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Abstract

Labor automation is generally associated with a decrease in demand for mid-skill jobs, often routine-intensive, in favor of the others. This paper investigates its effects on fertility timing decisions using European panel data, by constructing a measure of local exposure to industrial robotics, and by adopting a Fixed Effect with Two-Stage Least Squares methodology. Higher exposure is associated with an anticipation of fertility in low- and high-skilled regional labor markets, and with its postponement in medium-skilled ones. An optimal stopping model, in which individuals adjust the timing based on their future labor opportunities, formalizes the causal intuition. Its numerical application, based on survey data, suggests that the effect of an increase in observed automation on the willingness to postpone fertility is concave with respect to education, consistently with the Routine-Biased Technological Change hypothesis.

Keywords: Automation, Demography, Fertility, Robots.

JEL Codes: J13, J21, J24, O33

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1 Introduction

Technological development is one of the major forces that affect the labor market and, in turn, the life-course decisions of families. One of the most important historical demographic events, the so-called "Baby Boom", has been linked by Greenwood et al. (2005) to the progress in the home-sector technology. The jump in fertility rates, which occurred after the Second World War, was accompanied by a bust in the availability of time-saving household appliances, which, they argue, allowed parents to dedicate more time to child-rearing activities. La Ferrara et al. (2012) provide evidence that soap operas portraying small families reduced fertility in Brazil. In high education and low fertility contexts such as Germany, Billari et al. (2019) argue that the broadband Internet makes it easier to reconcile career and motherhood, hence increasing fertility rates.

More recently, industrial automation has become an important focal point in the discussions about the future of jobs. Robots can either decrease the demand for labor, by performing tasks previously carried out by some human workers, or increase it, because of positive spillovers in the market due to higher industrial productivity. Acemoglu and Restrepo (2020) refer to these dynamics as the displacement and productivity effects, respectively. While being the debate on which of the two effects dominates still ongoing, there is a consensus on the existence of a job polarization, i.e. a process consisting in a decline of the share of jobs of medium-skilled workers in favor of low-skilled and high-skilled ones, as shown by Autor et al. (2006) for the US and by Goos et al. (2009) for the EU. They argue that among the determinants of such a phenomenon, which include offshoring, increasing female labor force participation, and aging, technical progress is the strongest driver. The idea is that automating technology tends to replace routine tasks. This hypothesis is usually referred to as the "Routine-Biased Technological Change", and has replaced the old "Skill-Biased Technological Change" one, proposed by Katz and Autor (1999), according to which the risk of replacement decreases monotonically with education. As observed by Autor et al. (2003), routine jobs, both manual and cognitive, are typical of middle-skilled workers. Examples are clerical and organizational jobs, book-keeping, repetitive production, storing and manipulation of information. These activities are technically complex, but follow precise rules (what programmers would call an if-then-else order), which makes them easy to perform for a machine. In turn, workers that perform non-routine tasks can witness an increase in the demand for their skills, thanks to the demand for new jobs and to the possibility to specialize in their area of comparative advantage by outsourcing repetitive tasks. In this sense, Autor et al. (2003) distinguish between abstract and manual non-routine activities. Abstract ones are characterized by problem solving, creativity, oratory skills, and intuition.

Managers, lawyers, engineers, and scientists, who typically have a high level of schooling, for instance, need these skills. Nonroutine manual activities, instead, require environmental adaptability, mobility, proprioception, empathy, visual and language recognition, and personal interaction ability. Workers whose jobs are based on these skills are often located at the bottom of the schooling distribution. Drivers, janitors, cooks, health assistants, or waiters do not necessarily need a degree, but perform tasks that are often beyond the limits of a machine. In order to give support to the Routine-Bias hypothesis, Autor and Dorn (2013) propose a model where the reduction of the cost of automatable routine tasks reduces the demand for mid-skilled tasks and reallocates low-skilled labor into service occupations. Goos et al. (2014) construct a Routine Intensity Index for different occupations and show that, in 16 European countries, the index tends to be higher for medium-paying occupations than for low- and high-paying ones.

As machines are able to perform more and more tasks, many individuals may feel the pressure of a continuously shrinking demand for labor. A decrease in the prospects of individuals for their immediate future has often been linked to a delay in fertility (Schneider (2015), Sommer (2016), Comolli (2017)). The aim of this paper is to understand how the transformation of labor driven by industrial automation affects demographic decisions, specifically regarding the timing of fertility. This can have a relevant impact on the demography of a country, as it can cause a fall in fertility rates (Balasch and Gratacós (2012)). Moreover, d'Albis et al. (2017) argue that the probability of having the first child decreases more when it is driven by unrealized labor market integration than when it is due to investment in education or career. Understanding how the current transformation of labor due to technical change is influencing family decisions can be important to identify policy targets.

This article creates a bridge between two different areas of research. The first regards the effect that industrial robots, which this analysis uses as a proxy for labor automation, have on wages and employment. Industrial robots are defined by the International Federation of Robotics (IFR) as automatically controlled, reprogrammable, and multipurpose manipulators. This definition excludes other tools that can replace labor but need a human controller, such as ICT technologies. However, it provides an internationally comparable measure of automation technologies (Jurkat et al. (2022)). The second area relates to demographic behavior, with a focus on the timing of births.

The first step of the paper is an empirical analysis that looks at the relation between automation and fertility behavior. It does so by focusing on the interaction between automation and the educational structure of the labor markets, using the Routine-Biased Technological Change assumption as a premise. The units of observations are NUTS2 regions in Europe, where the link between skill levels and the routineness of different classes of occupations has been empirically explored. The empirical methodology follows the local labor market approach of Acemoglu and Restrepo (2020) and relies on panel data collected by Eurostat and the IFR. The identification strategy assumes that the exposure to automation of an industry is proportional to the historical sectoral employment ratio and to the usage of industrial robots in the country. The explanatory variable can be thought of as a Bartik-style instrument, since a common industry shock, namely the exponential increase in the European stock of robots started after the mid-1990s, is weighted with the pre-shock specialization in that sector. The measure of exposure interacts with three indicator functions. These indicate whether the share of the female population with a certain level of schooling (incompleted secondary, secondary or post-secondary, and tertiary) is relatively high compared to the other European regions. The fixed-effect model shows that the interaction between the indicator of low and high education with the exposure variable is negatively correlated with the mean age at first birth. The correlation is positive, instead, when the exposure variable interacts with the middle education indicator.

Possible concerns about endogeneity may arise due to the interrelation between demographic trends and the adoption of robots (Acemoglu and Restrepo (2021)). Therefore, the industry-level spread of robots in the automation-leading countries that are absent in the dataset is used to construct an instrumental variable. The Two-Stage Least Squares (2SLS) analysis reduces the concern about the reverse causality between fertility and automation. Further robustness checks exclude the possibility that the results are driven by the specification of the education operators or by specific industries, and account for the time of pregnancy by leading forward the outcome.

Final evidence regards fertility rates and its age-specific dynamics. The relation between robotics and Total Fertility Rates is pretty unclear, but seems to point to an increase in fertility in middle-skilled regions, probably due to the fall in opportunity cost for the workers who bear the reduction in labor demand the most. Using age-specific fertility rates on the left-hand side of the equations, the results are consistent with the findings on the tempo effect. The plots of the coefficients show that in low- and high-education labor markets, automation makes women prefer to concentrate fertility when they are younger. The contrary occurs for regions with a prevalence of medium-educated women, where the tempo effect overlaps with a positive quantum one.

The second step consists of an optimal stopping model, based on a framework typical of Option Value Theory, that provides an economic intuition behind the above results. Children are considered an irreversible investment with a "career cost", in the sense of Adda et al. (2016), who interpret it as losses in terms of employment and earnings opportunities due to motherhood and child-rearing. While the model will be described in a formal way throughout the next sections, it may be useful to introduce here a basic intuition on how fertility decisions can be shaped by automation. Imagine a woman who wants to have a child and has to decide whether to bear it at present time, t_0, or at a generic future time, t_1. Assume also that between t_0 and t_1 some robots enter the labor market. If the woman observes that jobs are being created more than they are being displaced, then she would expect the cost of children to be higher in t_1 than in t_0, due to the higher demand for labor. As happens with investment decisions, the optimal choice is to invest, i.e. bear the child, when the cost is lower, hence at time t_0. Similarly, if she observes a prevalence of displacement over the production of jobs, childbirth will occur at t_1, when the career cost will be relatively lower than at t_0.

The model relates the expectation of individuals about the impact of robots to their education level, and estimates the relation between education and the involvement in the displacement of jobs using survey data collected by the International Social Survey Program. The estimated coefficients show that this relation is concave. This suggests that the Routine-Biased Technological Change hypothesis also relates to individuals' expectations. By using the estimated parameters to proxy for the concern of replacement, the model shows that a higher level of robotics increases the value of waiting to have children for agents with an average level of schooling, while reducing it for those at the extremes of the education range.

The rest of the paper is organized as follows. Section 2 reviews the literature to which this analysis contributes. Section 3 describes the construction of the predictor variable, the data sources, the econometric specification, and addresses endogeneity concerns. The results are presented in Section 4. It is followed by Section 5, which gives the theoretical intuition of the mechanism underlying the empirical results, with the aid of the optimal stopping model. Finally, Section 6 contains concluding remarks.

2 Literature

This paper links two different areas of literature, namely the consequences of robotics on employment and the influence of labor market risks on fertility timing choices.

2.1 Industrial robots and employment

The consequences of robots on the labor market are becoming a topic of great interest for many scholars, but their findings are often controversial.

Graetz and Michaels (2018) show that the adoption of industrial robots is associated with an increase in annual labor productivity growth, average wages, and total factor productivity in a country, with decreasing marginal gains. They do not find significant effects on overall employment, but they do find a reduction in the hours worked by low-skilled workers. Acemoglu and Restrepo (2020) developed a model in which robots and workers compete in the production of different tasks. Theoretically speaking, they argue that robots affect the economy in two directions. On the one hand, because of a displacement effect, i.e. the substitution of workers from tasks they were previously performing, employment and wages are affected negatively. On the other hand, wages and employment experience an increase due to a productivity effect, i.e. an expansion of the demand for labor because of positive spillovers due to automation. This can be due to the rise of the demand for non-automated tasks, and to the creation of new jobs as a result of technological progress. Using a Bartik-measure of US commuting-zone exposure to robots, they find, overall, a negative effect on employment and wages, higher for men than for women. However, they do not find positive and offsetting employment gains in any occupation or education group, as their model would instead suggest. Klenert et al. (2022) look at how robots affect European employment by skill types and find a positive effect. Sequeira et al. (2021) show, using US data, that while exposure to robots leads to a displacement of jobs in an initial stage, the productivity effect tends to overclass the losses as the penetration of robots in the labor market increases. Using panel data of Spanish manufacturing firms, Koch et al. (2021) find positive employment effects and estimate a job creation rate of 10%. Domini et al. (2022) use employer-employee data for French manufacturing firms and observe that automation is positively correlated with employment, and that such an effect does not appear to be heterogeneous among different types of jobs.

