Robots and the Gender Pay Gap: Evidence from Europe

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Abstract

Could automation make the gender pay gap worse? We provide the first large-scale evidence on the impact of one specific type of automation, industrial robots, on the gender pay gap using data on 20 European countries. Our results reveal that while robotisation increases both male and female earnings, it also increases the gender pay gap. We further present evidence that these results are driven by medium-skilled workers and countries with worse gender equality. Our preferred OLS estimates suggest that as the change in robot density (the number of robots per 10,000 workers) increases by 10 percent, the gender pay gap increases by approximately 0.4%.

Keywords: gender pay gap, earnings, Europe, automation, robots

JEL Codes: J00, J31, J71

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1. Introduction

Rapid advances in artificial intelligence (AI) technologies and robotisation have sparked recent discussions about their socio-economic effects and the future of work more generally. Technological innovations are quickly shifting the frontier between activities performed by humans and the ones performed by machines, transforming the world of work. This is particularly relevant for Europe, where exposure of workers to industrial robots in 2016 was on average 19% higher compared to the US (Chiacchio et al. 2018). Recent research projected that nearly 50 per cent of jobs in the United States face a high risk of being automated,[1] and estimates for other countries and regions are also in the high double digits.[2] However, fears that machines replace humans are not a new phenomenon and past waves of automation have not made human labour obsolete (Autor 2015). While public attention has focused on the potential of new technologies to replace humans, as technologies are used for specific tasks and skills, the challenge of automation may be more its distributional impact. For example, advances in robotisation may hinder efforts and progress towards closing gender gaps. Moreover, the wide variation in gender pay gaps across industries could be exacerbated by robotisation and firms in specific industries may struggle to meet their gender equality targets.

In this paper, we provide the first large-scale evidence on the impact of one particular type of automation, industrial robots, on the gender pay gap in Europe. We combine data from the EU Structure of Earnings Survey (EU-SES) with data on the deliveries and stock of industrial robots from the International Federation of Robotics (IFR) for a sample of 20 European countries and covering the time period from 2006 to 2014. The data covers workers that can be directly impacted by industrial robots, namely those employed in firms of at least 10 people in the manufacturing, mining and quarrying, utilities, construction, and education

[1] See Frey and Osborne (2017).
[2] See Nedelkoska and Quintini (2018), Chiacchio et al. (2018), Manyika (2017), World Bank (2016).

and research and development sectors. We estimate OLS and 2SLS regressions of the gender earnings gap on changes in the number of robots per worker, controlling for a number of demographic and firm characteristics, as well as country and year fixed effects.

We find that while robotisation increases both male and female earnings, it also widens the gender pay gap. These increases in the gender pay gap are driven by medium-skilled occupational groups, and Eastern European countries as well as countries that score low on gender equality. Our preferred OLS estimates suggest that as the change in robot density (the number of robots per 10,000 workers) increases by 10 percent, the gender pay gap increases by approximately 0.4%.

Our paper is related to a growing literature that examines the impact of automation on jobs in the United States (Acemoglu and Restrepo 2017, Frey and Osborne 2017, Mann and Puttmann 2017), Europe (Graetz and Michaels 2018, Chiacchio et al. 2018), the ASEAN members (Chang et al. 2016), and a group of developed and developing countries (Autor and Salomons 2017, McKinsey Global Institute 2017, PricewaterhouseCoopers 2017, UNCTAD 2017). Three stylized facts have emerged from these investigations: 1) automation raises labour productivity; 2) automation cuts the jobs of some groups, with manufacturing jobs most affected by automation; and 3) evidence on the impact of automation on wages is inconclusive.

The paper is organized as follows: Section 2 reviews the relevant literature. Section 3 describes the data and empirical approach. Section 4 presents the results, and Section 5 concludes.

2. Related literature

Our study contributes to two strands of literature: research on the effects of automation on the gender pay gap, and research on the labour market effects of industrial robots. Most literature on the gender pay gap focuses on supply-side explanations such as human capital factors (Blau

& Kahn 2017). There is much less evidence on how demand-side factors such as automation affect the pay gap. A few papers have studied the gendered effects of computerisation and found that the increased use of computers in the late twentieth century has contributed to the narrowing of the gender pay gap (e.g Weinberg 2000, Black & Spitz-Oener 2010, Yamaguchi 2018). A few reports such as by the IMF (Brussevich et al. 2018) and the World Economic Forum (World Economic Forum 2018) look at the likely future gender-specific impacts of automation. They find that female workers face a higher risk of automation compared to male workers (Brussevich et al. 2018) and that gender gaps in artificial intelligence skills may exacerbate existing gender gaps in the labour market in the future, when these skills are increasingly demanded. However, these studies that try to predict the future impact of different types of automation come with considerable uncertainty, and there is no evidence to date on industrial robots.

Research on industrial robots has to date focused on overall labour market impacts but not studied gender inequality. While recent US evidence suggests that industrial robot exposure reduces both employment and wages (Acemoglu and Restrepo 2017), evidence from Europe paints a more optimistic picture. A recent paper (Graetz and Michaels, 2018) studies robotisation from 1993 to 2007 in 14 European and 3 non-European countries and finds that increased robot use is associated with increases in both labour productivity and wages. Moreover, robots are found to reduce the share of hours worked by low-skilled workers relative to middle-skilled and high-skilled workers.

Given that a large majority of industrial robots are installed in the manufacturing sector and that they are used for routine cognitive and manual tasks, they affect people in different industries and occupations to different extents. This implies that robotisation may affect men and women differently. As women continue to be employed in different jobs than men, occupational and industry differences account for a substantial part of the gender wage gap;

moreover, women tend to be employed at lower levels of the hierarchy within occupations (Blau & Kahn 2017). Based on this variation of the share of females by industry and occupation, we can think of two main channels of why robots could affect the gender pay gap. The first is a 'mechanic' sex composition effect, which means that robotisation may affect the gender earnings gap simply because it changes the sex composition of different parts of the work force. For example, robots may be more likely to replace typically male jobs. On the other hand, robotisation may increase the demand for certain skills such as ICT that men are more likely to possess. Secondly, there may be a 'task change effect' (see Black and Spitz-Oener 2010, Juhn et al. 2014). For example, robotisation may make work in blue-collar occupations less physically demanding weakening the comparative advantage of men. The overall impact of these channels is unclear, and subject to empirical investigation.

While the gender wage gap has substantially narrowed over the last half-century, a substantial and persistent gap remains (Kunze et al. 2017). The timing of rapid increases in the use of industrial robots has coincided with slowing progress towards closing the remaining gender pay gap in a number of countries. However, there is no robust evidence examining the relationship between automation and gender pay gap to date.

