Industrial Robots and Fertility Timing in Europe*

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Abstract

This paper links the effects that automation has on labor to fertility timing decisions. The intuition behind such a relation is formalized by an optimal stopping model of fertility, where having a child is viewed as an investment. Its opportunity cost is modeled as a stochastic process, which changes are due to the displacement and productivity effects of automation, the first being assumed to concern routine workers the most. The model suggests that labor automation increases the value of waiting to have children for agents with a medium level of education, while it decreases it for those at the extremes of the education distribution. European panel data at the regional level are then used to give empirical support to the theoretical predictions, by constructing a measure of local exposure to industrial robotics. Higher exposure is associated with a postponement of fertility in regional labor markets with a high share of women with secondary education, and with an anticipation of it in regions with a prevalence of women with either primary or tertiary education.

Keywords: Automation, Robots, Fertility, Demography.

JEL Codes: J13, J24

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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 WWII, 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 television, in particular 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 broadband internet make 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. As machines can often outperform workers in many tasks, many individuals are concerned by the possibility of being replaced by robots. Comolli (2017) shows that the expectation of individuals about their future financial situation, even in the absence of a current impact, can lead to a postponement or a preponement of fertility. 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 an example, Balasch and Gratacós (2012) link low fertility rates in Europe to the increasing tendency of Europeans to delay childbearing. 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 is influencing family decisions is important to identify family-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 "enables an internationally and temporally comparable measurement of a class of technologies that are capable of replacing human labor in a range of tasks" (Chiacchio et al. (2018)). The second area relates to the optimal time to have children. A seminal work by Ranjan (1999) suggested that income uncertainty is an important driver of fertility timing. This was followed by other works which investigated how the uncertainty driven by generic labor market risks (Sommer (2016)), or by specific

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events such as WWII (Chabé-Ferret and Gobbi (2018)) and the Great Recession (Schneider (2015)), affected fertility timing. Here, the focus is on the effects of technological progress in the labor market as a determinant of childbearing timing preferences.

The first step of the paper consists of an optimal stopping model, typically used in Option Value Theory, that provides an economic intuition behind the possible tempo effect of automation on fertility. Children are considered an irreversible investment and, therefore, they come with a cost. This can be viewed as the "career cost" of children, interpreted by Adda et al. (2016) as the losses in terms of earnings opportunities and accumulation of experience due to motherhood. 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. 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 (Acemoglu and Restrepo (2020) refer to these as the displacement and productivity effects, respectively). If the woman imagine the productivity effect to outclass the displacement, 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 it happens for investment decisions, the optimal choice is to invest, i.e. bear the child, when the cost is low, hence at time t_0. Similarly, if she expects the displacement to be the prevalent effect in the future, childbearing will occur at t_1, when the career cost will be relatively lower than today.

The model relates the expectation of individuals about the impact of robots to their education level, and assumes that the concern about the substitution of jobs by robots is higher for routine workers. This is an assumption consistent with findings in the literature that investigates the effect of robots on different types of jobs (e.g. de Vries et al. (2020), Cirillo et al. (2021)). The relation is estimated through a mediation analysis, using individual data by the International Social Survey Programme (2017). The level of schooling is used as the independent variable, the level of worriedness about loosing the job in the future as the outcome, and the Routine Task Intensity (RTI) index (retrieved from Goos et al. (2014)) act as a mediator. The estimated coefficients capture the relation between education and the concern about loosing the job for young women, specifically driven by how much repetitive the tasks of the job are. The analysis suggests that such a relation is concave, and that the Routine-Biased hypothesis, formulated by Goos et al. (2014) in opposition to the Skill-Biased one theorized by Katz and Autor (1999), not only regards the type of tasks performed by workers, but it is also reflected on their expectations about their future employment. By

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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 with extremely low or high schooling levels.

The second step is an empirical analysis, at the European regional level, that tests the above proposition by using panel data from Eurostat and the International Federation of Robotics (IFR). The empirical methodology follows the local labor market approach of Acemoglu and Restrepo (2020). The identification strategy assumes that, in a geographic area, the exposure to robotics in an industry is proportional to the historical employment in that industry and to the usage of industrial robots in the country. The explanatory variable can be thought as a Bartik-style instrument, since a common industry shock (the penetration of robots in the country in a given year) is weighted for the historical regional specialization in that industry. The measure of exposure interacts with three indicator functions. These indicate whether, in a region, the share of the female population with a certain level of schooling (primary, secondary, or 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 on 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 US, highly correlated with the one in Europe, is used as an instrumental variable. The Two-Stages Least Squares (2SLS) analysis suggests that the possibility of reverse causality between fertility and automation can be excluded.

