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Abstract: In this study we examine whether the long-term structural changes in the labour market, driven by automation, affect fertility. Adoption of industrial robots in the EU has tripled since the mid-1990s, tremendously changing the conditions of participating in the labour market. On the one hand, new jobs are created, benefitting largely the highly skilled workers. On the other hand, the growing turnover in the labour market and changing content of jobs induce fears of job displacement and make workers continuously adjust to new requirements (reskill, upskill, increase work efforts). The consequences of these changes are particularly strong for the employment and earning prospects of the low and middle educated workers. Our focus is on six European countries: Czechia, France, Germany, Italy, Poland and the United Kingdom. We link regional data on fertility and employment structures by industry from Eurostat (NUTS-2) with data on robot adoption from the International Federation of Robotics. We estimate fixed effects linear models with instrumental variables in order to account for the external shocks which may affect fertility and robot adoption in parallel. Our findings suggest robots tend to exert a negative impact on fertility in highly industrialised regions, regions with relatively low educated populations and those which are technologically less advanced. At the same time, better educated and prospering regions may even experience fertility improvements as a result of the technological change. The family and labour market institutions of the country may further moderate these effects.

Keywords: fertility, employment, industrial robots, technological change, Europe

JEL codes: J11, J13

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1. Introduction

Over the last two decades, technological advancements in production, including cutting-edge industrial robots, have tremendously transformed the labour markets in advanced market economies, creating new career opportunities, but also inducing fears of job displacement (OECD, 2019). Only in the EU, the stock of industrial robots per 10.000 manufacturing workers has tripled since the mid-1990s reaching 114 in 2019 (International Federation of Robotics, 2020). Because of the scale and speed of automation and its possible consequences for workers, there has been an explosion of studies on how technological advancements in production affect employment (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020), wages (Dauth et al., 2021), social and economic inequalities (Aksoy et al., 2021; de Vries et al., 2020) and more recently workers' physical and mental health (Abeliansky and Beulman, 2019; Gihleb et al., 2022). With this study, we contribute to this discussion by examining how automation, and more specifically the adoption of industrial robots, influences fertility; an outcome which so far has been largely neglected in the scientific debate.

In our view, automation may affect fertility since it alters the conditions of participating in the labour market and with it the economic well-being of the family and the strategies of its adult members adopted to combine paid work with care. Past research has clearly demonstrated that individuals tend to postpone or even abstain from having children during economic downturns (Cherlin et al., 2013; Sobotka et al., 2011), usually in response to an increase in unemployment and growing instability of employment (Adsera, 2004; Schneider, 2015; Bellani, 2020; Matysiak et al., 2021). The feeling of economic uncertainty may also hinder fertility decisions irrespective of the real economic conditions (Vignoli et al., 2020). Notably, fertility usually declines more strongly in response to worsening of employment prospects for men and young workers as well as in countries offering weaker social protection in case of a job loss (Comolli, 2017; Alderotti et al., 2021).

Past research has largely concentrated on examining fertility consequences of short-term changes in labour market conditions, caused by cyclical swings in the economy and reflected in upward and downward moves in (un)employment or work conditions. Much less has been done on how fertility reacts to long-term structural changes in the labour markets, driven, for instance, by globalization or technological change. These changes may not necessarily affect (un)employment, but may increase uncertainty, push workers into poorly paid low quality jobs or increase workers' effort to catch up with quickly changing demands in the labour market in terms of skills or availability (Autor et al., 2006; Green et al., 2022). In fact, Seltzer (2019) demonstrated that the cyclical approach performed very well in predicting a decline in fertility rates during the Great Recession in the US, but completely failed in its aftermath when envisioning a fertility rebound.

This study contributes to the discussion on labour markets and fertility by investigating how the long-term structural changes in the labour market, driven by robot adoption, affect childbearing. Robot adoption mirrors technological innovation and is a marker of economic and labour market transformation (Dottori, 2021). So far, little attention has been paid to this topic in fertility research. A notable exception among the published papers is the study by Anelli et al. (2021) who investigated the effects of the adoption of industrial robots on marriage and fertility in the US. Our focus is on Europe, where, despite large cross-country diversity, workers are much better protected against job loss or poverty (Esping Andersen, 1990). By exploiting variation in robot penetration across NUTS-2 regions, we examine how robotization influenced fertility in six European countries, namely: Czechia, Germany, France, Italy, Poland and the United Kingdom (UK). These countries differ in the penetration of automation, labour market and family policy regimes and gender norms. They also constitute good cases for examination as they provide a reasonable number of NUTS-2 regions for obtaining robust empirical findings (with Czechia pooled together with Poland).

2. Literature review

2.1. Automation, employment and economic uncertainty

The fear that automation will lead to a massive job destruction has been a concern for at least two centuries since the first industrial revolution began (OECD, 2019). Even though the industrial revolution didn't, in the end, lead to unemployment, but to an expansion of job opportunities and improvement in living standards, fear of automation persisted. In the 21st century, we are facing a new wave of anxiety that robots will take over our jobs – this time it is about cutting-edge industrial robots (Dekker et al., 2017).

The adoption of robots and machines will indeed change the ways we work and lead to a larger turnover in the labour market. Some jobs, in particular those which require performing routine tasks, will likely be destroyed or substantially changed (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2020). In the OECD countries, it was estimated that around 10 – 14% of jobs will be fully replaced by robots and for 25% - 32% around 50-70% of tasks will be automated in the next two decades (Nedelkoska and Quintini, 2018; Arntz et al., 2017). Yet, automation does not only destroy jobs but also creates new ones. These are largely jobs which require non-routine highly cognitive skills and offer good working conditions (Acemoglu and Autor, 2011). New jobs are also created in the lower-skill service sector, but they often offer poor social protection, are low paid and/or unstable (Autor, 2019).

Empirical research demonstrated the effects of automation on labour market outcomes to be unequivocal and clearly depend on workers' education and skills, the sector they are employed in and the overall economic and institutional environment. Automation seems to exert particularly negative effects on employment and/or earning opportunities of low-and-middle educated workers, both in the US (Acemoglu and Restrepo, 2020) and in Europe, though in the latter to a lower extent (Graetz and Michaels, 2018). Robots usually destroy jobs in manufacturing (Jung and Lim, 2020) but create new jobs in the service sector (for the US case see Acemoglu and Restrepo, 2020; for the UK see Kariel, 2021). At the same time, highly educated workers, performing nonroutine cognitive tasks, are likely to benefit from the ongoing changes (de Vries et al., 2020). Automation is also more likely to bring increases in employment in companies and regions which are more technologically advanced and better prepared to embrace the benefits brought about by technological progress. It was demonstrated, for instance, that regions with higher shares of knowledge and creative workers are better able to adapt to changes driven by digitalisation and thus are less vulnerable to automation shocks (Crowley et al 2021). Last but not least, the effects of robotisation on employment and earnings may differ across the countries and depend on their institutional settings. The labour substituting effect of robots tends to be stronger in countries with higher labour costs (Jung and Lim, 2020; Bachmann et al., 2022) and is argued to increase with a decline in employment protection legislation (Traverso et al., 2022).

Much less is known about how automation affects men's versus women's employment and earning opportunities, with few empirical findings suggesting mixed results. While Acemoglu and Restrepo (2020) find no gender differences in automation effects in the US, Brussevich et al. (2019) argue that women in OECD countries may be more exposed to automation as they are more often employed in jobs which involve routine tasks (see also Piasna and Drahokoupil, 2017 for the same conclusions for the EU). Robotisation also seems to increase gender wage inequalities in Europe by disproportionately benefiting men in medium- and high-skill occupations (Aksoy et al., 2021). At the same time, however, there is evidence that women are more quickly moving away from the routine-intense jobs into non-routine jobs in the service sector (Black and Spitz-Oener, 2010; Cortes et al., 2021) and that the pace of such job reallocation is faster in countries more advanced in robotization (Aksoy et al., 2021).

Overall, whether the new wave of automation will indeed lead to declines in employment is not yet clear. There is, however, evidence that it increases turnover in the labour market, requires readjustment from workers and increases uncertainty. The aforementioned studies by Arntz et al (2017) and Nedelkoska and Quinitni (2018) demonstrate that robots substantially change the task content of jobs, requiring employees to change the ways they perform work. A study from Norway found that around 40% of workers fear being replaced by a machine, which lowers their job satisfaction (Schwabe and Castellacci, 2020). Abeliansky and Beulman (2019) demonstrated negative effects of robot adoption on workers' mental health in Germany. Robot adoption was also found to increase death rates due to substance and alcohol abuse (Gihleb et al., 2022; O'Brien et al., 2022). Finally, the fear of robots was found to be particularly pronounced among the blue collar workers, most exposed to negative effects of automation, and in countries with weaker safety nets (Dekker et al., 2017).

2.2. Automation and fertility

A large body of the literature has provided evidence that weakening employment prospects, increase in unemployment and economic uncertainty lead to postponement of fertility or even lower fertility rates (Adsera, 2004; Schneider, 2015; Comolli, 2017; Matysiak et al., 2021). This is particularly true in countries offering weak safety nets for the unemployed (Mills et al., 2005). Growing instability of employment has also more negative consequences on fertility when it concerns men than women who, instead, may treat unemployment as an opportunity window for childbearing (Schmitt, 2012, Kreyenfeld and Andersson, 2014). These gender differences in the role of unemployment or precarious employment for fertility are, however, gradually in decline with an increase in women's education, changing gender roles and growing instability of men's employment (Oppenheimer, 1997). In a meta-study Alderotti et al. (2021) showed that in countries with high gender equality, such as Nordic Europe, or countries characterised by strongly unstable employment patterns among men, such as Southern Europe, women no longer use unemployment in order to have children. The same study showed that temporary contracts depress fertility more strongly if they are held by women than men.

Past research on labour market and fertility has, however, largely relied on conventional labour market indicators, such as (un)employment rate, wages or proportion of persons on specific contracts (e.g. temporary or part-time). These indicators excel in identifying short-term cyclical economic conditions, but are less able to capture long-term structural changes in the labour markets, driven for instance by globalization or technological change. These changes may not necessarily affect (un)employment, but may increase uncertainty, push workers into poorly paid low quality jobs or increase workers' effort to catch up with quickly changing demands in terms of skills or availability (Autor et al., 2006; Green et al., 2022). In particular, Seltzer (2019) showed that the cyclical approach performed very well in predicting a decline in fertility rates during the Great Recession in the US, but failed when envisioning a fertility rebound in its aftermath. Instead, fertility continued to fall despite a steep decline in unemployment in the post-crisis period (until the breakdown of the Covid-19 pandemic). This phenomenon was apparently driven by long-term structural changes in the labour market, caused by globalization and technological change. These changes started already before the Great Recession but accelerated throughout it as companies which implemented labour replacing technologies during the economic crisis were most likely to survive it (Hershbein and Kahn, 2018). With time the displaced workers found employment in the lower-skill service sector, which resulted in a decline in unemployment, but these jobs were of lower quality, at least in the US (Seltzer, 2019).

So far few studies have looked how these long-term structural transformations in the labour market affect fertility. Among them the majority concentrated on changes caused by globalization, in particular the detrimental role of import competition with China for employment opportunities of middle-skilled workers, mostly male, in goods-producing industries. Studies consistently showed that increased import competition led to a decline in fertility, largely by a declining marriage value of men (Autor et al., 2019; Piriu, 2022; Giuntella et al., 2022). Researchers' interest in how technology-driven labour market changes affect fertility has been even scarcer. On one hand, it has been shown that technological complexity, that reflects the capacity to innovate, develop and create job opportunities, is positively associated with fertility (Innocenti et al., 2021). This is because it fosters a fertility-friendly context characterised by better employment prospects. On the other hand, technological upgrading driven by automation is likely to increase turnover in the labour market, increase uncertainty and force workers to re-skill, which, in turn, may decrease fertility. In the only published empirical study on the effect of robotization on fertility, Anelli et al. (2021) demonstrate that an increase in the adoption of industrial robots in the US led to an increase in cohabitation and divorce and a decline – though not significant – in the number of marriages. Their findings also point to a decline in marital fertility and an increase in out-of-wedlock births.

3. Country context

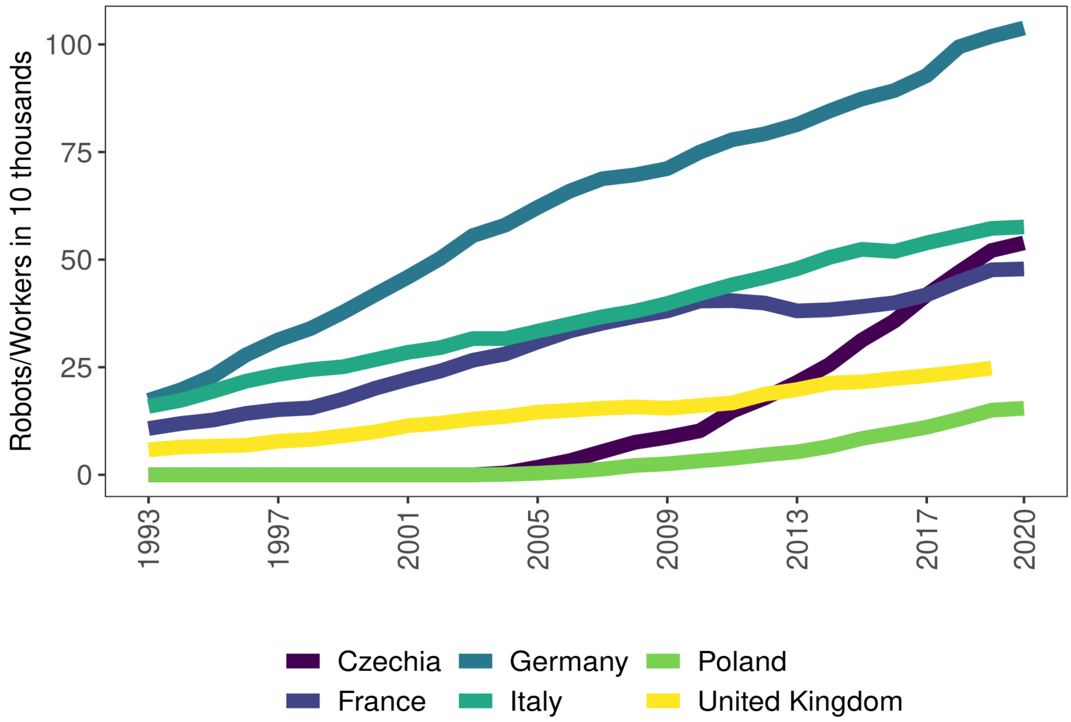
Our study is situated in six European countries, namely: Czechia, Germany, France, Italy, Poland and the UK. Among them France and UK have had the highest fertility for about four decades (with TFR oscillating between 1.7 to 2.0), though on a slow but gradual decline since the onset of the Great Recession. Germany and Italy had been the lowest-low fertility countries (with TFR below 1.35) since the mid 1980s and Czechia and Poland since the late 1990s / early 2000s. However, while Germany and in particular Czechia experienced some increase in fertility over the last 15 years, Italy and Poland remained at the fairly low levels with TFR oscillating between 1.25-1.45 (Eurostat Statistics Database, 2022).

