Robots, jobs, and optimal fertility timing

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Abstract

This paper examines how industrial robots influence the timing of childbirth in Europe. Higher exposure to robots is associated with earlier fertility in low- and high-skilled regional labor markets and with a delay in medium-skilled ones. The underlying mechanisms are rationalized through a model of fertility, parameterized with data on individuals' expectations about the displacement and creation of jobs due to automation. Variations in the simulated timing of childbirth are associated with corresponding changes in childlessness rates. The results establish a link between the Routine-Biased Technological Change hypothesis and demographic behavior.

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1 Introduction

Industrial automation is transforming the global economy by reshaping job markets and altering labor demand. Unlike the temporary disruptions caused by economic recessions or market shocks, these technological advances can lead to structural changes in individuals' employment prospects, permanently influencing life-course choices. Although there is lively debate regarding the effects of robots on labor (Graetz and Michaels 2018, Acemoglu and Restrepo 2020, Dauth et al. 2021), these economic transformations may also affect various aspects of family formation, including marriage, household composition, and timing of childbirth.

This paper examines how industrial robots affect fertility timing decisions—a topic increasingly central to European policy debates due to the trend toward delayed childbearing, yet often considered in isolation from recent technological progress. Adopting a shift-share measure of regional exposure, the findings indicate that, overall, robot adoption has no significant effect on the average age at first birth. However, its impact varies sharply with local skill composition: automation leads to earlier fertility in regions with large concentrations of low- and high-skilled workers, and to a postponement effect for mid-skill populations. Age-specific fertility rates show that at the skill extremes, births rise among younger cohorts and fall at older ages, offsetting across the reproductive span so that total fertility remains broadly stable, whereas the opposite pattern holds for medium-skilled groups.

A two-stage least squares analysis, leveraging cross-country correlations in robot usage, mitigates reverse causality concerns between automation and demographic outcomes. Robustness checks take into account industry and country effects, alternative education measures, time-varying labor and welfare regimes, cyclicality, and other innovation metrics. Finally, an event-study approach exploiting growth rate differences in robot adoption across country groups reveals no significant pre-trends in the regional mean age at first birth.

The relationship between robotization and the timing of fertility, which follows an inverse U-shape with respect to education, parallels the impact of robot adoption on employment, as documented by Dixon et al. (2021). Such employment polarization arises from the process known as "Routine-Biased Technological Change" (Autor et al. 2006; Goos et al. 2009), whereby routine middle-skilled tasks become automated, heightening demand for non-routine jobs. The latter include those requiring advanced cognitive skills, such as problem solving and creativity, common in highly educated professions, as well as those requiring interpersonal and adaptive abilities, such as empathy and nimbleness, often associated with lower-skilled jobs.[1]

[1]This view replaced the earlier "Skill-Biased Technological Change" hypothesis proposed by Katz and

Two mechanisms may therefore explain the findings. First, economic models suggest that greater uncertainty can prompt individuals to delay having children (Ranjan 1999). In this context, job insecurity among workers at risk of displacement could lead to later births, while those with more stable employment may choose to have children sooner. Second, the economic literature shows that couples often time births to avoid periods of high female wages (Ward and Butz 1980). Hence, an intertemporal substitution effect may arise: women anticipating decreasing opportunity costs delay childbearing. Conversely, those anticipating better career prospects may opt for earlier childbirth, mindful that postponing pregnancy becomes increasingly costly.

A model of fertility timing provides a formal economic explanation for these findings. In this setting, childbirth is treated as an irreversible investment with associated costs, echoing the idea of Adda et al. (2017) regarding the career cost of parenthood. The introduction of robots into the market can occasionally alter the level of volatility and shift the opportunity cost through displacement and productivity effects, with expectations parameterized using survey data. The framework includes postponement-driven childlessness, a margin which may be concealed by fertility rate trends (Gobbi 2013, Baudin et al. 2015).

Model simulations reproduce the direction of the empirically observed shifts in mean age at first birth, with the uncertainty channel exerting only a minimal effect; by contrast, discrete changes in cost—reflecting the substitution hypothesis—have a pronounced impact that aligns more closely with the empirical findings. Changes in fertility timing are correspondingly associated with varying childlessness rates among mid- and high-education cohorts, whereas the effect remains negligible for low-education groups.

The paper contributes to two areas of literature, namely the link between industrial automation and family behavior, and the analysis of fertility timing decisions. Concerning the former, this study complements the research of Anelli et al. (2021), who argue that robots reduce the marriage market value of men, leading to lower marriage rates in the US, and Matysiak et al. (2023), who find that the introduction of robots slightly lowers birth rates among the less-educated groups in some European countries. The focus here is on the tempo rather than on the quantum effect, and on how automation's impact on fertility unfolds across various educational levels.

Building on Ranjan (1999), economic theory has explored the idea that uncertainty in the outcomes of parenthood (Iyer and Velu 2006), earnings volatility (Sommer 2016), and pregnancy risks (de la Croix and Pommeret 2021) can incentivize fertility postponement. Empirical research provides abundant evidence on how fluctuations in labor market conditions influence the timing of childbirth, drawing on cross-national differences in welfare

Autor (1999), which asserted that the risk of replacement decreases monotonically with education.

systems (Bhaumik and Nugent 2011), shifts in consumption volatility around World War II (Chabé-Ferret and Gobbi 2018), and disease outbreaks such as pandemics (Luppi et al. 2020). Compared with these cyclical economic swings, technological change permanently alters certain market conditions, notably the demand for skills; industrial automation therefore represents a source of long-term structural transformation in labor markets.

The paper proceeds as follows. Section 2 details the data sources and identification assumptions; Section 3 discusses the econometric approach and results; Section 4 provides insights from the model; and Section 5 concludes.

2 Data

The analysis primarily relies on data from the International Federation of Robotics (2020) and the Eurostat regional database.

The dataset comprises an unbalanced panel covering the years 2000 to 2021, with 59 regions across seven European countries: Austria, Finland, Germany, the Netherlands, Slovakia, Spain, and Sweden. The restriction to these countries is due to the availability of comprehensive historical data on sector-specific employment levels, which are necessary to construct the shift-share measure of robot penetration.[2] Despite the limited number of regions, the sample is diverse, including Mediterranean, Northern, Scandinavian, and Eastern European countries.

This section details the sources and the main variables of interest, highlighting potential identification challenges.

2.1 Industrial robots

Information on the distribution of industrial robots, broken down by country, year, and sector, is sourced from the International Federation of Robotics (IFR). The IFR defines robots as automatically controlled, reprogrammable, and multipurpose manipulators, excluding labor-replacing tools requiring a human operator, such as ICT technologies. This definition provides a globally and temporally consistent measure of industrial automation (Jurkat et al. 2022).

The data have some limitations. First, the smallest geographic unit reported is the country, which implies that there is no information on the internal distribution of robot stocks. Thus the need for the use of a shift-share measure of robot exposure. Second, while

[2] Borusyak et al. (2021) demonstrate the consistency of the shift-share instrument under conditions of extended time periods relative to units and a substantial number of shocks.

the data for manufacturing sectors are detailed, information for other sectors is aggregated. This is not a major limitation, as around 99% of robots are used in manufacturing. Lastly, approximately one-third of industrial robots are unclassified. Following the methodology of Acemoglu and Restrepo (2020), unclassified robots are proportionally allocated based on the classified data.

Figure 1 shows the growth of industrial robot stocks in Europe and the United States from 1993 to 2019. The deployment of industrial robotics has significantly increased since the early 1990s in the United States and the mid-1990s in Europe, exhibiting exponential growth with a slight slowdown during the Great Recession.

2.2 Regional data on labor and demographics

Data on historical employment, which are used to construct the explanatory variable in conjunction with the IFR's robot stock data, are sourced from the Structural Business Statistics (SBS) database of Eurostat. It disaggregates regional employment by sector (NACE 1.1 level) and dates back to 1995. Although the manufacturing-sector data are comprehensive, other sectors exhibit numerous gaps. To address this, employment shares for agriculture and fishery are supplemented with data from the Annual Regional Database of the European Commission's Directorate-General for Regional and Urban Policy (ARDECO). The remaining sectors are then obtained by subtracting employment in manufacturing, agriculture, and fishery from total industry employment. Alongside these two macro categories, the dataset ultimately includes 11 distinct manufacturing industries: food; textiles; wood; paper; plastics + chemicals + rubber; minerals; metals; machinery; electronics; vehicles; and other manufacturing sectors.[3]

Demographic and educational data from 2000 onwards were obtained from the Eurostat regional database. Education levels are classified according to the International Standard Classification of Education (ISCED): levels 0–2 refer to less than primary, primary, and lower secondary education; levels 3–4 denote upper secondary and post-secondary non-tertiary education; and levels 5–8 cover tertiary education. For simplicity, these three groups are called low, medium, and high, respectively.

The models described in Section 3 include the median age of the female population, to account for the age structure of the region, and log Gross Domestic Product as an economic indicator.[4] Regional data lacks information on average wages and salaries, but provides em-

[3]The source of historical sectoral employment data differs from that used by Matysiak et al. (2023), who employed aggregated microdata. While the SBS data cover fewer regions, they provide a consistent starting point from 1995—before the surge in robot adoption across Europe—thereby ensuring the reliability of the Bartik measure.

[4]The mean age is absent in Eurostat regional data.

ployment rates for the population aged 25-64 and 25-34.[5] The latter is considered throughout the paper, as it more closely represents the reproductive age group. Moreover, the impact of robots on employment has predominantly been observed among younger workers (Dauth et al. 2021).

Throughout the analysis, education and labor variables refer to the female population. As shown in Appendix A.1, while industrial robots exert a strong, heterogeneous effect on employment and fertility timing among females, their impact on males is minor and concentrated among the medium-educated.

2.3 Predictor variables and identification assumptions

The following paragraphs outline the predictor variables and assumptions used to explore the impact of exposure to industrial robotics on fertility.

Shift-share measure of robot exposure. The explanatory variable quantifies regional labor market exposure to industrial robotics at the European regional (NUTS2) level, using a Bartik-style instrument. It assumes a uniform distribution of robots across industries within a country's regions, leveraging variation in pre-sample employment distribution by sector and the evolution of robot stocks by sector across countries.

Following standard practice with shift-share measures, the variable is based on the industrial composition of local labor markets before the surge in industrial automation. Utilizing historical differences in the industrial specializations of regions mitigates endogeneity concerns due to the possibility that current employment levels are shaped by the same unobserved factors influencing the adoption of robots. The baseline period is set to 1995, the earliest year in the European regional time series and the start of the exponential rise in industrial robotics in Europe (see Figure 1). A more recent baseline could increase the sample size, but may also increase the likelihood that the sectoral employment distribution has been affected by the increase in robot usage after 1995.

The regional exposure to industrial automation is calculated as follows:

$$Exp_{rt} = \sum_i \left(\frac{Empl_{ir}^{1995}}{Empl_r^{1995}} \times \frac{StockRobots_{ict}}{Empl_{ic}^{1995}} \right), \tag{1}$$

where r, t, c, and i represent region, year, country, and industry, respectively. $Empl_{ir}^{1995}$ denotes the employment in industry i within region r, and $Empl_r^{1995}$ is the total employment

[5] The absence of salary levels should not be a major limitation for this analysis, as Bhaumik and Nugent (2011) found that it is employment rather than financial risks that matter for fertility timing decisions.

in the region. The term $\frac{StockRobots_{ict}}{Empl_{ic}^{1995}}$ indicates the robot stock in year t, per thousand workers in 1995, in industry i.

Instrumental variable. Despite the exogenous nature of variations in regional sectoral specialization and the use of fixed effects that minimize omitted variable bias, concerns about endogeneity related to countries' robot adoption strategies may still persist. For instance, domestic or sector-specific shocks could affect both robot usage and its outcomes at the same time. Furthermore, Acemoglu and Restrepo (2021) shows that a high old-age dependency ratio in a country is associated with automation trends, indicating a possible reverse causality link between demographics and robots.

To tackle endogeneity, an instrumental variable is devised using robot stock data from Denmark, France, and Italy. These countries, not included in the panel, are among the leading European countries in robot adoption.[6] Among the countries in the dataset, Germany is an outlier which can threaten the reliability of the 2SLS results. Robustness checks indicate that excluding it from the analysis does not alter the main findings.

The instrumental variable is defined as:

$$Exp_{rt}^{IV} = \frac{1}{3} \sum_{j \in EU3} \sum_{i} \left(\frac{Empl_{ir}^{1995}}{Empl_{r}^{1995}} \times \frac{StockRobots_{ijt}}{Empl_{ij}^{1995}} \right), \tag{2}$$

where $j \in EU3$ refers to Denmark, France, and Italy, and $StockRobots_{ijt}$ is the robot stock in industry i, in country j, year t. $Empl_{ij}^{1995}$ indicates the 1995 sectoral employment in the country. The relevance and validity of Exp_{rt} stem from the global nature of the industrial robot supply and the unlikelihood that automation trends in one country would directly influence fertility outcomes in another.