3. Data and empirical strategy

3.1 Data

Two main datasets are used in this analysis. The first is data on the deliveries and stock of robots by country, industry, and year from the International Federation of Robotics (IFR 2017). The IFR compiles these data from yearly surveys provided by nearly all industrial robot suppliers worldwide, and uses the ISO8373 definition of an industrial robot as "an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (IFR 2017). Dedicated industrial robots that are designed to perform only a single task are not included in the dataset. The data is provided at the industry level, with broad categories outside of manufacturing, more detailed categories within manufacturing, and a residual category 'other non-manufacturing' which comprises a large part of the service sector.

The second main source of data is the EU-Structure of Earnings Survey (EU-SES), which is a large enterprise sample survey with the objective to provide accurate and harmonised data on earnings from EU Member States and Candidate Countries (European Commission 2014). The statistics are at the individual level and include information on earnings, and individual and firm characteristics for enterprises with at least ten employees in all sectors except public administration and are collected four-yearly since 2002. The SES is based on a two-stage sample. In the first stage, usually a stratified random sample of local units is drawn and in the second stage, a simple random sample of employees is taken within each of the selected local units. It excludes the self-employed, those working in small firms, and those working in the public sector, and while it is not nationally representative of the adult working population, it is ideally suited for our purposes because it covers the population of employees that can be directly affected by robotisation. Another advantage of the dataset is that the information collected relates to the earnings paid to each job holder, and does not cover earnings by the same person from a different job. Finally, it is the only source of data that provides harmonised information on labour market earnings and a harmonised industry classification at the 2-digit level of NACE for a large sample of European countries, which allows us to combine it with the robotisation data at the country and industry level.

EU-SES and IFR data provide industry classifications at different levels of aggregation and we are able to match the data by country, industry, and year for 20 countries, 12 industries, and the years 2006, 2010, and 2014. The 12 industries comprise 8 within-manufacturing and 4 non-manufacturing industries, and we exclude the category 'other non-manufacturing'.

The analysis sample contains 24,215 observations and the unit of analysis is a demographic cell, defined by country, industry, year, four age groups, eight occupational groups, and two firm size categories.[3] Included in the sample are all employees aged 20 to 59 with positive earnings information and positive number of work hours. We drop the occupational groups 'armed forces' and 'agricultural workers' and any observations with missing values for any of the key variables used in the analysis.

Our key robots measure 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 'robotisation':

$$rob = IHS\left[\frac{number\ of\ robots_t}{10{,}000\ employees_{2000}} - \frac{number\ of\ robots_{t-4}}{10{,}000\ employees_{2000}}\right] \tag{1}$$

where t refers to a year. We use 4-year changes because the EU-SES is a four-yearly survey. The number of robots per 10,000 workers, also referred to as robot density, is calculated based on a constant base year so that changes in robot density do not arise because of changes in the number of workers employed in an industry.[4] Since the distribution of the change in robot density is highly skewed with a few large outliers but also a substantial number of zeros and negative values, the natural logarithm is an unsuitable transformation, and we follow common practice and apply the inverse hyperbolic sine transformation (Bellemare & Wichman 2019).

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

$$GPG = \frac{median\ male\ earnings - median\ female\ earnings}{median\ male\ earnings} \tag{2}$$

[3] The provided survey weights are used to collapse the individual-level data containing approximately 22 million individuals. Cells with less than five observations on female earnings or on male earnings are deleted.
[4] The data on total employment by country and industry come from the EUKLEMS dataset, downloaded from http://www.euklems.net/.

Median earnings are based on the gross earnings in the reference month, and we adjust the earnings of parttime employees to their fulltime equivalent.[5] This is because in some countries it is very common for women to work parttime and including fulltime workers only would lead to a very selective sample. We also study the effect of robotisation on male and female earnings. In line with the transformation of the regressor, we use the IHS transformation of male and female median monthly earnings in the analyses.

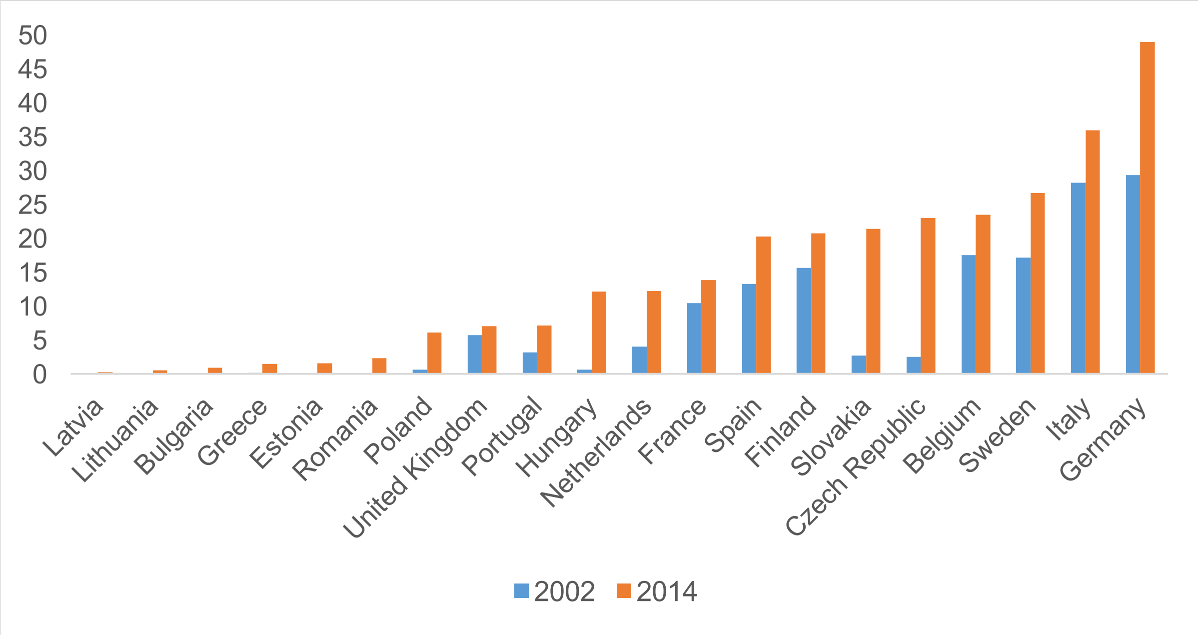
3.2 Descriptive statistics and trends in robotisation

Table A.1 in the appendix presents summary statistics for the analysis sample of employees aged 20 to 59 and working in one of the 12 industries for which data on industrial robots is available. Given that most services sectors are not contained in our sample it is not surprising that males are overrepresented (44% mean share of females in each cell). The gender gap in median monthly earnings in the sample is 11%. The median monthly male earnings are EUR1,781 and female earnings are EUR 1,559. The mean change in robot density (robots per 10,000 employees) is 9.6.