The analysed countries also represent different welfare regimes which define the extent to which workers are protected against a job loss and supported in case of unemployment, all of which may matter for their fertility decisions (Adsera, 2005; Bastianelli et al., 2022). Germany and France are typically classified into the conservative/ employment-centred regimes (Esping-Andersen, 1990; Amable, 2003; Walther, 2006), based on strong employment protection and coordinated bargaining systems which allow for a "solidaristic wage setting" (Amable, 2003: 15). The two countries tend to offer generous income support for the unemployed and institutional support in job search (Tamesberger, 2017). Employment protection is also high in Italy, but is strictly directed at protecting workers on permanent contracts, leaving workers on temporary contracts often trapped in the secondary labour market (Pinelli et al., 2017). The UK, instead, is an example of liberal welfare state (Esping-Andersen, 1990), with a very low employment protection and low public support for the unemployed, offered only to those in the highest need (Caroleo and Pastore, 2007). Finally, Czechia and Poland belong to the post-socialist transitional regime with strong market orientation, low levels of state intervention, weak unions and limited support for the unemployed (Visser, 2011), providing rather low support for the unemployed (Tamesberger, 2017). They also display much lower labour costs than the remaining countries (Eurostat Statistics Database, 2022).

Family policies and the gender norms represent another element of the country context which may affect fertility responses to the changing labour market conditions. Whereas France stands out for its very good childcare coverage, Germany for a long time adhered to a modernized male breadwinner policy and only recently started to invest in childcare (Fagnani, 2012). Consequently, while it is common for mothers in France to work full-time, many women in Germany switch to part-time jobs after they become mothers (Fagnani, 2007). In Italy, childcare is seen as a private issue, which results in strong gender inequalities both in paid and unpaid work (Menniti et al., 2015). Childcare provision in the UK is also weak and care usually has to be purchased on the market (Yerkes and Javornik, 2019). Mothers usually work part-time or make use of flexible work arrangements which are available in the UK on a wider scale than in other studied countries (Chung and Horst, 2018). Poland and Czechia also display low childcare provision (Szelewa and Polakowski, 2008). Interestingly, mothers usually return to full-time employment after birth though in Czechia much later than in Poland (Matysiak, 2011).

Finally, the analysed countries differ in the robot penetration. The process of robot adoption in the old EU member states (Germany, France and Italy) and the UK started in the early 1990s (see Figure 1). In all these countries robots are predominantly employed in the automotive industry, apart from Italy where the allocation of robots across industries is more balanced with 26% in the metal, 17% in the automotive and 12% in the plastic and chemical industry (International Federation of Robotics, 2020). Germany is a clear leader in robot adoption worldwide (Dauth et al., 2021). It is followed by France and Italy where the robot penetration, measured by the number of robots per 10,000 employees, in 2019 was around half of that in Germany. Even lower penetration is observed in the UK which is an example of the Western European country with relatively slow adoption of industrial robots. The two post-socialist countries, Czechia and Poland, also display lower levels of robotisation, but the process of robot adoption started much later there, in the late 2000s. Robotisation in Czechia was very dynamic, due to the rapid development of its automotive industry, with the penetration rate surpassing the French one in 2017. The process in Poland was slower though gradual. None of the countries of our interest experienced a decrease or stagnation in robot penetration during the Great Recession.

Fig 1. Industrial robot penetration in 6 European countries by calendar year.



Sources: International Federation of Robotics (IFR) and Eurostat. Calculated by summing robot stocks and employment for the following 1 digit industries: Industry, Manufacturing, and Construction. Time series are constrained by data availability, as IFR publishes robot stock from 1993 onwards (2020 is the last available year). Figure prepared by the authors in R ggplot2.

4. Research objectives and hypotheses

In this study, we extend the work by Anelli et al (2021) and examine the effects of long-term structural changes in the labour market, driven by adoption of industrial robots, on regional fertility rates in six European countries - Czechia, France, Germany, Italy, Poland and the United Kingdom. As we demonstrated in Section 2.1, automation may benefit certain groups of workers (e.g. highly educated, working in the service sector) and diminish the earning/employment opportunities of the others (e.g. low and middle educated workers in the manufacturing sector). We thus do not expect it affects regional fertility rates in any uniform way. Instead, we anticipate the fertility effects of robot adoption to depend on the structural conditions of the regional labour markets. First, we expect robot adoption to be more likely to reduce fertility in those regions which used to have large employment in manufacturing before the onset of robotisation **(H1).** This expectation is formed due to the fact that industrial robots are largely employed in manufacturing, leading to a larger job destruction, turnover and uncertainty there rather than in the service sector. Second, we hypothesise that the negative fertility effects of robot adoption will be more evident in regions where the proportion of men employed in manufacturing at early stages of automation was larger, making men more exposed to robotisation **(H2)**. This is because fertility is less likely to decline in a reaction to a deterioration in women's than men's employment conditions. Next, we expect stronger fertility declines in response to robot adoption in regions with a larger proportion of low and middle educated workers **(H3)** since they are the ones which are mainly negatively affected by automation, either by being at risk of job displacement or having to compete with displaced workers for jobs. Last but not least, we anticipate that fertility effects of robot adoption depend on the region's capacity to embrace technological change. Consistently with past research showing that employment effects of robot adoption are weaker or even positive in regions which invest in modern technologies, we expect that fertility will be less likely to decline in response to automation in technology- and knowledge-intensive regions **(H4)**. Finally, fertility effects of robot adoption may also vary across the studied countries since they display substantial differences in welfare regimes, the gender normative context and penetration of automation. We abstain, however, from formulating specific hypotheses on the role of the specific cross-country differences for our findings since a comparison of only six countries which vary in numerous important dimensions precludes testing such hypotheses. We rather discuss our findings from the perspective of the cross-country differences presented in Section 3.

5. Methodology

5.1 Data

Our study is based on regional NUTS-2 data. The Nomenclature of territorial units for statistics (NUTS) is a hierarchical system for dividing up the economic territory of the European Economic Area, the UK, and Switzerland for the purpose of data collection and socio-economic analyses. NUTS-2 regions are roughly equally populated, with population ranging from 0.8 - 3 million, and these are the smallest geographical units for which employment data is available in Eurostat for all 6 countries of our interest. We observe the countries fairly since the start of the robotization till 2017. This means we cover the years 1997-2017 for the old EU member states and the UK and 2007-2017 for Czechia and Poland. Covering fully the 1990s for the old EU member states was not possible due to data availability.

To measure fertility, we use TFR and the age-specific fertility rates for the following age groups: 20-24, 25-29, 30-34, 35-39, 40-44, 45+. These data have been provided by Eurostat at the NUTS-2 level since 1990. They are computed by combining national statistics on births by mother's age and population of women by age. They are fairly complete with some missing data in fertility of women aged 45+ (around 10% of all observations). We use simple linear interpolation to supply them.

To measure worker's exposure to automation we use data on industrial robot stocks provided by the International Federation of Robotics (henceforth: IFR). IFR provides annual data on the operational stock of industrial robots[1] by country and industry since 1993. The industries are coded according to the International Standard Industrial Classification of all economic activities (ISIC, UN, 2008). The stocks of robots are provided by IFR at 1 digit level for all ISIC industries, and max 3 digits for manufacturing industries. The IFR data is complete. We utilise records at 1 digit for three following 'heavy' industries: Mining and quarrying, Electricity, gas, water supply, and Construction. We utilise records at 2 digits for the remaining 13 manufacturing industries[2] to match our regional employment structure data, which is also coded in 2-digit industry categories. We don't include non-industrial categories such as Services, Public Administration, or Education, as those industries employ predominantly service, not manufacturing robots, and at a much smaller scale than robots operating in manufacturing or 'heavy' industries (Hajduk and Koukolova, 2015).

The data on robots are linked to data on regional employment structures by industry using the methodology developed by Acemoglu and Restrepo (2020) and described in detail in Section 5.2. Eurostat has provided NUTS-2 regional employment structures by 2-digit industry codes classified according to Nomenclature of Economic Activities (NACE Rev. 1.2 before 2008, NACE Rev. 2 after 2008) since 1986. We reclassify these data to the ISIC classification to match them to robot stocks. Moreover, since our main covariate (explained in detail in Section 5.2) relies on summation of employment numbers over time, impute missing records of the regional employment structure. Finally, changes in the past NUTS classifications require reclassifying regional codes to one, consistent version. Both reclassifications and the imputation are described in detail in the Appendix.

Besides fertility rates, Eurostat online database provides us also with NUTS-2 level controls by calendar year, as well as potential moderators, which we interact with our main

[1] According to the definition given by IFR, industrial robots are fully autonomous machines that do not require a human operator. Their main tasks are handling operations and machine tending (55% of all European robots fall into this category) and welding and soldering (22% of all European robots) (Jurkat et al., 2022).

[2] Automotive/Other vehicles, Basic Metals, Electrical/electronics, Food and beverages, Glass, ceramics, stone, mineral products (non-automotive), Industrial machinery, Metal products (non-automotive), Paper, Pharmaceuticals, Cosmetics, Rubber and plastic products (non-automotive), Textiles, Wood and furniture, All other manufacturing branches/other chemical products not elsewhere classified.

explanatory variable in order to test our research hypotheses. We include the following set of controls at the regional level: share of population aged 15-24, share of population aged 25-49, share of population aged 50+, share of highly educated (ISCED levels 5-8), ratio of share of highly-educated women to share of highly-educated men, the square of the latter and women's economic activity rate. The variables denoting population structure by age are introduced to control for any variation in population exposed to childbearing. We also account for the population education level given the educational gradient in fertility (Wood et al., 2014). The share of highly educated women relative to highly educated men and the square of this ratio aim at capturing the difficulties to find a partner in regions with better educated female population (Bellani et al., 2017) given that partners tend to form unions if they have similar education levels or he is better educated than she (de Hauw et al., 2017). Finally, women's economic activity rate is also tightly linked to fertility.

The potential moderating variables are settled at the regional level as well. They are the initial (measured around the onset of robot adoption) proportion of workers employed outside of manufacturing (used to test H1), the initial proportion of women employed in manufacturing over the proportion of men in manufacturing (H2), proportion of highly educated persons (time-varying) (H3) and the proportion of workers employed in technology and knowledge-intensive sectors (time-varying) (H4). The control and moderating variables are fairly complete. Any missing values were imputed via linear interpolation. This was done in 14% of cases for population structure by education, and max. 25% for employment data. There are no cases when the entire time series for specific regions are missing.

After accounting for the NUTS reclassifications and excluding foreign territories (see the Appendix), we have data for 34 NUTS 2 regions in Germany, 22 in France, 20 in Italy, 35 in the UK, 16 in Poland, and 8 in Czechia. We pool the data for Czechia and Poland due to the smaller number of regions in the two post-socialist countries and their similarities when it comes to labour market and family policy institutions, economic developments and delayed start of automation in comparison to Western Europe. In total, we have 680 observations for Germany, 440 for France, 400 for Italy, 700 for the UK and 240 for Czechia and Poland jointly.

5.2 Methods

Our methodology relies on regressing fertility rates against workers' exposure to robotisation as well as a set of control variables mentioned in Section 5.1, separately for Germany, Italy, France, the UK and the group formed by Czechia and Poland .

We quantify workers' exposure to robotisation following the methodology developed by Acemoglu and Restrepo (2020) and used, among others, in Dauth et al. (2021), Anelli et al. (2021), and O'Brien et al. (2022):

$$Exposure\ to\ robots_{r,t} = \sum_{i=1}^{N} \frac{empl_{r,i,t_0}}{empl_{r,t_0}} \left(\frac{robots_{i,t}^{C}}{empl_{i,t_0}}\right) \qquad Eq.\ 1$$

where $robots_{i,t}^{C}$ is the country-level stock of robots across industries in year t; $empl_{i,t_0}$ identifies the total number of workers (in 10 thousands) employed in sector i in t_0, i.e. at the start of the robotisation (hereafter initial) and $\frac{empl_{r,i,t_0}}{empl_{r,t_0}}$ denotes the initial distribution of employment in industry i across regions. Effectively, $\frac{robots_{i,t}^{C}}{empl_{i,t_0}}$ captures robots adopted in industry i and country c replacing its initial employment, while $\frac{empl_{r,i,t_0}}{empl_{r,t_0}}$ disaggregates it onto regions. We set t_0 to 1994 for Western European countries and to 2004 for Czechia and Poland, as those are years when robotization started in those respective countries (see Section 3). The measure defined in *Eq. 1* is known as "shift-share instrument" or "Bartik instrument" (Goldsmith-Pinkham et al., 2020).

While exposure to robots is already considered exogenous, as its variation relies on employment shares before robotization had started, concerns about endogeneity of $robots_{i,t}^{C}$ might still appear, i.e. when external factors affect both the robot adoption and fertility. These may be global, domestic or sector-specific shocks, such as economic recession or policy changes. To address this issue, we follow Acemoglu and Restrepo (2020) and instrument the industry-specific stock of robots in country c $robots_{i,t}^{C}$ with industry-specific stock of robots in other countries, which serve as a proxy for advancements in robotization in developed economies. Dauth et al. (2021) proposed using industry-specific stocks of robots from several advanced economies as instruments of robot stocks in Germany (overidentified IV model). We thus build an overidentified model for each country with $k =$ {Germany, France, UK, Italy, Spain, Sweden, Norway, Finland, United States of America} instruments. In models for Germany, France, UK, and Italy, we exclude the country of interest and the US, and thus apply 7 instruments. The US' industry-specific stocks of robots is excluded since robots (relative to workforce) in that country were used on a smaller scale than in Western Europe (International Federation of Robotics, 2020) - thus the US cannot be considered as a pioneer of robotization which the Western European countries would follow. In models for Poland and Czechia, all

9 instruments are applied. Those external instruments are likely relevant, as industrial robots are manufactured by only a few international companies, which set global trends in industrial robot adoption. Thus, robot adoption in one developed economy is a good proxy for robot adoption in another one, with a similar socio-economic context. The proposed set of instruments should also be valid, as there is no reason to expect that robot adoption in one developed economy has a direct influence on fertility rates in another one. To test the instruments' relevance and validity of the overidentifying restrictions, we compute Kleibergen-Paap rk LM statistic, and Hansen J statistic (Wooldridge, 2010) and report it along with full model results in the Appendix.