The relationship between the instrumental and the endogenous variables can be assessed through:

$$Exp_{rt} = \kappa + \pi Exp_{rt}^{IV} + \mu_r + \lambda_t + \varepsilon_{rt}, \tag{3}$$

where μ_r and λ_t denote regional and yearly fixed effects, respectively. Table 1 shows that a unit increase in the instrument correlates with a 1.35 increase in robot exposure.

Labor market skill level variations. Due to the data being aggregated, it is unfeasible to analyze demographic outcomes for specific educational cohorts individually. The exposure variable is thus interacted with three indicators identifying regions where the proportions of women with low, medium, and high educational attainment exceed the annual European

[6] Acemoglu and Restrepo (2020) considers Denmark, Finland, France, Italy, and Sweden for the construction of the instrument.

average. Formally:

$$\mathbb{1}^{e}_{rt} = \begin{cases} 1 & \text{if share e-educ female population} > \text{EU yearly average} \\ 0 & \text{otherwise,} \end{cases}$$

where $e \in \{\text{L:=Low, M:=Medium, H:=High}\}$, describes the skill structure of the local labor market. Interacting the regressor with the indicators rather than the shares simplifies the interpretation of coefficients, circumventing issues from non-linear relationships, outliers, and skewed distributions. However, the robustness of findings is preserved when these indicators are replaced with the educational attainment ratios.

The interaction of the regressor with regional education levels is meant to identify different skill structures of regional populations, overcoming the absence of fertility outcomes categorized by education level in Eurostat. To support the plausibility of this assumption, Appendix A.1 provides evidence that adopting the same strategy to examine the effect of robots on employment rates of young workers yields results consistent with the literature on automation and job polarization. While a non-linear impact of robots on female employment is observed, a similar pattern is not evident for male employment. This discrepancy supports the argument proposed by Cerina et al. (2021), who suggests that job polarization is primarily generated by women, who are sorted into jobs that are more likely to benefit from the productivity impact of technological change (Cortés et al. 2024). As further evidence, Appendix A.2 also shows that this non-monotonic pattern is maintained when considering the limited data on unemployment rates among low-, medium-, and high-skilled workers and their long-term relationship with robot exposure.

2.4 Summary statistics

Table 2 displays the descriptive statistics for the main variables involved in the analysis. The demographic outcomes are the average age at first birth and age-specific fertility rates. The mean age for the first birth is 30.5 years, with a standard deviation of approximately 0.57 years within the same region. Figure 2 shows the mean age-specific fertility rates for ages 18 to 44. The highest value, 0.11, is observed between ages 30 and 31, creating a bell-shaped curve that decreases towards the edges of the age range.

In terms of educational attainment, about one-quarter of the sample did not complete secondary education, while another quarter achieved tertiary education. The remaining half of the population completed secondary education but did not advance to university-level studies.

The dataset comprises slightly more than a thousand observations with non-missing values for robot exposure. This measure, aggregated from the exposure scores across the 13 industries, requires dropping any observation with missing data in even one of the considered industries, thereby reducing the sample size. The average exposure score is 1.86, with a standard deviation of 0.91. The instrumental variable displays a similar mean and a tighter distribution.

The table's last three rows present the summary statistics for the skill indicators. The $\mathbb{1}^M$ and $\mathbb{1}^H$ indicators have a value of one for approximately half of the regions, while the $\mathbb{1}^L$ indicator applies to 34% of them. The non-negligible within-region standard deviations suggest that regions may display fluctuating values of these indicators over time. Robustness checks will address potential confounding effects from these year-to-year changes within the same regions.

3 The effect of industrial robots on fertility timing

This section describes the fixed-effect model employed to examine the relationship between automation and fertility, utilizing both OLS and 2SLS estimators. It outlines the findings related to the regional mean age of women at their first birth, and explores the interaction between quantum and tempo effects through age-specific fertility rates. It then presents robustness checks to address potential issues with the model's specification. Finally, it discusses the plausible absence of pre-existing trends in the mean age at first birth.

3.1 Fixed-effect model

As a first step of the analysis, the model estimates the direct impact of robot exposure on the regional mean age at first birth through the following equation:

$$Y_{rt} = \alpha + \beta Exp_{rt-\tau} + \iota Ed_{rt-\tau} + \psi X_{rt-\tau} + \mu_r + \lambda_t + \varepsilon_{rt}, \tag{4}$$

where r and t represent region and year, respectively. Y_{rt} stands for the outcome variable. $Ed_{rt-\tau}$ includes the percentage levels of education. Control variables, represented by the matrix $X_{rt-\tau}$, include the median age of the female population, lagged Gross Domestic Product, and lagged employment rates of women aged 25 to 34. The latter two and the regressor, $Exp_{rt-\tau}$, are lagged by $\tau = 2$ years to consider pregnancy duration and labor market adjustments, while the median age accounts for the female age distribution in the region. μ_r and λ_t are regional and yearly fixed effects, controlling for unobservable, time-invariant differences across regions and time trends in the outcomes. ε_{rt} denotes the idiosyncratic error term, with standard errors clustered at the regional level to account for potential correlations across different time periods within the same region.

The second step involves interacting the exposure variable with the three indicators outlined in Section 2.3. Incorporating all three simultaneously can lead to collinearity, as the indicators sum up to one. Therefore, the models include each interaction term in isolation. This is represented by:

$$\begin{aligned} Y_{rt} = \alpha + \beta_e(\mathbb{1}^e_{rt-\tau} \times Exp_{rt-\tau}) + \eta Exp_{rt-\tau} \\ + \rho_L \mathbb{1}^L_{rt-\tau} + \rho_M \mathbb{1}^M_{rt-\tau} + \rho_H \mathbb{1}^H_{rt-\tau} + \iota Ed_{rt-\tau} + \psi X_{rt-\tau} + \mu_r + \lambda_t + \varepsilon_{rt}, \end{aligned} \tag{5}$$

where β_e, with $e \in \{L, M, H\}$, isolates the component of the exposure effect attributable solely to the corresponding skill segment. $\mathbb{1}^L_{rt-\tau}$, $\mathbb{1}^M_{rt-\tau}$, and $\mathbb{1}^H_{rt-\tau}$ are included in all models to prevent the comparison group from implicitly being a combination of the remaining two groups. The inclusion of $Ed_{rt-\tau}$ further addresses this issue.

3.2 Results

Table 3 reports the coefficients derived from examining the relationship between robot exposure and the average age at first birth, as specified in Equation (4). These coefficients are not significant, showing no impact when estimated using OLS and 2SLS, regardless of whether the analysis focuses solely on exposure or includes education shares in the region, median age of the female population, female employment rates, and log GDP.

Table 4 presents the coefficients obtained from regressing the exposure variable interacted with education level indicators, according to Equation (5). These coefficients reveal that the impact of robot exposure on the average age at first birth varies non-linearly across different skill levels in local labor markets. There is a negative association for both low- and high-skill cohorts, with coefficients of -0.324 and -0.234 years respectively, as shown in Columns (1) and (3). For medium-skill groups, robot exposure correlates with an increase in the age at first birth by 0.225 years, as reported in Column (2). The 2SLS coefficients, displayed in the last three columns, exhibit a consistent trend, showing a slight reduction in the impact for the low-skill fraction of workers. The coefficients are approximately a third of the within standard deviation of the outcome.

To further explore how robotics influence demographic trends, age-specific fertility rates for women aged 18 to 40 are used as new dependent variables in Equation (5). This produces 22 outcomes and corresponding coefficients. The OLS and 2SLS results are graphically illustrated in Figure 3, where β_L, β_M, and β_H depict an S-shaped trajectory in each plot.

For regions where low-skill labor prevails the correlation at 18 years is negligible, gradually increasing to peak at approximately 0.008 for the 25-year-old cohort. After age 28, it becomes negative, bottoming out at -0.01 at age 32, and then stabilizes close to zero for cohorts around age 38. In the medium-skill scenario, the trend starts slightly negative, around -0.002 for ages 21 to 26, shifts to zero at age 27, and then sharply rises until age 31, where it results in an increase in fertility by 0.008. The positive effect at the end of the reproductive period more than compensate the initial negative coefficients. Following this peak, the coefficient decreases to zero by age 40. The high-skill case echoes the low-education one on a narrower scale. The coefficients hover around 0.004 from ages 20 to 25, decline to zero by age 28, continue decreasing to -0.005 for ages 30 to 34, and rise back to zero at age 38. The 2SLS results, displayed alongside the OLS findings, show similar patterns but with more pronounced fluctuations.

The S-shaped relationships between robot exposure and age-specific fertility rates, where the peak effects correspond to almost a within standard deviation in age specific fertility rates (see Figure 2), underline the dynamics of advancing fertility in the low- ad high-skill scenarios, since an enhanced fertility rate within one segment of the reproductive-age population is counterbalanced by a reduced rate in the other segment. As for the mid-skill case, the final increase in fertility, surpassing the initial decrease, produces an overall positive effect on fertility rates for this cohort. This may suggest that the reduction in childrearing costs outweighs the income effect.[7]

Mechanisms. Two mechanisms may underlie the impact of industrial robots on fertility timing. The first is an uncertainty channel: if robots displace mid-skilled workers to a greater extent than other groups, these individuals face a heightened risk of job loss or wage volatility. Because childbearing is irreversible, delaying it until economic prospects become clearer can be optimal. This idea was formalized by Ranjan (1999), who shows that fertility decisions can be modeled similarly to investments under uncertainty (Dixit and Pindyck 1994). Mid-skilled workers who face potential displacement may postpone starting a family until they secure more stable employment, whereas high- or low-skilled workers—whose prospects are relatively less disrupted or may even be enhanced by automation—are less likely to feel the same need to delay.

The second is an intertemporal substitution channel: when wages and job opportunities increase, the opportunity cost of childrearing rises, leading to lower fertility. This dynamic predominantly affects second earners, given their typically greater involvement in childcare. Couples aim to time childbirth for periods when these opportunity costs are lowest, as

[7]When looking at the relation between income and fertility rates, Strulik (2024) keeps the per-child time cost fixed and varies only income and education.

discussed by Ward and Butz (1980) and Ermisch (1988). If industrial automation raises productivity and wages among certain groups, these workers may choose to accelerate child-bearing, anticipating higher incomes and wishing to secure family planning before potential future career disruptions. Conversely, workers expecting wage declines may prefer to delay childbearing further, since lower wages would reduce the opportunity cost of having children.

The model in Section 4 presents a simple theoretical framework, which formalizes these two causal channels by incorporating stylized facts about how technology affects individuals with different education level.

3.3 Robustness

This section outlines the tests conducted to address potential weaknesses in the proposed specification. Standard errors calculated via bootstrapping over local labor markets, as suggested by Goldsmith-Pinkham et al. (2020), are shown in Table 5. These errors consistently stay below the conventional threshold for statistical significance. The robustness checks include assessing the influence of the vehicle sector on the Bartik measure, refining the formulation of the education indicator, examining the extent to which specific national characteristics may influence the results, and addressing concerns related to cyclicality as well as the impact of other classes of technological innovation.

1. Addressing the vehicle sector's influence. A typical concern regarding shift-share measures, highlighted by Goldsmith-Pinkham et al. (2020), is that its variation may be driven by specific sectoral trends, which could compromise causal interpretation. The vehicle sector is of particular concern due to the automotive industry's significant adoption of robots across Europe.[8] Table 6 presents the Rotemberg weights for the industries used in constructing the Bartik measure. It highlights a disproportionately high weight assigned to the vehicle sector compared to other industries.

To address the issue, Table 7 presents coefficients after excluding the vehicle sector from the exposure variable and incorporating it as a separate control, following Acemoglu et al. (2020). These coefficients are larger than those from the baseline analysis, in some cases doubling. Table 8 adjusts for region-specific trends across quartiles of employment share in the vehicle sector. The coefficients remain consistent with the primary findings, with a slight decrease in statistical significance in the 2SLS estimates for low-skill markets.

[8] See Figure 2 in Acemoglu and Restrepo (2020) for an illustration of the increasing robot penetration in such sector compared to other industries in European and American labor markets between 1993 and 2007.

2. Refining the education measure. The time variability of $\mathbb{1}^L_{rt}$, $\mathbb{1}^M_{rt}$, and $\mathbb{1}^H_{rt}$, as reflected by the within-region standard deviations in Table 2, raises questions about their link to labor market dynamics affected by robot adoption. It is possible that educational pursuits may adjust in response to changes in skill demand driven by automation. Utilizing skill indicators based on the shares from 2002, rather than annual variations, Table 9 reports results closely aligned with the baseline model.[9]

Another specification, interacting the regional female education level percentages instead of binary indicators, is reported in Table 10. This analysis confirms the direction of OLS coefficients, showing a decrease in the mean age at first birth by about 0.004 years for both low- and high-education levels per unit increase in robot exposure and a 1% rise in the respective education share. Conversely, the mid-skill group sees a 0.009 increase. The 2SLS estimates exhibits a threefold increase in the high-skill coefficient compared to OLS, but indicate a null effect for the low-skill group.[10]

3. Addressing country-specific influences. The potential for time-varying, country-specific influences—such as variations in social policies, welfare systems, and labor protections—presents an additional concern. Including country-year effects might overly restrict variability, especially since the study covers a limited number of regions within each country. Therefore, countries in the data are categorized according to their economic regimes: Austria, Germany, and the Netherlands adhere to the Rhineland regime, which emphasizes a coordinated market economy. In contrast, Finland and Sweden follow the Nordic model, characterised by high social welfare. Spain and Slovakia are classified in isolation. By using these categories in conjunction with years as fixed effects, the results demonstrate that the findings are not driven by time-varying socioeconomic differences, as indicated in Table 11.

