierarchy.

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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: Effect of robotization on log monthly earnings, OLS, Individual Level Analysis

Outcome	Log monthly earnings				
	(1)	(2)	(3)	(4)	(5)
Robotization*Female	-0.023**	-0.021*	-0.018**	-0.022***	-0.022***
	(0.012)	(0.011)	(0.005)	(0.006)	(0.006)
Robotization	0.041***	0.046***	0.036***	0.032***	0.047***
	(0.007)	(0.007)	(0.009)	(0.010)	(0.009)
Female	-0.228***	-0.240***	-0.215***	-0.223***	-0.169***
	(0.024)	(0.023)	(0.025)	(0.033)	(0.038)
Observations	13,585,311	13,585,311	13,585,311	13,585,311	13,585,311
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
ICT capital	No	No	No	No	Yes

Notes: The table reports results from OLS regressions of the logarithm of monthly earnings on robotization (that is, the IHS of robots per 1,000 workers at t-4). All regressions include a constant. Demographic controls include three age group dummies and seven occupational group dummies. Job controls include a full-time worker dummy and a dummy variable indicating firm size is larger than 250 employees. ICT capital is per 1,000 workers. 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. * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, own calculations.

Table A.3: Effect of robotization on log monthly earnings, IV, Individual Level Analysis

	(1)	(2)	(3)	(4)	(5)
Panel A: IV replaceable hours 2nd stage – outcome: log monthly earnings					
Robotization*Female	-0.072**	-0.071**	-0.065*	-0.064*	-0.119**
	(0.029)	(0.028)	(0.038)	(0.035)	(0.049)
Robotization	0.054***	0.059***	0.054***	0.050**	0.081***
	(0.011)	(0.011)	(0.019)	(0.021)	(0.022)
Female	-0.184***	-0.195***	-0.141***	-0.130*	-0.116*
	(0.034)	(0.032)	(0.054)	(0.073)	(0.078)
First stage F-stat	14.32	13.51	17.53	15.34	16.41
Panel B: IV robotic arms 2nd stage – outcome: log monthly earnings					
Robotization*Female	-0.093	-0.118***	-0.098**	-0.077*	-0.095**
	(0.052)	(0.033)	(0.040)	(0.041)	(0.035)
Robotization	0.085***	0.089***	0.054**	0.047*	0.099***
	(0.021)	(0.021)	(0.023)	(0.024)	(0.038)
Female	-0.145***	-0.186***	-0.119***	-0.140*	-0.150**
	(0.034)	(0.032)	(0.054)	(0.073)	(0.064)
First stage F-stat	9.65	9.88	8.76	10.11	9.91
Panel C: IV replaceable hours and robotic arms 2nd stage – outcome: log monthly earnings					
Robotization*Female	-0.061*	-0.079***	-0.060*	-0.069*	-0.075**
	(0.030)	(0.023)	(0.030)	(0.033)	(0.032)
Robotization	0.064***	0.061***	0.057***	0.060**	0.077***
	(0.013)	(0.021)	(0.012)	(0.025)	(0.020)
Female	-0.156***	-0.123***	-0.133***	-0.128*	-0.102**
	(0.038)	(0.030)	(0.039)	(0.060)	(0.041)
First stage F-stat	10.13	10.76	9.93	10.76	10.48
Overidentification test p-value	0.813	0.766	0.886	0.819	0.838
Observations	13,585,311	13,585,311	13,585,311	13,585,311	13,585,311
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
ICT capital	No	No	No	No	Yes

Notes: The table reports results from IV regressions of the logarithm of monthly earnings on robotization (that is, the IHS of robots per 1,000 workers at t-4). 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 a full-time worker dummy and a dummy variable indicating firm size is larger than 250 employees. ICT capital is per 1,000 workers. 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. * $p<0.1$, ** $p<0.05$, *** $p<0.01$. Sources: EU-SES, IFR, EU KLEMS, own calculations.

Table A.4: 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.

Table A.5: 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. Data unweighted. * p<0.1, ** p<0.05, *** p<0.01. Sources: EU-SES, IFR, EU KLEMS, own calculations.

Table A.6: Robustness to inclusion of country by year fixed effects

Outcome	Gender pay gap				
	(1)	(2)	(3)	(4)	(5)
	Panel A: OLS				
IHS robotization	0.007**	0.006*	0.004*	0.004**	0.004**
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Elasticity	0.0682	0.0539	0.0353	0.0351	0.0352
	Panel B: IV replaceable hours				
IHS robotization	0.023***	0.026**	0.018*	0.019*	0.019*
	(0.008)	(0.010)	(0.010)	(0.011)	(0.011)
1st stage F-stat	17.57	19.80	18.42	16.27	16.36
Elasticity	0.213	0.239	0.169	0.175	0.177
Observations	24,215	24,215	24,215	24,215	24,215
Country-specific time trends	yes	yes	yes	yes	yes
Country & year FE	no	yes	yes	yes	yes
Demographic & 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 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 A.7: Robustness to the inclusion of broad industry fixed effects, OLS