Our model takes the following form:

$$fertility_{r,t} = \alpha Exposure\ to\ robots_{r,t-2} + \beta Controls_{r,t-1} + \eta_r + v_t + \varepsilon_{r,t} \qquad \textit{Eq. 2}$$

where $fertility_{r,t}$ denotes regional total and age-specific fertility rates, α is our parameter of interest capturing the effect of workers' exposure to robotization on fertility in region r, η_r corresponds to region individual effects and v_t are time dummies. In order to test hypotheses H1-H4 we interact $Exposure\ to\ robots_{r,t-2}$ with the potential moderators listed in Section 5.1. In all models we control for a set of demographic and socioeconomic characteristics of a region, $Controls_{r,t-1}$, enumerated in Section 5.1, which may confound the effects of robot penetration on fertility. They are lagged by 1 year to avoid simultaneity issues. At the same time, we lag the exposure to robots by 2 years to account for the pregnancy and the fact that, once exposed to labour market changes, workers might take some time to decide whether to have a child or not. *Eq. 2* is estimated using the two-stage least squares approach with a fixed effects "within" estimator (Wooldridge, 2010). Standard errors are clustered at the region level to acknowledge for within-region dependence of the observations and robustify the model to serial correlation.

6. Results

Our full model estimates along with the IV tests are displayed in Tables 3-27 in the Appendix (basic models as expressed by Eq. 2 in Tables 3-7 and models with interactions in Tables 8-27). In all 175 regressions for the different countries and fertility rates the instrument was relevant (as indicated by the Kleibergen-Paap rk Wald F statistic) and the overidentifying restrictions were valid with the Hansen J p-value exceeding the 5% significance level in 153 regressions, and the 1% in 8 cases. In 14 cases, it was not possible to conduct the Hansen J test, due to the fact that the number of clusters (regions) was smaller than the sum of the number of exogenous regressors and the number of excluded instruments (Frisch and Waugh, 1933; Baum et al., 2002). Those 14 cases correspond to the models for Italy and Czechia with Poland in which we introduced two interactions at once to test the H2. However, given that the overidentifying restrictions were valid in all other cases for those country samples, it is reasonable to assume that they are valid also in the remaining 14 cases.

6.1 Overall effects of robot adoption on fertility

We find few rather small effects of robot adoption on fertility. Total fertility is affected significantly only in Italy. This effect is negative: an increase in workers' exposure to robots by 1 robot per 10.000 workers reduces the total fertility rate by 0.00118. This effect is entirely driven by the negative effect of automation on fertility at young ages, in particular in the 25-29 group. Apart from Italy, we also find negative fertility effects in Germany, the leader of robot adoption worldwide, for certain age-specific fertility rates. These effects are weaker and, in contrast to Italy, emerge only at older ages (i.e. for age groups 35-39 and 40-44).

Table 1. Exposure to robots (α) coefficients from basic 2SLS models (Eq. 2).

Country	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Germany	-0.00016	0.00004	0.00002	-0.00002	-0.00011***	-0.00005***	-0.000001
France	0.00003	-0.00010	0.00009	0.00012	-0.00001	-0.00004	0.000003
Italy	-0.00118*	-0.00020	-0.00090***	-0.00012	0.00014	-0.00005	0.00001
United Kingdom	0.00168	-0.00087	0.00079	0.00133	0.00109	0.00039*	-0.000002
Czechia & Poland	0.00053	0.00010	-0.00044	0.00050	0.00025*	-0.00005	-0.00001

*** 1% ** 5% * 10%. Sample sizes: 680 observations for Germany, 440 for France, 400 for Italy, 700 for the UK, and 240 for Poland and Czechia jointly.

We do not find significant negative effects on fertility in other countries of our interest. In some of them we even identify a significant positive influence of robots on fertility at higher ages. For instance, an increase in exposure to robots by 1 robot per 10.000 workers results in an increase in 35-39 fertility rate 0.00025 in Czechia and Poland and a gain in the 40-44 fertility rate by 0.00039 in the UK. We don't observe any statistically significant findings for France.

6.2 Workforce sectoral composition

Since robots are mostly employed in manufacturing, we hypothesised that the negative fertility effects will be most likely to emerge in regions with large manufacturing sectors (H1). With few exceptions, our findings are largely consistent with this expectation (see the main effects in Table 2).

Table 2. Exposure to robots (α) and its interaction with the initial (start of observation period) share of workers employed in manufacturing.

Country	Measure	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Germany	Exposure to robots	-0.0022*	-0.0012***	-0.00137***	0.00037	0.00009	-0.000029	-0.00000
	Exposure to robots # Initial share of workers out of manufa-cturing	0.00003**	0.00002***	0.00002***	-0.00001	-0.00000	-0.00000	0.00000
France	Exposure to robots	0.00163	0.00062	0.00212	0.00013	-0.00082	-0.00045**	-0.00008*
	Exposure to robots # Initial share of workers out of manufa-cturing	-0.00002	-0.00001	-0.00003	-0.00000	0.00001	0.000006*	0.000001*
Italy	Exposure to robots	-0.00264	-0.00051	-0.00201	-0.00085	0.00069	0.00039**	-0.00013**
	Exposure to robots # Initial share of workers out of manufa-cturing	0.00002	0.000005	0.00002	0.00001	-0.000007	-0.00001**	0.000002***

United Kingdom	Exposure to robots	-0.0223**	-0.00584	-0.00094	-0.00088	-0.00384	-0.00155	0.00012
	Exposure to robots # Initial share of workers out of manufa-cturing	0.00031**	0.000065	0.00002	0.00003	0.00006	0.00003	-0.00000
Czechia & Poland	Exposure to robots	0.00627	0.00295***	-0.00337**	0.00275	0.00251***	0.00004	0.00001
	Exposure to robots # Initial share of workers out of manufa-cturing	-0.00009*	-0.00005***	0.00005**	-0.00004	-0.00004***	-0.00000	-0.00000

*** 1% ** 5% * 10%. Sample sizes: 680 observations for Germany, 440 for France, 400 for Italy, 700 for the UK, and 240 for Poland and Czechia jointly.

We observe a clearly negative effect of robot adoption on total fertility in those German regions which were initially highly industrialised. It is strongly driven by fertility reduction at young ages (20-24 and 25-29). This negative effect is significantly weaker in regions with a smaller initial proportion of workers employed in manufacturing. We also detect some negative fertility effects of robots in the French and British regions with initially large manufacturing sectors. In the UK, the negative effects on age-specific fertility in those regions are not significant but the negative effect on total fertility is significant. In France, they emerge at the highest reproductive ages: 40-44 and 45+. In Italy, most of the effects in highly industrialised regions are insignificant except for those at higher reproductive ages where the pattern is unclear (positive effect of robot adoption in highly industrialised regions at ages 40-44 and negative at ages 45+). Some inconsistency is also detected in Czechia and Poland though it seems that the effects of robot adoption there tend to be rather positive in highly industrialised regions: the main effects at all reproductive ages, but for 25-29, are positive though significant only at ages 20-24 and 35-39.

6.3 Gender composition of manufacturing workers

Next, we expected that fertility effects of robot adoption will be more negative in regions where men were more exposed to automation than women (H2). Apart from the UK and the cluster built by Czechia and Poland, we do not find evidence for this hypothesis. Our findings even suggest the reverse, namely that robot adoption in Germany, France and Italy leads to stronger fertility decline in regions where the initial ratio of women's to men's employment share in manufacturing was larger (see the interaction between exposure to robots and the ratio of women's versus men's employment share in manufacturing). These negative effects, obtained net of the regional employment in manufacturing and women's activity rate, are largely significant at young reproductive ages. Interestingly, in Italy and to some extent in France we even find traces of positive effects of robot adoption in regions with initially large manufacturing sectors which are dominated by men (see the α coefficient).

Table 3. Exposure to robots (α), interaction of exposure to robots with the initial share of workers employed out of manufacturing and interaction of exposure to robots with the initial ratio of women's to men's employment share in manufacturing.

Country	Measure	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Germany	Exposure to robots	0.00079	-0.00041	-0.00018	0.00064	0.00053	0.00000	0.00001
	Exposure to robots # Initial share of workers out of manufacturing	0.00001	0.00001**	0.00001**	-0.00001	-0.00001	-0.00000	-0.00000
	Exposure to robots # Initial ratio of women's versus men's share in manufacturing	-0.0035***	-0.00093*	-0.00141***	-0.00031	-0.00052**	-0.00004	-0.00001

France	Exposure to robots	0.0049	0.00188*	0.00352**	0.0008	-0.00098*	-0.00056**	-0.00012**
	Exposure to robots # Initial share of workers out of manufacturing	-0.00002	-0.00000	-0.00003	-0.00000	0.00001	0.000005*	0.000001*
	Exposure to robots # Initial ratio of women's versus men's share in manufacturing	-0.00681**	-0.00307***	-0.00292*	-0.00122	0.00049	0.00036	0.00011**
Italy	Exposure to robots	0.0144***	0.00535***	0.0067***	-0.00056	0.00038	0.00116***	-0.00014*
	Exposure to robots # Initial share of workers out of manufacturing	-0.00011**	-0.00004**	-0.00005***	0.00001	-0.00000	-0.00001***	0.000002**
	Exposure to robots # Initial ratio of women's versus men's share in manufacturing	-0.0137***	-0.00462***	-0.00693***	-0.00039	0.00025	-0.0006***	0.00002
United Kingdom	Exposure to robots	-0.0378***	-0.0103	-0.00187	-0.00319	-0.00486	-0.00202	-0.00024
	Exposure to robots # Initial share of workers	0.00042***	0.0001	0.00003	0.00004	0.000069	0.000028	0.000001

	out of manufacturing							
	Exposure to robots # Initial ratio of women's versus men's share in manufacturing	0.0187*	0.00487	0.00091	0.00303	0.00177	0.00073	0.00043**
Czechia & Poland	Exposure to robots	0.00195	0.00041	-0.00436	0.00246	0.00178**	-0.00013	-0.000023
	Exposure to robots # Initial share of workers out of manufacturing	-0.00007	-0.00003*	0.00005*	-0.00004	-0.00003***	0.000000	-0.00000
	Exposure to robots # Initial ratio of women's versus men's share in manufacturing	0.00402	0.00228***	0.00099	0.0003	0.00063	0.00014	0.00002

*** 1% ** 5% * 10%. Sample sizes: 680 observations for Germany, 440 for France, 400 for Italy, 700 for the UK, and 240 for Poland and Czechia jointly.

The findings for the UK and Czechia and Poland are more consistent with our expectations. In the UK, the interaction between exposure to robotization and the ratio of women’s and men’s employment in manufacturing is positive at all reproductive ages and significant in the models for the total fertility. At the same time, the α coefficient, denoting the effect of robot adoption on fertility in highly industrialised regions where employment in manufacturing is dominated by men, is negative, suggesting that robotization reduces fertility in such regions. In Czechia and Poland, the interaction between exposure to robotization and ratio of women’s and men’s employment in manufacturing is positive at all reproductive ages (like in the UK), but significant only at ages 20-24.

6.4 Educational attainment of the population

Subsequently, we test the hypothesis that robots exert a more negative impact on fertility in lower educated regions (H3). We find clear support for this hypothesis in Germany and Italy. There is some evidence for this hypothesis also in the remaining countries but for France where our findings suggest the opposite.

Table 4. Exposure to robots (α) and its interaction with the share of the highly-educated population (ISCED 5-8).

Country	Measure	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Germany	Exposure to robots	-0.00161***	-0.00027*	-0.00011	-0.00045**	-0.00044***	-0.00014***	-0.00001**
	Exposure to robots # Share of highly educated	0.00005***	0.00001**	0.00001	0.00002**	0.00001***	0.000003**	0.0000003**
France	Exposure to robots	0.0015**	0.00058**	0.00105***	0.00019	-0.00027	-0.00015**	-0.00001
	Exposure to robots # Share of highly educated	-0.000054**	-0.00002***	-0.00003**	-0.00000	0.00001	0.000004*	0.000000
Italy	Exposure to robots	-0.00292*	-0.00102	-0.00124**	0.0002	-0.00016	-0.0002*	0.00001
	Exposure to robots # Share of highly educated	0.0001	0.00004*	0.00002	-0.00001	0.00002	0.00001**	-0.00000
United Kingdom	Exposure to robots	0.00026	-0.00049	0.00171*	0.00063	0.00008	-0.00016	-0.00009**

	Exposure to robots # Share of highly educated	0.00003	-0.000009	-0.00002	0.00001	0.00002	0.00001	0.000002***
Czechia & Poland	Exposure to robots	-0.00018	0.00039	-0.00182***	0.00023	0.00066***	0.00002	-0.00003***
	Exposure to robots # Share of highly educated	0.000021	-0.00002	0.00007**	0.00001	-0.00002**	-0.00000	0.000001**

*** 1% ** 5% * 10%. Sample sizes: 680 observations for Germany, 440 for France, 400 for Italy, 700 for the UK, and 240 for Poland and Czechia jointly.

In Germany, we identify a significantly negative effect of exposure to robots on fertility in regions characterised by lower educational attainment of the population: an increase in the exposure to robotization by 1 robot per 10,000 workers leads to a decline in total fertility by 0.0016 there (the coefficient α). Negative and mostly significant fertility effects are found at all reproductive ages. They clearly weaken with an increase in the proportion of highly educated individuals in a region (see the coefficients associated with the interaction term). We find some traces of a similar pattern in Italy and Czechia and Poland, but the estimated effects are significant only at some ages and in Czechia and Poland some reversed findings are also obtained for the age group 35-39. The educational attainment of the regional population does not seem to matter for the effects of robotization on fertility in the UK (except for highest reproductive ages where the findings are consistent with our expectations). Finally, in France we find that robotization has a positive influence on fertility in regions with fairly low educated populations, which is in contrast to our hypothesis H3.

6.5. Region's orientation at investments in knowledge and technology

Finally, we expected the fertility effects of robotization to be less negative or more positive in regions which are better able to embrace technological change. We operationalise this ability with the regional investment in technology and knowledge-intensive sectors, measured by its employment. Only a few findings are consistent with this hypothesis.

On the one hand, we find the interaction term between exposure to robotization and employment in technology and knowledge-intensive sectors to be significantly negative at lower reproductive ages (25-29) in Germany and the United Kingdom. On the other hand, however, the interaction term turns often positive and significant at high reproductive ages. This latter finding emerges clearly in Germany, but also to a lower extent in France, United Kingdom and Czechia and Poland, suggesting fertility recuperation (or higher order fertility) encouraged by increasing employment/earning opportunities and growing prosperity of the region.

Table 5. Exposure to robots (α) and its interaction with the share of workers employed in technology and knowledge-intensive sectors.