Another bias could emerge if one country disproportionately affects the results, given the study's limited geographical scope. Therefore, the regression is repeatedly conducted by sequentially excluding each country, in order to ensure that potential country-specific shocks do not distort the overall findings. Figure 4 mitigates this concern. In particular, the 2SLS coefficients obtained by excluding Germany address the concerns mentioned in Section 2 regarding potential issues with the 2SLS strategy due to Germany's advanced adoption of robots.

[9] 2002 is the earliest year all six combinations of the three indicators are present; 2000 and 2001 had only 4 and 5 combinations, respectively, due to missing observations in Eurostat's initial education data.

[10] Excluding data from the year 2019 onwards results in a negative and statistically significant coefficient. The loss of statistical significance may be due to the confounding effects of the Covid-19 pandemic.

4. Long-term intervals. Considering intervals that exceed one year between panel time points reduces worries that cyclical factors could affect outcomes beyond the adoption of robots. The coefficients derived from three-year and five-year intervals, starting in 2002 and 2000 respectively, are displayed in Tables 12 and 13, respectively. The findings from these extended intervals align with the results from the annual interval analysis.

5. Incorporating technological innovation. The final models incorporate control variables for technological innovations that could influence the outcome alongside robotics. Regional investment in Research and Development (R&D) and the number of patents in the high-tech sector are used as proxies for innovation. Due to missing data for both variables, each is included separately to avoid losing too many observations.

Tables 14 and 15 confirm the robustness of the primary results when accounting for these indicators of innovation. The inclusion of R&D investment reveals a slight reduction in the impact on labor markets that have higher levels of education, suggesting that in regions with a significant presence of highly-skilled workers, investments in research may offset some of the variations attributable to the adoption of robots.

3.4 Pre-trends in mean age at first birth

This section shows the plausible absence of pre-existing trends in the outcome of interest. Studies on robot exposure in the US exploited historical data to add pre-trend changes in the outcome as a control variable (Acemoglu and Restrepo 2020, Anelli et al. 2021). Due to the absence of regional European data on ages at birth before year 2000, the check here adopts a different methodology, which resembles an event study in a Difference-in-Differences setting.

Specifically, we can leverage the fact that the countries in the dataset experienced their peak growth rates in robot adoption at different times. Figure 5 shows that Austria, Netherlands, and Slovakia initially had low growth rates in robot usage compared to the other countries in the dataset, but their rates increased over time and eventually exceeded those of the others. For simplicity, let us call these countries the "late adopters". In contrast, Germany, Finland, and Spain saw a surge in robot usage at the beginning of the study, followed by a decline in growth rates. Sweden also displayed a decreasing growth rate, albeit more moderately. Let us call these countries the "early adopters".

If there exists a trend in mean age at first birth, coinciding with the effect of robot adoption, we may investigate whether such trend begins later for late adopters compared to early adopters. Should the late adopters not reflect the early adopters' trends initially, yet follow them later, it could suggest that the dynamics of the outcome are influenced by increased robot usage rather than pre-existing trends. This can be estimated through the following equation:

$$Y_{rt} = \alpha + \beta_e^{yrs}(\sum \mathbb{1}_{rt-\tau}^{e} \times \mathbb{1}_{year}) + \rho_L \mathbb{1}_{rt-\tau}^{L} + \rho_M \mathbb{1}_{rt-\tau}^{M} + \rho_H \mathbb{1}_{rt-\tau}^{H} + \iota Ed_{rt-\tau} + \psi X_{rt-\tau} + \mu_r + \lambda_t + \varepsilon_{rt}, \tag{6}$$

where $\mathbb{1}_{year}$ represents the set of dummy variables for the different years. The other covariates are as in Equation 5.

Provided that the core findings of the paper remain consistent across both categories, as shown by Tables 16 and 17, Figure 6 compares the coefficient plots for the two groups across the three educational levels. The coefficients represent the change in the outcome as opposed to year 2000. Early adopters with low education levels exhibited a smooth and rapid decline in the average age at first childbirth during the initial period of the panel. This decline most likely began before 2001. The coefficients appear to stabilize over time. For the late adopters, the coefficients were close to zero at the beginning of the panel years, and we begin to observe a decline in the outcome around 2002-2003. In the middle education case, we see a specular pattern among early adopters, with a rapid and continuous increase likely starting before 2001. When examining the late adopters, the coefficients hover around zero until 2004, after which the increase begins. Finally, there is a decline for high education cohorts among early adopters in 2002, with stabilization thereafter. For the late adopters, the decrease begins around 2004, maintaining values close to zero until 2006.

Overall, the coefficient plots indicate a trend in the average age at first childbirth that reflects the impact of automation. However, regions that experienced a later surge in automation show these trends starting a few years after those that experienced an early boom. This may suggest that the results reported in Section 3.2 are not related to any pre-existing patterns prior to the increase in robot adoption.

4 A model of fertility timing

This section reports stylized facts on how the impact of automation technology is distributed with respect to education, and proposes a model of optimal fertility age that incorporates both the uncertainty and the substitution channels mentioned in Section 3.2.

4.1 Stylized facts on education and beliefs about automation

The data source used to estimate the impact of automation on individuals' labor prospects is the second wave of the Work Orientations survey by the International Social Survey Programme (1999), where individuals in several countries were interviewed in 1997 regarding their attitudes towards work. The dataset contains a 1-to-5 score on individuals' expectation about technologies automating jobs in the upcoming future. Specifically, the survey asks: 'New kinds of technology are being introduced more and more in [country]: computers, robots, and so on. Do you think these new technologies will over the next few years...' The respondent can choose between five possible answers: '1, Greatly increase the number of jobs?', '2, Slightly increase the number of jobs?', '3, Make no difference to the number of jobs?', '4, Slightly reduce the number of jobs?', or '5, Greatly reduce the number of jobs?'. The score thus indicates an optimistic attitude when the value is less than 3, and a pessimistic one when it is greater than 3. Henceforth, let us refer to this variable as the concern level. van Hoorn (2022) demonstrates that it is a valid measure of both perceived and objective risks of being replaced by machines, by comparing it with different measures of job routineness and task automatability. By restricting the sample to women aged 18 to 45, the following equation estimates the relation between education and the concern about technology replacing jobs:

$$Concern_i = \alpha + \theta_1 s_i + \theta_2 s_i^2 + Age_i + \zeta_c + \varepsilon_i, \tag{7}$$

where s_i represents the years of schooling, limited to 18, representing the typical duration required to obtain a master's degree. The concern and education levels are scaled to the intervals (-1,1) and (0,1), respectively. The model controls for the individual's age and includes a set of country-fixed effects, ζ_c. Standard errors, ε_i, are clustered at the country level.

Both linear and quadratic specifications are estimated to check for the presence of non-linearities. Table 18 presents the OLS estimates, obtained using survey weights. The education level's non-squared term shows a non-statistically significant coefficient. When the squared term is included, the coefficients become significantly different from zero, suggesting a concave relationship, with $\theta_1 = 0.702$ and $\theta_2 = -0.696$. Appendix A.3 provides several robustness checks to assure that the non-monotonicity is preserved when using categorical variables of education and when considering more recent surveys.

4.2 The model

Fertility timing is modeled through a dynamic optimization framework. At each point in time, an individual faces the binary decision of whether to have a child. The optimization involves determining the optimal timing to cease delaying childbirth. Utility can be viewed as the happiness derived from being a parent. The cost consists of the time and resources the parent must allocate to child-rearing instead of other activities, such as working and accumulating experience (Adda et al. 2017).

Payoff of having children. Childbearing occurs within an individual's fertility window, which we can reasonably assume begins at 18 years of age, as in de la Croix and Pommeret (2021). The optimal childbearing time is influenced by various factors. For instance, starting a family while young can be burdensome for certain individuals, particularly those pursuing higher education, due to the necessity of completing their studies and the availability of significant work opportunities. Conversely, delaying childbirth too much poses risks such as potential health complications associated with advanced maternal age. To account for these issues, a penalty factor is introduced into the payoff structure, which escalates as individuals approach the limits of their fertility window and reaches its minimum at a preferred age, varying among agents based on their educational level.

The benefits of having children can be defined as follows:

$$P_{it} = R_i \,(1 - \chi_{it}),$$

where R_i represents the payoff of having a child at the desired age. Such a payoff of childbirth is unaffected by the woman's age itself.[11] The penalty χ_{it} is determined by:

$$\chi_{it} = \begin{cases} \tau_1 \times (T_i - t) & \text{if } t < T_i, \\ \tau_2 \times (t - T_i) & \text{if } t > T_i, \end{cases}$$

where

$$T_i = \mathcal{N}(\bar{T}, \mathrm{sd}(T)) \; + \; \nu \times \left(s_i - \tfrac{1}{2}\right)$$

denotes the agent's preferred age for having children, normally distributed around a mean $\bar{T}$, and with standard deviation $\mathrm{sd}(T)$. ν is a parameter influencing the correlation between the desired birth age and schooling. The education level, s_i, is drawn from a Beta distribution, which has support $(0, 1)$.

The agent chooses the optimal childbearing age, t^*, by minimizing the difference between the benefits and costs of having children. The age at childbirth is given by:

$$\text{Age at birth} = \begin{cases} t^* & \text{with probability } \pi(t), \\ \infty & \text{with probability } 1 - \pi(t), \end{cases}$$

where $\pi(t)$ represents the probability of a successful pregnancy. Fertility is assumed to be a

[11] This assumption is supported by Myrskylä and Margolis (2014) and Baetschmann et al. (2016), who suggest that the happiness of becoming a parent is not age-dependent.

one-shot attempt, with failure leading to childlessness.

The cost process. As in previous theories of fertility timing, the opportunity cost is modeled as a Brownian motion. In addition to the volatility component, the cost is subject to occasional variations due to industrial robots entering the market. The process takes the following form:

$$dC_t = \sigma_i \, C_t \, dW_t \;+\; \Gamma\big(C_t\big) \, dN_t, \tag{8}$$

where C_t represents the opportunity cost at time t. dW_t denotes an increment of a standard Brownian motion. The volatility term, σ_i, quantifies uncertainty, capturing the magnitude of its random fluctuations. dN_t is the increment of a Poisson process, with N_t taking the value 1 according to an arrival rate, Δ_t, of new robots in the industries. $\Gamma\big(C_t\big)$ is a function representing how automation impacts the cost and takes different forms depending on whether the uncertainty or substitution effect is being considered.

4.3 Simulation

The problem is solved by backward induction. The optimal stopping time is determined as the point where the utility of stopping exceeds the discounted expectation of future utility. The model is simulated by drawing 100,000 agents with varying education levels, which influence their preferred age at childbirth and their expectations regarding the effects of automation on job opportunities.

Distribution of automation shock. Based on the relationship between individuals' education and the impact automation has on their labor prospects, the distribution of the automation shock is modeled as a quadratic function, incorporating estimated parameters:

$$\Theta = T(\theta_1 s_i + \theta_2 s_i^2)^e, \tag{9}$$

where the operator T represents a linear transformation ensuring that the function's minimum and maximum values correspond to -1 and 1. Raising to the power of e helps achieve a smoother variation for extreme levels of education, as suggested by the coefficients in Table A7 in the Online Appendix.

Calibration The unit of time is assumed to be one-third of a year. The parameters are calibrated based on existing literature, and their values are summarized in Table 19. As in de la Croix and Pommeret (2021), the yearly discount rate is set to $r = 0.02$, the volatility σ is set to increase with education, ranging in the interval $(0.036, 0.072)$, and the probability of successful fertility is represented by a logistic function with parameters that reproduce the share of natural conception reported by Léridon (2005).

In an online survey asking women when they would prefer to start having children, Harper and Botero-Meneses (2022) finds an average age of around 30, which is also the peak of the mean age at birth observed in Figure 2, with a standard deviation of 3.3. These values are used for $\bar{T}$ and $\mathrm{sd}(T)$, respectively. The adjustment factor ν is set to 3.75 to obtain a correlation of 0.2 between the preferred age and the education level, as found by van Balen et al. (1997).

The payoff of having a child and the penalties for deviating from such an age are taken from Natividade et al. (2020), who construct a comprehensive measure of the desire to have children and analyze its relation with the age of the respondents. The values are chosen to resemble their Figure 2, namely $R = 3.5$, $\tau_1 = 0.17$, and $\tau_2 = 0.05$. The choice of values for the initial cost of having children has limited impact on the overall outcome, provided that it remains sufficiently above zero.[12] It is set to two times higher than the payoff associated with having a child at the preferred age, drawing on estimates of social and health costs of teen mothers (Hoffman and Maynard 2008).