Using data from the IFR, Figure 1 shows that the level of robot density varies substantially across countries. With almost 50 robots per 10,000 employees in 2014, Germany exhibits the highest level in Europe. On the other hand, Latvia, Lithuania, and Bulgaria have the lowest robot density in our sample, with less than 1 robot per 10,000 workers. Furthermore, the figure shows that many countries have seen high levels of growth in the number of robots per worker.

[5] All earnings are based on Euros and in constant 2015 prices, using exchange rates and CPI information from the Eurostat database.

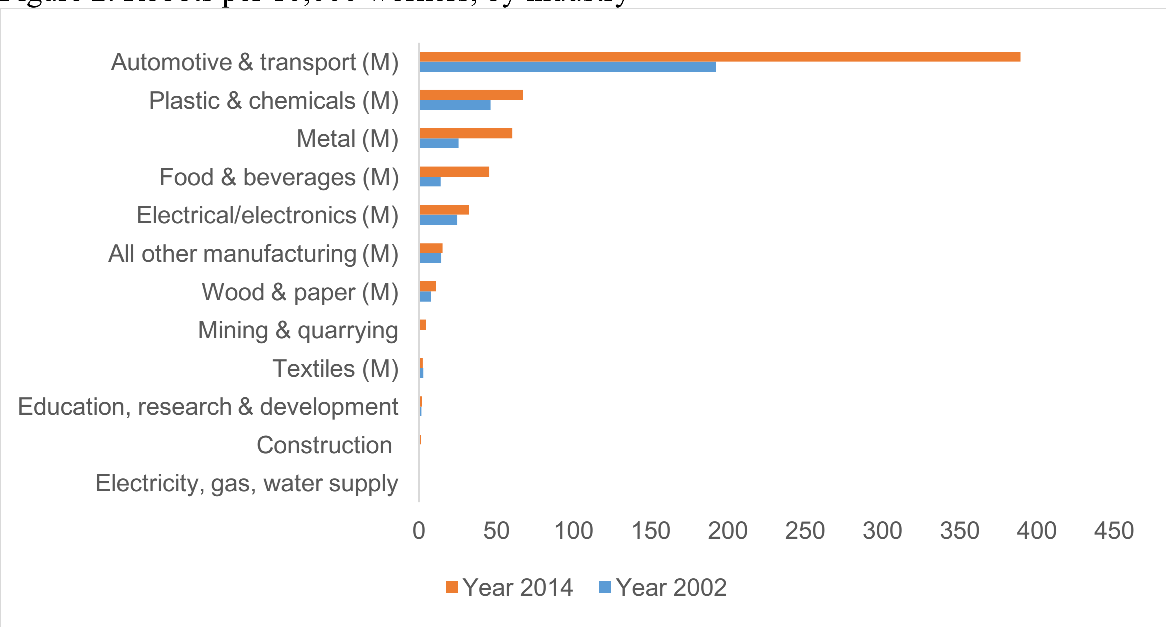
Figure 1. Robots per 10,000 workers, by country



Sources: IFR, EUKLEMS, authors' calculations.

Robot density shows a large variation across industries as well (Figure 2), with the automotive and transport industry having by far the highest density of robots. Moreover, the vast majority of industrial robots is employed within manufacturing.

Figure 2. Robots per 10,000 workers, by industry



Sources: IFR, EUKLEMS, authors' calculations.

Figure A.1 in the appendix shows the gender pay gap by country and year. In the majority of countries, the pay gap has decreased over the study period from 2006 to 2014. The size of the pay gap varies from a low of 2% in Bulgaria in 2006 to a high of 21.7% in Estonia in 2006.

3.3 Empirical strategy

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

$$GPG_{cid} = \beta_0 + \beta_1\, rob_{ci} + \beta_2 controls_{cid} + \delta + \theta + u_{cid} \qquad (3)$$

where GPG is the gender pay gap in country c, industry i, and demographic cell d, as defined in equation (2). Rob is our main regressor of robotisation defined in equation (1). In our preferred specification, we control for demographic factors (age group and occupational group), sex composition (the share of females and the change in share of females between last and current survey year), labour market factors (share of fulltime workers and a dummy for firm size greater than 250 employees), as well as a measure of changes in information and communication technology (ICT) capital[6]. To account for other unobservable characteristics, we include a full set of country and year fixed effects. The country dummies δ control for all time-invariant variation in the outcome variable associated with factors that vary cross-nationally. Year dummies θ capture the impact of shocks that affect all countries simultaneously. Robust standard errors, two-way clustered by country and industry and adjusted for cases with few clusters are used (Graetz & Michaels 2018). All regressions are weighted by within-country industry employment shares.

[6] This is measured by the real fixed capital stock in computing, communications, and computer software and databases equipment in 2010 prices, per 1,000 workers. This data is obtained from the EUKLEMS database.

Ideally, our robotisation measure only captures robot adoptions driven by exogenous improvements in technology. However, our OLS models are subject to potential omitted variable bias and reverse causality. 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). It is also possible that a shock to relative female labour demand in an industry may affect firms' decision to adopt robots. To account for these possibilities, we use an instrumental variables strategy similar to related literature on industrial robots (Acemoglu & Restrepo 2017; Dauth et al. 2018). That is, we instrument robotisation in a specific country, industry, and year by robotisation in that same country and industry in the United States. While this instrument does not address all potential endogeneity concerns, it allows to filter out variation in robotisation from domestic and Europe-specific factors and instead captures only the variation resulting from industries in which the use of robots has been concurrent outside of Europe.

4. Results

4.1 Main results

Table 1 shows the baseline results of the relationship between robotisation and the gender earnings gap. Panel A shows OLS coefficients, Panel B reports coefficients from the IV model, and Panel C shows the 1st stage of the IV model. Column (1) of Panel A shows that, without any controls, higher robotisation is associated with a higher gender pay gap; the elasticity estimate suggests that a ten percent increase in robotisation is associated with a 0.7 percent increase in the gender pay gap.[7] We add country and year fixed effects in column (2), demographic and sex composition controls in column (3), labour market controls in column

[7] Elasticities for the models using the inverse hyperbolic sine transformation are calculated following Bellemare & Wichman (2019).