Country	Measure	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Germany	Exposure to robots	-0.00006	0.0001	0.00015**	-0.00003	-0.00015***	-0.00005***	-0.000003*
	Exposure to robots # Share employed in technology- and know-ledge sectors	-0.00002	-0.00001	-0.00005***	0.00001	0.00002*	0.00001	0.000001**
France	Exposure to robots	-0.00015	-0.00019*	0.00006	0.00013	-0.00004	-0.00007***	-0.000002
	Exposure to robots # Share employed in technology- and know-ledge sectors	0.00007	0.00003	0.00002	-0.00000	0.00001	0.00001*	0.000002
Italy	Exposure to robots	-0.00116*	-0.00013	-0.00117***	-0.00017	0.00037***	-0.00001	0.000002

	Exposure to robots # Share employed in technology- and know-ledge sectors	0.000005	-0.00002	0.0001	0.00002	-0.00008	-0.00001	0.000002
United Kingdom	Exposure to robots	0.00161	-0.0008	0.00122	0.00151	0.00071	0.00016	-0.00001
	Exposure to robots # Share employed in technology- and know-ledge sectors	0.00001	0.00000	-0.00020*	-0.00005	0.00012	0.00007*	-0.00000
Czechia & Poland	Exposure to robots	0.00119	0.00025	-0.00047	0.00096	0.00039*	-0.00009**	-0.00003***
	Exposure to robots # Share employed in technology- and know-ledge sectors	-0.00031	-0.00004	-0.00003	-0.00022	-0.00006	0.00002	0.000006**

*** 1% ** 5% * 10%. Sample sizes: 680 observations for Germany, 440 for France, 400 for Italy, 700 for the UK, and 240 for Poland and Czechia jointly.

7. Discussion

Industrial robots substantially change the conditions of participating in the labour markets and thereby may also affect fertility. On the one hand, there is evidence that robots destroy jobs, increase turnover in the labour market and make workers adjust to the new demands in the labour markets (reskill, upskill or increase work effort to follow the new work guidelines or even keep the job). On the other hand, however, robots may also increase productivity and thereby contribute to the expansion of new jobs, in particular in regions with highly educated workforce open to technological innovations. In this study we examined whether these long-term structural changes, driven by adoption of industrial robots, affect regional fertility rates in six European countries. We find that fertility effects of robot adoption vary across regions, depending on workforce education, employment structure and region's capacity to embrace technological change. Briefly, our findings suggest that robots tend to exert a negative influence on fertility in regions where substantial numbers of workers are exposed to losing their jobs due to automation, i.e. highly industrialised regions (except for Czechia and Poland) and regions with relatively low educated populations (except for France). These findings are in line with our hypotheses H1 and H3. We also find the fertility effects to be more negative in less technologically advanced regions where robotisation is unlikely to boost productivity and create new jobs (consistently with the hypothesis H4). The negative fertility effects are clearly most evident at young ages, especially in regions with large manufacturing sectors and to some extent in regions with lower educated populations. This finding may suggest postponement of fertility to higher ages, though fertility recuperation at older ages does not emerge clearly from our study, except for regions which are strongly oriented at knowledge and technological innovations.

We also observe some country differences in fertility effects of robot adoption but the pattern is not very clear. We see the negative effects of robots on fertility to be most pronounced in Germany which is most advanced in automation among the studied countries. This is despite the strong employment protection in the country. We also observe some negative effects in Italy and less so in the UK. Robotization in these two countries has progressed more slowly than in Germany, but employment protection is weaker there (in Italy low protection concerns disproportionately the young workers) and support for the unemployed is more limited. We also find the effects of robot adoption to be less disruptive for fertility and even to encourage it in Czechia and Poland. This finding, even though seemingly striking, may be explained by the fact that robots are less likely to replace labour in countries with lower labour costs (Jung and Lim, 2020; Bachmann et al., 2022), which Czechia and Poland undoubtedly are in comparison to the Western European states. Finally, we were puzzled by the fact that consistently with hypothesis H2 we found less negative effects of robot adoption in those British, Polish and Czech regions where the ratio of women's to men's initial employment in manufacturing was higher but such findings were not obtained for Germany, France or Italy even though the division of paid work between partners in Germany or Italy is not less asymmetric than in Poland or the UK (Matysiak and Steinmetz, 2008; Matysiak and Vignoli, 2013). One possible explanation for this finding might be related to the fact that women working in manufacturing moved out into the service sector much more quickly than men. Such phenomenon was indeed observed in countries most advanced in automation (Cortes et al., 2021; Black and Spitz-Oener, 2010), which Germany, Italy and France indeed are. At the same time, the new jobs in the service sector turned out to be characterised by high insecurity and precarity with employers requiring from workers great deal of flexibility (Allen and Henry 1997, Reimer 1998).

Despite some inconsistencies our findings suggest that long-term structural changes, driven by automation, can indeed affect fertility as it was proposed by Seltzer (2019). Nonetheless, it does not seem robotisation is primarily responsible for fertility declines observed in the aftermath of the Great Recession in most advanced countries. It exerts a negative influence on fertility in certain regions (highly industralised or low/middle educated), but these effects are compensated by fertility increases in better educated and dynamically developing regions. It is likely, however, that fertility may be affected also by other components of structural labour market changes, driven by digitalisation, such as implementation of digital automats which also replace workers but are not classified as industrial robots, or spread of remote work. This hypothesis still remains to be verified.

Our study also has limitations that we acknowledge. First, being a macro-level study it may not be able to uncover the pathways and mechanisms through which automation affects fertility choices. While we learn that robotisation reduces fertility in regions with larger manufacturing sectors or less educated populations, we do not learn whether it is exactly the workers who are exposed to robotisation or their partners who reduce fertility and what are the exact reasons behind this behaviour. This study is one of the first attempts of studying the role of labour market changes, driven by automation, for fertility and more research, involving individual-level data, is needed to investigate more closely how exposure to automation affects workers' childbearing choices, taking into account workers' gender, the couple context (labour market situation of the other partner), the firm characteristics (such as propensity to innovate) or the country context (such as specific welfare and labour market policies). Second, we also faced data limitations. Due to the anonymisation procedures at Eurostat some of our data were missing and had to be imputed. As a result our main measure, exposure to robots, contains measurement error, which causes its increased variance in comparison with a perfect measurement. Thus, we expect all regression lines that we fitted to be biased towards 0 (regression dilution/attenuation; Fuller, 1987). Our measure of exposure to robotisation faces other problems as well. Although it is at the forefront of economic research on automation and employment (Acemoglu and Restrepo, 2020; Dauth et al., 2021), it assumes that regional employment structure by sector remains unchanged over time. This assumption is needed in order to keep exposure to robots exogeneous, as the regional employment shares by sector are measured before the start of robotisation. Finally, we did not account for possible spatial spillovers which may take place if workers commute to jobs outside of the regions of their residence (Monte et al., 2018). According to our best knowledge, in econometric literature exploiting sectoral composition as a source of local labour demand shocks (Bartik shocks) and in particular discussing the exposure to robots, no solutions to the two above-mentioned issues have been offered so far. We underline them as important areas for future research.

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References

Abeliansky, A. L., & Beulmann, M. (2019). *Are they coming for us? Industrial robots and the mental health of workers*. CEGE Discussion Paper No 379, https://ideas.repec.org/p/zbw/cegedp/379.html

Acemoglu, D., & Autor, D. (2011). Chapter 12 - Skills, Tasks and Technologies: Implications for Employment and Earnings. In D. Card & O. Ashenfelter (Eds.), *Handbook of Labor Economics* (Vol. 4, pp. 1043-1171). Elsevier. https://doi.org/https://doi.org/10.1016/S0169-7218(11)02410-5

Acemoglu, D., & Restrepo, P. (2020). Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy*, *128*(6), 2188-2244. https://doi.org/10.1086/705716

Adsera, A. (2005). Vanishing Children: From High Unemployment to Low Fertility in Developed Countries. *American Economic Review*, 95(2), 189-193. https://doi.org/10.1257/000282805774669763

Adsera, A. C. (2004). Changing fertility rates in developed countries. The impact of labor market institutions. *Journal of Population Economics*, 17(1), 17-43. https://doi.org/10.1007/s00148-003-0166-x

Aksoy, C. G., Özcan, B., & Philipp, J. (2021). Robots and the gender pay gap in Europe. *European Economic Review*, *134*, 103693. https://doi.org/10.1016/j.euroecorev.2021.103693

Alderotti, G., Vignoli, D., Baccini, M., & Matysiak, A. (2021). Employment Instability and Fertility in Europe: A Meta-Analysis. *Demography*, *58*(3), 871-900. https://doi.org/10.1215/00703370-9164737

Allen, J., and N. Henry. Ulrich Beck's risk society at work: labour and employment in the contract service industries. *Transactions of the Institute of British Geographers* (1997): 180-196.

Amable, B. (2003). *The Diversity of Modern Capitalism*. Oxford University Press. https://doi.org/10.1093/019926113x.001.0001

Anelli, M., Giuntella, O., & Stella, L. (2021). Robots, Marriageable Men, Family, and Fertility. *Journal of Human Resources*, 1020-11223R11221. https://doi.org/10.3368/jhr.1020-11223r1

Arntz, M., Gregory, T., & Zierahn, U. (2017). Revisitinng the risk of automation. Economics Letters 159:157-160.

Autor, D. (2019). Work of the Past, Work of the Future. *National Bureau of Economic Research Working Paper Series*, *No. 25588*. https://doi.org/10.3386/w25588

Autor, D., Dorn, D., & Hanson, G. (2019). When Work Disappears: Manufacturing Decline and the Falling Marriage Market Value of Young Men. *American Economic Review: Insights*, *1*(2), 161-178. https://doi.org/10.1257/aeri.20180010

Autor, D. H., Katz, L. F., & Kearney, M. S. (2006). The Polarization of the U.S. Labor Market. *American Economic Review* 96(2): 189-194.

Bachmann, R., Gonschor, M., Lewandowski, P., & Madoń, K. (2022). The impact of robots on labour market transitions in Europe. IBS Working Papers No 1/2022. https://ibs.org.pl/en/publications/the-impact-of-robots-on-labour-market-transitions-in-europe/

Bastianelli, E., Guetto, R., & Vignoli, D. (2022). The impact of labour market deregulation reforms on fertility in Europe. *Econometrics Working Papers Archive 2022_04*, Universita' degli Studi di Firenze, Dipartimento di Statistica, Informatica, Applicazioni "G. Parenti".

Baum, C.F., Schaffer, M.E., & Stillman, S. (2002). ivreg2: Stata module for extended instrumental variables/2SLS and GMM estimation. Statistical Software Components S425401, Boston College Department of Economics, revised 10 May 2022; http://ideas.repec.org/c/boc/bocode/s425401.html

Bellani, D., Esping-Andersen, G., & Nedoluzhko, L. (2017). Never partnered: A multilevel analysis of lifelong singlehood. *Demographic Research*, 37(4), 53-100. https://doi.org/https://www.demographic-research.org//volumes/vol37/4/files/readme.37-4.txt

Bellani, D. (2020). The institutional and cultural framing of the educational stratification in fertility. A review of the role of labor market institutions and attitudinal orientations. *Research in Social Stratification and Mobility*, *66*, 100482. https://doi.org/10.1016/j.rssm.2020.100482

Black, S. E., & Spitz-Oener, A. (2010). Explaining Women's Success: Technological Change and the Skill Content of Women's Work. *Review of Economics and Statistics,* 92(1), 187-194. https://doi.org/10.1162/rest.2009.11761

Brussevich, M., Dabla-Norris, E., & Khalid, S. (2019). Is Technology Widening the Gender Gap? Automation and the Future of Female Employment. *IMF Working Papers*, *19*/91, https://doi.org/10.5089/9781498303743.001

Caroleo, F. E., Pastore, F. (2007). The Youth Experience Gap: Explaining Differences Across EU Countries. Working Paper of the Faculty of Economics, Finance and Statistics, University of Perugia, https://core.ac.uk/download/pdf/6963991.pdf

Cherlin, A., Cumberworth, E., Morgan, S. P., & Wimer, C. (2013). The Effects of the Great Recession on Family Structure and Fertility. *The ANNALS of the American Academy of Political and Social Science*, *650*(1), 214-231. https://doi.org/10.1177/0002716213500643

Chung, H., & Van Der Horst, M. (2018). Women's employment patterns after childbirth and the perceived access to and use of flexitime and teleworking. *Human Relations*, *71*(1), 47-72. https://doi.org/10.1177/0018726717713828

Comolli, C. L. (2017). The fertility response to the Great Recession in Europe and the United States: Structural economic conditions and perceived economic uncertainty. *Demographic Research*, 36(51), 1549-1600. https://doi.org/https://www.demographic-research.org//volumes/vol36/51/files/readme.36-51.txt

Cortes, G. M., Jaimovich, N., & Siu, H. E. (2021). The Growing Importance of Social Tasks in High-Paying Occupations: Implications for Sorting. *Journal of Human Resources.* https://doi.org/10.3368/jhr.58.5.0121-11455R1

Crowley, F., Doran, J., & McCann, P. (2021). The vulnerability of European regional labour markets to job automation: the role of agglomeration externalities. *Regional Studies*, 55(10-11), 1711-1723. https://doi.org/10.1080/00343404.2021.1928041

Dauth, W., Findeisen, S., Suedekum, J., & Woessner, N. (2021). The Adjustment of Labor Markets to Robots. *Journal of the European Economic Association 19(6): 3104-3153.* https://doi.org/10.1093/jeea/jvab012

De Hauw, Y., Grow, A., & Van Bavel, J. (2017). The Reversed Gender Gap in Education and Assortative Mating in Europe. *European Journal of Population*, *33*(4), 445-474. https://doi.org/10.1007/s10680-016-9407-z

De Vries, G. J., Gentile, E., Miroudot, S., & Wacker, K. M. (2020). The rise of robots and the fall of routine jobs. *Labour Economics*, *66*, 101885. https://doi.org/https://doi.org/10.1016/j.labeco.2020.101885

Dekker, F., Salomons, A., & Waal, J. V. D. (2017). Fear of robots at work: the role of economic self-interest. *Socio-Economic Review*, 15(3), 539-562. https://doi.org/10.1093/ser/mwx005

Dottori, D. (2021). Robots and employment: evidence from Italy. *Economia Politica*, 38(2), 739-795. https://doi.org/10.1007/s40888-021-00223-x

Esping-Andersen, G. (1990). The Three Worlds of Welfare Capitalism. Princeton University Press.