The arrival rate of robots, Δ_t, is set to $\frac{1}{6.5}$ based on Karastoyanov and Karastanev (2018), who examine how long robots are typically used before needing replacement with newer models. Concerning the curvature of the distribution function of the automation shock Θ, the parameters related to its relationship with education are those found in Column (2) of Table 18.

Considering a null impact of automation and assuming a balanced distribution of education centered at mid-level attainment ($s \sim \mathrm{Beta}(1.5, 1.5)$), we obtain a bell-shaped distribution of ages at birth, as shown in Figure 7, slightly skewed to the right as often observed in the data (Li and Pantano 2023). The mean optimal age at birth is 30.4, close to the value found in Table 2, while the percentage of women with no children is 10.2%; a reasonable ratio when considering the literature on childlessness (Baudin et al. 2015, Baudin et al. 2018).

4.4 Numerical results

Let us now consider three populations with different education distributions: one with a prevalence of mid-skilled agents ($s \sim \mathrm{Beta}(3, 3)$), one with education values concentrated on the lower extreme of the spectrum ($s \sim \mathrm{Beta}(1, 5)$), and one with education values concentrated on the higher end ($s \sim \mathrm{Beta}(5, 1)$).

[12] Since changes in the cost are modeled as percentage variations, it cannot fall below zero. An initial cost near zero would incentivize agents to have children immediately.

Varying volatility. The first experiment involves altering the magnitude of volatility for each agent in a manner that varies with their education level, as defined by Equation 9, i.e.,

$$\Gamma\big(\mathrm{C}_t\big) = \sigma_i(\Theta(s_i)\phi)\, C_t\, dW_t.$$

This equation states that, when the shift occurs depending on Δ_t, volatility varies by a percentage ϕ. The relationship between the average age at birth, as well as the ratio of childlessness, and the volatility shock is represented in Figure 8. The trend in the age at birth shows a decreasing age for low- and high-skilled populations and vice versa for the mid-skilled. The magnitude of the variation is extremely limited. There is no available research linking industrial robots to volatility indices. However, during the Dot-Com bubble, which represents a technological shock likely to have a higher effect on uncertainty compared to robots, the VIX index rose from around 10 to approximately 25 over five years, meaning an average yearly increase in the index of around 20%. The plot shows that a yearly 20% variation leads to an anticipation or postponement of fertility by less than 0.01 years. This negligible impact suggests that changes in volatility are not the primary factor behind the observed variation in fertility timing, since the results indicate that adding one robot per thousand workers increases the average age at first birth by about one-fifth to one-third of a year. The childlessness pattern reflects the trend in age at birth and reports variations in the ratio close to zero as well.

Introducing sudden shifts. To account for the substitution effect, we can introduce the expected future impact of robots on job vacancies by adding a jump process to the Brownian motion. This takes the form

$$\Gamma\big(\mathrm{C}_t\big) = \omega \times \Theta(s_i)\, \mathrm{OC}_t,$$

where ω introduces a sudden percentage change in the variable, distributed according to $\Theta(s_i)$. The above formulation facilitates comparison with the results in Section 3. ω can be considered as the labor market churn produced by automation, i.e., the share of jobs that get displaced for a certain spectrum of workers and created for others. Dixon et al. (2021) estimate a decrease in mid-skilled jobs of around 3% to 8%, with gains in employment redistributed among low- and high-skilled workers, consequent to a percentage increase in firms' investment in robots. Appendix Table A2 reports that one more robot per thousand workers is associated with a 9% reduction in jobs for the mid-skilled population, and with increasing rates for the other two skill categories. We may therefore assume, as a benchmark for comparing the simulation with the paper's results, a value of ω that hovers around these levels.

The relationship between ω and the mean age at birth is represented in Figure 9. The change in age at birth tends to be greater in magnitude across different values of the change in employment. A variation in employment by 5% leads to a postponement in the mid-skilled scenario by around 0.2 years and an anticipation by approximately 0.1 and 0.3 years for low- and high-education cases, respectively. The relationship tends to be fairly linear and is closer in magnitude to the correlation found in Section 3, compared to the uncertainty channel case. On the childlessness side, there is an almost null effect for the low-skilled population, with a slight increase for high values of ω. This is likely due to a minor effect that anticipating childbearing has on individuals who already plan to have children when young, making the increase in childlessness driven by mid-skilled individuals overtake it. In the mid- and high-skill population cases, the rate increases and decreases, respectively, by around 0.8% for a 5% change in employment due to robots.

5 Conclusion

Industrial automation displaces workers in routine jobs—typically those with mid-level education—while simultaneously creating new opportunities in non-routine occupations. This study examines its impact on fertility timing choices.

Greater robot exposure anticipates childbearing in regions with high proportions of low- or high-skilled women, whereas it produces a postponement among mid-skilled populations. These patterns are reflected in shifts in both the mean age at first birth and the distribution of age-specific fertility across cohorts.

A dynamic fertility model provides two possible explanations for these results. First, the introduction of robots into the labor market shifts job uncertainty, leading to delayed births among workers at risk of displacement and earlier births among those enjoying improved employment prospects. Second, increasing automation raises future opportunity costs for individuals who benefit from the productivity effect while reducing them for those who do not, thereby fostering a preference for childbearing when costs are anticipated to be lower. A numerical application of the model, using parameters based on expectations derived from survey data, supports the idea that the impact of rising automation on the inclination to delay fertility is concave with respect to educational attainment. Quantitatively, the second channel better represents the findings of the paper and shows that movements in fertility timing are accompanied by aligned changes in childlessness rates.

The balance between variations in fertility throughout the life course suggests that we should not fear large reductions in cohort sizes or their consequences for intergenerational redistribution systems. However, the findings point to a substantial reshuffling of birth timings among different education groups. Postponement may potentially lead certain groups to involuntary childlessness, while anticipation by other groups with more favorable economic factors may reduce this risk. This may support policies facilitating the childbearing decision in periods that are more biologically suitable and less prone to risky pregnancies, particularly for groups that are more exposed to competition with robots.

Future research could address this study's limitations related to data aggregation by using detailed employer-employee datasets. Another avenue for research could involve assessing the effects of different types of automation technologies beyond robots, such as Artificial Intelligence (AI), which might have varying impacts on labor demand, especially in high-skilled sectors. Understanding the effects of diverse technologies on labor and family dynamics might offer a comprehensive perspective on navigating the upcoming structural shifts in the labor market.

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Data availability The following data sources have been used for the analysis in this article:

- Data on operational stock of robots from International Federation of Robotics (https://ifr.org/worldrobotics/).
- Publicly available data from Eurostat regional database (https://ec.europa.eu/eurostat/web/regions/database)
- Publicly available data from ARDECO database (https://urban.jrc.ec.europa.eu/ardeco/explorer?lng=en)
- Publicly available data from the International Social Survey Program (https://www.gesis.org/en/issp/data-and-documentation/work-orientations/1997)

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Tables

Table 1: Correlation of the Robot Exposure score with the instrumental variable.

Dependent variable:	*Exposure*
$Exposure^{IV}$	1.35***
	(0.31)
Observations	1003
Within R-squared	0.21

The model includes regional and year fixed effects. Robust standard errors clustered at the regional level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Summary statistics.

Variable	Mean	Within Std. Dev.	Min.	fMax.	N
% fem pop with ISCED0-2	28.21	5.43	3	73.2	1168
% fem pop with ISCED3-4	44.57	3.43	10.7	75.3	1168
% fem pop with ISCED5-8	27.22	5.83	7.1	57.7	1168
Mean age first birth	30.52	0.57	26.4	33	1137
Median age women	42.51	1.89	24.7	54.2	1137
Fem. Employment	72.53	3.91	38.7	86.6	1225
Log GDP	10.86	0.19	8.48	14.29	1180
Exposure to Robotics	1.86	0.91	0	12.49	1298
Exposure to Robotics^{IV}	1.79	0.43	0.19	4.95	1003
$\mathbb{1}^{L}_{rt}$	0.34	0.15	0	1	1168
$\mathbb{1}^{M}_{rt}$	0.53	0.19	0	1	1168
$\mathbb{1}^{H}_{rt}$	0.52	0.19	0	1	1168

Table 3: Effect of robot exposure on mean age at first birth. Baseline estimation without interactions.

	OLS			2SLS		
Mean age at first birth	(1)	(2)	(3)	(4)	(5)	(6)
Exp_{rt-2}	0.046	0.040	0.041	0.132	0.116	0.060
	(0.038)	(0.037)	(0.046)	(0.095)	(0.093)	(0.083)
$\%Low\,Educ_{rt-2}$		0.009	0.008		-0.007	-0.004
		(0.009)	(0.009)		(0.009)	(0.008)
$\%Med\,Educ_{rt-2}$		0.012	0.002		0.004	-0.005
		(0.009)	(0.008)		(0.008)	(0.008)
Median Age			0.084**			0.069*
			(0.041)			(0.039)
$Fem\,Employment_{rt-2}$			-0.008**			-0.006
			(0.004)			(0.004)
$Log\,GDP_{rt-2}$			0.150			-0.187
			(0.498)			(0.442)
Observations	1,171	1,164	1,164	997	994	994
KP F-Stat				18	21	29
Within R-squared	0.00	0.02	0.08			

All models control for region and year fixed effects. Robust standard errors clustered at the regional level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Effect of robot exposure on mean age at first birth. Baseline estimation with interactions.

	OLS			2SLS		
Mean age at first birth	(1)	(2)	(3)	(4)	(5)	(6)
$Exp_{rt-2} \times \mathbb{1}^{L}_{rt-2}$	-0.324***			-0.253***		
	(0.051)			(0.077)		
$Exp_{rt-2} \times \mathbb{1}^{M}_{rt-2}$		0.225***			0.222***	
		(0.043)			(0.057)	
$Exp_{rt-2} \times \mathbb{1}^{H}_{rt-2}$			-0.234***			-0.248***
			(0.052)			(0.071)
Exp_{rt-2}	0.044	-0.185***	0.057	0.113*	-0.152	0.119*
	(0.039)	(0.059)	(0.037)	(0.063)	(0.103)	(0.061)
$\mathbb{1}^{L}_{rt-2}$	0.377***	0.118	0.173*	0.359***	0.108	0.161*
	(0.110)	(0.080)	(0.101)	(0.105)	(0.083)	(0.096)
$\mathbb{1}^{M}_{rt-2}$	-0.095	-0.483***	-0.120	-0.087	-0.484***	-0.111
	(0.074)	(0.100)	(0.078)	(0.068)	(0.126)	(0.067)
$\mathbb{1}^{H}_{rt-2}$	0.026	0.027	0.231**	0.039	0.034	0.277**
	(0.068)	(0.060)	(0.091)	(0.063)	(0.057)	(0.104)
$\%Low\,Educ_{rt-2}$	-0.013*	-0.007	-0.011	-0.020**	-0.018**	-0.024**
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
$\%Med\,Educ_{rt-2}$	0.005	0.004	-0.004	-0.002	-0.001	-0.010
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Median Age	0.090**	0.054	0.030	0.079**	0.038	0.008
	(0.037)	(0.042)	(0.041)	(0.036)	(0.042)	(0.043)
$Fem\,Employm_{rt-2}$	-0.007**	-0.009**	-0.009**	-0.007**	-0.007*	-0.009**
	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)
$Log\,GDP_{rt-2}$	0.060	0.020	-0.012	-0.315	-0.286	-0.441
	(0.479)	(0.470)	(0.540)	(0.427)	(0.415)	(0.494)
Observations	1,164	1,164	1,164	994	994	994
KP F-Stat				19	15	17
Within R-squared	0.21	0.21	0.20			

All models control for region and year fixed effects. Robust standard errors clustered at the regional level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Wild bootstrap results over regions, with 999 repetitions, for the main coefficients reported in Table 4.

Mean age at birth	$Exp_{rt-2} \times \mathbb{1}^H_{rt-2}$	$Exp_{rt-2} \times \mathbb{1}^H_{rt-2}$	$Exp_{rt-2} \times \mathbb{1}^H_{rt-2}$
OLS			
z	-6.3845	5.1984	-4.4955
$P > \lvert z \rvert$	0.0000	0.0000	0.0010
2SLS			
z	-3.3498	3.9672	-3.6015
$P > \lvert z \rvert$	0.0090	0.0040	0.0010

Table 6: Rotemberg weights.

Industry	NACE 1.1 code	Rotemberg Weight
Wood	DD	1.00e-09
Textiles	DB	.0300051
Other industries	Difference	.0311049
Agriculture & fishery	A+B	.0320919
Paper	DE	.0367107
Mineral	DI	.0395314
Other manufacturing	Difference	.0449754
Electronics	DL	.0485427
Machinery	DK	.0810629
Food	DA	.1051417
Metal	DJ	.1115606
Plastics, chemicals, rubber	DG+DH	.1469664
Vehicles	DM	.2923063

Table 7: Robustness check: drop vehicle sector.