(4), and a control for our measure of ICT density in column (5). Our preferred specification in column (5) suggests that as robotisation increases by 23 percent (the mean level of robotisation in the sample), the gender pay gap increases by approximately 0.8 percent.

To understand whether this positive relationship between robotisation and a higher gender pay gap is explained by rising or falling male and female earnings, in Table 2 we directly study the effect of robotisation on the inverse hyperbolic sine transformation (IHS) of male and female earnings. Robotisation increases both male and female earnings, but the effect is larger for male earnings. The OLS estimates of the full specification in columns (2) and (4) reveal that a 10 percent increase in robotisation increases male earnings by 0.15 percent and female earnings by 0.1 percent.

4.2 Heterogeneity

Previous literature has found evidence of skill-biased and routine-biased technological change (e.g. Card & DiNardo 2002; Goos et al. 2014). Therefore, we expect heterogeneous effects of robotisation on the gender pay gap across skill-based occupational groups as well as across the earnings distribution.

Table 3 studies heterogeneity by three broad skill-based occupational groups, low-skilled (elementary occupations, and plant and machine operators/assemblers), medium-skilled (clerical support workers, service and sales workers, and craft and related trade workers), and high-skilled occupations (managers, professionals, and technicians and associate professionals). OLS results shown in Panel A.1 reveal that the relationship between robotisation and the gender pay gap is statistically significant at the five percent level for medium-skilled and high-skilled occupational group and that the effect is larger for the medium-skilled occupational group. By contrast, the relationship between robotisation and the gender pay gap is not statistically significant for the low-skilled group. In terms of effect size, when robotisation increases by 10 percent, the gender pay gap among the medium-skilled increases by 0.8 percent on average. Panels B1 and C1 suggest that robotisation mainly increases both male and female earnings among low-skilled and medium-skilled workers. However, while this effect is similar for both male and female low-skilled, the effect among medium-skilled is larger for male earnings than for female earnings.

In Table 4, we study the effect of robotisation on male and female earnings using quantile regression. As these results are based on unweighted data and standard errors clustered by country only, we report corresponding OLS coefficients in column (6). While the OLS coefficients are smaller than those of the weighted regressions in Table 2, the finding that there is a positive and statistically significant association between robotisation and male as well as female earnings remains. Similarly, the coefficient on male earnings remains larger than that on female earnings. A comparison across columns shows that quantile regression estimates differ across quantiles. Coefficients are largest for the lower decile of male and female earnings (column (1)) and decrease for higher deciles. A higher level of robotisation raises the lower decile of earnings by more than the higher deciles. Hence, while robotisation increases gender inequality, it decreases overall earnings inequality.

Our analysis sample contains a heterogeneous group of 20 European countries. To study heterogeneity across regions, we start by splitting the sample into two broad regions in Table 5, Western Europe in column (1) and Eastern Europe and Greece in column (2). We find that the association between higher robotisation and a higher gender pay gap is statistically significant only among the Eastern Europe and Greece sample. Among this sample, robotisation has a positive and statistically significant effect on male earnings but there is no significant effect on female earnings. On the other hand, there is no significant association between robotisation and male or female earnings for the Western Europe sample.

The sample of countries also differs in terms of gender equality. Therefore, we use the Gender Gap Index of the World Economic Forum (Hausmann et al. 2011) to split our sample into equally-sized groups of ten countries with a high GGI score, hence higher levels of gender equality, and ten countries with a low GGI score, that is, lower levels of gender equality. Results in Table 6 indicate that robotisation increases the pay gap among the sample of low GGI countries only.

In sum, the results suggest that robotisation increases male and female earnings but also the gender pay gap, and that these increases in the gender pay gap are driven by medium-skilled occupational groups, and Eastern European as well as countries that score lower on gender equality.

4.3 Robustness checks

We perform a range of subsample analyses, using the full specification with all control variables as in column (5) of Table 1. First, we show that results are not driven by the automotive industry or by Germany, the industry and country, respectively, with the highest level of robotisation (Table A2). The results also remain very similar when we exclude the residual industry 'other manufacturing' (Table A2).

Next, we show that results do not substantively change when we use alternative measures of the gender pay gap, namely the gender gap in median hourly earnings, and the gender gap in median monthly earnings, not adjusting part-time earnings pro rata (Table A3).

While using the IHS transformation is the most appropriate functional form for our analysis, we also check the robustness of results to using the natural logarithm of robotisation and earnings (Table A4). In order to not lose too many observations, we add a constant of 1 to changes in robot density. Results stay similar: robotisation increases both male and female earnings as well as the gender pay gap, and this increase in the gender pay gap is driven by medium-skilled occupations. Finally, in Table A.5 we bootstrap standard errors, and results are robust to this check.

4.4 Channels

In order to identify the mechanisms behind the results from the previous section, it is necessary to analyse the employment effects of robotisation. Unfortunately, the EU-SES data has the drawback that there is no information on individuals' work history. Hence, it is not possible to study whether robotisation affects switching across industries, occupational groups, and employment status. However, in Section 2 we identified mechanic changes in sex composition of cells as one potential channel that could account for our findings, and we test for this channel.

In Table 7 we analyse whether robotisation affects the share of females in a cell. Results show that while, overall, there is no significant association between robotisation and the share of females, among the medium-skilled group robotisation lowers the share of females. This suggests that changes in sex composition may be one channel underlying the results that we find for the medium-skilled group.

In Table 8, we study the relationship between robotisation and the gender gap in monthly paid hours. We do not find any evidence that there is a significant relationship, overall, or among any of the skill-based occupational groups.

5. Conclusion

Automation constitutes one of the key systemic transformations that workplaces are facing. Not only does it impact labour productivity and employment but it also has important distributional impacts. In this paper, we focus on one such distributional aspect, which has not been explored in previous research, namely the gender wage gap. We provide the first large-scale evidence on the impact of a specific type of automation, industrial robots, on the gender pay gap using a data set including 20 European countries and over 24,000 observations based on the earnings of approximately 22 million individuals.

Our results reveal that a higher robotisation increases both male and female earnings but it also increases the gender gap in earnings. This effect is driven by those in medium-skilled occupations and countries with a worse record of gender equality measures. We find some evidence that changes in the sex composition may be one channel driving our results. Our results are compatible with recent evidence, which has found that a higher use of industrial robots per worker increases labour productivity and wages in a sample of 17 industrial countries, most of them in Europe (Graetz and Michaels 2018).