In this study, the influence of robots on employment is related to family decisions. In a recent work, Anelli et al. (2021) study the implications of industrial robotics on the marriage market. They first document gender heterogeneity on how automation influences labor outcomes. On average, they find that the negative effects of automation tend to be suffered by men, who are frequently employed in the manufacturing sector. Women, who often work in the service field, are more likely to benefit from the productivity effect of robots. The unbalanced effect of automation depending on gender has also been documented by Ge and Zhou (2020), who find that automation reduces wages for both men and women in the US, but more for the former. As a consequence of the decreasing marriage market value of men, the marriage rates tend to be lower, while cohabitation and divorces higher, in American communities more exposed to industrial robotics. The analysis in this paper abstracts from the formation of the family and focuses on the decision about when to give birth.

2.2 Fertility timing

Among the determinants of fertility timing behavior, such as the well-known increasing education enrolment (see for example Monstad et al. (2008) and Bhrolcháin and Éva Beaujouan (2012)) and cultural norms (Chabé-Ferret (2019)), an important one is labor market risk. The intuition about the link between income fluctuations and fertility timing has been introduced by Ranjan (1999). With a two-period model, he shows that higher uncertainty leads individuals to postpone fertility when their income is below a certain threshold and to anticipate it when it is above. Empirical works find that uncertainty (Sommer (2016)) or specific events that worsen individuals' prospects, such as the Great Recession (Schneider (2015)) and pandemics (Luppi et al. (2020)), make individuals prefer to postpone childbearing.

The model proposed in Section 5 is based on theories typically used to study the optimal time to make irreversible investments with pay-offs subject to uncertainty (Merton (1973), Dixit and Pindyck (1994)). The idea of adopting the Real Option Approach (ROA) to study demographic behavior has been proposed by Iyer and Velu (2006), who suggest that uncertainty in the net payoff of having children creates a pure value of delaying childbearing, due to the possibility to see how uncertainty resolves. Option Value Theory, they argue, may perform better than the Net Present Value (NPV) approach in explaining empirical findings in demography. In India, as an example, southern countries have a low median age at sterilization compared to northern ones (IIPS (2000)). At the same time, there is evidence from South India that the uncertainty associated with having a child has decreased due to employment in small-scale industry and developed local markets (Desai and Jain (1994)), and to better access to maternal and child health-care facilities (Sen and Drèze (1997)). This reduction in the risk, Iyer and Velu (2006) argue, may be the reason why women in southern India decide to concentrate childbearing at young ages.

Successive work has followed the idea of ROA as a tool for studying demographic behavior. By calibrating a similar investment model with Colombian data, Zuluaga (2018) shows that fertility is also delayed due to uncertainty in the cost of childbearing. Bhaumik and Nugent (2011) present empirical evidence of ROA, trying to separate the insurance mechanism from the option value effect due to uncertainty, which move the timing choice in opposite directions. Their setting is eastern Germany during the country's reunification, when the welfare system was sufficiently strong to rule out the insurance value of children and isolate specific sources of uncertainty. They show that employment-related risks (but not financial ones) had a negative impact on the likelihood of childbirth, and they argue that empirical research should measure different types of market risks in order to provide further evidence for the validity of the ROA in modelling demographic phenomena. Instead of focusing on the dynamics that precede the act of procreation, de la Croix and Pommeret (2021) observe that income uncertainty may arise as a consequence of maternity itself. This may be due to health consequences, losses in earnings opportunities, or a reduction in social network sizes, for instance. Therefore, they propose a model where motherhood introduces risks in the asset dynamics of the mother, and show that postponement arises as a consequence as well.

The aforementioned studies model market risk as a Wiener process, as they are interested in uncertainty from generic sources. The main difference of the model proposed in Section 5, compared to the above ones, is the addition of a jump process to describe the possibility that labor automation may substitute or create jobs, affecting the cost, in terms of career opportunities, of becoming a parent.

The next section arranges the empirical set-up that aims at exploring whether industrial automation and its consequences for workers is a determinant of demographic behavior.

3 Empirical method

The empirical methodology follows the local labor market approach used by Acemoglu and Restrepo (2020) for the US. This section describes the construction of the variable that captures the level of robot exposure, along with the identifying assumptions behind it. Then, it reports the data sources and the summary statistics of the main variables used in the analysis. Finally, the fixed effect model is described, along with a discussion on possible endogeneity concerns.

3.1 Identification and predictor variables

The explanatory variable is identified at the level of European regions (NUTS2) and is intended to represent how much a regional labor market is exposed to advances in industrial robotics. It is constructed as a Bartik-style instrument: By assuming that the distribution of robots within industries is uniform across the regions within a country, the variable exploits the variation in the pre-sample distribution of employment in a given sector across regions, and the evolution in the stock of robots in that sector across countries. The baseline year is set to 1995, which is the earliest year in the time series of the Eurostat regional database. It is also the year after which the exponential rise in industrial robotics in Europe began (see Figure 1). Using a more recent year would increase the sample size, as earlier data have fewer missing observations. However, it may increase the likelihood that the sectoral employment distribution is influenced by the post-1995 rise of robots usage. Since it is based on the pre-existing industrial composition of regions before the boom in the adoption of robots, the variable relies on the historical differences in the industrial specializations of European regions, hence avoiding correlation between current employment and other variables in the analysis.

The measure of exposure in a given industry is calculated by multiplying the regional baseline employment share in the region by the ratio of robots to employed worker in the country. After that, the industry-specific scores are summed up to obtain the regional exposure to industrial automation:

$$Exposure_{rt} = \sum_i \frac{Empl_{ir}^{1995}}{Empl_r^{1995}} \frac{StockRobots_{ict}}{Empl_{ic}^{1995}}, \tag{1}$$

where the subscripts r, t, c, and i denote the region, year, country, and industry, respectively. $Empl_{ir}^{1995}$ represents the number of workers employed in industry i and in region r, and $Empl_r^{1995}$ is the total employment in the region. $\frac{StockRobots_{ict}^{c}}{Empl_{ic}^{1995}}$ denotes the number of robots at t per thousand workers in 1995 in industry i.

The aggregation of data does not allow to evaluate separately the demographic outcomes of different education-cohorts of individuals. To bypass the limitation, the exposure variable interacts with three indicators that isolate regions where the female population with a certain level of education is relatively high. These are constructed by comparing the share of women with low, medium, and high education with the yearly average in the other European regions. Specifically, let us define the following three indicators:

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

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

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

Hence, the operator $\mathbb{1}_{rt}^{e}$, where $e \in \{\text{L, M, H}\}$, takes value 1 if the share of e-skilled women in region r in year t is greater than the average share in the other European regions in year t. Substantially, they indicate the skill-structure of a local labor market.

3.2 Fixed-effect model

In the regression model, the exposure variable interacts with the three indicators described in Section 3.1. It takes the form:

$$Y_{rt} = \alpha + \beta_L(\mathbb{1}^L_{rt} * Exposure_{rt}) + \beta_M(\mathbb{1}^M_{rt} * Exposure_{rt}) + \beta_H(\mathbb{1}^H_{rt} * Exposure_{rt}) + \\ + \eta Exposure_{rt} + \rho_L \mathbb{1}^L_{rt} + \rho_M \mathbb{1}^M_{rt} + \rho_H \mathbb{1}^H_{rt} + \mu_r + \lambda_t + \varepsilon_{rt}, \quad (2)$$

where the subscripts r and t indicate region and year. Y_{rt} is the outcome variable (mean age at first birth and fertility rates). μ_r and λ_t are fixed-effects at regional and year level, which control for unobservable and time-invariant differences across regions, and for time trends in the outcome. ε_{rt} is the idyosincratic error term. Standard errors are clustered at the regional level, as the errors for the same region in different time periods are likely to be correlated. The model also controls for the median age of the female population and, when the age at birth acts as outcome, log population. The coefficients β_L, β_M, and β_H represent the changes in the outcome associated with a unitary increase in the level of exposure to robotics when the corresponding indicator of the level of regional education is equal to one. The Routine-Biased Technological Change hypothesis makes it reasonable to expect that $sgn\beta_M \neq sgn\beta_L = sgn\beta_H$. In other words, as low- and high-skilled labor markets benefit from automation at the expense of mid-skilled ones, we may expect fertility outcomes to be affected in opposite directions as well, ceteris paribus.

Note that Equation (2) may suffer from collinearity problems. Clearly, the three indicators are constructed with percentages that are negatively correlated with each other: The higher the share of individuals with a certain level of education, the lower is the share of those with the other two levels, as they sum up to one. The operator reduce the collinearity that we would have by using the percentages. However, a Variance Inflation Factor (VIF) test, which gives values slightly higher than 5, suggests that some collinearity between the operators remains. Hence, the model is estimated both by including all the three interaction terms and by including them one by one, i.e. by estimating:

$$Y_{rt} = \alpha + \beta_e(\mathbb{1}^e_{rt} * Exposure_{rt}) + \eta Exposure_{rt} + \rho \mathbb{1}^e_{rt} + \zeta X_{rt} + \mu_r + \lambda_t + \varepsilon_{rt}, \quad (3)$$

where $\mathbb{1}^e_{rt} \in \{\mathbb{1}^L_{rt}, \mathbb{1}^M_{rt}, \mathbb{1}^H_{rt}\}$ and $\beta_e \in \{\beta_L, \beta_M, \beta_H\}$.

3.2.1 Two-Stage Least Squares

Despite being the omitted variable bias very limited due to the use of fixed-effects, there may still remain some concerns about reverse causality. Acemoglu and Restrepo (2021) found that there exists a link between the demography of a country and its tendency to automate labor. They document a positive relationship between aging and technological change, intended both for the automation of jobs and innovation. As aging creates a shortage of middle-aged workers specialized in manual production tasks, firms operating in countries undergoing faster aging tend to employ more automation of labor.

To address endogeneity, Acemoglu and Restrepo (2020) exploited the spread of robots in five European countries, ahead in the adoption of robots compared to the others, as a proxy for automation in the US. I adopt a symmetric strategy and construct an instrument for the explanatory variable using the stock of robots in Denmark, France, and Italy, which are not included in the dataset and are among those countries that lead the adoption of automated technologies. The instrumental variable is as follows:

$$Exposure_{rt}^{IV} = \frac{1}{3} \sum_{j \in EU3} \left(\sum_{i} \frac{Empl_{ij}^{1995}}{Empl_{r}^{1995}} \frac{StockRobots_{it}^{j}}{Empl_{i}^{j,1995}} \right), \tag{4}$$

where $StockRobots_{it}^{j}$ represents the stock of robots used in industry i, in year t, in the country $j \in EU3$, where $EU3$ is the set of countries considered. $Empl_{i}^{j,1995}$ denotes the historical employment in industry i in country j[1]. Note that the industrial specialization ratio is exogenous per se, as it is constructed using historical values.

When using the Two-Stage Least Squares (2SLS) approach, the instrument needs to be correlated with the endogenous variable and that its effect on the outcome is only indirect, through the endogenous variable. Since there are few international companies that provide industrial robots and, hence, drive the global trend in automation, we can reasonably assume the relevance of $Exposure_{rt}^{IV}$. We may also expect that the instrument is valid, as it is unlikely that automation trends in a country directly affect fertility choices in the others. Let us estimate the following equation to assess the existence of a relation between the instrumented and instrumental variables:

$$Exposure_{rt} = \kappa + \pi Exposure_{rt}^{IV} + \mu_r + \lambda_t + \varepsilon_{rt}, \tag{5}$$

where μ and λ are as in Equation 3. The result of model 5 is reported in Table 1, which shows a statistically significant coefficient for π. An additional unit in the instrument corresponds to an increase of 1.3 units in $Exposure$, with the probability that the effect is null below 1%.