	OLS			2SLS		
Mean age at first birth	(1)	(2)	(3)	(4)	(5)	(6)
$Exp_{rt-2} \times \mathbb{1}^{L}_{rt-2}$	-0.455***			-0.422***		
	(0.099)			(0.126)		
$Exp_{rt-2} \times \mathbb{1}^{M}_{rt-2}$		0.355***			0.455***	
		(0.085)			(0.115)	
$Exp_{rt-2} \times \mathbb{1}^{H}_{rt-2}$			-0.476***			-0.408***
			(0.075)			(0.102)
Observations	1,164	1,164	1,164	994	994	994
KP F-Stat				26	22	22
Within R-squared	0.19	0.20	0.25			

All models control for female median age, lagged female employment, lagged GDP, region and year fixed effects. Robust standard errors clustered at the regional level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Robustness check: fixed effects for historical employment share quartiles in vehicle sector by year.

	OLS			2SLS		
Mean age at first birth	(1)	(2)	(3)	(4)	(5)	(6)
$Exp_{rt-2} \times \mathbb{1}^{L}_{rt-2}$	-0.338***			-0.216*		
	(0.056)			(0.109)		
$Exp_{rt-2} \times \mathbb{1}^{M}_{rt-2}$		0.235***			0.218***	
		(0.045)			(0.077)	
$Exp_{rt-2} \times \mathbb{1}^{H}_{rt-2}$			-0.237***			-0.236**
			(0.056)			(0.095)
Observations	1,164	1,164	1,164	994	994	994
KP F-Stat				9	7	8
Within R-squared	0.21	0.22	0.20			

All models control for female median age, lagged female employment, lagged GDP, region and year fixed effects. Robust standard errors clustered at the regional level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Robustness check: interaction between exposure and the education indicators, where the indicators refer to year 2002 for all the observations.

	OLS			2SLS		
Mean age at first birth	(1)	(2)	(3)	(4)	(5)	(6)
$Exp_{rt-2} \times \mathbb{1}^{L}_{r,02}$	-0.325***			-0.241***		
	(0.055)			(0.086)		
$Exp_{rt-2} \times \mathbb{1}^{M}_{r,02}$		0.380***			0.329***	
		(0.050)			(0.074)	
$Exp_{rt-2} \times \mathbb{1}^{H}_{r,02}$			-0.302***			-0.260***
			(0.081)			(0.093)
Observations	1,081	1,081	1,081	911	911	911
KP F-Stat				17	15	17
Within R-squared	0.21	0.26	0.21			

All models control for female median age, lagged female employment, lagged GDP, region and year fixed effects. Robust standard errors clustered at the regional level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10: Robustness check: interaction between exposure and the shares of low, medium, and high-skilled population.

	OLS			2SLS		
Mean age at first birth	(1)	(2)	(3)	(4)	(5)	(6)
$Exp_{rt-2} \times \%\,Low_{rt-2}$	-0.005**			-0.001		
	(0.002)			(0.003)		
$Exp_{rt-2} \times \%\,Med_{rt-2}$		0.009***			0.008***	
		(0.002)			(0.002)	
$Exp_{rt-2} \times \%\,High_{rt-2}$			-0.004*			-0.009***
			(0.002)			(0.003)
Observations	1,164	1,164	1,164	994	994	994
KP F-Stat				11	18	12
Within R-squared	0.11	0.17	0.11			

All models control for female median age, lagged female employment, lagged GDP, region and year fixed effects. Robust standard errors clustered at the regional level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11: Robustness check: country socioeconomic regime - year fixed effects.

	OLS			2SLS		
Mean age at first birth	(1)	(2)	(3)	(4)	(5)	(6)
$Exp_{rt-2} \times \mathbb{1}^{L}_{rt-2}$	-0.310***			-0.326***		
	(0.049)			(0.057)		
$Exp_{rt-2} \times \mathbb{1}^{M}_{rt-2}$		0.189***			0.180***	
		(0.043)			(0.043)	
$Exp_{rt-2} \times \mathbb{1}^{H}_{rt-2}$			-0.195***			-0.233***
			(0.050)			(0.050)
Observations	1,164	1,164	1,164	994	994	994
KP F-Stat				20	21	21
Within R-squared	0.24	0.24	0.22			

All models control for female median age, lagged female employment, lagged GDP, region and year fixed effects. Robust standard errors clustered at the regional level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12: Robustness check: three-year intervals.

	OLS			2SLS		
Mean age at first birth	(1)	(2)	(3)	(4)	(5)	(6)
$Exp_{rt} \times \mathbb{1}^{L}_{rt}$	-0.462***			-0.360***		
	(0.067)			(0.124)		
$Exp_{rt} \times \mathbb{1}^{M}_{rt}$		0.282***			0.270***	
		(0.057)			(0.084)	
$Exp_{rt} \times \mathbb{1}^{H}_{rt}$			-0.273***			-0.348***
			(0.070)			(0.105)
Observations	350	350	350	293	293	293
KP F-Stat				4	14	4
Within R-squared	0.33	0.31	0.28			

All models control for female median age, female employment, GDP, region and year fixed effects. Robust standard errors clustered at the regional level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13: Robustness check: five-year intervals.

	OLS			2SLS		
Mean age at first birth	(1)	(2)	(3)	(4)	(5)	(6)
$Exp_{rt} \times \mathbb{1}^{L}_{rt}$	-0.498***			-0.472***		
	(0.066)			(0.070)		
$Exp_{rt} \times \mathbb{1}^{M}_{rt}$		0.299***			0.316***	
		(0.071)			(0.098)	
$Exp_{rt} \times \mathbb{1}^{H}_{rt}$			-0.287***			-0.323**
			(0.100)			(0.126)
Observations	210	210	210	210	210	210
KP F-Stat				14	14	15
Within R-squared	0.49	0.43	0.40			

All models control for female median age, female employment, GDP, region and year fixed effects. Robust standard errors clustered at the regional level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 14: Robustness check: add R&D investments as control variable.

	OLS			2SLS		
Mean age at first birth	(1)	(2)	(3)	(4)	(5)	(6)
$Exp_{rt-2} \times \mathbb{1}^{L}_{rt-2}$	-0.319***			-0.237**		
	(0.089)			(0.104)		
$Exp_{rt-2} \times \mathbb{1}^{M}_{rt-2}$		0.227***			0.219***	
		(0.055)			(0.072)	
$Exp_{rt-2} \times \mathbb{1}^{H}_{rt-2}$			-0.149**			-0.136*
			(0.057)			(0.076)
$R\&D_{rt-2}$	0.047	0.040	0.054	-0.011	0.009	0.022
	(0.034)	(0.034)	(0.035)	(0.046)	(0.050)	(0.050)
Observations	745	745	745	630	630	630
KP F-Stat				12	12	11
Within R-squared	0.19	0.19	0.15			

All models control for female median age, lagged female employment, lagged GDP, region and year fixed effects. Robust standard errors clustered at the regional level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 15: Robustness check: add number of high tech patents as control variable.

	OLS			2SLS		
Mean age at first birth	(1)	(2)	(3)	(4)	(5)	(6)
$Exp_{rt-2} \times \mathbb{1}^{L}_{rt-2}$	-0.506***			-0.466***		
	(0.083)			(0.092)		
$Exp_{rt-2} \times \mathbb{1}^{M}_{rt-2}$		0.338***			0.292***	
		(0.081)			(0.079)	
$Exp_{rt-2} \times \mathbb{1}^{H}_{rt-2}$			-0.381***			-0.373***
			(0.071)			(0.095)
$Patents_{rt-2}$	-4.47e-05	-1.22e-04	2.46e-05	1.60e-04	4.79e-06	1.51e-04
	(2.79e-04)	(3.31e-04)	(4.02e-04)	(3.06e-04)	(3.97e-04)	(4.61e-04)
Observations	699	699	699	544	544	544
KP F-Stat				28	31	26
Within R-squared	0.35	0.33	0.32			

All models control for female median age, lagged female employment, lagged GDP, region and year fixed effects. Robust standard errors clustered at the regional level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 16: Effect of robot exposure on mean age at first birth when the sample is limited to Austria, Netherlands, and Slovakia.

	OLS			2SLS		
Mean age at first birth	(1)	(2)	(3)	(4)	(5)	(6)
$Exp_{rt-2} \times \mathbb{1}^{L}_{rt-2}$	-0.143*			-0.207***		
	(0.076)			(0.072)		
$Exp_{rt-2} \times \mathbb{1}^{M}_{rt-2}$		0.243**			0.378***	
		(0.095)			(0.097)	
$Exp_{rt-2} \times \mathbb{1}^{H}_{rt-2}$			-0.296***			-0.336***
			(0.051)			(0.074)
Observations	460	460	460	391	391	391
KP F-Stat				11	11	12
Within R-squared	0.32	0.35	0.41			

All models control for female median age, lagged female employment, lagged GDP, region and year fixed effects. Robust standard errors clustered at the regional level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 17: Effect of robot exposure on mean age at first birth when the sample is limited to Finland, Germany, Spain, and Sweden.

		OLS			2SLS	
Mean age at first birth	(1)	(2)	(3)	(4)	(5)	(6)
$Exp_{rt-2} \times \mathbb{1}^{L}_{rt-2}$	-0.307***			-0.238***		
	(0.063)			(0.079)		
$Exp_{rt-2} \times \mathbb{1}^{M}_{rt-2}$		0.147***			0.133***	
		(0.042)			(0.043)	
$Exp_{rt-2} \times \mathbb{1}^{H}_{rt-2}$			-0.223***			-0.222***
			(0.045)			(0.064)
Observations	704	704	704	603	603	603
KP F-Stat				19	13	20
Within R-squared	0.60	0.55	0.60			

All models control for female median age, lagged female employment, lagged GDP, region and year fixed effects. Robust standard errors clustered at the regional level in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 18: Correlation between education years and concern of technology replacing jobs, in the second wave of the Work Orientations survey (International Social Survey Programme 1999)

	(1)	(2)
Concern		
Educ	-0.151	0.702**
	(0.098)	(0.258)
$Educ^2$		-0.696***
		(0.173)
Observations	8,330	8,330
R-squared	0.146	0.149

All models control for age and country fixed effects. Robust standard errors clustered at the country level in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Table 19: Calibration of parameters - summary

Parameter	Description	Value	Source
r	Annual discount rate.	0.02	de la Croix and Pommeret (2021)
σ_i	Volatility	$0.036 + s_i \times 0.036$	de la Croix and Pommeret (2021)
$\pi(t)$	Success rate of pregnancy	$\frac{0.96\ \exp(3.5-0.33\,t)}{0.012+\exp(3.5-0.33\,t)}$	Léridon (2005)
R	Happiness of having children at the preferred age.	3.5	Natividade et al. (2020)
τ_1	Penalty for deviating from preferred age for having children when nearing youth.	0.17	Natividade et al. (2020)
τ_2	Penalty for deviating from preferred age for having children when nearing seniority.	0.05	Natividade et al. (2020)
κ	Cost of children when 18 years-old	7	Hoffman and Maynard (2008)
$\bar{T}$	Average preferred age for having a child.	30	Harper and Botero-Meneses (2022)
$sd(T)$	Standard deviation of preferred age for having a child.	3.3	Harper and Botero-Meneses (2022)
ν	Adjustment factor for correlation between T and education.	3.75	van Balen et al. (1997)
Δ_t	Arrival rate of new industrial robots	1/6.5	Karastoyanov and Karastanev (2018)
(θ_1, θ_2)	Curvature of the relation between concern for automation and education.	(0.702, -0.696)	Data from International Social Survey Programme (1999)

Figures

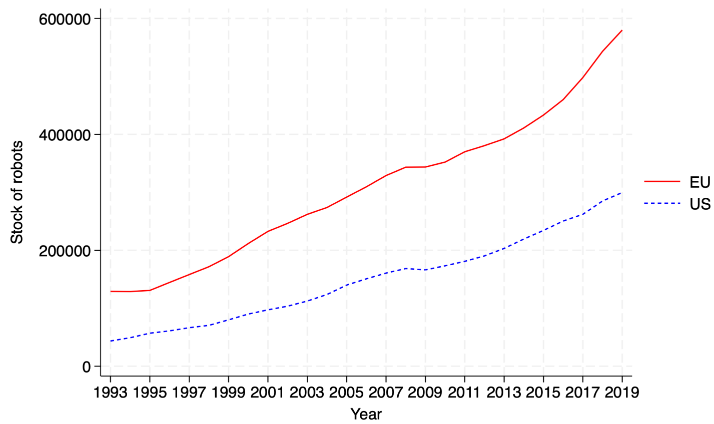


Figure 1: Evolution of the stock of industrial robots in Europe and the US.

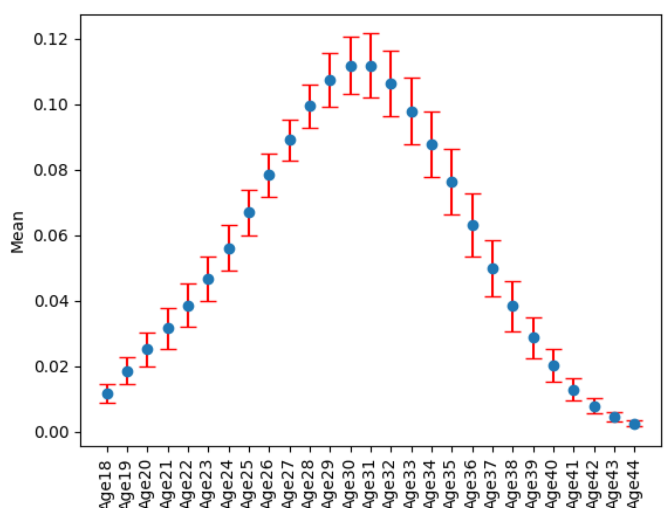


Figure 2: Mean and within standard deviation of age-specific fertility rates.