Eurostat (2022). Eurostat Statistics Database. Data retrieved on 29.08.2022. https://ec.europa.eu/eurostat/data/database

Fagnani, J. (2007). Family policies in France and Germany. *Community, Work & Family*, *10*(1), 39-56. https://doi.org/10.1080/13668800601110769

Fagnani, J. (2012). Recent reforms in childcare and family policies in France and Germany: What was at stake? *Children and Youth Services Review*, *34*(3), 509-516. https://doi.org/https://doi.org/10.1016/j.childyouth.2011.10.011

Frisch, R., & Waugh, F. V. (1933). Partial Time Regressions as Compared with Individual Trends. *Econometrica*, 1(4), 387-401. https://doi.org/10.2307/1907330

Fuller, W. A. (1987). *Measurement Error Models*. John Wiley & Sons, Inc. https://doi.org/https://doi.org/10.1002/9780470316665

Gihleb, R., Giuntella, O., Stella, L., & Wang, T. (2022). Industrial Robots, Workers' Safety, and Health. *National Bureau of Economic Research Working Paper Series*, *No. 30180*. https://doi.org/10.3386/w30180

Giuntella, O., Rotunno, L., & Stella, L. (2022). Globalization, Fertility and Marital Behavior in a Lowest-Low Fertility Setting. *National Bureau of Economic Research Working Paper Series, No. 30119*. https://doi.org/10.3386/w30119

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik Instruments: What, When, Why, and How. *American Economic Review*, *110*(8), 2586-2624. https://doi.org/10.1257/aer.20181047

Graetz, G., & Michaels, G. (2018). Robots at Work. *The Review of Economics and Statistics*, *100*(5), 753-768. https://doi.org/10.1162/rest_a_00754

Green, F., Felstead, A., Gallie, D., & Henseke, G. (2022). Working Still Harder. *ILR Review*, *75*(2), 458-487. https://doi.org/10.1177/0019793920977850

Hajduk, M., & Koukolová, L. (2015). Trends in Industrial and Service Robot Application. *Applied Mechanics and Materials*, 791, 161-165. https://doi.org/10.4028/www.scientific.net/AMM.791.161

Hershbein, B., & Kahn, L. B. (2018). Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings. *American Economic Review*, *108*(7), 1737-1772. https://doi.org/10.1257/aer.20161570

Innocenti, N., Vignoli, D., & Lazzeretti, L. (2021). Economic complexity and fertility: insights from a low fertility country. *Regional Studies,* 55(8), 1-15. https://doi.org/10.1080/00343404.2021.1896695

International Federation of Robotics. (2020). The structure of the distribution of industrial robots in individual countries/regions. In *World Robotics 2020: Industrial Robots*. International Federation of Robotics.

Jung, J. H., & Lim, D.-G. (2020). Industrial robots, employment growth, and labor cost: A simultaneous equation analysis. *Technological Forecasting and Social Change*, 159, 120202. https://doi.org/10.1016/j.techfore.2020.120202

Jurkat, A., Klump, R., & Schneider, F. (2022). Tracking the Rise of Robots: The IFR Database. Jahrbücher für Nationalökonomie und Statistik.

Kariel, J. (2021). Job Creators or Job Killers? Heterogeneous Effects of Industrial Robots on UK Employment. *Labour*, *35*(1), 52-78. https://doi.org/10.1111/labr.12192

Kreyenfeld, M., & Andersson, G. (2014). Socioeconomic differences in the unemployment and fertility nexus: Evidence from Denmark and Germany. *Advances in Life Course Research*, *21*, 59-73. https://doi.org/https://doi.org/10.1016/j.alcr.2014.01.007

Matysiak, A., & Steinmetz, S. (2008). Finding Their Way? Female Employment Patterns in West Germany, East Germany, and Poland. *European Sociological Review,* 24(3), 331-345. http://www.jstor.org/stable/25209167

Matysiak, A. (2011). Fertility developments in Central and Eastern Europe: The role of work-family tensions. *Demográfia–English Edition*, *54*(5), 7-30.

Matysiak, A., & Vignoli, D. (2013). Diverse Effects of Women's Employment on Fertility: Insights From Italy and Poland. *European Journal of Population*, 29(3), 273-302. https://doi.org/10.1007/s10680-013-9287-4

Matysiak, A., Sobotka, T., & Vignoli, D. (2021). The Great Recession and Fertility in Europe: A Sub-national Analysis. *European Journal of Population*, *37*(1), 29-64. https://doi.org/10.1007/s10680-020-09556-y

Menniti, A., Demurtas, P., Arima, S., & De Rose, A. (2015). Housework and childcare in Italy: a persistent case of gender inequality. *Genus*, 71(1), 79-108. https://www.jstor.org/stable/genus.71.1.79

Mills, M., Blossfeld, H.-P., & Klijzing, E. (2005). Becoming an Adult in Uncertain Times. In H.-P. Blossfeld, E. Klijzing, M. Mills, & K. Kurz (Eds.), *Globalization, Uncertainty and Youth in Society* (1 ed., pp. 423-441). Routledge. https://doi.org/https://doi.org/10.4324/9780203003206

Monte, F., Redding, S. J., & Rossi-Hansberg, E. (2018). Commuting, Migration, and Local Employment Elasticities. *American Economic Review*, *108*(12), 3855-3890. https://doi.org/10.1257/aer.20151507

Nedelkoska, L., & Quintini, G. (2018). Automation, skills use and training. OECD Social, Employment and Migration Working Paper No 202. https://doi.org/doi:https://doi.org/10.1787/2e2f4eea-en

O'Brien, R., Bair, E. F., & Venkataramani, A. S. (2022). Death by Robots? Automation and Working-Age Mortality in the United States. *Demography*, *59*(2), 607-628. https://doi.org/10.1215/00703370-9774819

OECD. (2019). OECD *Employment Outlook 2019: The Future of Work.* Paris: OECD.

Oppenheimer, V. K. (1997). Women's Employment and the Gain to Marriage: The Specialization and Trading Model. *Annual Review of Sociology*, *23*(1), 431-453. https://doi.org/10.1146/annurev.soc.23.1.431

Piasna, A., & Drahokoupil, J. (2017). Gender inequalities in the new world of work. *Transfer: European Review of Labour and Research*, 23(3), 313–332. https://doi.org/10.1177/1024258917713839

Pinelli, D., Torre, R., Pace, L., Cassio, L., & Arpaia, A. (2017). *The Recent Reform of the Labour Market in Italy: A Review*. European Economy Discussion Paper No 72. https://ec.europa.eu/info/sites/default/files/economy-finance/dp072_en.pdf

Piriu, A. A. (2022). Globalization and Gender-Specific Patterns in Individual Fertility Decisions. *Population and Development Review*, *48*(1), 129-160. https://doi.org/10.1111/padr.12453

Reimer, S. (1998). Working in a risk society. Transactions of the Institute of British Geographers, 23(1), 116-127.

Schmitt, C. (2012). Labour market integration, occupational uncertainty, and fertility choices in Germany and the UK. *Demographic Research*, *S12*(12), 253-292. https://www.demographic-research.org/special/12/12/

Schneider, D. (2015). The Great Recession, Fertility, and Uncertainty: Evidence From the United States. *Journal of Marriage and Family*, 77(5), 1144-1156. http://www.jstor.org/stable/24582726

Schwabe, H., & Castellacci, F. (2020). Automation, workers' skills and job satisfaction. *PLOS ONE*, *15*(11), e0242929. https://doi.org/10.1371/journal.pone.0242929

Seltzer, N. (2019). Beyond the Great Recession: Labor Market Polarization and Ongoing Fertility Decline in the United States. *Demography*, *56*(4), 1463-1493. https://doi.org/10.1007/s13524-019-00790-6

Sobotka, T., Skirbekk, V., & Philipov, D. (2011). Economic Recession and Fertility in the Developed World. *Population and Development Review*, *37*(2), 267-306. https://doi.org/10.1111/j.1728-4457.2011.00411.x

Szelewa, D., & Polakowski, M. P. (2008). Who cares? Changing patterns of childcare in Central and Eastern Europe. *Journal of European Social Policy*, *18*(2), 115-131. https://doi.org/10.1177/0958928707087589

Tamesberger, D. (2017). Can welfare and labour market regimes explain cross-country differences in the unemployment of young people? *International Labour Review*, *156*(3-4), 443-464. https://doi.org/10.1111/ilr.12040

Traverso, S., Vatiero, M., & Zaninotto, E. (2022). Robots and labor regulation: a cross-country/cross-industry analysis. *Economics of Innovation and New Technology*, 1-23. https://doi.org/10.1080/10438599.2022.2063122

United Nations. Statistical Division. (2008). International Standard industrial classification of all economic activities (ISIC) (No. 4). United Nations Publications.

Vignoli, D., Guetto, R., Bazzani, G., Pirani, E., & Minello, A. (2020). A reflection on economic uncertainty and fertility in Europe: The Narrative Framework. *Genus*, *76*(1). https://doi.org/10.1186/s41118-020-00094-3

Visser, J. (2011). *ICTWSS : Database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts in 34 countries.* Amsterdam Institute for Advanced Labour Studies (AIAS), University of Amsterdam http://www.uva-aias.net/208.

Walther, A. (2006). Regimes of youth transitions. *YOUNG*, *14*(2), 119-139. https://doi.org/10.1177/1103308806062737

Wood, J., Neels, K., & Kil, T. (2014). The educational gradient of childlessness and cohort parity progression in 14 low fertility countries. *Demographic Research*, *31*, 1365-1416. http://www.jstor.org/stable/26350100

Wooldridge, J. M. (2010). Econometric Analysis of Cross Section and Panel Data. The MIT Press. http://www.jstor.org/stable/j.ctt5hhcfr

Yerkes, M. A., & Javornik, J. (2019). Creating capabilities: Childcare policies in comparative perspective. *Journal of European Social Policy*, *29*(4), 529-544. https://doi.org/10.1177/0958928718808421

Appendix

Reclassifying industry

The regional employment structure data are aggregates obtained from the European Union Labour Force Survey microdata. We reclassify them to 16 ISIS categories that we operationalize for the robot data using the correspondence table available through the online resources of the United Nations Statistics Division (see Table 1). As can be seen in the table, in some cases, it involves summing employment for 2 or 3 NACE categories to match the ISIC category.

Imputing regional employment structures

Eurostat anonymizes records where employment in a specific region, industry, and year was above zero but below 1,000 people, i.e. information is missing for such records. As a result, 50% of employment records were initially missing in the data. In the cases when only observations for specific years for a given region-industry are missing, we impute it by drawing a number between 0 and 1000 from a uniform distribution. In the cases when the entire time series for a given region-industry is missing, we impute it with median employment for that industry in the country, normalized to a 0-1000 range. Since our main explanatory measure (described in detail in the section 5.2 in the main text) relies on a sum of employment over industries, it would be impossible to construct it without assumptions about the missing data. We decided to choose the imputation with median instead of the mean, to robustify the imputed data to extreme values in existing data. One should bear in mind that, after imputation, there is a measurement error in our regional employment data. Thus, the regression coefficient corresponding to our main measure will be downward-biased (regression dilution bias; Fuller, 1987).

Reclassifying NUTS 2 codes

The NUTS classification of regions underwent a few reclassifications in its history. Eurostat usually publishes regional data for specific years for regions which were operative depending on then-current NUTS classification. To obtain a balanced panel, we reclassify all regional codes, which simply changed name, to the NUTS 2016 classification, using crosswalks available on the Eurostat web page. For the countries and time frame we consider in our analysis, there are eight cases when two or three regions split or merged resulting in changes in the NUTS classification (see Table 2). In those instances, we sum up/average (depending on a variable) data for the smaller regions to obtain consistent data for the larger region. We exclude 5 French overseas territories with distinct socioeconomic setups, not directly comparable to European regions (Guadeloupe, Martinique, French Guiana, La Reunion, and Mayotte).

Table 1. ISIC-NACE industry codes crosswalk for sectors used in our analysis.

Category	IFR (ISIC)	REGIONAL EMPLOYMENT (na112d)	REGIONAL EMPLOYMENT (nace2d)
All other manufacturing branches/other chemical products n.e.c.	91, 20-21	30, 37, 23	32, 33, 19
Automotive/Other vehicles	29-30	34, 35	29, 30
Basic metals	24	27	24
Construction	F	45	41, 42, 43
Electrical/electronics	26-27	31, 32, 33	26, 27
Electricity, gas, water supply	E	40, 41	35, 36
Food and beverages	10-12	15, 16	10, 11, 12
Glass, ceramics, stone, mineral products (non-automotive)	23	26	23
Industrial machinery	28	29	28
Metal products (non-automotive)	25	28	25
Mining and quarrying	C	10, 11, 12, 13, 14	05, 06, 07, 08, 09
Paper	17-18	21, 22	17, 18
Pharmaceuticals, cosmetics	19	24	20, 21
Rubber and plastic products (non-automotive)	22	25	22
Textiles	13-15	17, 18, 19	13, 14, 15
Wood and furniture	16	20, 36	16, 31

Table 2. NUTS-2 region splits/merges over years (1994-2017).