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

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Tables

Table 1. Baseline results, dependent variable gender pay gap

	(1)	(2)	(3)	(4)	(5)
Dependent variable			Gender gap in earnings		
			Panel A. OLS		
Ihs robotisation	0.0074***	0.0059*	0.0045**	0.0038**	0.0038**
	(0.0028)	(0.0030)	(0.0022)	(0.0019)	(0.0019)
Elasticity	0.0678	0.0539	0.0416	0.0351	0.0352
			Panel B. IV 2nd stage		
Ihs robotisation	0.0147**	0.0168**	0.0131*	0.0111	0.0112
	(0.0073)	(0.0083)	(0.0078)	(0.0075)	(0.0075)
Elasticity	0.134	0.154	0.120	0.101	0.102
F stat	11.58	11.89	11.51	11.21	11.40
			Panel C. IV 1st stage		
Ihs US robotisation	0.2920***	0.3183***	0.3004***	0.2938***	0.2923***
	(0.0858)	(0.0923)	(0.0886)	(0.0877)	(0.0866)
Observations	24,215	24,215	24,215	24,215	24,215
Country & year FE	no	yes	yes	yes	yes
Demographic factors	no	no	yes	yes	yes
Sex composition	no	no	yes	yes	yes
Labour market factors	no	no	no	yes	yes
ICT capital	no	no	no	no	yes

Notes: Within-country industry employment shares used as survey weights. Robust standard errors in brackets, clustered two-way by country and industry, and adjusted for small number of clusters. Significance levels:
* p<0.1, ** p<0.05, *** p<0.01.

Table 2. Effect of robotisation on IHS of median male and female earnings

	(1)	(2)	(3)	(4)
Dependent variable.	Ihs male earnings	Ihs male earnings	Ihs female earnings	Ihs female earnings
		Panel A. OLS		
Ihs robotisation	0.0187**	0.0152***	0.0120**	0.0109**
	(0.0082)	(0.0052)	(0.0060)	(0.0044)
Elasticity	0.0186	0.0151	0.0119	0.0109
		Panel B. IV		
Ihs robotisation	0.0537*	0.0521**	0.0343	0.0392*
	(0.0324)	(0.0253)	(0.0277)	(0.0218)
Elasticity	0.0535	0.0518	0.0341	0.0390
F stat	11.89	11.40	11.89	11.40
Observations	24,215	24,215	24,215	24,215
Country & year FE	yes	yes	yes	yes
Demographic factors	no	yes	no	yes
Sex composition	no	yes	no	yes
Labour market factors	no	yes	no	yes
ICT capital	no	yes	no	yes

Notes: Within-country industry employment shares used as survey weights. Robust standard errors in brackets, clustered two-way by country and industry, and adjusted for small number of clusters. Significance levels:
* p<0.1, ** p<0.05, *** p<0.01.

Table 3. Heterogeneity by skill-based occupational groups

	(1)	(2)	(3)
Subsample	Low-skilled	Medium-skilled	High-skilled
	Panel A1. Dependent variable gender pay gap, OLS		
Ihs robotisation	0.0013	0.0085**	0.0019**
	(0.0025)	(0.0034)	(0.0008)
Elasticity	0.0120	0.0776	0.0171
	Panel A2. Dependent variable gender pay gap, IV		
Ihs robotisation	-0.0064	0.0266***	0.0100
	(0.0091)	(0.0095)	(0.0064)
Elasticity	-0.0586	0.243	0.0918
F stat	12.53	11.92	10.57
	Panel B1. Dependent variable IHS male earnings, OLS		
Ihs robotisation	0.0135***	0.0189***	0.0098*
	(0.0035)	(0.0065)	(0.0059)
Elasticity	0.0135	0.0188	0.00980
	Panel B2. Dependent variable IHS male earnings, IV		
Ihs robotisation	0.0530**	0.0571**	0.0401
	(0.0236)	(0.0289)	(0.0271)
Elasticity	0.0528	0.0568	0.0399
F stat	12.53	11.92	10.57
	Panel C1. Dependent variable IHS female earnings, OLS		
Ihs robotisation	0.0131***	0.0087**	0.0078
	(0.0038)	(0.0042)	(0.0059)
Elasticity	0.0130	0.00864	0.00774
	Panel C2. Dependent variable IHS female earnings, IV		
Ihs robotisation	0.0627***	0.0251	0.0284
	(0.0224)	(0.0219)	(0.0270)
Elasticity	0.0624	0.0250	0.0282
F stat	12.53	11.92	10.57
Observations	6,399	7,991	9,825
Country & year FE	yes	yes	yes
Demographic factors	yes	yes	yes
Sex composition	yes	yes	yes
Labour market factors	yes	yes	yes
ICT capital	yes	yes	yes

Notes: Within-country industry employment shares used as survey weights. Robust standard errors in brackets, clustered two-way by country and industry, and adjusted for small number of clusters. Significance levels:
* p<0.1, ** p<0.05, *** p<0.01.

Table 4. Quantile regression

	(1)	(2)	(3)	(4)	(5)	(6)
Quantile	0.1	0.3	0.5	0.7	0.9	OLS
	Panel A. Dependent variable IHS male earnings					
Ihs robotisation	0.0148***	0.0099***	0.0080***	0.0066***	0.0044***	0.0104***
	(0.0051)	(0.0029)	(0.0025)	(0.0020)	(0.0017)	(0.0025)
R-squared	0.9146	0.9220	0.9237	0.9214	0.9086	0.9245
	Panel B. Dependent variable IHS female earnings					
Ihs robotisation	0.0129***	0.0084***	0.0072***	0.0063***	0.0035*	0.0079***
	(0.0022)	(0.0024)	(0.0021)	(0.0017)	(0.0020)	(0.0019)
R-squared	0.9238	0.9306	0.9324	0.9310	0.9216	0.9330
Observations	24,215	24,215	24,215	24,215	24,215	24,215
Country & year FE	yes	yes	yes	yes	yes	yes
Demographic factors	yes	yes	yes	yes	yes	yes
Sex composition	yes	yes	yes	yes	yes	yes
Labour market factors	yes	yes	yes	yes	yes	yes
ICT capital	yes	yes	yes	yes	yes	yes

Notes: SEs clustered by country (2-way clustering not possible) and no weights used. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.