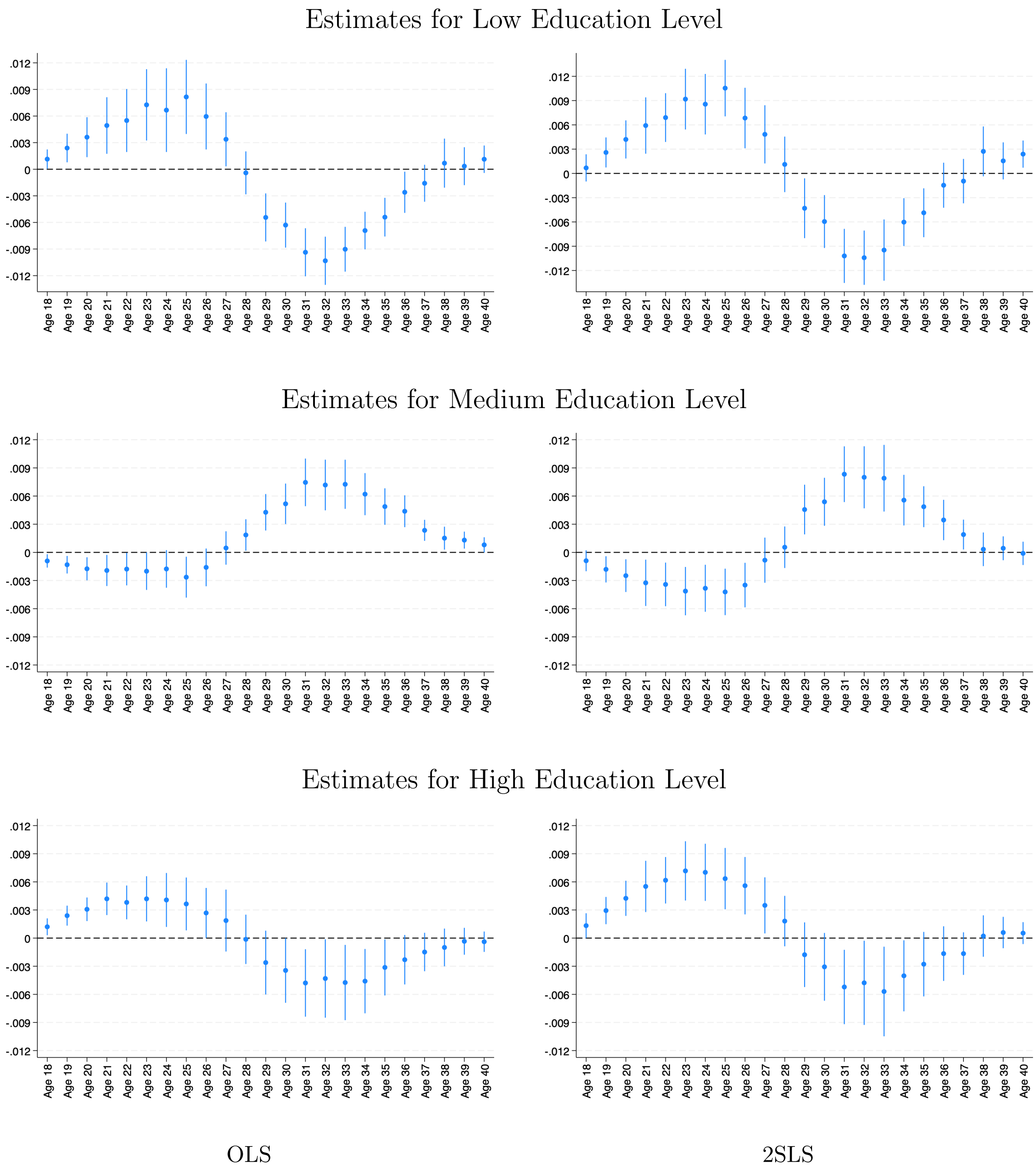
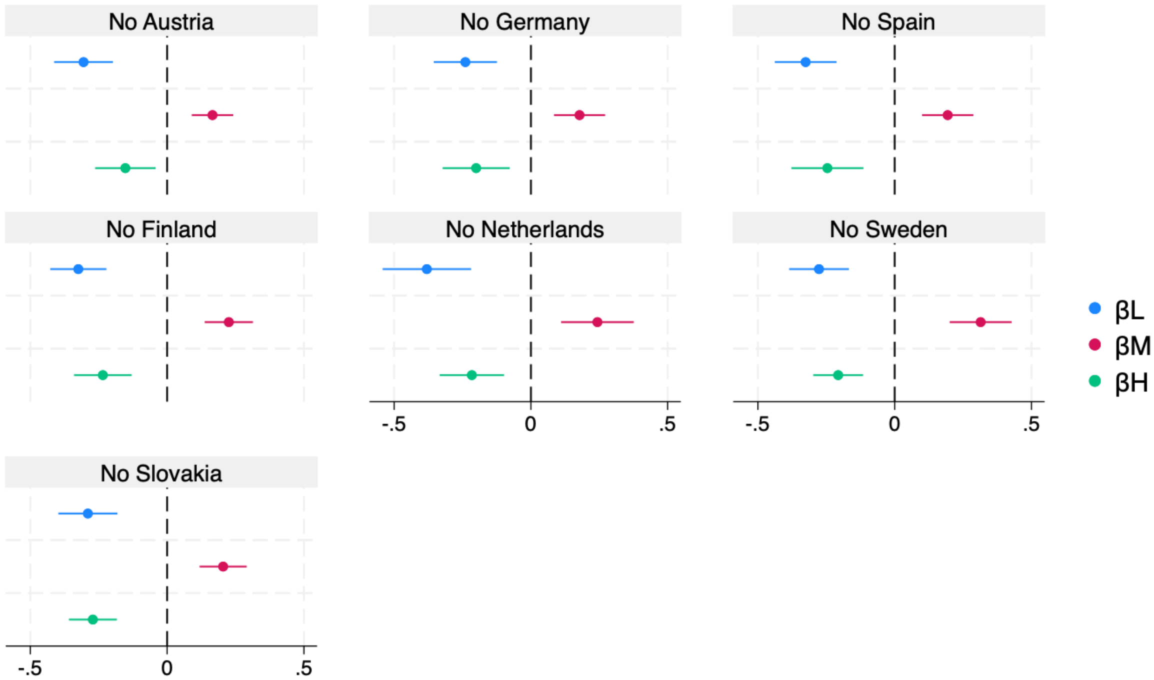
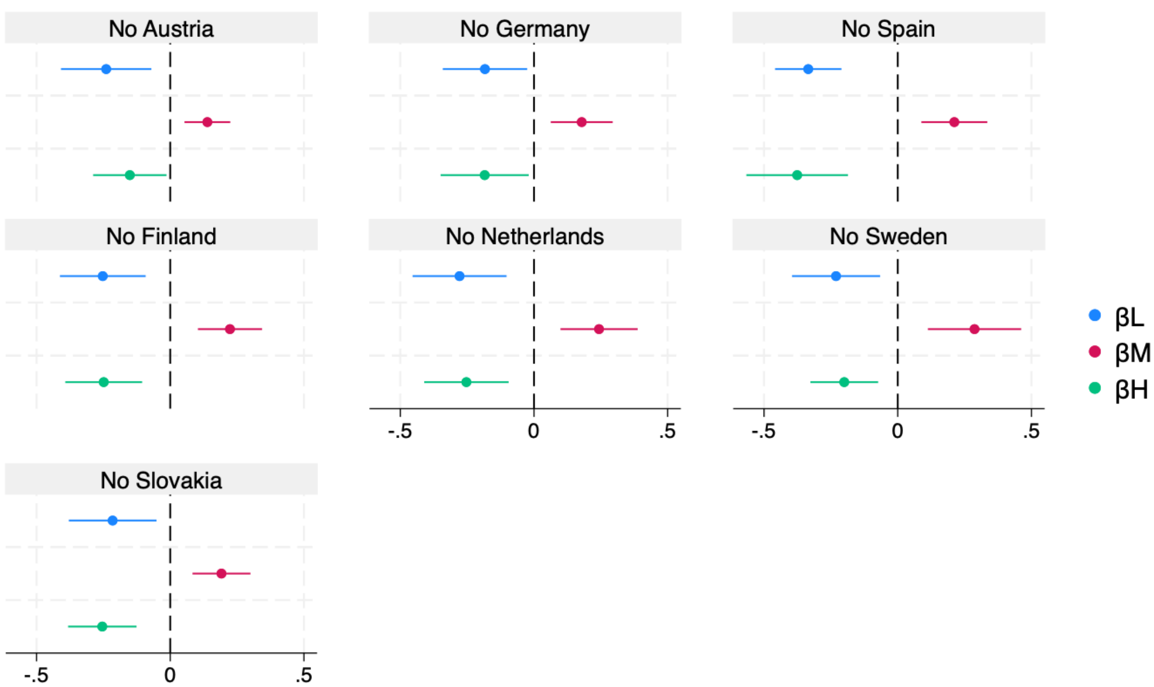


Figure 3: Effect of robot exposure on age-specific fertility rates.



OLS.



2SLS.

Figure 4: Regressions results of Equation (5), with mean age at birth as outcome, by excluding countries one-by-one.

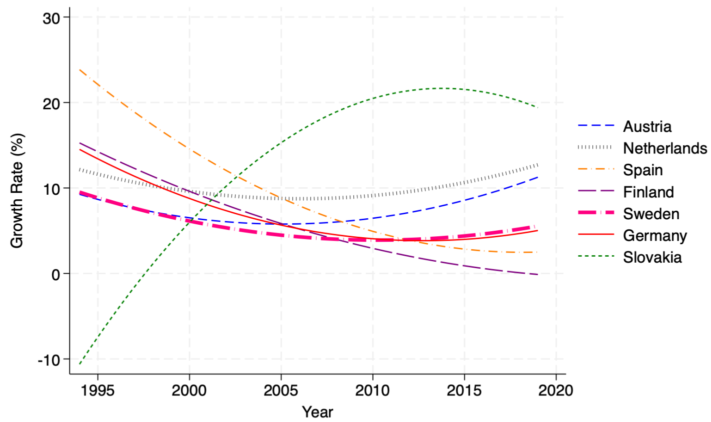


Figure 5: Growth trend in robot adoption by country.

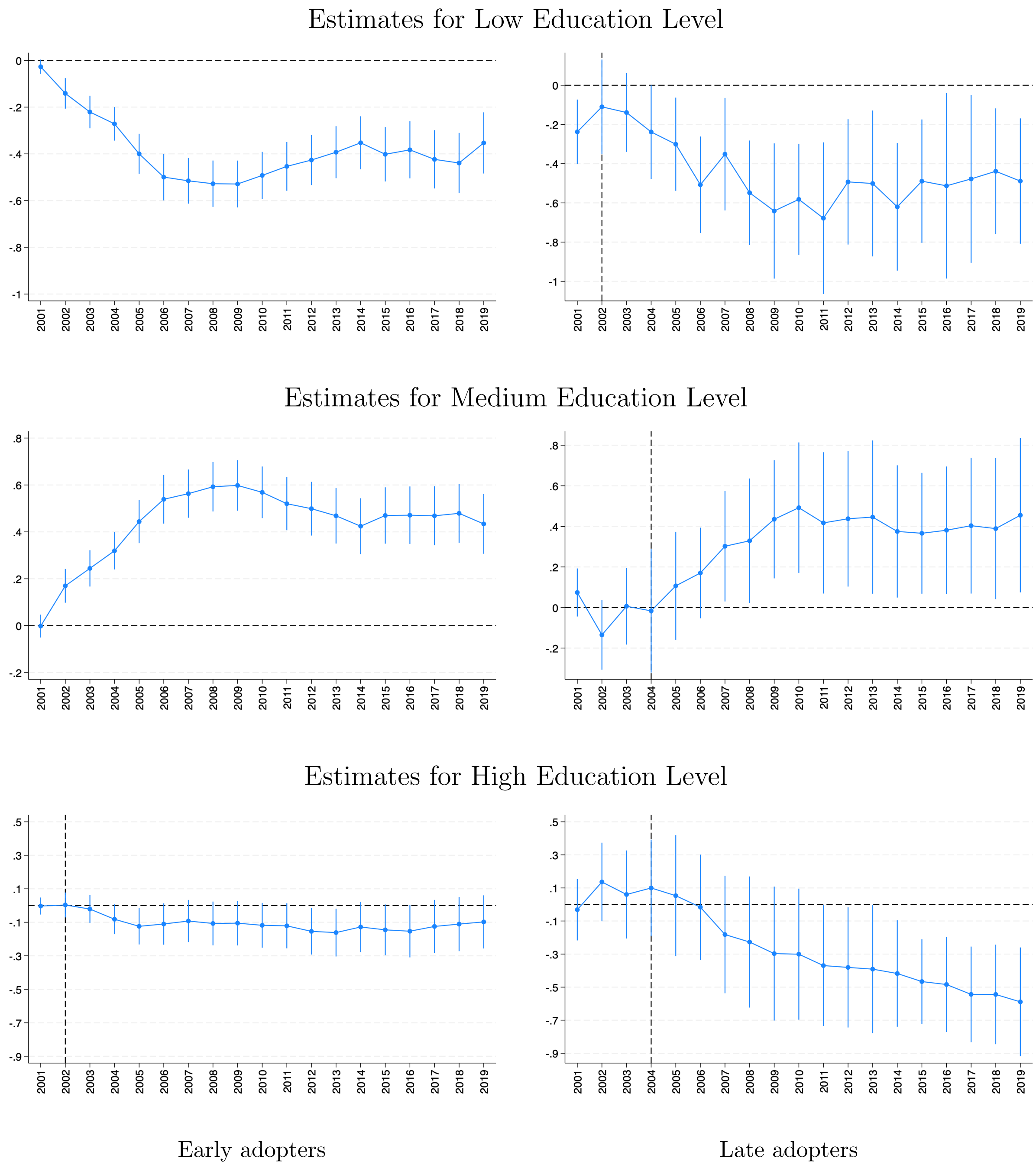


Figure 6: Coefficient plots on interaction between education indicators and years. Left: Spain, Finland, Sweden, Germany. Right: Austria, Netherlands, Slovakia.