Final evidence regards the dynamics of fertility. A positive correlation is found between robotics and Total Fertility Rates in middle-skilled regions, probably due to the fall in opportunity cost for the workers that bear the reduction in labor demand the most. Using age-specific fertility rates as outcomes of the analysis, the results are consistent with the findings on timing. The plots of the coefficient linked to the interactions of the exposure score with the education indicators follow an S-shaped pattern. In low- and high-education regions, the effect of robots on fertility is positive at the beginning of the reproductive life and turns negative at the end. The contrary happens for regions with a prevalence of medium-educated women.

The rest of the paper is organized as follows. Section 2 reviews the literature to which this analysis contributes. Section 3 describes the optimal stopping model. It is followed by Section 4, which regards the empirical analysis that provides evidence to the model's

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propositions. Section 4.1 discusses the identifying assumption of the analysis and the construction of the measure for the exposure to robots. Section 4.2 reports the data sources and the summary statistics. The fixed-effect model is described in Section 4.3. The results, along with robustness and endogeneity checks, are presented in Section 5. Finally, Section 6 contains concluding remarks.

2 Literature

This paper links two different areas of literature: the consequences of robotics on employment and the determinants of the optimal time of fertility.

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 findings are often controversial. In general, studies at the aggregate level usually find a negative correlation between robots adoption and employment, which losses are mostly concentrated in the low- and middle-skill cohorts of workers. On the contrary, analyses that rely on micro-level data tend to find a positive labor demand effect, even for low-skilled jobs.

From the aggregate point of view, 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. They do not find significant effects on overall employment but do find a reduction in the hours worked by low and middle-skilled workers. Acemoglu and Restrepo (2020) developed a model where robots and workers compete in the production of different tasks. Theoretically speaking, they argue that industrial robots affects 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 measure of American commuting-zone exposure to robots, they find, overall, a negative effect on employment and wages, higher for men than for women. They do not find, surprisingly, positive and offsetting employment gains in any occupation or education group, as their model would instead suggest. Following the same local labor market approach, estimations by Chiacchio et al. (2018) point to a prevalence of

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the displacement over the productivity effect in the EU, particularly for young cohorts, but do not find significant effects on wages.

From a micro-perspective, Dauth et al. (2017) linked employer-employee data in Germany and do not find, overall, a negative impact of robots on employment: While industrial robots have a negative effect on employment in the German manufacturing sector, they find evidence of a positive spillover effect in non-manufacturing sectors that counterbalances the employment losses in manufacturing. Using a panel data-set of Spanish manufacturing firms, Koch et al. (2019) find positive employment effects, especially pronounced for high- and low-skilled workers. Domini et al. (2020) 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 effect of robots on employment is linked 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. On average, men tend to experience a drop, whereas women witness a rise, in income. This happens because the former are more frequently employed in the manufacturing sector and the latter in the service one, hence benefiting more 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 males and female in the US, but more for the formers. 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 of a couple already formed about when to give birth.

2.2 Optimal fertility time

The intuition about the link between income uncertainty 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.

The model proposed in Section 3 builds on theories typically used to study the optimal time to make irreversible investments with payoffs subject to uncertainty (Merton (1973), Dixit and Pindyck (1994)). The idea to use Real Option Approach (ROA) to study demographic behavior started with 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

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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 witness a low median age at sterilization compared to northern ones (IIPS (2000)). At the same time, there is evidence from South India that uncertainty associated with having a child has reduced 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 uncertainty, Iyer and Velu (2006) argue, may be the reason why women in southern India decide to concentrate childbearing at young ages. By calibrating a similar investment model with Colombian data, Zuluaga (2018) shows that fertility is delayed also because of uncertainty in the cost of childbearing. Bhaumik and Nugent (2011) present empirical evidence of the Real Option Approach by considering, as a setting, 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 uncertainty in order to provide evidence for the validity of the ROA in modeling 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 uncertainty as a Wiener process, as they are interested in uncertainty from generic sources. The main difference of the model proposed in Section 3, 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.

3 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. Time is continuous and at each unit of time the individual, plausibly a woman, decides whether or not to bear a child. The choice variable is hence binary. If the child is born, the agent gains the net benefit of being a parent but has to forego the potential value of waiting. If she delays childbearing, she keeps

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the pure value of waiting, which is related to the possibility to see how the uncertainty will resolve. 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 the parent has to assign to child-rearing instead of other activities, such as working and accumulating experience. The model is based on the assumption that the workers' concern about being substituted by robots is proportional to the degree of routineness of their job. Hence, the displacement effect, which decreases the career cost of having children, mainly concern individuals that can carry out routine jobs. The productivity effect, which increases the cost, mostly matters for agents that carry out non-routine tasks.