Table 5. Heterogeneity by region

	(1)	(2)
Subsample	Western Europe	Eastern Europe & Greece
	Panel A1. Dependent variable gender pay gap, OLS	
ihs_c_rd	0.0015	0.0077**
	(0.0015)	(0.0035)
	Panel A2. Dependent variable gender pay gap, IV	
ihs_c_rd	0.0027	0.0153*
	(0.0071)	(0.0081)
F stat	4.534	9.527
	Panel B1. Dependent variable IHS male earnings, OLS	
ihs_c_rd	0.0054	0.0230**
	(0.0035)	(0.0090)
	Panel B2. Dependent variable IHS male earnings, IV	
ihs_c_rd	0.0456*	0.0492*
	(0.0253)	(0.0269)
F stat	4.534	9.527
	Panel C1. Dependent variable IHS female earnings, OLS	
ihs_c_rd	0.0041	0.0137
	(0.0029)	(0.0087)
	Panel C2. Dependent variable IHS female earnings, IV	
ihs_c_rd	0.0444*	0.0306
	(0.0233)	(0.0231)
F stat	4.534	9.527
Observations	11,038	13,177
Country & year FE	yes	yes
Demographic factors	yes	yes
Sex composition	yes	yes
Labour market factors	yes	yes
ICT capital	yes	yes

Notes: Within-country industry employment shares used as survey weights. Robust standard errors in brackets, clustered two-way by country and industry, and adjusted for small number of clusters. Significance levels: * p<0.1, ** p<0.05, *** p<0.01. Eastern European countries plus Greece: Bulgaria, Czech Republic, Estonia, Greece, Hungary, Lithuania,Latvia, Poland, Romania, Slovakia. Western European countries: Belgium, Germany, Spain, Finland , France, Italy, Netherlands,Portuga,Sweden,United Kingdom.

Table 6. Heterogeneity by GGI score (WEF Gender Gap Index of country, 2006 index)

	(1)	(2)
Subsample	High GGI score	Low GGI score
	Panel A1. Dependent variable gender pay gap, OLS	
ihs_c_rd	0.0012	0.0064**
	(0.0014)	(0.0029)
	Panel A2. Dependent variable gender pay gap, IV	
ihs_c_rd	0.0048	0.0140**
	(0.0104)	(0.0067)
F stat	5.149	14.98
	Panel B1. Dependent variable IHS male earnings, OLS	
ihs_c_rd	0.0065*	0.0217***
	(0.0037)	(0.0068)
	Panel B2. Dependent variable IHS male earnings, IV	
ihs_c_rd	0.0568*	0.0480**
	(0.0340)	(0.0242)
F stat	5.149	14.98
	Panel C1. Dependent variable IHS female earnings, OLS	
ihs_c_rd	0.0052*	0.0145**
	(0.0030)	(0.0059)
	Panel C2. Dependent variable IHS female earnings, IV	
ihs_c_rd	0.0515**	0.0318
	(0.0259)	(0.0218)
F stat	5.149	14.98
Observations	10,401	13,814
Country & year FE	yes	yes
Demographic factors	yes	yes
Sex composition	yes	yes
Labour market factors	yes	yes
ICT capital	yes	yes

Notes: Within-country industry employment shares used as survey weights. Robust standard errors in brackets, clustered two-way by country and industry, and adjusted for small number of clusters. Significance levels: * p<0.1, ** p<0.05, *** p<0.01. High GGI countries: Belgium, Germany, Estonia, Spain, Finland, Lithuania, Latvia, Netherlands, Sweden, UK. Low GGI countries: Bulgaria, Czech Republic, France, Greece, Hungary, Italy, Poland, Portugal, Romania, Slovakia

Table 7. Alternative outcome variable: share of females

	(1)	(2)	(3)	(4)
Dependent variable	female	female	female	female
Subsample	Full sample	Low-skilled	Medium-skilled	High-skilled
		Panel A. OLS		
Ihs robotisation	-0.0132	-0.0006	-0.0154**	-0.0179
	(0.0105)	(0.0129)	(0.0075)	(0.0134)
		Panel B. IV		
Ihs robotisation	-0.0327	0.0277	-0.0446	-0.0526
	(0.0470)	(0.0668)	(0.0372)	(0.0558)
F stat	12	11.58	13.02	11.22
Observations	24,215	6,399	7,991	9,825
Country & year FE	yes	yes	yes	yes
Demographic factors	yes	yes	yes	yes
Sex composition	no	no	no	no
Labour market factors	yes	yes	yes	yes
ICT capital	yes	yes	yes	yes

Notes: Within-country industry employment shares used as survey weights. Robust standard errors in brackets, clustered two-way by country and industry, and adjusted for small number of clusters. Significance levels:
* p<0.1, ** p<0.05, *** p<0.01.

Table 8. Alternative outcome variable: gender gap in hours paid last month

	(1)	(2)	(3)	(4)
Dependent variable	gap_hours_w	gap_hours_w	gap_hours_w	gap_hours_w
Subsample	Full sample	Low-skilled	Medium-skilled	High-skilled
		Panel A. OLS		
Ihs robotisation	0.0001	-0.0017	0.0014	-0.0005
	(0.0011)	(0.0023)	(0.0012)	(0.0005)
		Panel B. IV		
Ihs robotisation	-0.0024	-0.0123*	0.0015	-0.0010
	(0.0042)	(0.0075)	(0.0048)	(0.0022)
F stat	11.40	12.53	11.92	10.57
Observations	24,215	6,399	7,991	9,825
Country & year FE	yes	yes	yes	yes
Demographic factors	yes	yes	yes	yes
Sex composition	yes	yes	yes	yes
Labour market factors	yes	yes	yes	yes
ICT capital	yes	yes	yes	yes

Notes: Within-country industry employment shares used as survey weights. Robust standard errors in brackets, clustered two-way by country and industry, and adjusted for small number of clusters. Significance levels:
* p<0.1, ** p<0.05, *** p<0.01.