[1]Data are taken from EU KLEMS Growth and Productivity Accounts: March 2007 Release (van Ark and Jäger (2017)).

3.3 Data

The data used to examine the relation between industrial robotics and fertility timing is obtained by merging the datasets of the International Federation of Robotics (IFR) and Eurostat. It is an unbalanced panel, with information on 18 years (2000-2018), for 59 regions in 7 European countries, namely Austria, Finland, Germany, Netherlands, Slovakia, Spain, and Sweden. Despite being it a restricted number of regions, it is an heterogeneous sample, as it has a mediterranean, three western, two Scandinavian and a eastern European countries[2]. The following paragraphs describe the sources and report the descriptive statistics of the variables of interest, outlining possible criticalities in the analysis.

3.3.1 Industrial robots

Data on the stock of industrial robots at the country-year-sector level come from the International Federation of Robotics (IFR). The organization conducts annual surveys on the number of robots that have been sold in each country for different industries. It has information for 70 countries over the period 1993 to 2019. IFR defines industrial robots as "automatically controlled, reprogrammable, and multipurpose machines" (IFR, 2016). In other words, industrial robots are machines that are fully autonomous (do not require a human operator to work) and can be programmed to perform repetitive tasks.

The data has some limitations. First, the smallest geographic unit reported is the country. Therefore, information on the within-country distribution of the stocks of robots is missing. Second, while the division of the manufacturing industries is very detailed, the stocks referred to the other sectors are aggregated. Finally, about a third of industrial robots are not classified. As in Acemoglu and Restrepo (2020), unclassified robots are allocated in the same proportion as in the classified data.

Figure 1 reports the evolution of the stocks of industrial robots in Europe and the United States from 1993 to 2019. The use of industrial robotics has exploded since before 1993 in the United States and since 1995 in Europe, and it has been exponentially increasing, with a little slowdown during the Great Recession period.

3.3.2 Historical sectoral employment, demographics, and education

Historical data on employment, used to construct the explanatory variable along with the stocks of robots from the IFR, are taken from the Structural Business Statistics (SBS) Eurostat database, which breaks down information on regional employment to the sectoral

[2]The results do not change with the exclusion of each country one by one, which reassures on the possibility that one of the 7 countries is driving the effects.

(NACE) level. These data refer to the year 1995. While information on employment in the manufacturing sectors is sufficiently rich, the other industries have many missing observations. Therefore, employment in the agriculture and fishery industries, as well as total regional employment, are integrated using the Annual Regional Database of the Directorate General for Regional and Urban Policy of the European Commission (ARDECO). All the other sectors are considered together as the difference between the employment in all industries, minus the employment in manufacturing, agriculture, and fishery. This is not a problematic limitation, as industrial robotics interests almost entirely (around 99%) the manufacturing sector. We end up with information on 11 different manufacturing industries[3] at the two-digit level and the two groups of aggregated industries.

The demographics and education variables are gathered from the Eurostat regional database, starting from 2000. The variables that describe the level of education in the regional population are based on the International Standard Classification of Education (ISCED) measures. By ISCED0-2 we refer to individuals with less than primary, primary, and lower secondary education. ISCED3-4 defines upper secondary and post-secondary non-tertiary education. By ISCED5-8 we mean those who completed tertiary education. For the sake of simplicity, I refer to these three levels of schooling as low, medium, and high, respectively.

3.3.3 Summary statistics

Table 2 shows the descriptive statistics of the main variables used in the analysis. In terms of education, on average, 30% of the sample has less than secondary school, almost half has completed it, and a fourth has a degree. The shares of low- and high-educated tend to have a higher within standard deviation, compared to the mid-skill case (approximately a fifth versus a fifteenth of the mean). This is probably due to the increasing education trend. The use of the annual, rather than the overall, European average in the construction the indicators in Section 3.1 avoids that their values are due to such time trends.

The outcome variables are the mean age at first birth and the fertility rates for different age cohorts. The first birth usually occurs at the age of 30, with a standard deviation of around half a year within the same region. The mean fertility rate is 1.5. Age-specific fertility rates are shown for the 20 to 40 age range. The mean reaches the maximum of 0.108 at the age of 30, and decreases in a bell-shaped pattern when the age approaches 20 and 40, when the minimum reported values are zero.

Regarding the predictors, Table 3 reports the summary statistics of the robot exposure

[3]Food, textiles, wood, paper, plastic+chemicals+rubber, mineral, metal, machinery, electronics, vehicles, others.

variable, its instrument, and the three indicators. The observations in the panel reduce from almost 4000 to around 1100, when we consider nonmissing values for the exposure to robotics. Being it constructed by summing up the exposure scores of each of the 13 industries considered, a missing value for just one of the industries results in the observation being dropped, hence reducing the sample size. The exposure measure has a mean of 1.9 and a within standard deviation of 0.78. Figure 2 shows a map of Europe with four different levels of the variable in 2018 for the regions contained in the dataset. According to available data, Germany and the Netherlands appear as the most and the least exposed countries, respectively. There is heterogeneity in Spain, with the north being more exposed than the south. Similarly, in Sweden, the north and the south witness low and high exposure to robots, respectively. The only region in Finland for which the sample has information has a low level of automation. There is high spatial heterogeneity in Austria. In Slovakia, the level gradually decreases as it approaches the northeast.

Figure 3 plots the evolution over time of the average exposure to robots in the dataset. The graph suggests an exponential evolution. We witness a unitary increase in the variable (0.9 to 1.9) from 2000 to 2010. The value is approximately 3 in 2017, suggesting that the time range required to have a unitary change decreases with time. This exponential pattern of the variable is not due to chance, but follows a rule known as the "Moore's law", formulated by the engineer Gordon Moore, who, in 1965, noticed that the capacity of semiconductors doubled every 1.5-2 years. Since then, the Moore law typically refers to the fact that technical progress tends to be exponential.

The last three rows of Table 3 show the summary statistics for the skill indicators when the observations are reduced to those where the exposure score is not missing. $\mathbb{1}^M$ and $\mathbb{1}^H$ take a value of one for around half of the regions, while $\mathbb{1}^L$ is so for 35% of them. The within-standard deviations are relatively high and suggest that the same region may experience different values of the operators over time. Robustness checks are going to take into account confounding factor due to the indicators switching from year to year for the same region.

4 Results

This section reports the results of the model described in Section 3.2. All the tables show the OLS and 2SLS results of the regressions formalised by Equation (2), in the first column, and by Equation (3), in the last three columns, which refer to low-, mid-, and high-skill regions. First, it is shown that robots positively correlate with employment rates of young women in the first and third cases, but negatively in the second one, confirming the bias of automating technologies towards the routine-intensive middle class of workers. This enforces the causality intuition that fertility decisions as an outcome of automation are linked to employment dynamics. Then, the fixed effect model is used to explore the relation between robots and the mean regional age at birth, followed by some robustness checks. Finally, the consequences of automation on age-specific fertility rates are discussed by looking at how women of different ages react to increasing automation. Together, the results suggest a postponement of fertility for medium-skill labor markets and an anticipation for the other two cohorts, as a response to greater automation.

4.1 Employment rates

Before exploring demographic outcomes, Table 4 shows the coefficients obtained by regressing the robot exposure score on the regional employment rates of women aged 25 to 34 years[4]. The panel is here limited to the years 2000 to 2007 in order to avoid confounding effects of the Great Recession on labor outcomes, as in Graetz and Michaels (2018), Acemoglu and Restrepo (2020), and Ge and Zhou (2020).

When we look at Column (1) we have a positive coefficient, suggesting an increase in employment by 12% for an additional robot per thousand worker (with respect to the 1995 employment distribution), for the low-education cohort of regions. However, the statistical significance suggests that the effect is likely null for the other two education cohorts. The other three columns report coefficients that have significance values at the traditional levels, hence suggesting the possibility of a collinearity issue when the three operators are included together, as mentioned in Section 3.2. Columns (2) and (4) report an increase in employment rates for young women in low and high education labor markets by 11.6% and 3%, respectively. Column (3) reports a reduction by -5.2% for the middle-skill cohort. The captured within variation in the outcome goes from a minimum of 12% in the fourth column to a maximum of 32% in the first. The 2SLS coefficients, reported in the second half of the table, are consistent with the OLS ones and suggest that the effect is 1% greater in Column (4). The Kleibergen and Paap (2006) F-Statistics are pretty close to the traditional threshold of 10, with a minimum of 6 in Column (1) and a maximum of 23 in Column (3). Labor markets with a rich presence of low-skill women seems then to benefit the most from automation. This is most likely due to the gains of the employment rates in the service ("brain") over the manufacturing ("brawn") sector, where female labourers tend to be sorted more often than men[5] (see Autor et al. (2006) and Ngai and Petrongolo (2017)).

[4] Consistent results run also for all women in working age.

[5] If the same outcome is referred to men, the OLS results only point to an increase by around 3% in employment rates for the low-skill cohorts, which becomes non significant with the 2SLS estimation.

4.2 Mean age at first birth

This subsection describes the findings on the link between the regional exposure to robots and the mean age of women at their first birth.

Table 5 shows the baseline results. The coefficients related to the interaction terms have signs that are opposite to those found with respect to women's employment rates. Higher exposure is associated to an increase in the age at birth for the medium-educated cohorts of labor markets, and with a decrease otherwise. While the statistical significance levels reported by Column (1) are above the conventional values with respect to the interactions with $\mathbb{1}^L$ and $\mathbb{1}^M$, we cannot reject the hypothesis that the effect is null with respect to $\mathbb{1}^H$. However, the levels of statistical significance are all above 99% in the last three columns. As in the previous case, the loss of significance in the first specification is likely to be driven by collinearity. The coefficients in Column (1), obtained with the specification of Equation (2), suggest that, on average, low-education regions experience a decrease by -0.2 years in mean age at birth when a robot per thousand worker is added. Medium-education regions, experience an increase by around 0.22. Looking at Columns (2), (3), and (4) (estimated with Equation (3)), the values are around -0.365, 0.32, and -0.15. This corresponds to around 4 months for low- and high-skill cohorts, and 2 months for the high-skill case, and amount to a half and a fourth of the within standard deviation, respectively. The order of magnitude of the decrease of the age at birth, which appears higher for low-skill labor markets, seems to be on a similar proportion of those found for employment rates. To get an idea of the magnitude of such effects, let us consider again Figure 3. If we were in 2000, we would need around 10 years to witness a unitary increase in exposure to robots, hence a change in fertility timing by the estimated coefficients. If we were in 2010, we would need approximately 7 years to have another unitary increase in robots' adoption, and such an interval of years is likely to decrease over time due to Moore's law. The within R-Squared is on the range 21-to-33%. The Two-Stages estimates suggest an overestimation of the effect for Columns (2) and (3), now showing an absolute value of 0.3 years, and show F-Statistics of around 7[6].

4.2.1 Robustness checks

The following robustness checks have the aim of reassuring that the baseline effects do not change dramatically after some modifications to the specification. These checks take into account the possibility that the results may be due to the skill indicators, driven by specific sectors, or that the time of pregnancy should be taken into account when considering fertility

[6] The F-Statistics are higher than 10 when the equations exclude the regions of Germany, which is much more advanced in the adoption of robots compared to all the other countries. The coefficients remain almost invariant.

outcomes.