<table>
<tr><th>1994-1998</th><th>1999</th><th>2000-2001</th><th>2002-2003</th><th>2004</th><th>2005-2010</th><th>2011-2012</th><th>2013-2017</th><th>Action</th></tr>
<tr><td rowspan="2">DE40</td><td rowspan="2">DE40</td><td rowspan="2">DE40</td><td rowspan="2">DE40</td><td>DE41</td><td rowspan="2">DE40</td><td rowspan="2">DE40</td><td rowspan="2">DE40</td><td rowspan="2">sum DE41 and DE42 to DE40</td></tr>
<tr><td>DE42</td></tr>
<tr><td>DEB1</td><td>DEB1</td><td rowspan="3">DEB0</td><td>DEB1</td><td>DEB1</td><td>DEB1</td><td>DEB1</td><td>DEB1</td><td rowspan="3">sum DEB1, DEB2, and DEB3 to DEB0</td></tr>
<tr><td>DEB2</td><td>DEB2</td><td>DEB2</td><td>DEB2</td><td>DEB2</td><td>DEB2</td><td>DEB2</td></tr>
<tr><td>DEB3</td><td>DEB3</td><td>DEB3</td><td>DEB3</td><td>DEB3</td><td>DEB3</td><td>DEB3</td></tr>
<tr><td rowspan="3">DED0</td><td rowspan="3">DED0</td><td>DED2</td><td>DED2</td><td>DED2</td><td>DED2</td><td>DED2</td><td>DED2</td><td rowspan="3">sum DED2, DED4, and DED5 to DED0</td></tr>
<tr><td>DED4</td><td>DED4</td><td>DED4</td><td>DED4</td><td>DED4</td><td>DED4</td></tr>
<tr><td>DED5</td><td>DED5</td><td>DED5</td><td>DED5</td><td>DED5</td><td>DED5</td></tr>
<tr><td>DEE1</td><td>DEE1</td><td>DEE1</td><td>DEE1</td><td>DEE1</td><td rowspan="3">DEE0</td><td rowspan="3">DEE0</td><td rowspan="3">DEE0</td><td rowspan="3">sum DEE1, DEE2, and DEE3 to DEE0</td></tr>
<tr><td>DEE2</td><td>DEE2</td><td>DEE2</td><td>DEE2</td><td>DEE2</td></tr>
<tr><td>DEE3</td><td>DEE3</td><td>DEE3</td><td>DEE3</td><td>DEE3</td></tr>
<tr><td rowspan="2">IT31</td><td>ITH1</td><td>ITH1</td><td>ITH1</td><td>ITH1</td><td>ITH1</td><td>ITH1</td><td>ITH1</td><td rowspan="2">sum ITH1 and ITH2 to IT31</td></tr>
<tr><td>ITH2</td><td>ITH2</td><td>ITH2</td><td>ITH2</td><td>ITH2</td><td>ITH2</td><td>ITH2</td></tr>
<tr><td rowspan="2">UKI1</td><td rowspan="2">UKI1</td><td rowspan="2">UKI1</td><td rowspan="2">UKI1</td><td rowspan="2">UKI1</td><td rowspan="2">UKI1</td><td>UKI3</td><td>UKI3</td><td rowspan="2">sum UKI3 and UKI4 to UKI1</td></tr>
<tr><td>UKI4</td><td>UKI4</td></tr>
<tr><td rowspan="3">UKI2</td><td rowspan="3">UKI2</td><td rowspan="3">UKI2</td><td rowspan="3">UKI2</td><td rowspan="3">UKI2</td><td rowspan="3">UKI2</td><td>UKI5</td><td>UKI5</td><td rowspan="3">sum UKI5, UKI6, and UKI7 to UKI2</td></tr>
<tr><td>UKI6</td><td>UKI6</td></tr>
<tr><td>UKI7</td><td>UKI7</td></tr>
<tr><td rowspan="2">PL12</td><td rowspan="2">PL12</td><td rowspan="2">PL12</td><td rowspan="2">PL12</td><td rowspan="2">PL12</td><td rowspan="2">PL12</td><td rowspan="2">PL12</td><td>PL91</td><td rowspan="2">sum PL91 and PL92 to PL12</td></tr>
<tr><td>PL92</td></tr>
</table>

Table 3. Full basic model results for Germany (see Table 1 in Section 6.1).

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	-0.000159	0.0000438	0.0000217	-0.0000215	-0.000110***	-0.0000484***	-0.00000125
Share of population aged 15-24	-1.141**	-0.821***	-0.424***	0.710***	-0.179**	-0.164***	-0.0135***
Share of population aged 25-49	2.184*	-0.0586	-0.579	1.537***	0.978***	0.0514	-0.0156
Share of population aged 50+	0.522	-0.257*	-0.430**	1.106***	0.141	-0.167***	-0.0225***
Share of highly educated population	-0.00173	-0.00133**	-0.00335***	0.000463	0.00182***	0.000682***	0.0000721***
Ratio of share of highly-educated women to share of highly-educated men	-0.651***	-0.0780**	-0.140**	-0.223***	-0.127***	-0.021	-0.00263*
Square of ratio of share of highly-educated women to highly-educated men	0.522***	0.0711***	0.124***	0.161***	0.0980***	0.0183***	0.00183**
Share of economically active women	-0.000723	-0.000145	0.00125*	-0.000427	-0.000933*	-0.000450**	-0.0000538***
Kleibergen-Paap rk Wald F statistic	347.778	347.778	347.778	347.778	347.778	347.778	347.778
Hansen J p-value	0.4002	0.3592	0.4523	0.0432	0.0281	0.2845	0.2264

*** 1% ** 5% * 10%. N=680, 20 years, 34 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 4. Full basic model results for France (see Table 1 in Section 6.1).

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	0.000026	-0.000102	0.0000935	0.000118	-0.0000115	-0.0000356	0.00000348
Share of population aged 15-24	-3.278	-3.082***	-0.0862	0.299	0.34	0.0384	0.026
Share of population aged 25-49	-7.505***	-3.952***	-1.944**	-0.307	-0.212	-0.189	0.00224
Share of population aged 50+	-6.268***	-2.929***	-1.067*	-0.579	-0.645***	-0.336***	-0.0457***
Share of highly educated population	0.00187	0.000263	0.00035	0.000389	0.000697**	0.000121	0.0000129
Ratio of share of highly-educated women to share of highly-educated men	0.223	-0.0326	-0.106	0.17	0.147**	0.0642**	0.00710**
Square of ratio of share of highly-educated women to highly-educated men	-0.109	0.0116	0.0409	-0.0771*	-0.0637***	-0.0274**	-0.00259**
Share of economically active women	-0.00113	0.000105	0.000387	-0.000880*	-0.000793***	-0.000354***	-0.00000468
Kleibergen-Paap rk Wald F statistic	1042.809	1042.809	1042.809	1042.809	1042.809	1042.809	1042.809
Hansen J p-value	0.6166	0.2884	0.3651	0.4868	0.4660	0.1540	0.8730

*** 1% ** 5% * 10%. N=440, 20 years, 22 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 5. Full basic model results for Italy (see Table 1 in Section 6.1).

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	-0.00118*	-0.000196	-0.000898***	-0.000116	0.00014	-0.0000473	0.00000823
Share of population aged 15-24	-9.167***	-4.185***	-3.894***	0.368	-0.686	-0.461***	-0.0355*
Share of population aged 25-49	-7.001***	-1.823***	-4.355***	-0.810***	0.14	-0.167*	-0.02
Share of population aged 50+	-6.623***	-2.395***	-3.063***	-0.321*	-0.373**	-0.264***	-0.0108
Share of highly educated population	-0.00181	-0.000107	-0.00257**	-0.00181*	0.000255	0.00118***	0.000136*
Ratio of share of highly-educated women to highly-educated men	-0.0448	-0.109	-0.0746	0.105	0.0448	-0.0258	-0.00212
Square of ratio of share of highly-educated women to highly-educated men	0.0536	0.0511*	0.0308	-0.0308	-0.00361	0.0113	0.000552
Share of economically active women	0.00296	0.00197***	0.000202	-0.000201	0.00083	0.0000921	0.0000639
Kleibergen-Paap rk Wald F statistic	175.284	175.284	175.284	175.284	175.284	175.284	175.284
Hansen J p-value	0.2683	0.3285	0.1599	0.7500	0.1742	0.5438	0.3200

*** 1% ** 5% * 10%. N=400, 20 years, 20 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 6. Full basic model results for the UK (see Table 1 in Section 6.1).

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	0.00168	-0.000872	0.000793	0.00133	0.00109	0.000386*	-0.00000172
Share of population aged 15-24	0.555	-2.063***	0.595	2.364***	1.35	0.16	-0.0840***
Share of population aged 25-49	-0.491	-1.086*	-0.437	1.422	0.803	-0.0106	-0.0516*
Share of population aged 50+	2.041	0.0326	0.372	1.462**	0.918	0.032	-0.0430*
Share of highly educated population	0.000193	0.000994	-0.000392	-0.00058	-0.000765**	-0.000104	0.0000304*
Ratio of share of highly-educated women to share of highly-educated men	1.032***	0.213*	0.241*	0.367***	0.224**	0.0436	-0.000287
Square of ratio of share of highly-educated women to highly-educated men	-0.490***	-0.107*	-0.105	-0.169***	-0.110***	-0.0223	-0.0000613
Share of economically active women	-0.00260*	-0.000123	-0.000653	-0.000624	-0.000863**	-0.000277**	-0.0000203
Kleibergen-Paap rk Wald F statistic	137.303	137.303	137.303	137.303	137.303	137.303	137.303
Hansen J p-value	0.0363	0.0847	0.6383	0.0140	0.0815	0.1513	0.0684

*** 1% ** 5% * 10%. N=700, 20 years, 35 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 7. Full basic model results for Poland and Czechia (see Table 1 in Section 6.1).

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	0.000530	0.000104	-0.000436	0.000501	0.000253*	-0.0000469	-0.0000119
Share of population aged 15-24	-1.043	-0.893	0.506	2.092***	-1.640***	-0.801***	-0.0889***
Share of population aged 25-49	-6.482**	-2.873***	-1.501	1.013	-1.432***	-0.683***	-0.0819***
Share of population aged 50+	-3.253***	-1.658***	-0.478	1.379**	-1.273***	-0.616***	-0.0698***
Share of highly educated population	0.00325	-0.00108	0.000824	0.00320***	0.000581	-0.000123	0.0000267
Ratio of share of highly-educated women to share of highly-educated men	0.151	0.0122	-0.263***	0.166	0.171**	0.0228	0.00496*
Square of ratio of share of highly-educated women to highly-educated men	-0.0445	-0.00413	0.104***	-0.0581	-0.0580**	-0.00915	-0.00182*
Share of economically active women	0.00692**	0.00185	0.00518***	0.000411	-0.000553	0.0000953	-0.0000223
Kleibergen-Paap rk Wald F statistic	45.992	45.992	45.992	45.992	45.992	45.992	45.992
Hansen J p-value	0.1429	0.0456	0.0299	0.2654	0.1859	0.1341	0.1430

*** 1% ** 5% * 10%. N=240, 10 years, 24 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 8. Full interaction model results for Germany (see Table 2 in Section 6.2). Interaction of exposure to robots with the initial share of workers out of manufacturing.

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	-0.00220**	-0.00121***	-0.00137***	0.000373	0.000085	-0.0000287	-0.00000116
Exposure to robots # Initial share of workers out of manufacturing	0.0000287**	0.0000176***	0.0000195***	-5.39E-06	-0.00000269	-2.61E-07	-2.46E-09
Share of population aged 15-24	-0.970*	-0.716***	-0.307**	0.678***	-0.195**	-0.166***	-0.0136***
Share of population aged 25-49	2.222*	-0.044	-0.564*	1.544***	0.980***	0.0525	-0.0157
Share of population aged 50+	0.732	-0.134	-0.293	1.075***	0.124	-0.168***	-0.0226***
Share of highly educated population	-0.00101	-0.00088	-0.00285***	0.000306	0.00174***	0.000673***	0.0000722***
Ratio of share of highly-educated women to share of highly-educated men	-0.646***	-0.0742**	-0.136**	-0.225***	-0.128***	-0.0211	-0.00262*
Square of ratio of share of highly-educated women to share of highly-educated men	0.488***	0.0505**	0.101***	0.168***	0.101***	0.0186**	0.00183**
Share of economically active women	-0.00115	-0.000417	0.000951	-0.00033	-0.000887*	-0.000444**	-0.0000539***
Kleibergen-Paap rk Wald F statistic	766.125	766.125	766.125	766.125	766.125	766.125	766.125
Hansen J p-value	0.1929	0.0330	0.0706	0.1691	0.1063	0.4316	0.2074

*** 1% ** 5% * 10%. N=680, 20 years, 34 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 9. Full interaction model results for France (see Table 2 in Section 6.2). Interaction of exposure to robots with the initial share of workers out of manufacturing.

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	0.00163	0.000616	0.00212	0.000125	-0.000815	-0.000453**	-0.0000814*
Exposure to robots # Initial share of workers out of manufacturing	-0.0000231	-0.0000102	-0.0000289	-1.85E-07	0.0000114	0.00000589*	0.00000120*
Share of population aged 15-24	-3.384	-3.126***	-0.205	0.294	0.383	0.0605	0.0307
Share of population aged 25-49	-7.723***	-4.047***	-2.212**	-0.31	-0.109	-0.135	0.0133
Share of population aged 50+	-6.429***	-3.001***	-1.272**	-0.579	-0.563***	-0.294***	-0.0371***
Share of highly educated population	0.00191	0.000283	0.000402	0.000392	0.000679**	0.000112	0.000011
Ratio of share of highly-educated women to share of highly-educated men	0.251	-0.0215	-0.0753	0.171	0.136**	0.0586**	0.00590*
Square of ratio of share of highly-educated women to share of highly-educated men	-0.12	0.00693	0.0282	-0.0777	-0.0592**	-0.0250**	-0.00209*
Share of economically active women	-0.00122	0.0000695	0.000292	-0.000887*	-0.000762***	-0.000338***	-0.00000112
Kleibergen-Paap rk Wald F statistic	443.790	443.790	443.790	443.790	443.790	443.790	443.790
Hansen J p-value	0.5146	0.1284	0.1813	0.3136	0.2227	0.4156	0.8597

*** 1% ** 5% * 10%. N=440, 20 years, 22 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 10. Full interaction model results for Italy (see Table 2 in Section 6.2). Interaction of exposure to robots with the initial share of workers out of manufacturing.

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	-0.00264	-0.000509	-0.00201	-0.000852	0.000687	0.000390**	-0.000127**
Exposure to robots # Initial share of workers out of manufacturing	0.0000216	0.00000471	0.0000157	0.0000104	-0.00000734	-0.00000598**	0.00000186***
Share of population aged 15-24	-9.648***	-4.294***	-4.221***	0.155	-0.551	-0.346***	-0.0720***
Share of population aged 25-49	-7.148***	-1.855***	-4.464***	-0.882***	0.192	-0.125	-0.0330**
Share of population aged 50+	-6.888***	-2.454***	-3.251***	-0.445*	-0.289	-0.194***	-0.0326***
Share of highly educated population	-0.00252	-0.000274	-0.00302***	-0.00210**	0.00041	0.00132***	0.0000898
Ratio of share of highly-educated women to share of highly-educated men	-0.0113	-0.102	-0.0507	0.121*	0.034	-0.0347	0.000651
Square of ratio of share of highly-educated women to share of highly-educated men	0.0419	0.0485	0.0225	-0.0362	0.0000231	0.0143*	-0.000397
Share of economically active women	0.00299	0.00198***	0.000197	-0.000208	0.000852	0.000105	0.0000606
Kleibergen-Paap rk Wald F statistic	188.524	188.524	188.524	188.524	188.524	188.524	188.524
Hansen J p-value	0.2720	0.1686	0.1761	0.6730	0.4647	0.1289	0.2605

*** 1% ** 5% * 10%. N=400, 20 years, 20 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 11. Full interaction model results for the UK (see Table 2 in Section 6.2). Interaction of exposure to robots with the initial share of workers out of manufacturing.