Appendix tables

Table A.1. Summary statistics (weighted)

	High-skilled occupation		Medium-skilled occupation		Low-skilled occupation		Total	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Gender pay gap, monthly median earnings	0.10	0.00	0.11	0.00	0.13	0.00	0.11	0.00
IHS male median monthly earnings	8.13	0.01	7.65	0.01	7.52	0.01	7.83	0.01
IHS female median monthly earnings	8.01	0.01	7.52	0.01	7.37	0.01	7.69	0.01
Female median monthly earnings	2,049	19	1,265	13	1,087	13	1,559	11
Male median monthly earnings	2,312	22	1,453	15	1,281	15	1,781	12
IHS of change in robot density	0.97	0.02	1.10	0.02	1.25	0.03	1.08	0.01
Change in robot density (per 10,000 workers)	8.50	0.47	9.87	0.57	11.19	0.71	9.60	0.32
Share females	0.41	0.00	0.51	0.00	0.40	0.01	0.44	0.00
Change in share females	0.01	0.00	-0.01	0.00	0.00	0.00	0.00	0.00
Gender gap in monthly hours paid	0.03	0.00	0.04	0.00	0.06	0.00	0.04	0.00
Share fulltime workers	0.90	0.00	0.87	0.00	0.88	0.00	0.88	0.00
IHS of change in ICT density	0.90	0.02	0.94	0.02	0.97	0.03	0.93	0.01
Dummy firmsize > 250	0.48		0.47		0.46		0.47	
Age 20 to 29	0.20		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		0.10	
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)	0.10		0.10		0.12		0.10	
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	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		0.10		0.14	
Industry: education, research, development	0.27		0.23		0.17		0.23	
Elementary occupations	0.00		0.00		0.57		0.14	
Managers	0.27		0.00		0.00		0.11	
Professionals	0.35		0.00		0.00		0.15	
Technicians & associate professionals	0.38		0.00		0.00		0.16	
Clerical support workers	0.00		0.44		0.00		0.15	
Service & sales workers	0.00		0.24		0.00		0.08	
Craft & related trade workers	0.00		0.32		0.00		0.11	
Plant & machine operators, assemblers	0.00		0.00		0.43		0.10	

Figure A1. Gender gap in median monthly earnings (PT earnings adjusted to FT equivalent), by country and year (weighted)

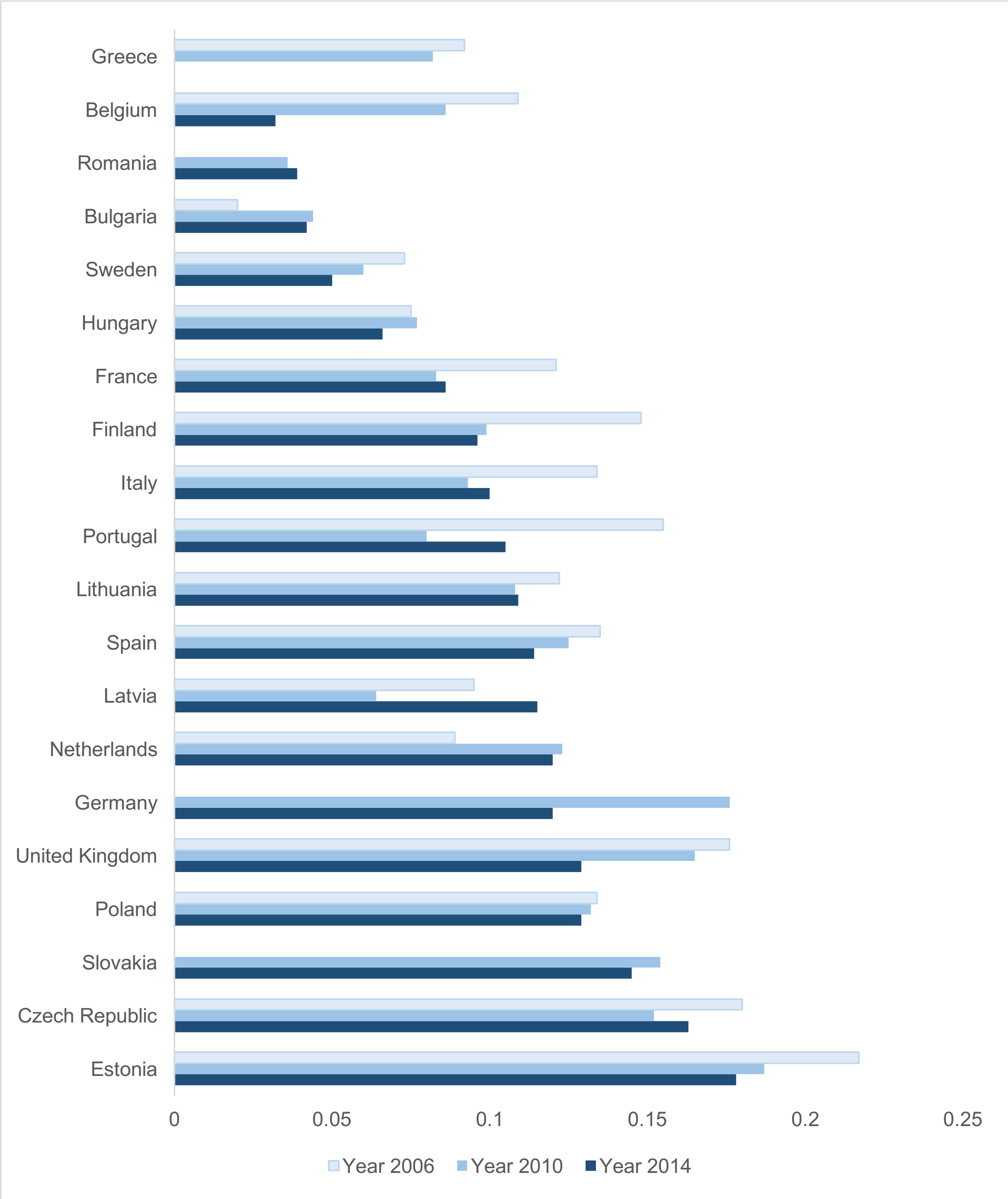

Table A2. Robustness check sample without Germany / transport industry / other manufacturing