Outcome	Gender pay gap				
	(1)	(2)	(3)	(4)	(5)
Robotization	0.004**	0.002*	0.002*	0.003**	0.003**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Elasticity	0.037	0.017	0.017	0.023	0.023
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
Broad industry fixed effects	Yes	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 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. Broad industry fixed effects include four industry dummies (not including fixed effects for within-manufacturing industries). 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.8: Effect of robotization on gender gap in monthly earnings, IV - cell-level sample with no age restriction

	(1)	(2)	(3)	(4)	(5)
Panel A: IV replaceable hours 2nd stage – outcome: gender pay gap					
Robotization	0.018***	0.020*	0.022*	0.023**	0.023**
	(0.005)	(0.010)	(0.010)	(0.009)	(0.009)
First stage F-stat	18.88	17.78	18.12	18.45	18.37
Panel B: IV robotic arms 2nd stage – outcome: gender pay gap					
Robotization	0.017**	0.021**	0.017*	0.020	0.021
	(0.007)	(0.008)	(0.008)	(0.011)	(0.012)
First stage F-stat	6.88	7.21	7.45	8.31	7.99
Panel C: IV replaceable hours and robotic arms 2nd stage – outcome: gender pay gap					
Robotization	0.027***	0.028**	0.025**	0.024*	0.026*
	(0.009)	(0.010)	(0.010)	(0.012)	(0.009)
First stage F-stat	10.14	10.41	10.89	11.41	11.66
Overidentification test p-value	0.777	0.813	0.828	0.921	0.913
Observations	30,612	30,612	30,612	30,612	30,612
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 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 five 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.9: 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.

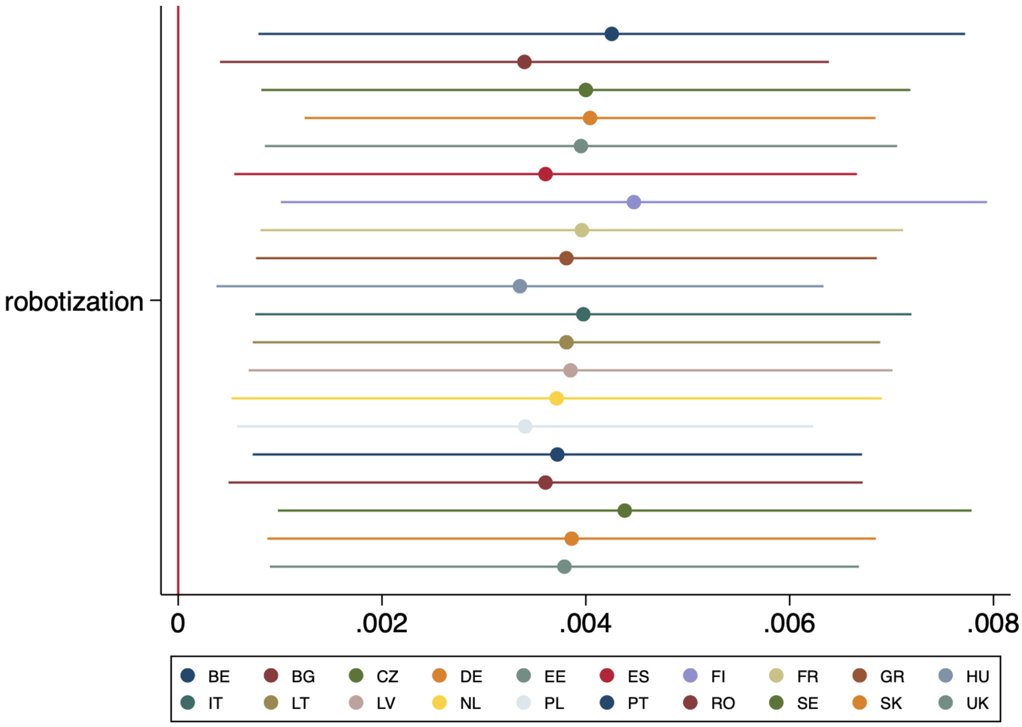

Figure 4: Robustness to the exclusion of individual countries, OLS

Sources: EU-SES, IFR, EU KLEMS, authors' calculations. Notes: Each row shows the coefficient on the robotization variable with a 90 percent confidence interval, from a separate OLS regression of the gender gap in monthly earnings on robotization. Each regression includes 19 countries and the country named in the legend is the excluded country. All specifications include country fixed effects, year fixed effects, demographic controls, job controls, sex composition, and the IHS of changes in ICT capital.