Table 6 reports the results obtained by interacting the exposure variable with the regional share of women with primary, secondary or post-secondary, and tertiary education, instead of using the operators. As the shares sum up to one, the first column is likely to suffer much more from collinearity compared to the case in which the indicators are used. Indeed, in Column (1) the coefficients are all positive, with low statistical significance in the OLS case, and null significance in the 2SLS specification. However, when the education shares are considered one by one, as shown in Columns (2), (3), and (4), the signs are consistent with the baseline estimates, and the effects are statistically significant at the conventional levels. A percentage point increase in the share of women with low education, combined with the addition of a robot per thousand workers, decreases the mean age at first birth by 0.01 years. We have a postponement by a similar amount in the mid-education case. When the interaction regards tertiary education the reduction is -0.006. For a within standard deviation increase in the education shares, the coefficients amount to 0.0614, 0.0345, and 0.033, respectively. The 2SLS suggests an underestimation of the coefficient in Column (4), which is now on the same magnitude as the other two.

An additional concern arises by noticing that $\mathbb{1}^{L}_{rt}$, $\mathbb{1}^{M}_{rt}$, and $\mathbb{1}^{H}_{rt}$ can switch over time, as reported by the within standard deviations in Table 3. We may be concerned that these switches are associated with labor market changes triggered by the adoption of robots itself. By reconstructing the skill operators using only the shares observed in year 2000, rather than looking at the shares in each year, we get the results reported in Table 7. The OLS values are on the same line as those presented in Table 5. The 2SLS estimates suggest a change in the outcome by half a year for low-skill labor markets and by a third for mid- and high-skill ones.

Table 8 shows the coefficients obtained by dropping the vehicle sector from the exposure variable and adding it in isolation as a control. This aims to ensure that the effects of the explanatory variable are not driven by the automobile industry, which has adopted much more robots than any other industry[7]. the coefficients increase by approximately 0.1 for all the three skill cohorts. The F-Statistic values are higher compared to the previous case and are in the range of 11 to 23.

Finally, Table 9 takes into account the concern that fertility outcomes may be only observed after some time due to the pregnancy interval. It does so by leading the outcome variable by one year. The OLS coefficients are pretty similar to the baseline estimates, with

[7]See Figure 2 in Acemoglu and Restrepo (2020), which compares the 1993-2007 increase in robot penetration in the automotive sector, both in the European and American labor market, with the one in the other industries.

a slight reduction in the 2SLS case. The next set of results focus on fertility rates, both from both the total and age-specific perspectives.

4.3 Total fertility rates

We now look at the relation between automation and fertility rates. We should interpret such an effect as resulting from the combined movements of income and opportunity cost, which determine the expenditures on the quantity and on the quality of children (Becker and Lewis (1973)). Ceteris paribus, a high income is associated with a higher desired number of children, as the parent can face a greater material cost. However, an increase in the wage usually comes with an increase in the opportunity cost, because the time not spent on working results in a higher loss in income. This is often related to a lower desired number of children and higher investment in their quality.

Table 10 shows the results obtained by regressing the Total Fertility Rate (TFR) on the level of robot exposure, with the usual four specifications, with the exception of dropping log population as a control variable, as its evolution goes along with fertility rates. Column (1), suggests that higher exposure is associated with an increase in fertility for mid-skilled labor markets by 0.05, which is confirmed when the exposure is looked in isolation in Column (3). This corresponds to around a half of the within standard deviation in the outcome. Column (2) and (4) report a negative coefficient, of around -0.035 and -0.02, respectively. Contrary to what happens when we consider the age at first birth as outcome variable, the Two-Stage Least Squares do not confirm the Ordinary Least Squares estimates. The coefficients in the first column point to a positive correlation for mid- and high-skilled cohorts. When considered in isolation, the significance values in all three cases do not exclude that the effects are actually null.

All considered, the relation between robots and total fertility rates is rather confusing and unconvincing, with little evidence of an increase of fertility for mid-skilled labor markets. The following section sheds more light on fertility dynamics by considering the tempo and the quantum effects simultaneously.

4.4 Age-specific fertility rates

To have a clearer view about how robotics change demographic dynamics, age-specific fertility rates of women aged 20 to 40 are used as new dependent variables in Equation (3). Therefore, each of the three specifications has 20 fertility outcomes and 20 related coefficients, which are graphically represented in Figures 4, 5, and 6, where the horizontal axes represent the age cohorts. β_L, β_M, and β_H follow an S-shaped path in the coefficient plots.

In low-skill regions (Figure 4), the correlation at 20 years of age is positive and amounts to 0.006. The coefficient increases and reaches a peak, corresponding to 0.008, for the cohort of 23-years old women. It turns negative at the age of 27 and reaches the minimum of 0.015 (one third more than the within standard deviation) at 31. It then stabilizes to zero at 37-38 years. The high-skill case (Figure 6) follow a similar path, with narrower fluctuations. The positive effect is around 0.0025 from the age of 20 to 25. It drops and turns negative at the age of 28, until it reaches a negative peak of -0.006 at the age of 32. After that, it slowly approaches zero. Both Figure 4 and 6 show a slight prevalence of the negative over the positive coefficients. This may be due to an increase in opportunity cost driven by higher opportunities for such labor markets, which increases the cost of childbearing.

In the middle-education case (Figure 5) the dynamic is opposite. The correlation is negative at the beginning of the reproductive life, with a value of around -0.004 being fairly continuous. It turns zero at the age of 27 and experiences a rapid increase until the age of 31, where it reports an increase in fertility by 0.012. After the peak, it rapidly reduces and reaches the zero at age 40. Contrary to the cases of low- and high-education regions, in medium-skill regions the postponement of childbearing appears to overlap with an increase in the optimal family size, with the additional children being born at the end of the reproductive life. This is likely to be due to the reduction in opportunity cost of raising children for such a cohort of workers, who bear the most of the negative employment effects of automation.

These S-shaped relations between robot exposure and age-specific fertility rates strenghten the preponement and postponement dynamics suggested by the effects on the regional mean age at first birth. In the following section, a simple model tries to provide a theoretical intuition of the decision-making process that drives the empirical findings presented up to now.

5 An optimal stopping model of fertility

The optimal stopping problem is based on Dixit and Pindyck (1994), who model the optimal time to make irreversible investments under uncertainty. The problem is faced by a woman, who act as the sole decision maker. This simplifying assumption derives from two observation. First, the cost of children in terms of lost time is mostly beared by the mother during pregnancy. Second, couples often have a close level of education (see Mare (1991), among others, for a discussion on assortative mating). As a consequence, the effect of robots on employment opportunities is likely to be shared between spouses in many families. Time is continuous and at each unit of time the woman decides whether or not to bear a child. The choice variable is hence binary. The maximization problem consists in deciding the rule regarding whether, at each period, the difference between benefits and cost of childbearing makes it optimal to stop delaying fertility. Benefits can intuitively be thought of as happiness and support when the parent is old. The cost consists of the time and resources that the parent has to assign to child-rearing instead of other activities, such as working and accumulating experience.

The expected impact of robots enters in the evolution of the cost through a jump process, which is modelled and estimated with survey data by linking education with the concern of replacement. The resolution of the model shows how the consequences of automation in terms of job opportunities shape the preference for postponement.

5.1 Set-up

Let us think about a woman willing to maximize her lifetime utility by deciding whether and how many children to have. This can be modeled using macroeconomic models or portfolio theory (see Iyer and Velu (2006) for a discussion on this). After she has decided on the desired family size, she needs to decide on the timing of fertility. We can assume that the decision to have children takes place from the moment a couple is formed until the biological age limit. During this period, she decides what is the optimal time to have the first child, the second, and so on. In a conventional Net Present Value (NPV) approach, the decision on the optimal time is dictated by the balance between the payoff and the cost, in present value, of the child.

Let R and C_t be the payoff and the cost of having children, both stated in present value terms. The payoff, meant as happiness, is assumed to be constant over time. Such an assumption is supported by Myrskylä and Margolis (2014) and Baetschmann et al. (2016), who provide evidence that the happiness of having a child is almost constant over any age. The opportunity cost, which can be interpreted as the loss in career opportunities due to the fact that a part of the available time has to be directed to child-rearing, evolves with time. In the NPV framework, the net benefits of having children, let us denote them by B_t, would be formally represented by:

$$B_t = R - C_t,$$

where the decision to have children would take place at time t if $R \geq C_t$, taking the discount factor and the biological clock into account. The NPV framework consists in a deterministic setup, where the variables change constantly and the individual knows perfectly how the cost evolves in the future. A more realistic scenario, where the entrance of robots is irregular and uncertain, can be described by including the option to wait, i.e. the gain linked to postponing the investment even when the net payoff is positive. This can be pursued using the Real Option Approach (ROA), which is conventionally employed for the study of the optimal time to make an investment which payoff unpredictably changes over time. If the cost (hence the net payoff) of childbearing is subject to uncertainty, then there exists a value in waiting to have a child, as delaying allows the individual to see how the cost evolves. To formalize this, we proceed in two steps. First, we define the cost process in such a way that the evolution of the opportunity cost is subject to stochastic changes. Then, the optimal stopping problem is solved by including the cost process in the value function.

5.2 The cost process

Consider the displacement and productivity effects as defined by Acemoglu and Restrepo (2020). The first is likely to translate into a fall in the opportunity cost, as the more the career opportunities shrink, the less the individual has to sacrifice if she has a child. The second effect translates into an increase in it, as the increase in the demand for new jobs is going to expand her career opportunities.

The cost follows a mixed Brownian motion - jump process[8], which takes the following form:

$$dC = \sigma C dz - C dq. \tag{6}$$

The first component, $\sigma C dz$, is the Brownian motion, i.e. a continuous-time process with three properties. First, it is a Markov process, which means that the probability distribution for future values only depends on the current one. Second, the probability distribution of the changes over a time interval does not depend on any other period. Third, its changes are normally distributed. dz represents the increment to the process, with $dz = \varepsilon_t \sqrt{dt}$, where $\varepsilon_t \sim N(0,1)$. σ is the instantaneous conditional standard deviation per unit of time. The Brownian motion component describes generic uncertainty with respect to the variable. In the context of fertility choices, the sources of such uncertainty may be related to labor market fluctuations, the financial situation, social and love relationships, or by technological change itself. The second component of the law of motion, Cdq, is the jump process. This consists of percentage changes in the variable that arrive at uncertain arrival times. Name $\lambda \in (0,1)$ the mean arrival rate of the event that causes a jump. The probability that such

[8] Dixit and Pindyck (1994) provide definitions of Brownian motion and jump processes in Sections 2 and 6, respectively, of Chapter 3. They describe how to solve investment timing models with dynamic programming in Chapter 5, where combined Brownian-Jump process are treated in Section 5.B.

an event occurs at a unit of time is λdt. dq takes the following values:

$$dq = \begin{cases} 0 & \text{with probability} \quad 1 - \lambda dt \\ \varphi & \text{with probability} \quad \lambda dt, \end{cases}$$

where $\varphi \in (-1, 1)$ represents the jump.

The process expressed by Equation (6) can be interpreted as follows. As time goes on, the opportunity cost of having a child fluctuates continuously, with little changes that can go up and down. However, over each time interval dt, there is a probability λ that some automated technology enters the market. This causes the cost to raise or drop depending on which between the displacement and the productivity effect prevails. It will then continue to fluctuate until the next jump occurs.