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	-0.0223**	-0.00584	-0.000935	-0.000879	-0.00384	-0.00155	0.000116
Exposure to robots # Initial share of workers out of manufacturing	0.000311**	0.0000647	0.0000225	0.0000278	0.0000636	0.0000251	-0.00000161
Share of population aged 15-24	0.814	-2.013***	0.613	2.400***	1.409	0.182	-0.0841***
Share of population aged 25-49	-0.458	-1.082*	-0.436	1.436	0.816	-0.00704	-0.0507*
Share of population aged 50+	2.117	0.0456	0.377	1.479**	0.939	0.0391	-0.0424*
Share of highly educated population	-0.000215	0.000912	-0.000421	-0.000624	-0.000852***	-0.000137	0.0000317*
Ratio of share of highly-educated women to share of highly-educated men	1.100***	0.227*	0.246*	0.375***	0.239**	0.0492	-0.000415
Square of ratio of share of highly-educated women to share of highly-educated men	-0.522***	-0.114**	-0.107	-0.173***	-0.117***	-0.025	0.000000392
Share of economically active women	-0.00232	-0.0000639	-0.000633	-0.000603	-0.000809**	-0.000255*	-0.0000222
Kleibergen-Paap rk Wald F statistic	118.083	118.083	118.083	118.083	118.083	118.083	118.083
Hansen J p-value	0.0505	0.1054	0.4370	0.1379	0.1993	0.2458	0.1026

*** 1% ** 5% * 10%. N=700, 20 years, 35 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 12. Full interaction model results for Poland and Czechia (see Table 2 in Section 6.2). Interaction of exposure to robots with the initial share of workers out of manufacturing.

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	0.00627	0.00295***	-0.00337**	0.00275	0.00251***	0.0000358	0.00000680
Exposure to robots # Initial share of workers out of manufacturing	-0.0000961*	-0.0000466***	0.0000472**	-0.0000392	-0.0000368***	-0.00000105	-0.000000341
Share of population aged 15-24	-3.114*	-1.784***	1.329*	1.092	-2.324***	-0.789***	-0.0990***
Share of population aged 25-49	-7.636***	-3.317***	-1.134	0.383	-1.763***	-0.660***	-0.0889***
Share of population aged 50+	-5.057***	-2.442***	0.252	0.518	-1.877***	-0.608***	-0.0785***
Share of highly educated population	0.00268	-0.00129	0.000988	0.00287***	0.000427	-0.000108	0.0000229
Ratio of share of highly-educated women to share of highly-educated men	0.0472	-0.0415	-0.206***	0.128	0.128*	0.0206	0.00468*
Square of ratio of share of highly-educated women to share of highly-educated men	-0.00664	0.0155	0.0831***	-0.0444	-0.0423*	-0.00834	-0.00172*
Share of economically active women	0.00687**	0.00181*	0.00521***	0.000402	-0.000579	0.0000925	-0.0000223
Kleibergen-Paap rk Wald F statistic	113.238	113.238	113.238	113.238	113.238	113.238	113.238
Hansen J p-value	0.5701	0.2830	0.2720	0.5985	0.3052	0.2425	0.5084

*** 1% ** 5% * 10%. N=240, 10 years, 24 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 13. Full interaction model results for Germany (see Table 3 in Section 6.3). Interaction of exposure to robots with the initial share of workers employed out of manufacturing and interaction of exposure to robots with the initial ratio of women's to men's employment share in manufacturing.

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	0.000791	-0.00041	-0.000178	0.00064	0.000532	0.000000707	0.00000748
Exposure to robots # Initial share of workers out of manufacturing	0.00000794	0.0000119**	0.0000114**	-7.27E-06	-5.84E-06	-0.000000475	-6.29E-08
Exposure to robots # Initial ratio of women's versus men's share in manufacturing	-0.00350***	-0.000933*	-0.00141***	-0.000308	-0.000520**	-0.000035	-0.00001
Share of population aged 15-24	-0.891*	-0.695***	-0.274*	0.685***	-0.183**	-0.165***	-0.0133***
Share of population aged 25-49	2.960***	0.148	-0.258	1.611***	1.088***	0.0587	-0.0136
Share of population aged 50+	1.117**	-0.0347	-0.131	1.109***	0.18	-0.165***	-0.0215***
Share of highly educated population	0.000668	-0.000426	-0.00218***	0.00045	0.00199***	0.000692***	0.0000770***
Ratio of share of highly-educated women to share of highly-educated men	-0.558***	-0.0505	-0.101**	-0.217***	-0.115***	-0.0201	-0.00237
Square of ratio of share of highly-educated women to share of highly-educated men	0.426***	0.0338	0.0755***	0.162***	0.0920***	0.0179**	0.00165*
Share of economically active women	-0.00279	-0.000858*	0.000298	-0.000472	-0.00113**	-0.000462**	-0.0000586***
Kleibergen-Paap rk Wald F statistic	1091.572	1091.572	1091.572	1091.572	1091.572	1091.572	1091.572
Hansen J p-value	0.2375	0.1597	0.2198	0.2598	0.2384	0.4486	0.2395

*** 1% ** 5% * 10%. N=680, 20 years, 34 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 14. Full interaction model results for France (see Table 3 in Section 6.3). Interaction of exposure to robots with the initial share of workers employed out of manufacturing and interaction of exposure to robots with the initial ratio of women's to men's employment share in manufacturing.

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	0.0049	0.00188*	0.00352**	0.000801	-0.000976*	-0.000558**	-0.000122**
Exposure to robots # Initial share of workers out of manufacturing	-0.0000207	-0.00000593	-0.0000278	-1.09E-06	0.00001	0.00000476*	0.000000961*
Exposure to robots # Initial ratio of women's versus men's share in manufacturing	-0.00681**	-0.00307***	-0.00292*	-0.00122	0.000492	0.000357	0.000112**
Share of population aged 15-24	-3.816	-3.298***	-0.391	0.207	0.407	0.0764	0.0365**
Share of population aged 25-49	-8.312***	-4.279***	-2.465***	-0.43	-0.0775	-0.114	0.0209
Share of population aged 50+	-6.641***	-3.077***	-1.363**	-0.626	-0.554***	-0.289***	-0.0348***
Share of highly educated population	0.00189	0.000259	0.000392	0.000393	0.000685**	0.000117	0.0000121
Ratio of share of highly-educated women to share of highly-educated men	0.209	-0.0463	-0.0928	0.166	0.141**	0.0626**	0.00695*
Square of ratio of share of highly-educated women to share of highly-educated men	-0.103	0.017	0.0353	-0.0757	-0.0612**	-0.0267**	-0.00252*
Share of economically active women	-0.00146	-0.0000106	0.00019	-0.000939*	-0.000753***	-0.000333***	0.00000123
Kleibergen-Paap rk Wald F statistic	1690.910	1690.910	1690.910	1690.910	1690.910	1690.910	1690.910
Hansen J p-value	0.5372	0.4071	0.3465	0.5274	0.3034	0.6399	0.3241

*** 1% ** 5% * 10%. N=440, 20 years, 22 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 15. Full interaction model results for Italy (see Table 3 in Section 6.3). I Interaction of exposure to robots with the initial share of workers employed out of manufacturing and interaction of exposure to robots with the initial ratio of women's to men's employment share in manufacturing.

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	0.0144***	0.00535***	0.00670***	-0.000561	0.000377	0.00116***	-0.000144*
Exposure to robots # Initial share of workers out of manufacturing	-0.000113**	-0.0000422**	-0.0000539***	9.85E-06	-4.66E-06	-0.0000121***	0.00000195**
Exposure to robots # Initial ratio of women's versus men's share in manufacturing	-0.0137***	-0.00462***	-0.00693***	-0.000394	0.000249	-0.000605***	0.0000188
Share of population aged 15-24	-9.652***	-4.258***	-4.167***	0.0656	-0.566	-0.344**	-0.0695***
Share of population aged 25-49	-7.275***	-1.887***	-4.520***	-0.907***	0.193	-0.129	-0.0322**
Share of population aged 50+	-7.050***	-2.489***	-3.310***	-0.494**	-0.291*	-0.200***	-0.0311***
Share of highly educated population	-0.00482	-0.000992	-0.00407***	-0.00232**	0.000416	0.00122***	0.000097
Ratio of share of highly-educated women to share of highly-educated men	0.0518	-0.0827	-0.0215	0.128*	0.0334	-0.0321	0.000403
Square of ratio of share of highly-educated women to share of highly-educated men	0.0231	0.043	0.0141	-0.0388	0.000114	0.0135	-0.000313
Share of economically active women	0.00216	0.00169**	-0.000252	-0.00021	0.000878*	0.0000692	0.0000614
Kleibergen-Paap rk Wald F statistic	2699.745	2699.745	2699.745	2699.745	2699.745	2699.745	2699.745
Hansen J p-value	x	x	x	x	x	x	x

*** 1% ** 5% * 10%. N=400, 20 years, 20 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 16. Full interaction model results for the UK (see Table 3 in Section 6.3). Interaction of exposure to robots with the initial share of workers employed out of manufacturing and interaction of exposure to robots with the initial ratio of women's to men's employment share in manufacturing.

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	-0.0378***	-0.0103	-0.00187	-0.00319	-0.00486	-0.00202	-0.000238
Exposure to robots # Initial share of workers out of manufacturing	0.000420***	0.0000973	0.0000303	0.0000433	0.0000692	0.0000277	0.000000923
Exposure to robots # Initial ratio of women's versus men's share in manufacturing	0.0187*	0.00487	0.000909	0.00303	0.00177	0.000732	0.000426**
Share of population aged 15-24	1.808	-1.733***	0.66	2.552***	1.484	0.217	-0.0622**
Share of population aged 25-49	0.0841	-0.925	-0.412	1.518*	0.852	0.0115	-0.0391
Share of population aged 50+	2.541	0.172	0.395	1.541**	0.964	0.0529	-0.0334
Share of highly educated population	-0.000252	0.000885	-0.000423	-0.000623	-0.000839***	-0.000135	0.0000313**
Ratio of share of highly-educated women to share of highly-educated men	1.062***	0.221*	0.244*	0.367***	0.231**	0.0468	-0.00144
Square of ratio of share of highly-educated women to share of highly-educated men	-0.506***	-0.111**	-0.106	-0.170***	-0.113***	-0.0239	0.000437
Share of economically active women	-0.0021	-0.00000855	-0.000618	-0.000567	-0.000786**	-0.000247*	-0.0000168
Kleibergen-Paap rk Wald F statistic	140.698	140.698	140.698	140.698	140.698	140.698	140.698
Hansen J p-value	0.2151	0.1699	0.3893	0.0803	0.0995	0.3877	0.3232

*** 1% ** 5% * 10%. N=700, 20 years, 35 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 17. Full interaction model results for Poland and Czechia (see Table 3 in Section 6.3). Interaction of exposure to robots with the initial share of workers employed out of manufacturing and interaction of exposure to robots with the initial ratio of women’s to men’s employment share in manufacturing.

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	0.00195	0.000411	-0.00436	0.00246	0.00178**	-0.000134	-0.0000227
Exposure to robots # Initial share of workers out of manufacturing	-0.0000722	-0.0000313*	0.0000517*	-0.0000380	-0.0000319***	0.000000178	-9.92e-08
Exposure to robots # Initial ratio of women's versus men's share in manufacturing	0.00402	0.00228***	0.000985	0.000298	0.000625	0.000137	0.0000230
Share of population aged 15-24	-2.668	-1.465***	1.391*	1.099	-2.214***	-0.761***	-0.0916***
Share of population aged 25-49	-7.436***	-3.153***	-1.119	0.377	-1.702***	-0.644***	-0.0838***
Share of population aged 50+	-4.702***	-2.185***	0.299	0.523	-1.787***	-0.585***	-0.0724***
Share of highly educated population	0.00316	-0.000990	0.00109	0.00289**	0.000517	-0.0000873	0.0000279
Ratio of share of highly-educated women to share of highly-educated men	-0.000703	-0.0676	-0.219***	0.125	0.122*	0.0193	0.00444*
Square of ratio of share of highly-educated women to share of highly-educated men	0.0120	0.0258*	0.0880***	-0.0430	-0.0397*	-0.00782	-0.00162*
Share of economically active women	0.00732**	0.00207**	0.00532***	0.000436	-0.000510	0.000108	-0.0000199
Kleibergen-Paap rk Wald F statistic	3345.217	3345.217	3345.217	3345.217	3345.217	3345.217	3345.217
Hansen J p-value	x	x	x	x	x	x	x

*** 1% ** 5% * 10%. N=240, 10 years, 24 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 18. Full interaction model results for Germany (see Table 4 in Section 6.4). Interaction of exposure to robots with the share of highly educated population (ISCED 5-8).

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	-0.00161***	-0.000271*	-0.000111	-0.000452**	-0.000435***	-0.000142***	-0.0000102**
Exposure to robots # Share of highly educated population	0.0000538***	0.0000117**	0.00000531	0.0000159**	0.0000118***	0.00000339**	0.000000334**
Share of population aged 15-24	-1.009*	-0.792***	-0.411***	0.750***	-0.149**	-0.156***	-0.0127***
Share of population aged 25-49	1.616	-0.182	-0.622	1.368***	0.844***	0.0133	-0.0190*
Share of population aged 50+	0.486	-0.265**	-0.425**	1.094***	0.127	-0.170***	-0.0227***
Share of highly educated population	-0.00789***	-0.00267***	-0.00398***	-0.00136**	0.000484	0.000298	0.0000338
Ratio of share of highly-educated women to share of highly-educated men	-0.555***	-0.0571	-0.131**	-0.195***	-0.106***	-0.0147	-0.00203
Square of ratio of share of highly-educated women to share of highly-educated men	0.468***	0.0594**	0.119***	0.145***	0.0861***	0.0148*	0.00149*
Share of economically active women	0.000785	0.000183	0.00142**	0.0000187	-0.000614	-0.000357*	-0.0000443**
Kleibergen-Paap rk Wald F statistic	903.478	903.478	903.478	903.478	903.478	903.478	903.478
Hansen J p-value	0.1312	0.3038	0.1785	0.2023	0.0447	0.1118	0.2687

*** 1% ** 5% * 10%. N=680, 20 years, 34 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 19. Full interaction model results for France (see Table 4 in Section 6.4). Interaction of exposure to robots with the share of highly educated population (ISCED 5-8).

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	0.00150**	0.000579**	0.00105***	0.000185	-0.000274	-0.000154**	-0.00000853
Exposure to robots # Share of highly educated population	-0.0000536**	-0.0000248***	-0.0000345**	-0.00000249	0.00000939	0.00000424*	0.000000421
Share of population aged 15-24	-2.923	-2.918***	0.148	0.315	0.275	0.00877	0.023
Share of population aged 25-49	-7.233***	-3.825***	-1.767**	-0.295	-0.261	-0.211	0.00000488
Share of population aged 50+	-6.211***	-2.903***	-1.032*	-0.576	-0.654***	-0.340***	-0.0461***
Share of highly educated population	0.00403*	0.00126*	0.00174*	0.00049	0.000319	-0.0000491	-0.00000386
Ratio of share of highly-educated women to share of highly-educated men	0.363	0.0322	-0.0171	0.176*	0.123**	0.0536*	0.00608
Square of ratio of share of highly-educated women to share of highly-educated men	-0.171	-0.0169	0.00187	-0.0801*	-0.0532***	-0.0227*	-0.00214
Share of economically active women	-0.00171	-0.000164	0.0000215	-0.000909*	-0.000696***	-0.000311***	-0.000000551
Kleibergen-Paap rk Wald F statistic	1467.181	1467.181	1467.181	1467.181	1467.181	1467.181	1467.181
Hansen J p-value	0.2501	0.3655	0.1157	0.1607	0.2895	0.6744	0.4483

*** 1% ** 5% * 10%. N=440, 20 years, 22 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 20. Full interaction model results for Italy (see Table 4 in Section 6.4). Interaction of exposure to robots with the share of highly educated population (ISCED 5-8).