This section describes how the set-up would be in a deterministic setting, and how uncertainty in the movements of the cost influences the "value of waiting" to bear a child. The expected impact of robots enters in the evolution of the cost through a Jump process, which is modeled on the basis of the aforementioned assumption. The resolution of the model leads to the propositions that are empirically addressed in Section 4.

3.1 The Net Present Value 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 portfolio theory (see Iyer and Velu (2006) for a discussion on this). After she has decided the desired family size, she needs to decide the timing of fertility.

Consider the reproductive life of a woman. We can assume that the decision of having 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 child, 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 investment.

Let us define R and C_t as the payoff and the cost of having children, both stated in present value terms. The payoff, meant as happiness, is here 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, changes with time. In the NPV framework, the net benefits of having children, let us denote them by B_t,

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would be formally represented by:

$$B_t = R - C_t,$$

where the decision to have children would take place at time t if $R \geq C_t$.

3.2 The value of waiting (Real Option Approach)

The NPV set-up can be enriched 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 by using the Real Option Approach (ROA), which is conventionally employed for the study of the optimal time to make an investment, whose 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.

3.2.1 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 in terms of income if she has a child. The second effect translates into an increase in opportunity costs, 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[1], which takes the following form:

$$dC = \sigma C dz - C dq. \tag{1}$$

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

[1]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.

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the context of fertility choices, the sources of such uncertainty may be related to job market opportunities, financial situation, or social and love relationships.

The second component of the law of motion, Cdq, is the jump process. This consists of discrete changes in the variable, which can be of fixed or random size, which arrives at uncertain arrival times. Name $\lambda \in (0,1)$ the mean arrival rate of the event that causes a jump. The probability that such an event happens at a unit of time is hence λdt. Therefore, dq takes the following values:

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

where $\varphi(h,\delta,\gamma)$ represents the jump, which is a function of education (given as exogenous) and two parameters that capture the expectations of agents about the impact of automation on labor. h denotes the number of years of formal education of the agent. $\delta \in (0,1)$ is the expected percentage drop in the opportunity cost due to the displacement effect, which is reasonably going to depend on the current rate at which jobs get substituted by machines, in the industrial sector where the individual is supposed to work. Analogously, $\gamma \in (0,1)$ represents the expected percentage rise in the cost due to the productivity effect.

The process expressed by Equation (1) 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 industrial robots enter the market. This causes the cost to raise or drop depending on δ, γ, and h. It will then continue to fluctuate until the next jump occurs.

The following paragraph describes in detail how the jump function is defined.

3.2.2 The jump

The jump function is modeled in such a way to allow the displacement and the productivity effects to affect individuals' career cost differently, based on their education. Such heterogeneity is modeled with a quadratic function that reproduces the indirect link, driven by the routine intensity of an individual's job, between education and the worriedness of becoming unemployed. Hence, the underlying assumption is that the concern about loosing the job because of its routineness explains the concern of being replaced by robots.

The dataset used to estimate such a relation is the fourth wave of the Work Orientations survey by the International Social Survey Programme (2017), which contains a 1-to-4 score on how much worried the individuals are about loosing their job and 7 education categories[2].

[2]From 0 to 6: No formal education, primary school, lower secondary, upper secondary, post-secondary

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The sample is restricted to European women no older than 40. Individuals are assigned, based on their ISCO code, a Routine Task Intensity (RTI) index, which values have been calculated by Goos et al. (2014).

In order to catch for non-linearities in the relation between education and the concern of loosing the job due to routineness of the tasks, the jump in the cost due to the displacement effect is weighted with the following quadratic function of education:

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

where $h \in (0, 6)$ indicates the level of formal schooling[3]. Our parameters of interest, θ_1 and θ_2, are estimated according to a mediation analysis using a Generalized Structural Estimation Modeling (gSEM), using the age and the country of residence as control variables, and clustering standard errors at the country level. The parameters represent the relation between education and worriedness, specifically driven by the fact that individuals with different levels of education tend to carry out jobs that differ in routineness. The estimation results are $\theta_1 = 0.0142701$ and $\theta_2 = -0.0024353$, with standard errors 0.00525 and 0.000829, respectively. The significance levels are above the 99% level, suggesting that the relation is not linear.

The jump in the cost is thus given by:

$$\varphi(h, \delta, \gamma) = p(h)(\delta) + [sup(p(h)) - p(h)](-\gamma), \tag{3}$$

where the displacement-driven change is multiplied by $p(h)$, which can be considered as the involvement of the individual in the substitution of jobs based on her education level, and the productivity-driven change is multiplied by the complement of $p(h)$.

Now that the evolution of the cost is known, the next step consists in solving the problem.