Before providing a functional form for the jump, the following paragraphs provide a general solution of the model.

5.3 The value function and the Bellman equation

Consider the value function of the problem (denote it as $F(C)$), which is an unknown function that maximizes the expected present value of the gains from investing in time t. It can be considered as the value of the investment opportunity, as it represents the best possible outcome of the objective function, hence:

$$F(C) = max_t \mathbb{E}[(R - C_t)e^{-\rho t}] \tag{7}$$

where $\mathbb{E}$ denotes the expectation, t is the time at which the investment is made, ρ is the discount rate, and the maximization problem is subject to Equation (6) for the evolution of the cost, C_t.

As the cost evolves stochastically, it is not possible to find an optimal time for the investment. Instead, the problem consists in finding a rule according to which each time the individual decides whether to stop to delay childbearing. This means to find a critical value of the cost, name it C^*, such that:

- If $C_t > C^*$, it is optimal to continue to wait;
- If $C_t < C^*$, it is optimal to stop waiting and bear the child;
- If $C_t = C^*$, the individual is indifferent between waiting and stopping.

To find C^*, we need to solve the Bellman equation of the problem. This is a functional equation in which the unknown is represented by the value function. In the case of an optimal stopping investment problem in continuous time, the Bellman equation is given by following equality[9]. Formally:

$$\rho F(C)dt = \mathbb{E}(dF), \tag{8}$$

where the value of the investment opportunity equals the cost of waiting.

5.4 Solution

Optimal stopping investment problems in continuous time are commonly solved by guessing the form of the value function and plugging it into the Bellman equation. By doing this we find the critical cost, defined by the following proposition.

Proposition 1 *The critical cost, below which the agent stops waiting to have children, is given by* $C^* = \frac{\omega}{\omega-1}R$*, where* $\frac{\omega}{\omega-1} \in (0,1)$*.*

Proof. In order to show Proposition 1, let us begin by expanding dF using the version of Ito's lemma for combined Brownian and Poisson processes:

$$\mathbb{E}(dF) = \frac{1}{2}\sigma^2 C^2 F''(C)dt - \lambda\{F(C) - F[(1-\varphi)C]\}dt, \tag{9}$$

where $F''(C)$ denotes the second derivative of F with respect to C. The first component that contributes to the expected value of the change in F is due to the continuous part of the process. The second component is the difference in the values of F before and after the jump.

Equation (8) can be rewritten by including Equation (9) in it and dividing by dt:

$$\frac{1}{2}\sigma^2 C^2 F''(C) - (\rho+\lambda)F(C) + \lambda F[(1-\varphi)C] = 0. \tag{10}$$

As in Zuluaga (2018), let us impose three boundary conditions that must be satisfied by $F(C)$:

$$F(\infty) = 0; \tag{11}$$

$$F(C^*) = R - C^*; \tag{12}$$

$$F'(C^*) = -1. \tag{13}$$

Equation (11) indicates that the investment opportunity F is null when the cost of having children tends to infinity. Equation (12), named "value matching condition", states that at

[9] See Section 1.E of Chapter 4 in Dixit and Pindyck (1994) for a proof.

the critical cost the investment opportunity is equal to the payoff net of such a cost. Equivalently, it can be interpreted by writing it as $C^* = R - F(C^*)$: The cost of childbearing should equal the payoff net of the losses due to the foregone opportunity to postpone. Equation (13) is named "smooth pasting condition" and is obtained by taking the derivative of the value matching equation with respect to the critical value C^*. It means that at the critical point the function shall be differentiable, i.e. not a kink[10].

To solve the problem, we make the typical guess in Option Value Theory for the solution of F:

$$F(C) = AC^{\omega}. \tag{14}$$

By taking the derivatives with respect to C of Equation (14), we have $F'(C) = \omega AC^{\omega-1}$ and $F''(C) = \omega(\omega-1)AC^{\omega-2}$. A is a constant to be determined, and ω is the root of the following equation:

$$\frac{1}{2}\sigma^2\omega(\omega-1) - (\rho+\lambda) + \lambda(1-\varphi)^{\omega} = 0, \tag{15}$$

which can be obtained by substituting F and F'' into Equation (10). It has two roots, $\omega_1 > 0$ and $\omega_2 < 0$, which have to be found numerically. The general solution can be expressed as $F(C) = A_1C^{\omega_1} + A_2C^{\omega_2}$. In order for Equation (11) to hold, A_1 should be equal to zero. Therefore, only the negative root should be considered. Referring to ω_2 as ω henceforth, Equation (14) reduces to:

$$F(C) = AC^{\omega}, \qquad \text{with} \quad \omega < 0.$$

To get C^*, take the derivative of $F(C^*)$ with respect to ω using Equation 13:

$$\omega AC^{*\omega-1} = -1. \tag{16}$$

Using Equation (12) in Equation (16), we get that the critical value below which the agent stops waiting is

$$C^* = \frac{\omega}{\omega-1}R, \tag{17}$$

where, since $\omega < 0$, $\frac{\omega}{\omega-1} \in (0,1)$[11]. ■

[10] These constraints diverge from Dixit and Pindyck (1994), who impose that $F(0) = 0$, $F(R^*) = R^* - C$, and $F'(R^*) = 1$. Hence, they assume that the option to wait goes to zero when the payoff of the investment goes to zero.

[11] By plugging C^* in Equation (12), we also get the constant: $A = \frac{1}{(\frac{\omega}{\omega-1}R)^{\omega}}R(1-\frac{\omega}{\omega-1})$.

5.5 Numerical application

We now assume a functional form of the jump and estimate it using survey data, in such a way that the jump process accounts for the involvement of the agent in the displacement and productivity processes. The problem is then solved to understand how the agent's preference for postponing fertility is shaped by higher automation in the market.

5.5.1 Work Orientation survey

The data source used to estimate the jump function is the second wave of the Work Orientations survey by the ISSP Research Group (1999), where individuals in 21 countries were interviewed in 1997 with respect to their work attitudes. The dataset contains a 1-to-5 score on how concerned individuals are about automating technologies that may destroy jobs in the future. van Hoorn (2022) shows that this variable is a valid measure of the perceived and objective risk of being replaced by machines, by comparing it with different measures of job routineness and tasks automatability. The survey has also 7 education categories, standardised by country: no formal education, incomplete primary school, completed primary school, incomplete secondary school, completed secondary school, incomplete university, completed university. By restricting the sample to women aged 20 to 40, let us estimate the following equation, that relates education with the concern of technology replacing jobs:

$$Concern_i = \alpha + \theta_1 h_i + \theta_2 h_i^2 + Age_i + \zeta_c + \varepsilon_i, \tag{18}$$

where θ_1 and θ_2 are the coefficients associated to education, h, and its squared term, included to account for non-linearities. 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. Table 11 shows the OLS estimates, obtained using survey weights. In Column (1) we only consider the non-squared education level, which shows a non-statistically significant coefficient. When we include the squared term in Column (2) the coefficients turn out to be significantly different from zero, suggesting a concave relation, with $\theta_1 = 0.269$ and $\theta_2 = -0.0308$.

A big source of concern of these estimates is the survey year. Among the ISSP Work orientation surveys, the second wave is the only one in which respondents are asked about their concern of automation, while the more recent ones only have a variable about the worriedness of losing their job for generic reasons. The educational requirements for the same categories of jobs may have changed over the years, and workers in the same occupational category today may have different skill levels compared to the past. In order to reduce this concern, I adopt a similar approach to the one used by van Hoorn (2022): For each two-digit ISCO occupational code, the averaged value of the 1997 worriedness variable is combined with the respondent of the fourth wave of the survey, conducted in 2015 (ISSP Research Group (2017))[12]. The coefficients obtained by estimating Equation (18) for the fourth wave respondents, using the averaged value as the outcome variable, are shown in Table 12. Column (1) reports a negative correlation between the outcome and the education level[13], and Column (2) confirms the concave relation between the two variables, with an increase in the R-Squared by 2%.

5.5.2 The jump equation

The jump equation is modeled in such a way that it allows the effects of the displacement and production of jobs to affect the cost of the career of individuals differently, depending on their education. It is given by:

$$\varphi(h, \delta, \gamma) = p(h)(\delta) + [1 - p(h)](-\gamma), \tag{19}$$

which is a function of education and two parameters that capture the expectations of agents about the impact of automation on labor. $\delta \in (0, 1)$ is the expected percentage drop in the opportunity cost due to the rate of displacement. Analogously, $\gamma \in (0, 1)$ represents the expected percentage increase in the cost due to the productivity effect. The involvement of the agent in the displacement of jobs is weighted by a function $p(h)$, defined as follows:

$$p(h) = \alpha + \theta_1 h + \theta_2 h^2, \tag{20}$$

where $h \in (0, 7)$ indicates the level of formal schooling and the function is normalized in such a way that the minimum and the maximum are 0 and 1. The involvement in the productivity process is instead weighted by the complement of $p(h)$. The values of θ_1 and θ_2 are those found in Column (2) of Table 11.

The next step is to solve the problem using this specification of the cost process and look at how the willingness to postpone fertility changes with different levels of displacement and productivity.

5.5.3 Comparative statics

The following proposition relates the education to the preference for postponing fertility as a reaction to increasing automation.

[12]The averaged 1997 variable highly correlates with the concern score for losing the job in the 2015 survey.

[13]In the fourth wave, the schooling levels are: no formal education, primary school, lower secondary, upper secondary, post secondary, lower level tertiary, and upper level tertiary.

Proposition 2 *An increase in the displacement and productivity rates of industrial robotics has a concave effect, with respect to education, on the value of postponing fertility.*

Proof. In order to show this, let us focus on $\frac{\omega}{\omega-1} \in (0,1)$. This fraction is representative of the waiting value. When $\frac{\omega}{\omega-1} \to 0$, ceteris paribus, the value of postponing fertility increases, as the parent waits for the opportunity cost to be much lower than the benefits of having children. To obtain it, Equation (**??**) is numerically solved in order to get ω as a function h. After this, Proposition 2 can be simply proved by doing comparative statics.

Figure 7 shows the obtained function for different levels of the productivity and displacement effects of robots. The blue line represents the values of $\frac{\omega}{\omega-1}$ for different levels of education, when both the productivity and displacement rates are null. In such a case the value of waiting is only affected by the discount factor, ρ, and by generic uncertainty, σ, which are set to have the conventional values of 0.99 and 0.05, respectively. The orange curve shows what happens when both δ and γ are equal to 10%, with the arrival rate λ set to 0.01[14]. This is associated with an increase in the value of waiting if the level of education is between 4 and 5 (incomplete and completed secondary). As h moves away from the middle of the interval, it reaches a threshold, in both directions, above which the value of waiting becomes lower compared to the blue line. The gray curve reports the result when the increase in displacement is greater than the increase in productivity by two times. In this case, the range of people who experience an increase in the postponement value is larger. On the contrary, when the productivity surpasses the displacement, as represented by the yellow curve, the range shrinks. The gray curve shifts much more from the orange curve than does the yellow one. This happens because increasing the magnitude of the jumps also increases uncertainty due to higher fluctuation of the cost. If $\delta > \gamma$, the incentive to postpone fertility due to the possibility of the cost being lower in the future sums up the postponement linked to greater uncertainty. When $\delta < \gamma$, the perceived possibility that the cost will increase and the increase in uncertainty influence the value of waiting in opposite directions. ■

This parsimonious theory adds up to the empirical findings in showing how heterogeneously individuals' fertility behavior is affected by the impact of automation on the labor market.