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Ihs male earnings	Ihs female earnings		Gender gap in earnings		
	Panel A1. Sample without Germany, OLS					
Ihs robotisation	0.0146***	0.0101**	0.0040**	0.0015	0.0083***	0.0025***
	(0.0051)	(0.0042)	(0.0017)	(0.0022)	(0.0032)	(0.0005)
Observations	23,031	23,031	23,031	6,100	7,556	9,375
	Panel A2. Sample without Germany, IV					
Ihs robotisation	0.0528**	0.0381*	0.0127*	-0.0053	0.0280***	0.0119*
	(0.0263)	(0.0224)	(0.0077)	(0.0090)	(0.0094)	(0.0068)
F stat	11.27	11.27	11.27	12.33	11.75	10.60
Observations	23,031	23,031	23,031	6,100	7,556	9,375
	Panel B1. Sample without transport industry, OLS					
Ihs robotisation	0.0149***	0.0097**	0.0049**	0.0015	0.0107***	0.0024***
	(0.0056)	(0.0046)	(0.0021)	(0.0030)	(0.0040)	(0.0005)
Observations	22,519	22,519	22,519	5,901	7,425	9,193
	Panel B2. Sample without transport industry, IV					
Ihs robotisation	0.0553*	0.0395	0.0142	-0.0088	0.0323***	0.0134*
	(0.0320)	(0.0277)	(0.0086)	(0.0112)	(0.0107)	(0.0073)
F stat	8.162	8.162	8.162	9.056	8.288	7.558
Observations	22,519	22,519	22,519	5,901	7,425	9,193
	Panel C1. Sample without residual category ‘other manufacturing’, OLS					
Ihs robotisation	0.0151***	0.0108**	0.0039**	0.0009	0.0086**	0.0021***
	(0.0056)	(0.0047)	(0.0020)	(0.0026)	(0.0036)	(0.0007)
Observations	22,389	22,389	22,389	5,823	7,350	9,216
	Panel C2. Sample without residual category ‘other manufacturing’, IV					
Ihs robotisation	0.0552**	0.0406*	0.0127*	-0.0037	0.0271***	0.0118*
	(0.0246)	(0.0212)	(0.0074)	(0.0081)	(0.0093)	(0.0067)
F stat	11.38	11.38	11.38	12.68	11.83	10.54
Observations	22,389	22,389	22,389	5,823	7,350	9,216
Country & year FE	yes	yes	yes	yes	yes	yes
Demographic factors	yes	yes	yes	yes	yes	yes
Sex composition	yes	yes	yes	yes	yes	yes
Labour market factors	yes	yes	yes	yes	yes	yes
ICT capital	yes	yes	yes	yes	yes	yes
Skill level	All occupations	All occupations	All occupations	Low-skilled	Medium-skilled	High-skilled

Notes: Within-country industry employment shares used as survey weights. Robust standard errors in brackets, clustered two-way by country and industry, and adjusted for small number of clusters. Significance levels:
* p<0.1, ** p<0.05, *** p<0.01.

Table A3. Robustness check alternative outcome Dependent var.: gender gap in hourly earnings / monthly earnings, parttime earnings not adjusted

	(1)	(2)	(3)	(4)
Subsample	Full sample	Low-skilled	Medium-skilled	High-skilled
Panel A1. Dependent variable gender gap in hourly earnings, OLS				
Ihs robotisation	0.0036*	0.0013	0.0080**	0.0018*
	(0.0020)	(0.0023)	(0.0036)	(0.0010)
Observations	23,719	6,262	7,793	9,664
Panel A2. Dependent variable gender gap in hourly earnings, IV				
Ihs robotisation	0.0112	-0.0047	0.0258***	0.0099
	(0.0070)	(0.0081)	(0.0089)	(0.0065)
Observations	23,719	6,262	7,793	9,664
F stat	11.78	12.73	12.37	10.92
Panel B1. Dependent variable gender gap in monthly earnings without adjusting PT earnings pro rata, OLS				
Ihs robotisation	0.0037*	0.0004	0.0085**	0.0017*
	(0.0022)	(0.0040)	(0.0033)	(0.0009)
Observations	24,215	6,399	7,991	9,825
Panel B2. Dependent variable gender gap in monthly earnings without adjusting PT earnings pro rata, IV				
Ihs robotisation	0.0097	-0.0151	0.0262**	0.0110
	(0.0097)	(0.0142)	(0.0120)	(0.0072)
Observations	24,215	6,399	7,991	9,825
F stat	11.40	12.53	11.92	10.57
Country & year FE	yes	yes	yes	yes
Demographic factors	yes	yes	yes	yes
Sex composition	yes	yes	yes	yes
Labour market factors	yes	yes	yes	yes
ICT capital	yes	yes	yes	yes

Notes: Within-country industry employment shares used as survey weights. Robust standard errors in brackets, clustered two-way by country and industry, and adjusted for small number of clusters. Significance levels:
* p<0.1, ** p<0.05, *** p<0.01.

Table A4. Alternative functional form: regressor ln of change+1 in robot density and instrument ln of change+1 in US robot density

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Ln male earnings	Ln female earnings		Gender gap in earnings		
			Panel A. OLS			
ln_c_rd_plus1	0.0294***	0.0220***	0.0066*	0.0010	0.0158***	0.0025
	(0.0078)	(0.0068)	(0.0035)	(0.0050)	(0.0054)	(0.0017)
			Panel B. IV			
ln_c_rd_plus1	0.0505**	0.0379**	0.0107	-0.0066	0.0255***	0.0095
	(0.0219)	(0.0188)	(0.0071)	(0.0086)	(0.0095)	(0.0058)
F stat	17.65	17.65	17.65	15.92	18.58	17.63
Observations	22,458	22,458	22,458	5,911	7,424	9,123
Subsample	Full sample	Full sample	Full sample	Low-skilled	Medium-skilled	High-skilled
Country & year FE	yes	yes	yes	yes	yes	yes
Demographic factors	yes	yes	yes	yes	yes	yes
Sex composition	yes	yes	yes	yes	yes	yes
Labour market factors	yes	yes	yes	yes	yes	yes
ICT capital	yes	yes	yes	yes	yes	yes

Notes: Within-country industry employment shares used as survey weights. Robust standard errors in brackets, clustered two-way by country and industry, and adjusted for small number of clusters. Significance levels:
* p<0.1, ** p<0.05, *** p<0.01.

Table A5. Robustness check bootstrapped standard errors

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Ihs male earnings	Ihs female earnings		Gender gap in earnings		
			Panel A. Standard errors two-way clustered			
Ihs robotisation	0.0104***	0.0079**	0.0022*	0.0002	0.0046**	0.0018
	(0.0035)	(0.0035)	(0.0013)	(0.0016)	(0.0022)	(0.0013)
			Panel B. Standard errors bootstrapped and two-way clustered (400 repetitions)			
Ihs robotisation	0.0104***	0.0079***	0.0022**	0.0002	0.0046***	0.0018
	(0.0024)	(0.0021)	(0.0009)	(0.0013)	(0.0015)	(0.0012)
Observations	24,215	24,215	24,215	6,399	7,991	9,825
Subsample	Full sample	Full sample	Full sample	Low-skilled	Medium-skilled	High-skilled
Country & year FE	yes	yes	yes	yes	yes	yes
Demographic factors	yes	yes	yes	yes	yes	yes
Sex composition	yes	yes	yes	yes	yes	yes
Labour market factors	yes	yes	yes	yes	yes	yes
ICT capital	yes	yes	yes	yes	yes	yes
SE bootstrap	no	no	no	no	no	no

Notes: No weights used. Significance levels: * p<0.1, ** p<0.05, *** p<0.01.