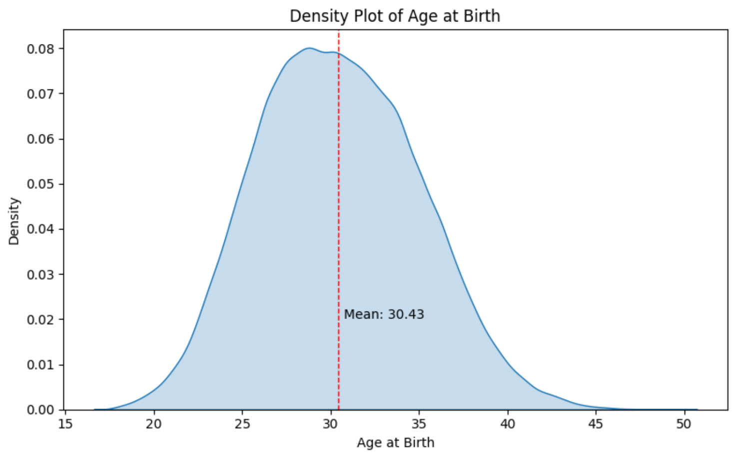


Figure 7: Density plot of simulated age at birth.

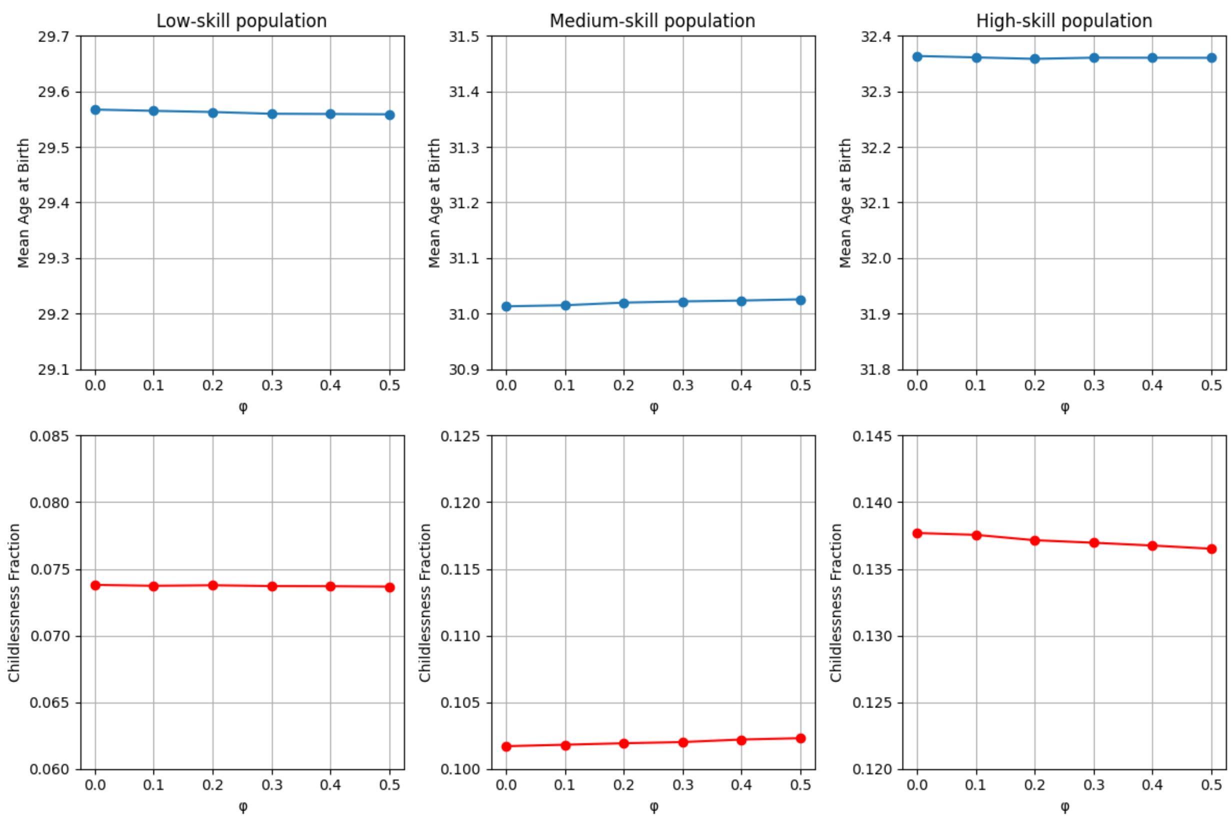


Figure 8: Relation between mean age at birth and childlessness rate with the change in volatility due to industrial robots, ϕ, in labor markets with education values concentrated on the left ($s \sim \text{Beta}(1, 5)$), center ($s \sim \text{Beta}(3, 3)$), and right ($s \sim \text{Beta}(5, 1)$) side of the distribution.

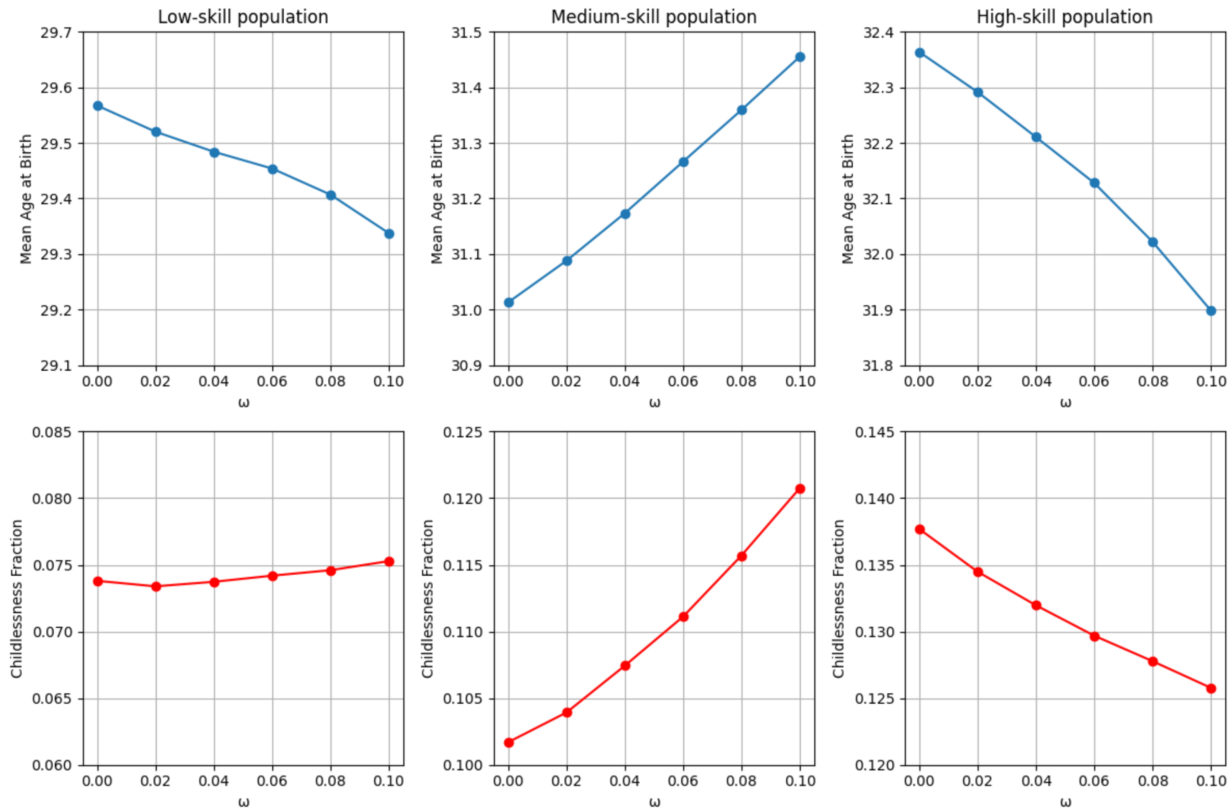


Figure 9: Relation between mean age at birth and childlessness rate with the change in employment rates due to industrial robots, ω, in labor markets with education values concentrated on the left ($s \sim \text{Beta}(1,5)$), center ($s \sim \text{Beta}(3,3)$), and right ($s \sim \text{Beta}(5,1)$) side of the distribution.

Robots, jobs, and optimal fertility timing

Online appendix

Claudio Costanzo*

June 4, 2025

A Supplementary results

This appendix explores the impact of robot exposure on regional employment rates for both women and men. It also analyzes the mean age at birth, with a specification where the education regressors and the employment control variable pertain to the male population. Additionally, it provides a simple analysis of the long-term relationship between robot adoption and unemployment rates categorized by educational attainment, for which data availability is scarce. A comparable analysis of wage impacts cannot be conducted due to the absence of yearly information in the Eurostat regional database. However, research on uncertainty and fertility postponement by Bhaumik and Nugent (2011) indicates that it is the risk associated with employment that influences decisions regarding the timing of fertility, rather than financial risks.

These supplemental findings serve two purposes. First, they reinforce the causal intuition that the observed dynamics linking robot exposure to fertility timing are likely due to a decrease in labor opportunities for workers in the middle of the skill distribution and an increase for those at the extremes. Second, they strengthen the identification assumption of the main analysis, which distinguishes specific education cohorts through the interaction of the regressor with the share of the population that has attained that level of education.

A.1 The effect of robots on employment

This section presents the results obtained by estimating, following the same format as Equations 4 and 5, the relation between robots and employment. The exposure score is lagged

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by $\tau = 1$ year to account for labor market adjustments. The panel is here limited to year 2007 in order to avoid distortions due to the Great Recession on labor outcomes, as it has been done in the previous literature that explored the effect of robotization on employment (Graetz and Michaels 2018, Acemoglu and Restrepo 2020, Klenert et al. 2023).[1] As in the main analysis, I focus on the employment data for those aged 25 to 34, as it more accurately reflects the population of reproductive age.

Female employment. The coefficients derived from regressing the robot exposure score on the regional employment rates of young women are presented in Table A1. Except for a within standard deviation increase in employment observed in the OLS specification without education shares as control variables, none of the coefficients exhibit statistically significant levels that suggest a non-zero effect. Table A2 shows the results obtained by interacting the regressor with the education shares indicators. These show non-monotonic movements in female employment rate, with low- and high-skilled labor markets benefiting at the expense of mid-skilled. The interaction coefficients indicate an 11-12% increase in employment for the low-skilled population, a decrease by around 9% in mid-skilled employment, and an increase by 5% when looking at the high-skilled. The magnitude of the coefficients is similar to those reported by Giuntella et al. (2024), who found an approximate 7% increase in unemployment in Chinese labor markets, based on longitudinal data. Labor markets with a rich presence of low-skill women seem to benefit the most from automation. This is likely due to the increased demand in the service sector.[2]

Male employment. The coefficients estimated for employment rates of 25-34 years old male population as outcome are shown in Table A3. The results point to a null direct effect of robots on male employment. When looking at the interactions with skill shares, the coefficients reported in Table A4 point to weak movements in employment for the low and middle-educated cohorts of labor markets. However, the effects turn null when estimated through two-stage least squares, suggesting a much weaker evidence, compared to the female case, of a polarized effect of automation on labor.

For completeness, Table A5 presents the coefficients from Equation 5 for the average age at childbirth, focusing on the education and employment variables for the male population.

[1] Indeed, by adding additional years, the coefficients obtained by interacting the exposure score with the labor market skill levels lose significance, until the signs sometimes reverse when the entire period is considered. Antón et al. (2022) detect a reversal of the effects between early and late time-periods. I stick to the period already explored by the literature and leave further discussion on such after-crisis distortions to future, honed, research.