6 Conclusion

The progress in industrial automation is having a great impact on the labor market and on the life-course decisions of individuals. From the labor perspective, automating technology

[14] Setting different values of λ does not change the results.

displaces routine workers (often middle-educated) and creates new opportunities for non-routine ones. This paper analyses how it affects fertility choices, specifically regarding the timing parents decide to bear children.

A fixed-effect model, which uses European panel data at the regional level, investigates such a relation by interacting a measure of exposure to industrial robots with three indicators about the level of education in a region. OLS and 2SLS estimations suggest a positive relation between automation and mean age at first birth in labor markets with a high share of women with secondary and post-secondary education compared to other European regions. Instead, it is negative in areas with a high share of women with less than secondary and those with tertiary education. This tempo effect is reflected in the correlation between robotics and age-specific fertility rates. In the first case, the relation is negative at the beginning of the reproductive life and gradually increases until it becomes positive. In addition, the tempo effect overlaps with a positive quantum one. In the second case, we observe an increase in fertility rates for young cohorts of women, which becomes negative later in life.

The causal intuition behind these findings is proposed by an optimal stopping model where children are considered as an irreversible investment, the cost of which corresponds to the losses in terms of career opportunities due to childbearing. By entering the market, robots increase the cost for individuals who benefit from the productivity effect, and reduces it for those who are involved in the displacement of jobs. The agent prefers to bear the child when the cost is expected to be lower. A numerical application of the model, with parameters estimated using individual-level data, suggests that the effect of an increase in observed automation on the agent's willingness to postpone fertility is concave with respect to the level of schooling.

From a policy perspective, these results suggest that family policies and managerial initiatives aimed at labor markets that undergo a process of technological innovation are likely to have a different efficacy depending on the age of workers.

The labor markets are rapidly evolving due to the progress in technology, and this has many consequences for the life-course decisions of families. Future research may encompass the limitations of this study due to the aggregation of data, for example by using detailed employer-employee data and a disaggregated measure of automation exposure. Another possible contribution is to consider different classes of automating technologies other than robots. Imagine the effect of Artificial Intelligence (AI) as an example. While industrial robots are more likely to benefit workers in the service sector, where women tend to have a comparative advantage (Ngai and Petrongolo (2017)), than those in manufacturing, AI may actually reduce the demand for them. Considering the impact of different technologies on labor and family outcomes can help to have an holistic view on how to face the ongoing structural transformation of the labor market.

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Tables

Table 1: Correlation of the instrumental Robot Exposure with Robot Exposure in the EU

Dependent variable:	*Exposure*
$Exposure^{IV}$	1.30***
	(0.29)
Observations	944
Within R-squared	0.20

*** p<0.01, ** p<0.05, * p<0.1

Standard errors in parentheses, clustered at the regional level. The model includes regional and year fixed-effects.

Table 2: Summary statistics

Variable	**Mean**	**Within Std. Dev.**	**Min.**	**Max.**	**N**
% fem pop with ISCED0-2	30.38	5.99134	2.7	86	3933
% fem pop with ISCED3-4	45.86136	3.122842	7.6	78.400	3947
% fem pop with ISCED5-8	23.8601	5.078249	5.7	63.9	3937
Mean age first birth	29.81726	0.6051883	24.3	33	3939
Tot fertility rate	1.526497	0.1024873	0.86	3.94	3939
Fertility rate age 20	0.0335646	0.0064064	0	0.202	3902
Fertility rate age 21	0.0406366	0.0072005	0.007	0.201	3902
Fertility rate age 22	0.047997	0.0081571	0.009	0.249	3902
Fertility rate age 23	0.0561294	0.0086788	0.011	0.219	3902
Fertility rate age 24	0.0659332	0.0092451	0.013	0.21	3902
Fertility rate age 25	0.0768485	0.0095298	0.018	0.248	3902
Fertility rate age 26	0.0875621	0.0092069	0.026	0.221	3902
Fertility rate age 27	0.0965485	0.0087703	0.036	0.209	3902
Fertility rate age 28	0.1036908	0.0088607	0.038	0.224	3902
Fertility rate age 29	0.1074729	0.0094945	0.044	0.204	3902
Fertility rate age 30	0.1076919	0.0102584	0.039	0.206	3902
Fertility rate age 31	0.1038191	0.0111652	0.031	0.183	3902
Fertility rate age 32	0.0962112	0.0114903	0.025	0.17	3902
Fertility rate age 33	0.0870912	0.0113728	0.021	0.174	3902
Fertility rate age 34	0.0770777	0.0110235	0.016	0.16	3902
Fertility rate age 35	0.0666758	0.0106238	0.011	0.144	3902
Fertility rate age 36	0.0552686	0.0095434	0.009	0.133	3902
Fertility rate age 37	0.0440755	0.0083683	0.007	0.129	3902
Fertility rate age 38	0.0342284	0.0071865	0.005	0.095	3902
Fertility rate age 39	0.0259646	0.0058953	0.003	0.088	3902
Fertility rate age 40	0.0185927	0.0047088	0	0.074	3902

Regional data drawn from Eurostat over the period 2000-2018.

Table 3: Summary statistics of the main explanatory variables.

Variable	**Mean**	**Within Std. Dev.**	**Min.**	**Max.**	**N**
Exposure to Robotics	1.90	0.78	0	12.06	1121
Exposure to Robotics^{IV}	1.75	0.40	0.18	4.66	944
$\mathbb{1}_{rt}^{L}$	0.35	0.16	0	1	1109
$\mathbb{1}_{rt}^{M}$	0.50	0.21	0	1	1109
$\mathbb{1}_{rt}^{H}$	0.60	0.18	0	1	1109

Table 4: Effect of robot exposure on employment rates of women aged 25-34, from 2000 to 2007.

Employment rates	(1) Equation (2)	(2) Equation (3)	(3) Equation (3)	(4) Equation (3)
Ordinary Least Squares				
$\mathbb{1}_{rt}^{L} * Exposure_{rt}$	11.93***	11.56***		
	(2.453)	(2.108)		
$\mathbb{1}_{rt}^{M} * Exposure_{rt}$	0.0938		-5.237***	
	(0.933)		(1.704)	
$\mathbb{1}_{rt}^{H} * Exposure_{rt}$	-0.565			2.929***
	(0.728)			(0.934)
Observations	460	460	460	460
Within R-squared	0.32	0.31	0.14	0.12
Two-Stage Least Squares				
$\mathbb{1}_{rt}^{L} * \widehat{Exposure}_{rt}$	11.11***	11.22***		
	(3.880)	(2.314)		
$\mathbb{1}_{rt}^{M} * \widehat{Exposure}_{rt}$	-0.415		-5.475***	
	(1.046)		(1.758)	
$\mathbb{1}_{rt}^{H} * \widehat{Exposure}_{rt}$	-0.422			3.965***
	(1.919)			(1.341)
KP F-Stat	6	10	23	12
Observations	290	290	290	290

*** p<0.01, ** p<0.05, * p<0.1

Standard errors are reported in parentheses and are clustered at the regional level. All models control for region and year fixed-effects, and for the isolated interacted variables.

Table 5: Effect of robot exposure on mean age at first birth. Baseline estimation.

Mean age at first birth	(1) Equation (2)	(2) Equation (3)	(3) Equation (3)	(4) Equation (3)
Ordinary Least Squares				
$\mathbb{1}^{L}_{rt} * Exposure_{rt}$	-0.199***	-0.365***		
	(0.0727)	(0.0424)		
$\mathbb{1}^{M}_{rt} * Exposure_{rt}$	0.224***		0.321***	
	(0.0705)		(0.0555)	
$\mathbb{1}^{H}_{rt} * Exposure_{rt}$	-0.00540			-0.153***
	(0.0353)			(0.0533)
Observations	1,073	1,073	1,073	1,073
Within R-squared	0.33	0.28	0.26	0.21
Two-Stage Least Squares				
$\mathbb{1}^{L}_{rt} * \widehat{Exposure}_{rt}$	-0.126	-0.299***		
	(0.0861)	(0.0632)		
$\mathbb{1}^{M}_{rt} * \widehat{Exposure}_{rt}$	0.224**		0.298***	
	(0.0909)		(0.0689)	
$\mathbb{1}^{H}_{rt} * \widehat{Exposure}_{rt}$	-0.000689			-0.162**
	(0.0331)			(0.0619)
KP F-Stat	4.1	8.0	7.0	7.6
Observations	913	913	913	913

*** p<0.01, ** p<0.05, * p<0.1

Standard errors are reported in parentheses and are clustered at the regional level. All models control for region and year fixed-effects, the isolated interacted variables, log population, and the median age of women in the region.

Table 6: Effect of robot exposure on mean age at first birth. Robustness check: Interaction between exposure and share of women with primary, secondary or post-secondary, and tertiary education.

Mean age at first birth	(1) Equation (2)	(2) Equation (3)	(3) Equation (3)	(4) Equation (3)
Ordinary Least Squares				
$\%Low\,Educ_{rt} * Exposure_{rt}$	0.0982*	-0.00992***		
	(0.0577)	(0.00276)		
$\%Med\,Educ_{rt} * Exposure_{rt}$	0.114*		0.0106***	
	(0.0583)		(0.00164)	
$\%High\,Educ_{rt} * Exposure_{rt}$	0.103*			-0.00634**
	(0.0581)			(0.00256)
Observations	1,068	1,068	1,068	1,068
Within R-squared	0.31	0.18	0.27	0.14
Two-Stage Least Squares				
$\%Low\,\widehat{Educ_{rt} * Exposure_{rt}}$	0.0640	-0.00842***		
	(0.115)	(0.00308)		
$\%Med\,\widehat{Educ_{rt} * Exposure_{rt}}$	0.0735		0.00909***	
	(0.115)		(0.00193)	
$\%High\,\widehat{Educ_{rt} * Exposure_{rt}}$	0.0602			-0.00950***
	(0.115)			(0.00276)
KP F-Stat	3.3	6.3	8.0	4.6
Observations	913	913	913	913

*** p<0.01, ** p<0.05, * p<0.1

Standard errors are reported in parentheses and are clustered at the regional level. All models control for region and year fixed-effects, the isolated interacted variables, log population, and the median age of women in the region.

Table 7: Effect of robot exposure on mean age at first birth. Robustness check: Interaction between exposure and the education indicators, where the indicators refer to year 2000 for all the observations.

	(1)	(2)	(3)	(4)
Mean age at first birth	Equation (2)	Equation (3)	Equation (3)	Equation (3)
Ordinary Least Squares				
$\mathbb{1}_r^L * Exposure_{rt}$	-0.127	-0.324***		
	(0.135)	(0.0573)		
$\mathbb{1}_r^M * Exposure_{rt}$	0.260*		0.362***	
	(0.131)		(0.0548)	
$\mathbb{1}_r^H * Exposure_{rt}$	-0.0264			-0.155**
	(0.0675)			(0.0775)
Observations	1,034	1,034	1,034	1,034
Within R-squared	0.27	0.22	0.27	0.17
Two-Stage Least Squares				
$\mathbb{1}_r^L * \widehat{Exposure}_{rt}$	-0.0594	-0.495***		
	(0.128)	(0.138)		
$\mathbb{1}_r^M * \widehat{Exposure}_{rt}$	0.188		0.301***	
	(0.139)		(0.0779)	
$\mathbb{1}_r^H * \widehat{Exposure}_{rt}$	-0.124			-0.300***
	(0.0798)			(0.0833)
KP F-Stat	3.2	8.5	6.8	3.9
Observations	876	876	876	876

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Standard errors are reported in parentheses and are clustered at the regional level. All models control for region and year fixed-effects, the isolated interacted variables, log population, and the median age of women in the region.