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	-0.00292*	-0.00102	-0.00124**	0.000195	-0.00016	-0.000203*	0.00000717
Exposure to robots # Share of highly educated population	0.000096	0.0000431*	0.0000183	-0.0000135	0.0000181	0.00000881**	-0.000000187
Share of population aged 15-24	-9.434***	-4.280***	-3.935***	0.367	-0.752	-0.487***	-0.0325
Share of population aged 25-49	-7.489***	-2.044***	-4.449***	-0.738**	0.0488	-0.211**	-0.0193
Share of population aged 50+	-6.478***	-2.325***	-3.034***	-0.350**	-0.349**	-0.251***	-0.0106
Share of highly educated population	-0.00806*	-0.00284*	-0.00373**	-0.00106	-0.00097	0.000602	0.000156
Ratio of share of highly-educated women to share of highly-educated men	0.00501	-0.0872	-0.0654	0.0993	0.0545	-0.0212	-0.00228
Square of ratio of share of highly-educated women to share of highly-educated men	0.0334	0.0423*	0.0271	-0.0285	-0.00762	0.00939	0.000624
Share of economically active women	0.00324	0.00207***	0.000244	-0.000195	0.0009	0.00012	0.0000604
Kleibergen-Paap rk Wald F statistic	393.028	393.028	393.028	393.028	393.028	393.028	393.028
Hansen J p-value	0.4075	0.2984	0.6674	0.3396	0.1435	0.3712	0.3528

*** 1% ** 5% * 10%. N=400, 20 years, 20 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 21. Full interaction model results for the UK (see Table 4 in Section 6.4). Interaction of exposure to robots with the share of highly educated population (ISCED 5-8).

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	0.000259	-0.000494	0.00171*	0.000626	0.0000798	-0.00016	-0.0000943**
Exposure to robots # Share of highly educated population	0.0000315	-0.00000892	-0.000023	0.0000146	0.0000236	0.0000124	0.00000205***
Share of population aged 15-24	0.646	-2.084***	0.553	2.414***	1.408	0.193	-0.0781***
Share of population aged 25-49	-0.342	-1.124*	-0.525	1.498*	0.906	0.0454	-0.0419
Share of population aged 50+	2.121	0.0141	0.333	1.505**	0.97	0.0612	-0.0378
Share of highly educated population	-0.000237	0.00111	-0.0000925	-0.000785	-0.00108**	-0.000271**	0.00000235
Ratio of share of highly-educated women to share of highly-educated men	1.026***	0.216*	0.251*	0.365***	0.217**	0.0404	-0.000719
Square of ratio of share of highly-educated women to share of highly-educated men	-0.486***	-0.109*	-0.11	-0.168***	-0.106**	-0.0205	0.000192
Share of economically active women	-0.00254	-0.000141	-0.000703	-0.000599	-0.000816**	-0.000253*	-0.0000166
Kleibergen-Paap rk Wald F statistic	106.778	106.778	106.778	106.778	106.778	106.778	106.778
Hansen J p-value	0.0832	0.3896	0.1509	0.1971	0.1096	0.0760	0.2256

*** 1% ** 5% * 10%. N=700, 20 years, 35 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 22. Full interaction model results for Poland and Czechia (see Table 4 in Section 6.4). Interaction of exposure to robots with the share of highly educated population (ISCED 5-8).

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	-0.000180	0.000386	-0.00182***	0.000231	0.000660***	0.0000187	-0.0000343***
Exposure to robots # Share of highly educated population	0.0000213	-0.0000195	0.0000727**	0.00000502	-0.0000241**	-0.00000291	0.00000119**
Share of population aged 15-24	-1.279	-1.324*	1.526**	1.855*	-2.075***	-0.825***	-0.0714***
Share of population aged 25-49	-6.913***	-3.142***	-1.102	0.726	-1.663***	-0.681***	-0.0746***
Share of population aged 50+	-3.418**	-2.027***	0.425	1.195	-1.650***	-0.638***	-0.0544***
Share of highly educated population	0.00276	-0.00102	0.000252	0.00297***	0.000713*	-0.0000897	0.0000178
Ratio of share of highly-educated women to share of highly-educated men	0.188	-0.00249	-0.190***	0.180	0.150**	0.0194	0.00613**
Square of ratio of share of highly-educated women to share of highly-educated men	-0.0585	0.00129	0.0770***	-0.0635	-0.0502*	-0.00787	-0.00225**
Share of economically active women	0.00684**	0.00196*	0.00479***	0.000406	-0.000420	0.000109	-0.0000286
Kleibergen-Paap rk Wald F statistic	204.214	204.214	204.214	204.214	204.214	204.214	204.214
Hansen J p-value	0.3575	0.3414	0.3279	0.5557	0.3803	0.3581	0.2856

*** 1% ** 5% * 10%. N=240, 10 years, 24 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 23. Full interaction model results for Germany (see Table 5 in Section 6.5). Interaction of exposure to robots with the share of workers employed in technology and knowledge-intensive sectors.

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	-0.0000577	0.0000956	0.000152**	-0.0000296	-0.000149***	-0.0000528***	-0.00000342*
Exposure to robots # Share of workers employed in technology- and knowledge-intensive sectors	-0.0000186	-0.0000136	-0.0000498***	0.00000508	0.0000223*	0.00000411	0.00000104**
Share of population aged 15-24	-1.140**	-0.826***	-0.540***	0.713***	-0.106	-0.147***	-0.0105**
Share of population aged 25-49	2.088*	-0.144	-0.784*	1.582***	1.055***	0.0626	-0.0118
Share of population aged 50+	0.482	-0.301*	-0.607***	1.130***	0.229*	-0.149***	-0.0186***
Share of highly educated population	-0.00175	-0.00129**	-0.00282***	0.000422	0.00149***	0.000607***	0.0000585***
Ratio of share of highly-educated women to share of highly-educated men	-0.661***	-0.0830**	-0.149**	-0.222***	-0.126***	-0.0211	-0.00251*
Square of ratio of share of highly-educated women to share of highly-educated men	0.523***	0.0720***	0.128***	0.161***	0.0958***	0.0178**	0.00172**
Share of economically active women	-0.000677	-0.000156	0.000951	-0.000406	-0.00073	-0.000402**	-0.0000456**
Share of workers employed in technology- and knowledge-intensive sectors	0.00563	0.00352	0.00432**	-0.00126	-0.0000482	0.000293	-0.0000361
Kleibergen-Paap rk Wald F statistic	414.164	414.164	414.164	414.164	414.164	414.164	414.164
Hansen J p-value	0.2354	0.5993	0.0961	0.1332	0.1012	0.1885	0.0672

*** 1% ** 5% * 10%. N=680, 20 years, 34 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 24. Full interaction model results for France (see Table 5 in Section 6.5). Interaction of exposure to robots with the share of workers employed in technology and knowledge-intensive sectors.

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	-0.000147	-0.000187*	0.0000601	0.00013	-0.0000432	-0.0000720***	-0.00000177
Exposure to robots # Share of workers employed in technology- and knowledge-intensive sectors	0.0000721	0.0000333	0.0000178	-1.27E-06	0.0000114	0.0000115*	0.00000163
Share of population aged 15-24	-3.397	-3.083***	-0.134	0.265	0.328	0.0253	0.0271
Share of population aged 25-49	-7.336***	-3.849***	-1.911**	-0.326	-0.182	-0.158	0.00782
Share of population aged 50+	-6.092***	-2.814***	-1.039*	-0.607	-0.611***	-0.300***	-0.0389***
Share of highly educated population	0.00179	0.000256	0.000316	0.000368	0.000690*	0.000118	0.0000139
Ratio of share of highly-educated women to share of highly-educated men	0.225	-0.0403	-0.103	0.175*	0.147***	0.0642**	0.00663*
Square of ratio of share of highly-educated women to share of highly-educated men	-0.109	0.0149	0.04	-0.0791*	-0.0634***	-0.0273**	-0.00240*
Share of economically active women	-0.00103	0.000161	0.000415	-0.000883*	-0.000779***	-0.000344***	-0.00000262
Share of workers employed in technology- and knowledge-intensive sectors	-0.00207	-0.00183	-0.000152	0.000656	-0.000469	-0.000504	-0.000116
Kleibergen-Paap rk Wald F statistic	1620.387	1620.387	1620.387	1620.387	1620.387	1620.387	1620.387
Hansen J p-value	0.4884	0.4575	0.4411	0.6228	0.5744	0.5741	0.5064

*** 1% ** 5% * 10%. N=440, 20 years, 22 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 25. Full interaction model results for Italy (see Table 5 in Section 6.5). Interaction of exposure to robots with the share of workers employed in technology and knowledge-intensive sectors.

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	-0.00116*	-0.000131	-0.00117***	-0.000172	0.000373***	-0.00000882	0.00000238
Exposure to robots # Share of workers employed in technology- and knowledge-intensive sectors	0.00000518	-0.0000191	0.0000995	0.0000193	-0.0000753	-0.0000135	0.00000231
Share of population aged 15-24	-9.110***	-4.234***	-3.602***	0.452	-0.918**	-0.497***	-0.0342
Share of population aged 25-49	-6.932***	-1.848***	-4.149***	-0.747**	-0.0103	-0.190**	-0.02
Share of population aged 50+	-6.601***	-2.414***	-2.950***	-0.291	-0.460***	-0.278***	-0.00995
Share of highly educated population	-0.00172	-0.000135	-0.00237**	-0.00171*	0.0000626	0.00116***	0.000128*
Ratio of share of highly-educated women to share of highly-educated men	-0.0485	-0.105	-0.0995	0.0994	0.0637	-0.0226	-0.00246
Square of ratio of share of highly-educated women to share of highly-educated men	0.054	0.0491*	0.0405	-0.0288	-0.0112	0.00994	0.000766
Share of economically active women	0.0033	0.00199**	0.000503	-0.0000225	0.000648	0.0000738	0.000046
Share of workers employed in technology- and knowledge-intensive sectors	-0.00621	0.000756	-0.0111**	-0.00445	0.00792**	0.00111	0.000212
Kleibergen-Paap rk Wald F statistic	1518.104	1518.104	1518.104	1518.104	1518.104	1518.104	1518.104
Hansen J p-value	0.4369	0.4616	0.3405	0.5515	0.2274	0.3733	0.2997

*** 1% ** 5% * 10%. N=400, 20 years, 20 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 26. Full interaction model results for the UK (see Table 5 in Section 6.5). Interaction of exposure to robots with the share of workers employed in technology and knowledge-intensive sectors.

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	0.00161	-0.000795	0.00122	0.00151	0.000712	0.000163	-0.00000639
Exposure to robots # Share of workers employed in technology- and knowledge-intensive sectors	0.00000614	0.00000432	-0.000202*	-0.0000451	0.000123	0.0000709*	-6.81E-08
Share of population aged 15-24	0.495	-2.144***	0.293	2.333**	1.564*	0.27	-0.0831***
Share of population aged 25-49	-0.679	-1.280*	-0.924	1.439	1.139	0.146	-0.0507*
Share of population aged 50+	1.941	-0.0794	0.119	1.468**	1.102	0.118	-0.0422*
Share of highly educated population	0.0000447	0.000878	-0.000413	-0.000479	-0.000754**	-0.000123	0.0000299
Ratio of share of highly-educated women to share of highly-educated men	1.003***	0.182	0.186	0.373***	0.264***	0.0614*	-0.000105
Square of ratio of share of highly-educated women to share of highly-educated men	-0.474***	-0.0908*	-0.0786	-0.173***	-0.129***	-0.0306**	-0.000151
Share of economically active women	-0.00270*	-0.000211	-0.000952*	-0.00061	-0.000678*	-0.00019	-0.0000206
Share of workers employed in technology- and knowledge-intensive sectors	0.00376	0.00340*	0.00706***	-0.00106	-0.00465**	-0.00199***	-0.00000187
Kleibergen-Paap rk Wald F statistic	113.586	113.586	113.586	113.586	113.586	113.586	113.586
Hansen J p-value	0.0949	0.2479	0.3943	0.1157	0.2888	0.3732	0.1786

*** 1% ** 5% * 10%. N=700, 20 years, 35 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

Table 27. Full interaction model results for Poland and Czechia (see Table 5 in Section 6.5). Interaction of exposure to robots with the share of workers employed in technology and knowledge-intensive sectors.

Covariate	TFR	FR 20-24	FR 25-29	FR 30-34	FR 35-39	FR 40-44	FR 45+
Exposure to robots	0.00119	0.000252	-0.000470	0.000960	0.000393*	-0.0000861**	-0.0000300***
Exposure to robots # Share of workers employed in technology- and knowledge-intensive sectors	-0.000313	-0.0000393	-0.0000320	-0.000215	-0.0000573	0.0000171	0.00000623**
Share of population aged 15-24	-2.890	-1.026	0.0226	0.862	-1.920***	-0.683***	-0.0503
Share of population aged 25-49	-8.137***	-2.969***	-1.901	-0.0993	-1.689***	-0.589***	-0.0536*
Share of population aged 50+	-4.727**	-1.767***	-0.889	0.403	-1.491***	-0.517***	-0.0369
Share of highly educated population	0.00188	-0.00116	0.000722	0.00223**	0.000320	-0.0000818	0.0000352
Ratio of share of highly-educated women to share of highly-educated men	0.167	0.0100	-0.261***	0.177	0.174***	0.0232	0.00539**
Square of ratio of share of highly-educated women to share of highly-educated men	-0.0521	-0.00350	0.103***	-0.0635	-0.0594**	-0.00917*	-0.00193**
Share of economically active women	0.00730**	0.00189*	0.00523***	0.000670	-0.000488	0.0000739	-0.0000298
Share of workers employed in technology- and knowledge-intensive sectors	0.0161*	0.00161	-0.00128	0.0117***	0.00355***	-0.000282	-0.0000526
Kleibergen-Paap rk Wald F statistic	94.567	94.567	94.567	94.567	94.567	94.567	94.567
Hansen J p-value	0.2895	0.3902	0.2151	0.4784	0.3056	0.6450	0.4738

*** 1% ** 5% * 10%. N=240, 10 years, 24 NUTS2 regions. Further controls include yearly dummies (partialled out). Standard errors are clustered at region level.

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