[2] See Autor et al. 2006 and Ngai and Petrongolo 2017 about the rise of the female-dominated service sector at the expense of male-dominated manufacturing one.

The results from the Ordinary Least Squares OLS and 2SLS analyses indicate that the patterns observed previously in the female population hold true only for the mid-educated labor markets.

Overall, the above results suggest a polarization in employment rates, as a consequence to higher exposure to robots, for the female population. The same outcome does not apply for male workers, who only experience a timid effect for the low and mid-skilled cohort of workers. The Routine-Biased view on the impact technological change is indeed particularly relevant when we consider female workers, who mostly account for the polarization in employment (Cerina et al. 2021). This is likely due to younger cohorts of women sorting into non-routine positions in the service sector at a quicker rate than men, departing from routine-intensive jobs (Black and Spitz-Oener 2010). Consistent with these findings, polarization in fertility timing is observed only within the female demographic.

A.2 The effect of robots on unemployment rates by education

While Eurostat lacks fertility data categorized by education level, it does provide unemployment statistics for workers aged 25-34, sorted by their educational attainment. However, this dataset has substantial gaps, rendering unreliable for accurate estimation. It only contains data for some Spanish regions, and very few (one to three) for some of the other countries in the dataset. Nevertheless, a simpler, bivariate analysis is still feasible to determine if the influence of automation on employment can still be observed within the data segmented by educational levels. This would reinforce the reliability of the identification strategy.

For this purpose, I examine the change ratio between unemployment rates and robot exposure from 1999, the earliest available year, to 2007. This timeframe allows us to observe long-term employment trends while controlling for the confounding effects of the Great Recession, in line with established practices in the literature. The observations are limited to Spanish regions.

The scatterplots in Figure A1 reveal consistent patterns. In the case of low-skilled workers, there seems to be a negative correlation between the change in robot adoption and unemployment rates. Conversely, for mid-skilled workers, unemployment decreased less in regions with larger shifts in exposure. We have a decrease in unemployment for the high-education cohort as well, but with a less clear pattern compared to the previous cases.[3]

Given the limited number of observations, this analysis alone cannot conclusively establish a clear relationship between automation, education, and employment. However, when combined with findings on fertility in Section 3.2, expectations about automation and jobs in

[3] Indeed, this is the only cohort that is pretty sensitive to change in the years considered, or in the elimination of outliers.

Section 4.1, and the aggregate employment impacts discussed in this appendix, the evidence points to a non-monotonic effect of robotics, varying with individuals' education levels, on both employment and fertility timing. Additionally, these results suggest that using the interaction between automation and the educational levels within the population can provide a valid identification strategy to understand how automation impacts different educational groups.

A.3 Education and concern for automation

This section complements the stylized facts about the inverse U-shaped relation between schooling level and the beliefs on the impact of automation on jobs, by showing that the non-linear relationship remains robust across various tests. As a first check, the formal level of education is used as explanatory variable. The survey contains seven education categories, standardized by country: no formal education, incomplete primary school, completed primary school, incomplete secondary school, completed secondary school, incomplete university, and completed university. The new coefficients are reported in Table A6 and retrace the non-monotonicity found with schooling years. In order to assure that the inverted-U shape relation is not due to the imposition of a tight structure on the data, we can additionally estimate a version of the regression with a looser structure. This is achieved by introducing binary indicators for each educational category, leading to the estimation of the following equation:

$$Concern_i = \alpha + \theta \sum_j D_j + Age_i + \zeta_c + \varepsilon_i, \tag{1}$$

where D_j represents a vector of the seven levels of educational attainment of the respondents. The coefficients in Table A7 show the deviation in the outcome with respect to different educational levels compared to the omitted category, i.e., individuals with no formal education. It reveals no significant difference in concern scores between individuals with no education and the educational categories in the opposite extreme, namely those who have not completed primary school and those who have completed university. Conversely, concern levels tend to escalate, relative to the absence of formal schooling, as we move towards the mid-range educational categories, covering primary, secondary, and incomplete university education.

A significant concern regarding these estimates stems from variations in survey years. Among the ISSP Work Orientation surveys, only the second wave specifically addresses respondents' apprehensions about automation, while more recent waves focus solely on general concerns regarding job loss. Over time, the educational prerequisites for various job categories may have evolved, potentially leading to differing skill levels among workers in the same occupational group. To mitigate this concern, I follow the methodology used by van

Hoorn (2022): I aggregate the average values of the 1997 worry variable for each two-digit ISCO occupational code with responses from the fourth wave of the Work Orientation survey (International Social Survey Programme 2017). The coefficients derived from estimating Equation (7) for respondents in the fourth wave, utilizing the averaged value as the outcome variable, are presented in Table A8. The table shows a negative correlation between the outcome and years of schooling. Including the squared term confirms a concave relationship between the two variables, with a 2% increase in the R-squared.

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Supplementary tables

Table A1: Effect of robot exposure on female young employment. Baseline estimation without interactions.

	OLS		2SLS	
Female employment	(1)	(2)	(3)	(4)
Exp_{rt-1}	3.098*	1.584	2.395	1.513
	(1.678)	(1.307)	(2.112)	(1.443)
$\%Low\,Educ_{rt-1}$		-1.036***		-1.055***
		(0.180)		(0.210)
$\%Med\,Educ_{rt-1}$		-0.551***		-0.642***
		(0.150)		(0.226)
Observations	517	401	233	231
KP F-Stat			34	33
Within R-squared	0.04	0.23		

All models control for region and year fixed-effects. Robust standard errors clustered at the regional level in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Table A2: Effect of robot exposure on female employment. Baseline estimation with interactions.

	OLS			2SLS		
Female employment	(1)	(2)	(3)	(4)	(5)	(6)
$Exp_{rt-1} * \mathbb{1}^{L}_{rt-1}$	10.78***			12.15***		
	(2.138)			(2.641)		
$Exp_{rt-1} * \mathbb{1}^{M}_{rt-1}$		-8.268***			-9.875***	
		(1.542)			(2.198)	
$Exp_{rt-1} * \mathbb{1}^{H}_{rt-1}$			4.717**			5.449***
			(1.918)			(1.867)
Observations	401	401	401	231	231	231
KP F-Stat				7	9	11
Within R-squared	0.37	0.35	0.30			

All models control for region and year fixed-effects. Robust standard errors clustered at the regional level in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Table A3: Effect of robot exposure on male employment. Baseline estimation without interactions.

	OLS		2SLS	
Male employment	(1)	(2)	(3)	(4)
$Exp_{rt-1} * \mathbb{1}^{H}_{rt-1}$	-0.284	-0.086	0.909	0.596
	(0.664)	(0.719)	(1.180)	(1.096)
$\%Low\,Educ_{rt-1}$		-0.418***		-0.355***
		(0.073)		(0.115)
$\%Med\,Educ_{rt-1}$		-0.262***		-0.199*
		(0.077)		(0.104)
Observations	517	401	233	231
KP F-Stat			34	40
Within R-squared	0.00	0.08		

All models control for region and year fixed-effects. Robust standard errors clustered at the regional level in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Table A4: Effect of robot exposure on male employment. Baseline estimation with interactions.

	OLS			2SLS		
Male employment	(1)	(2)	(3)	(4)	(5)	(6)
$Exp_{rt-1} * \mathbb{1}^{L}_{rt-1}$	1.967**			1.809		
	(0.757)			(1.144)		
$Exp_{rt-1} * \mathbb{1}^{M}_{rt-1}$		-1.246*			-0.793	
		(0.651)			(0.806)	
$Exp_{rt-1} * \mathbb{1}^{H}_{rt-1}$			0.124			-0.853
			(0.480)			(1.350)
Observations	401	401	401	231	231	231
KP F-Stat				14	42	28
Within R-squared	0.10	0.09	0.08			

All models control for region and year fixed-effects. Robust standard errors clustered at the regional level in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Table A5: Effect of robot exposure on mean age at first birth. Baseline estimation with education and labor variables referred to male population.

	OLS			2SLS		
Mean age at first birth	(1)	(2)	(3)	(4)	(5)	(6)
$Exp_{rt-2} \times \mathbb{1}^{L}_{rt-2}$	-0.224***			-0.108		
	(0.056)			(0.076)		
$Exp_{rt-2} \times \mathbb{1}^{M}_{rt-2}$		0.243***			0.206***	
		(0.045)			(0.062)	
$Exp_{rt-2} \times \mathbb{1}^{H}_{rt-2}$			0.006			-0.004
			(0.036)			(0.038)
Observations	1,164	1,164	1,164	994	994	994
KP F-Stat				18	16	15
Within R-squared	0.18	0.22	0.14			

All models control for region and year fixed-effects. Robust standard errors clustered at the regional level in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Table A6: Correlation between education level and concern of technology replacing jobs, in the second wave of the Work Orientations survey (International Social Survey Programme 1999)

	(1)	(2)
Concern		
Educ	-0.130	0.560**
	(0.080)	(0.234)
$Educ^2$		-0.534***
		(0.151)
Observations	8,792	8,792
R-squared	0.141	0.143

All models control for age and country fixed effects. Robust standard errors clustered at the country level in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Table A7: Correlation between binary coded education level and concern of technology replacing jobs, in the second wave of the Work Orientations survey (International Social Survey Programme 1999)

Concern	
Incomplete Primary	0.207
	(0.137)
Primary	0.271**
	(0.113)
Incomplete secondary	0.243**
	(0.116)
Secondary	0.251**
	(0.118)
Incomplete University	0.212*
	(0.119)
University	0.142
	(0.121)
Observations	8,792
R-squared	0.144

All models control for age and country fixed effects. Robust standard errors clustered at the country level in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Table A8: Correlation between education years of and averaged concern of technology replacing jobs by occupation in 1997, in the fourth wave of the Work Orientations survey (International Social Survey Programme 2017)

	(1)	(2)
Avg. 1997 Concern by occupation		
Educ	-0.280***	0.241*
	(0.025)	(0.129)
$Educ^2$		-0.395***
		(0.087)
Observations	8,615	8,615
R-squared	0.171	0.190

All models control for age and country fixed effects. Robust standard errors clustered at the country level in parentheses. * p<0.1; ** p<0.05; *** p<0.01.

Supplementary figures

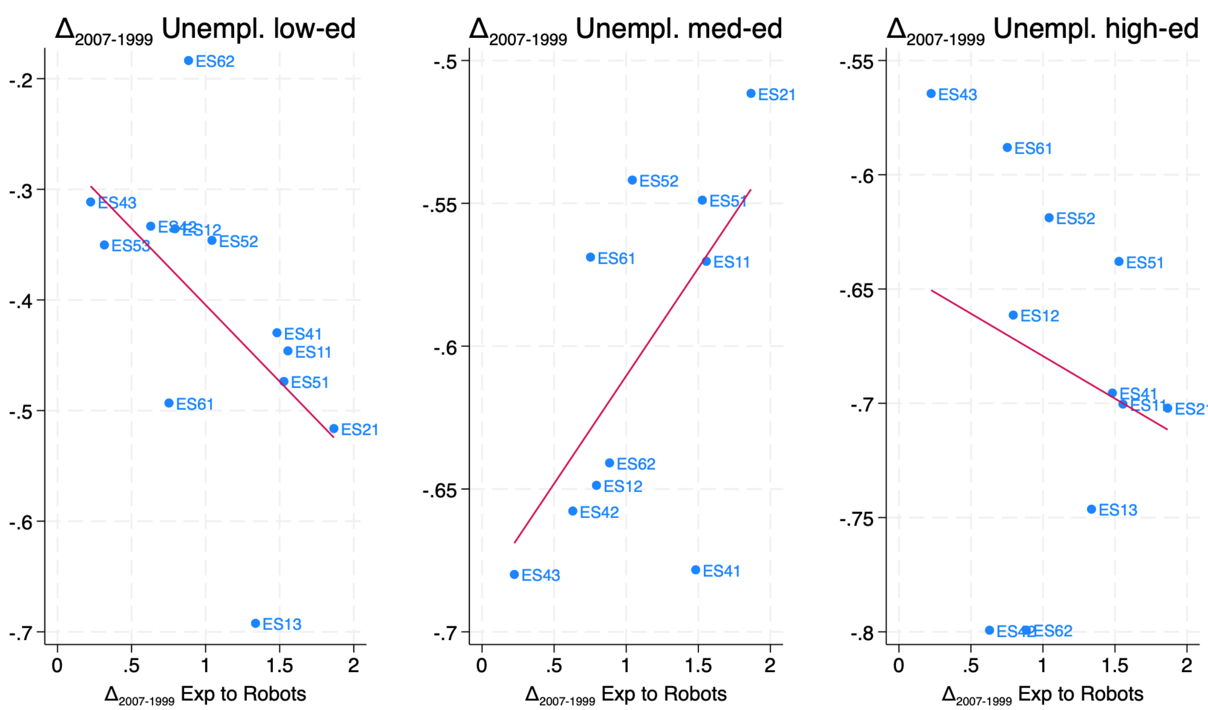

Figure A1: 2007-1999 relative difference in employment rates of low, medium, and high-educated 25-34 years old women, in Spanish regions.