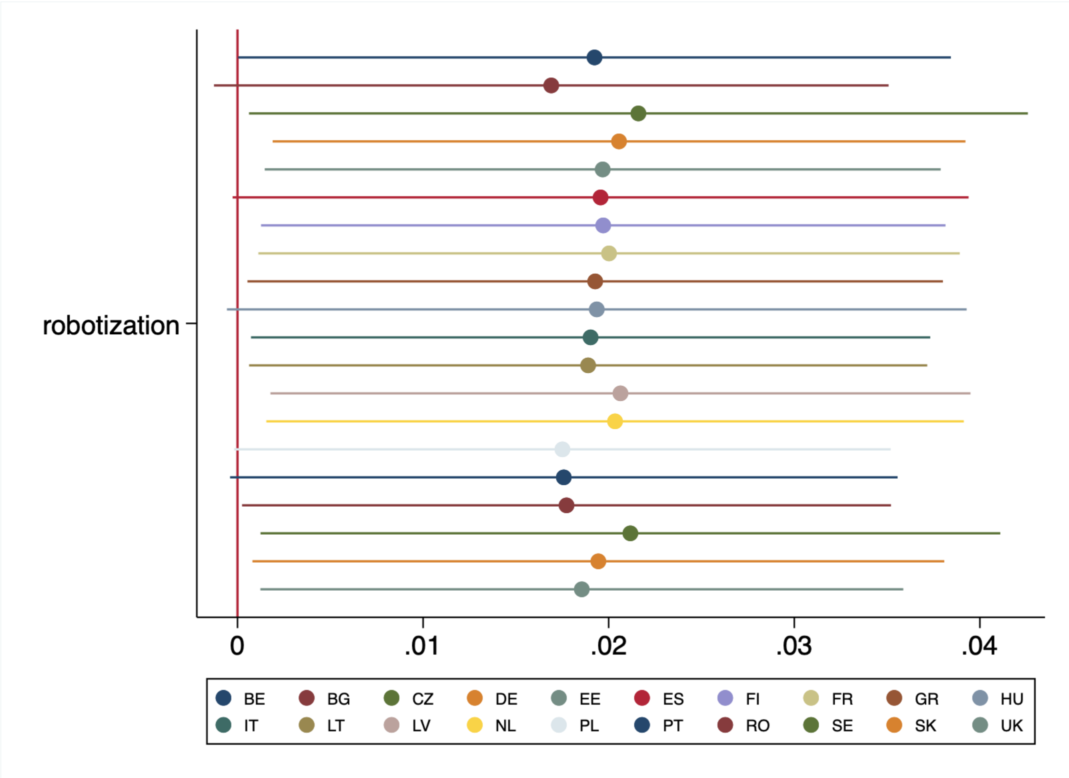

Figure 5: Robustness to the exclusion of individual countries, IV

Sources: EU-SES, IFR, EU KLEMS, authors' calculations. Notes: Each row shows the coefficient on the robotization variable with a 90 percent confidence interval, from a separate IV regression of the gender gap in monthly earnings on robotization. The instrumental variable is a measure of the share of hours in an industry performed by occupations prone to be replaced by robots. Each regression includes 19 countries and the country named in the legend is the excluded country. All specifications include country fixed effects, year fixed effects, demographic controls, job controls, sex composition, and the IHS of changes in ICT capital.

Table A.10: 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.

Table A.11: Alternative functional form: regressor ln + 1 in robotization

Outcome	ln (Male earnings)	ln (Female earnings)	ln (Gender pay gap)
	(1)	(2)	(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.12: Alternative functional form: regressor percentile of the change in robot density

Outcome	Change in gender pay gap	
	(1)	(2)
	OLS	IV (replaceable hours)
Percentile of the change in robot density	0.0003**	0.0011*
	(0.001)	(0.005)
1st stage F-stat		19.44
Observations	24,215	24,215
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. The instrumental variable is a measure of the share of hours in an industry performed by occupations prone to be replaced by robots. The regressor is the percentile of the change in robot density. 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.13: Robustness to controlling for capital/labor ratio

Outcome	Gender gap in monthly earnings	
	(1)	(2)
	OLS	IV (replaceable hours)
Robotization	0.005***	0.020*
	(0.001)	(0.010)
1st stage F-stat		16.40
Observations	24,215	24,215
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
Capital/labor ratio	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 capital/labour ratio refers to capital stock per worker and is defined as real fixed capital stock over total number of workers employed in a given industry. 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.14: 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.

Table A.15: Heterogeneity across Eastern and Western Europe

Subsample	Western Europe (1)	Eastern Europe (2)
Panel A: OLS - outcome: gender pay gap		
Robotization	0.004**	0.008**
	(0.002)	(0.003)
Panel B: IV replaceable hours - outcome: gender pay gap		
Robotization	0.019*	0.023*
	(0.011)	(0.012)
1st stage F-stat	16.37	10.53
Observations	24,215	12,870
Country and year FE	yes	yes
Demographic and job controls	yes	yes
Sex composition	yes	yes
ICT capital	yes	yes

Notes: Western European countries include Belgium, Finland, France, Germany, Greece, Italy, Netherlands, Portugal, Spain, Sweden, and UK. Eastern European countries include Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, 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.

Table A.16: 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.17: 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.18: 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).