Table 8: Effect of robot exposure on mean age at first birth. Robustness check: Drop vehicle sector.

Mean age at first birth	(1) Equation (2)	(2) Equation (3)	(3) Equation (3)	(4) Equation (3)
Ordinary Least Squares				
$\mathbb{1}^{L}_{rt} * Exposure^{no\,vehicl}_{rt}$	-0.196*	-0.457***		
	(0.113)	(0.0673)		
$\mathbb{1}^{M}_{rt} * Exposure^{no\,vehicl}_{rt}$	0.253**		0.441***	
	(0.126)		(0.0887)	
$\mathbb{1}^{H}_{rt} * Exposure^{no\,vehicl}_{rt}$	-0.161			-0.450***
	(0.121)			(0.0749)
Observations	1,073	1,073	1,073	1,073
Within R-squared	0.28	0.32	0.29	0.31
Two-Stage Least Squares				
$\mathbb{1}^{L}_{rt} * \widehat{Exposure}^{no\,vehicl}_{rt}$	-0.0512	-0.359***		
	(0.123)	(0.0870)		
$\mathbb{1}^{M}_{rt} * \widehat{Exposure}^{no\,vehicl}_{rt}$	0.353***		0.440***	
	(0.128)		(0.0784)	
$\mathbb{1}^{H}_{rt} * \widehat{Exposure}^{no\,vehicl}_{rt}$	-0.0751			-0.401***
	(0.134)			(0.0860)
KP F-Stat	11	23	15	16
Observations	913	913	913	913

*** p<0.01, ** p<0.05, * p<0.1

Standard errors are reported in parentheses and are clustered at the regional level. All models control for region and year fixed-effects, the isolated interacted variables, log population, the median age of women, and the exposure to robots in the vehicle sector.

Table 9: Effect of robot exposure on mean age at first birth leaded by a year.

Mean age at first birth$_{t+1}$	(1) Equation (2)	(2) Equation (3)	(3) Equation (3)	(4) Equation (3)
Ordinary Least Squares				
$\mathbb{1}^{L}_{rt} * Exposure_{rt}$	-0.201**	-0.349***		
	(0.0783)	(0.0472)		
$\mathbb{1}^{M}_{rt} * Exposure_{rt}$	0.202***		0.303***	
	(0.0700)		(0.0587)	
$\mathbb{1}^{H}_{rt} * Exposure_{rt}$	-0.0127			-0.141**
	(0.0344)			(0.0530)
Observations	1,034	1,034	1,034	1,034
Within R-squared	0.31	0.24	0.26	0.14
Two-Stage Least Squares				
$\mathbb{1}^{L}_{rt} * \widehat{Exposure}_{rt}$	-0.0820	-0.221***		
	(0.103)	(0.0740)		
$\mathbb{1}^{M}_{rt} * \widehat{Exposure}_{rt}$	0.198**		0.243***	
	(0.0844)		(0.0699)	
$\mathbb{1}^{H}_{rt} * \widehat{Exposure}_{rt}$	0.00144			-0.116**
	(0.0358)			(0.0564)
KP F-Stat	4.6	8.8	8.2	8.7
Observations	864	864	864	864

*** p<0.01, ** p<0.05, * p<0.1

Standard errors are reported in parentheses and are clustered at the regional level. All models control for region and year fixed-effects, the isolated interacted variables, log population, and the median age of women in the region.

Table 10: Effect of robot exposure on total fertility rates.

TFR	(1) Equation (2)	(2) Equation (3)	(3) Equation (3)	(4) Equation (3)
Ordinary Least Squares				
$\mathbb{1}_{rt}^{L} * Exposure_{rt}$	0.0122	-0.0353**		
	(0.0225)	(0.0161)		
$\mathbb{1}_{rt}^{M} * Exposure_{rt}$	0.0532**		0.0492***	
	(0.0246)		(0.0170)	
$\mathbb{1}_{rt}^{H} * Exposure_{rt}$	-0.00293			-0.0233*
	(0.0156)			(0.0127)
Observations	1,073	1,073	1,073	1,073
Within R-squared	0.24	0.20	0.22	0.18
Two-Stage Least Squares				
$\mathbb{1}_{rt}^{L} * \widehat{Exposure}_{rt}$	-0.00710	-0.0129		
	(0.0230)	(0.0215)		
$\mathbb{1}_{rt}^{M} * \widehat{Exposure}_{rt}$	0.0492*		0.0188	
	(0.0281)		(0.0235)	
$\mathbb{1}_{rt}^{H} * \widehat{Exposure}_{rt}$	0.0538*			0.0108
	(0.0319)			(0.0248)
KP F-Stat	4	8	7	8
Observations	908	908	908	908

*** p<0.01, ** p<0.05, * p<0.1

Standard errors are reported in parentheses and are clustered at the regional level. All models control for region and year fixed-effects, the isolated interacted variables, and the median age of women.

Table 11: Correlation between education level and concern of technology replacing jobs, in the second wave of the Work Orientations survey (ISSP Research Group (1999))

	(1)	(2)
Concern		
Education	-0.0292	0.269**
	(0.0315)	(0.106)
Education^2		-0.0308***
		(0.00910)
Observations	6,846	6,846
R-squared	0.150	0.153

*** p<0.01, ** p<0.05, * p<0.1

Standard errors are reported in parentheses and are clustered at the country-level. All models control for age and country fixed effects.

Table 12: Correlation between education level of and averaged concern of technology replacing jobs by occupation in 1997, in the fourth wave of the Work Orientations survey (ISSP Research Group (2017))

	(1)	(2)
Avg. 1997 Concern by occupation		
Education	-0.0397***	0.0262***
	(0.00271)	(0.00612)
Education^2		-0.00912***
		(0.000858)
Observations	13,658	13,658
R-squared	0.172	0.191

*** p<0.01, ** p<0.05, * p<0.1

Standard errors are reported in parentheses and are clustered at the country-level. All models control for age and country fixed effects.

Figures

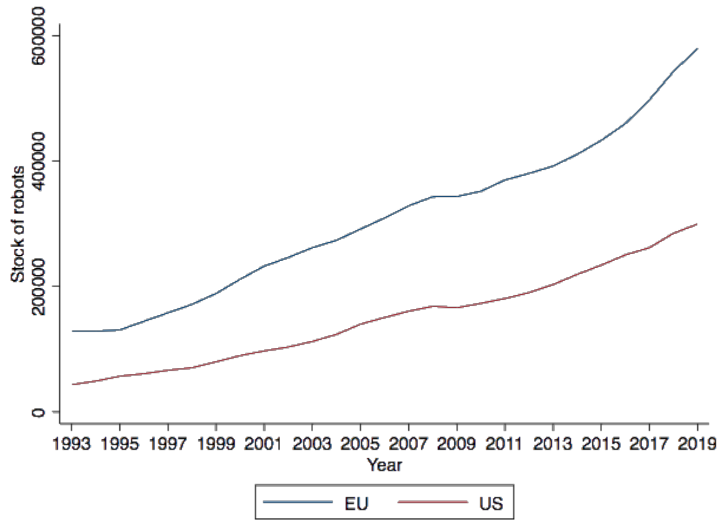

Figure 1: Evolution of the stock of industrial robots in Europe and the US.

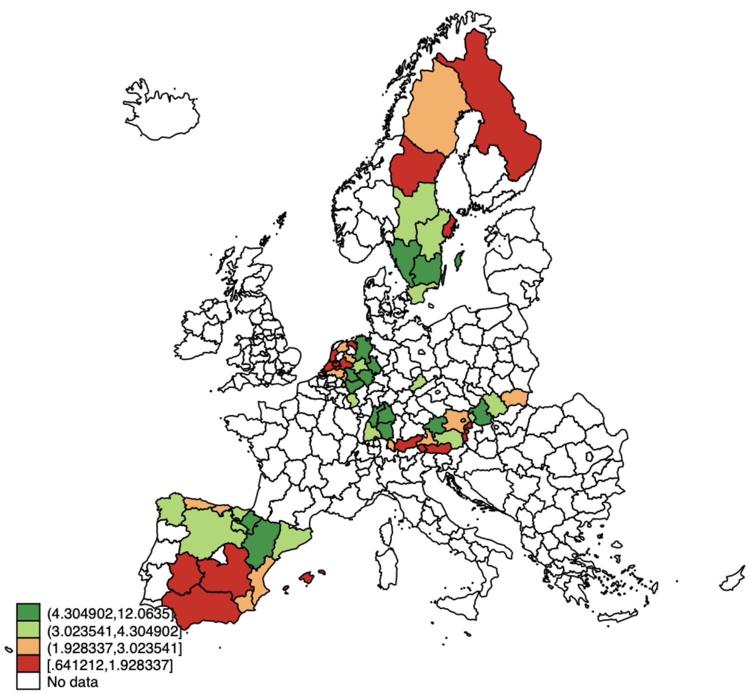

Figure 2: 2018 regional levels of the robot exposure score.

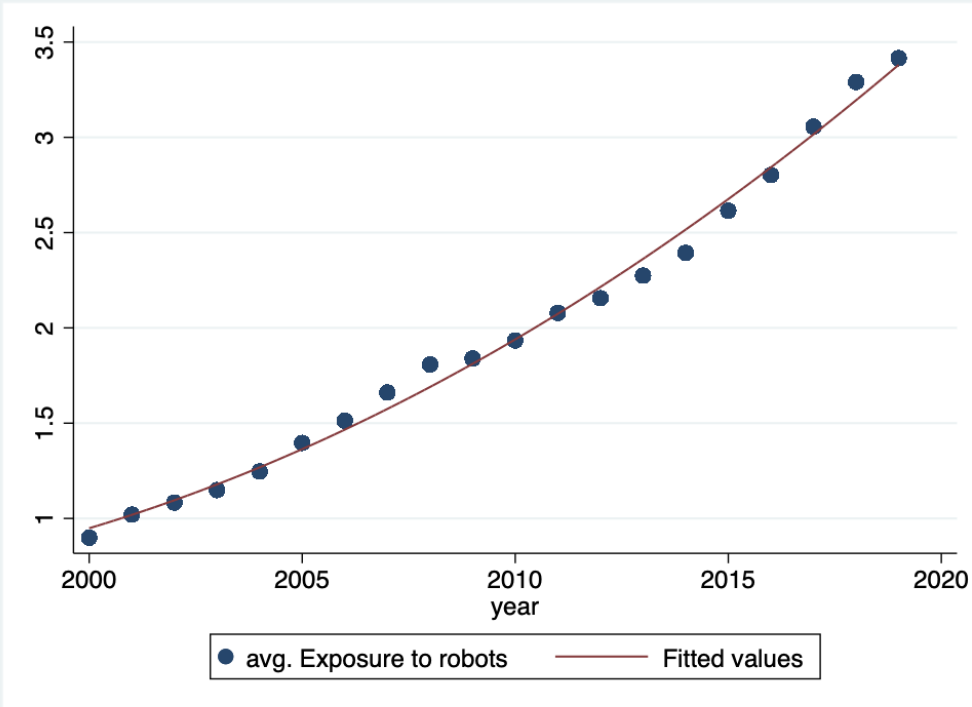

Figure 3: Evolution of average exposure to robots in Europe over time.

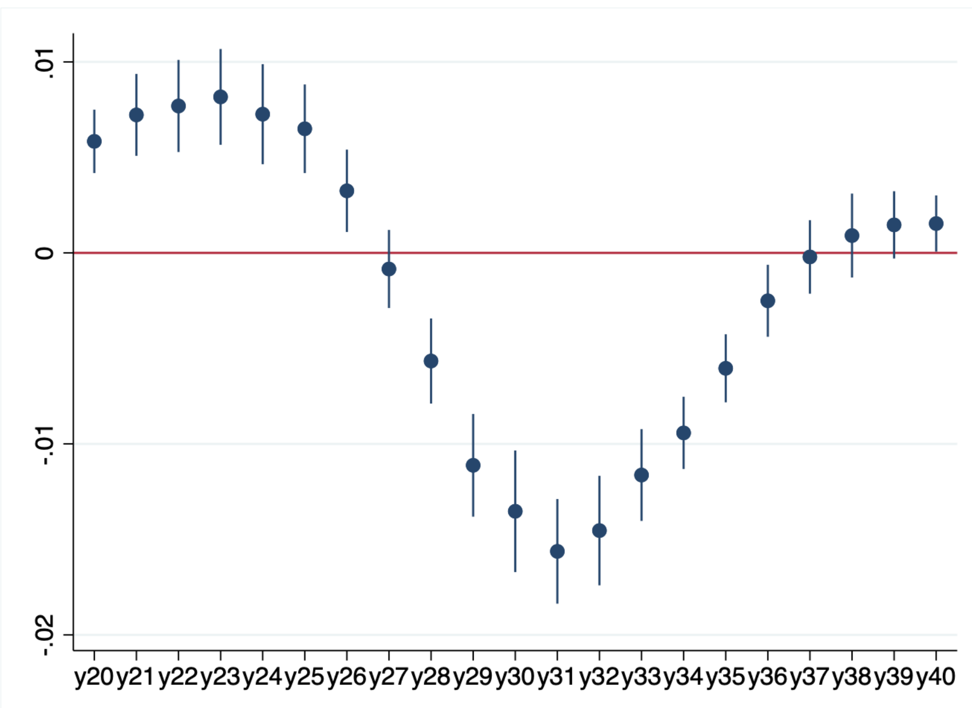

Figure 4: Coefficients β_L (on vertical axis) of Equation (3), where Y_{rt} represents age-specific fertility rates (on horizontal axis).

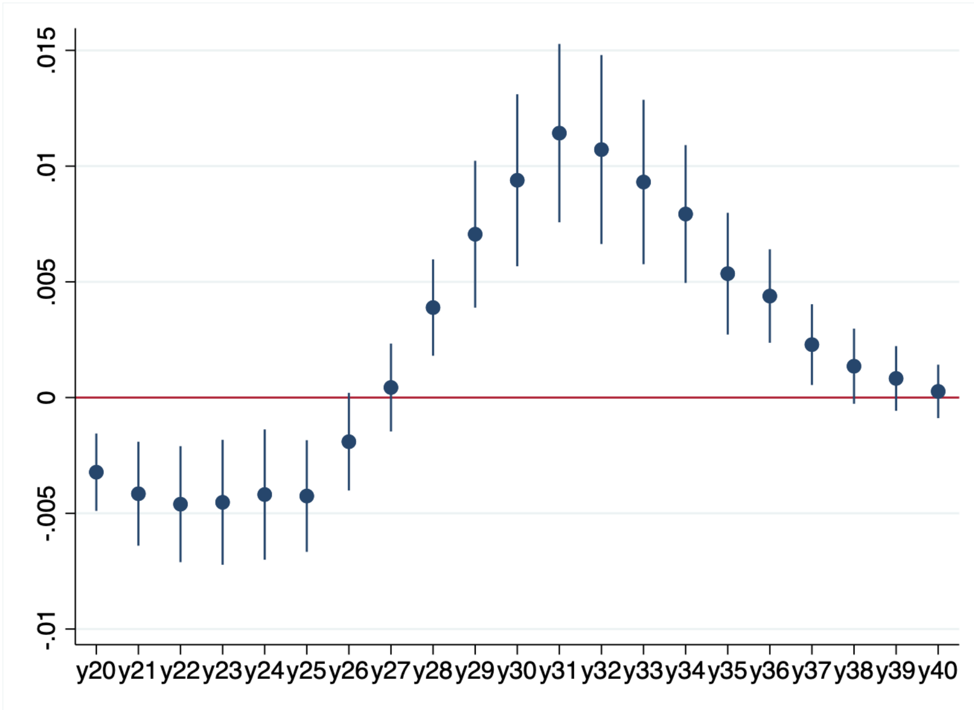

Figure 5: Coefficients β_M (on vertical axis) of Equation (3), where Y_{rt} represents age-specific fertility rates (on horizontal axis).

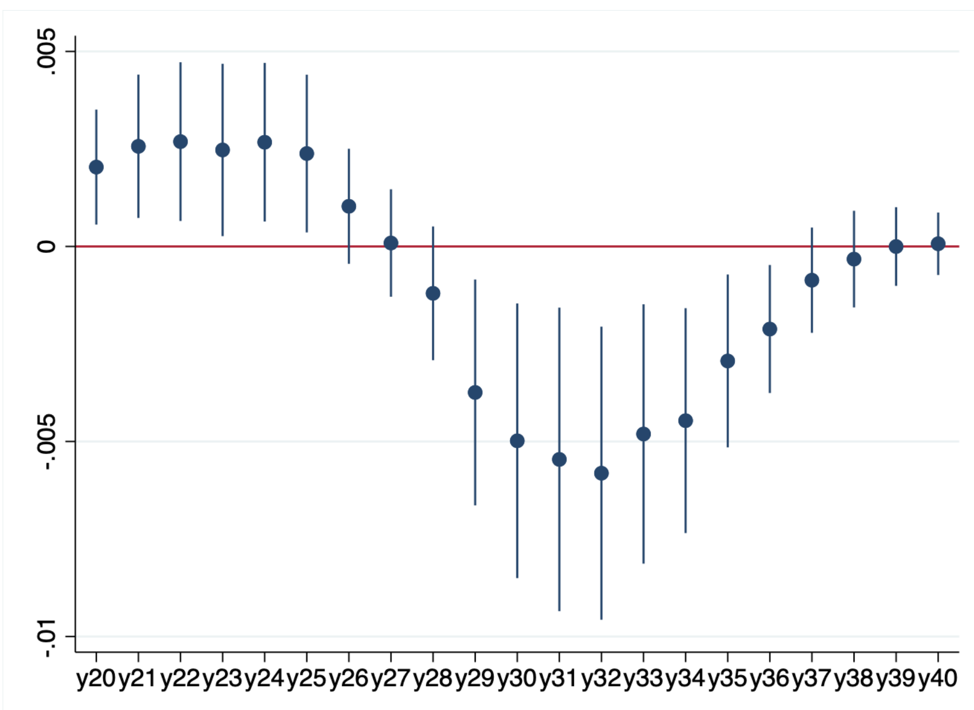

Figure 6: Coefficients β_H (on vertical axis) of Equation (3), where Y_{rt} represents age-specific fertility rates (on horizontal axis).

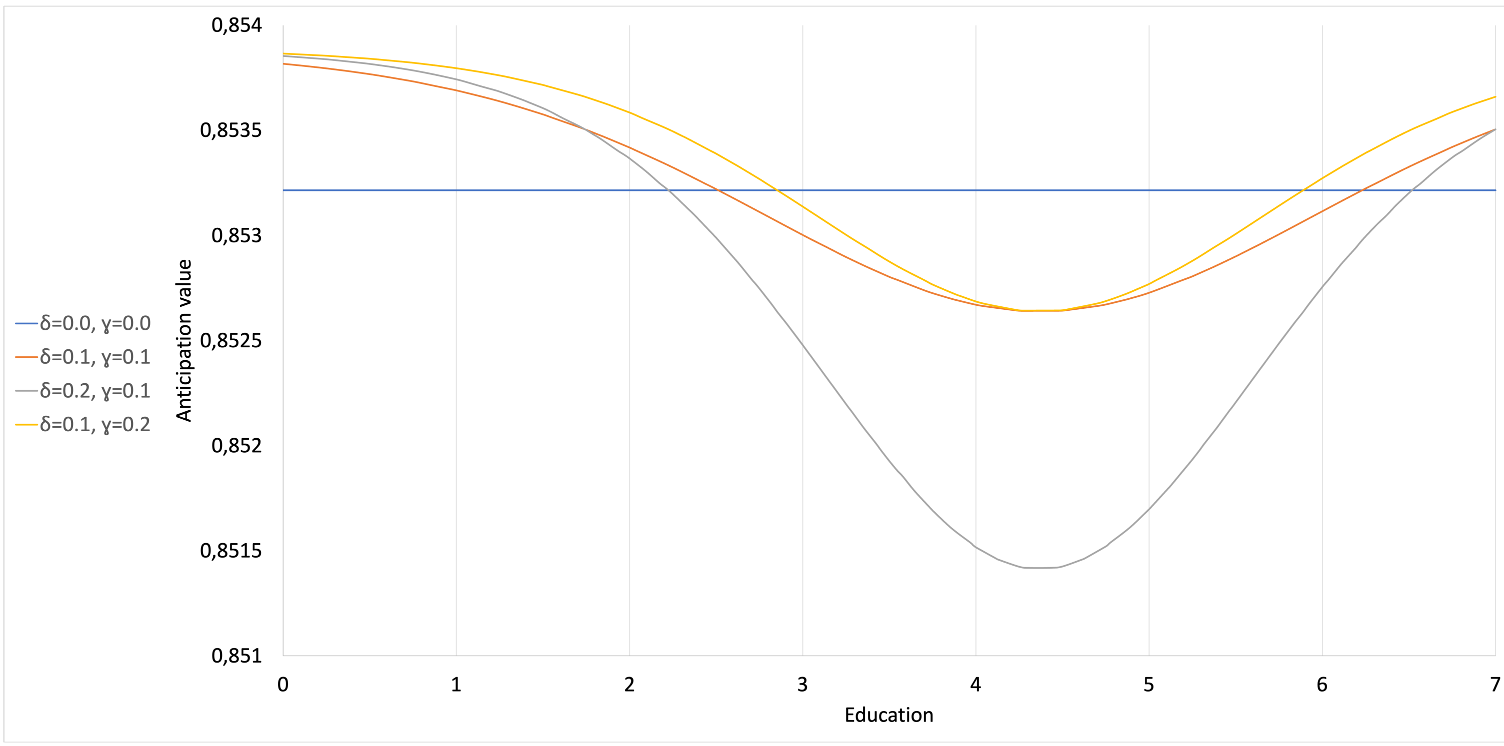

Figure 7: Values of $\frac{\omega}{\omega-1}$ (on the vertical axis) for different levels of h (on the horizontal axis). $\sigma = 0.05$, $\rho = 0.99$, $\lambda = 0.01$.