3.2.3 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 at time t. It can be considered as the value of the investment opportunity, as it represents the best possible outcome of the objective function. Formally:

$$F(C) = max_t \mathbb{E}[(R - C_t)e^{-\rho t}] \tag{4}$$

(non tertiary), lower-level tertiary, upper-level tertiary.

[3] The intercept α is set in such a way that $p(h) = 0$ at $h = 6$.

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where $\mathbb{E}$ denotes the expectation, t is the time at which the investment is made, ρ is the discount rate, i.e. how future gains are evaluated in the present, and the maximization problem is subject to Equation (1) 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 first 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. Notice that as long as the agent waits, her gain is the change in the value of the investment opportunity. In the case of an optimal stopping investment problem in continuous time, the Bellman equation is given by the equality between the return per unit of time that the decision-maker requires for holding the asset, and the expected rate of capital gain[4]. Formally:

$$\rho F(C)dt = \mathbb{E}(dF). \tag{5}$$

3.2.4 Results

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.

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

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:

$$\mathbb{E}(dF) = \frac{1}{2}\sigma^2 C^2 F''(C)dt - \lambda\{F(C) - F[(1-\varphi(h,\delta,\gamma))C]\}dt, \tag{6}$$

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

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

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the process. The second component is given by the jump part and consists of the difference in values of F at discretely different points.

Hence, Equation (5), which must be satisfied by $F(C)$, can be rewritten by including Equation (6) in it and dividing by dt:

$$\frac{1}{2}\sigma^2 C^2 F''(C) - (\rho+\lambda)F(C) + \lambda F[(1-\varphi(h,\delta,\gamma))C] = 0. \tag{7}$$

In addition, let us impose three boundary conditions that must be satisfied by $F(C)$:

$$F(\infty) = 0; \tag{8}$$

$$F(C^*) = R - C^*; \tag{9}$$

$$F'(C^*) = -1. \tag{10}$$

Equation (8) means that the investment opportunity F is null when the cost of having children tends to infinity. Equation (9), named "value matching condition", states that at 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 loss due to the foregone opportunity to postpone. Equation (10) 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 states that at the critical point the function shall be differentiable, i.e. not a kink[5].

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

$$F(C) = AC^{\beta}. \tag{11}$$

By taking the derivatives with respect to C of Equation (11), we have $F'(C) = \beta AC^{\beta-1}$ and $F''(C) = \beta(\beta-1)AC^{\beta-2}$. A is a constant to be determined and β is the root of the following equation:

$$\frac{1}{2}\sigma^2\beta(\beta-1) - (\rho+\lambda) + \lambda(1-\varphi(h,\delta,\gamma))^{\beta} = 0, \tag{12}$$

which can be obtained by substituting F and F'' in Equation (7). It has two roots, $\beta_1 > 0$ and $\beta_2 < 0$, which have to be found numerically. The general solution can be expressed as $F(C) = A_1 C^{\beta_1} + A_2 C^{\beta_2}$. In order for Equation (8) to hold, A_1 should be equal to zero and, hence, only the negative root shall be considered. Referring to β_2 as β henceforth, the above

[5]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.

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expression reduces to:

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

To get C^*, take the derivative of $F(C^*)$ with respect to β using Equation 10

$$\beta A C^{*\beta-1} = -1. \tag{13}$$

Using Equation (9) in Equation (13), we get that the critical value below which the agent stops waiting is

$$C^* = \frac{\beta}{\beta-1}R, \tag{14}$$

where, since $\beta < 0$, $\frac{\beta}{\beta-1} \in (0,1)$[6]. ■

The following proposition relates to the consequences of industrial robotics on fertility decisions.

Proposition 2 *An increase in the displacement and productivity rates of industrial robotics makes middle-skilled individuals prefer to postpone childbearing, whereas it makes those at the extremes of the skill distribution prefer to anticipate it.*

Proof. In order to show this, let us focus on $\frac{\beta}{\beta-1} \in (0,1)$. Such a fraction is representative of the value of waiting. When $\frac{\beta}{\beta-1} \to 0$, ceteris paribus, the value of postponing childbearing increases, as the parent waits for the opportunity cost to be much lower than the benefits of having children. To get it, the numerical solution of β as a function h, has to be included in $\frac{\beta}{\beta-1}$. After this, proposition 2 can be simply proved by doing comparative statics.

Figure 1 shows the obtained function for different levels of growth in the expectation of the productivity and displacement effects of robots. The blue line represents the values of $\frac{\beta}{\beta-1}$ for different levels of education, when both the expected rates of productivity and displacement are null. In such a case the value of waiting is only affected by generic uncertainty, which is common for everyone. The orange line shows what happens when both δ and γ are equal to 10%. This is associated with an increase in the value of waiting if the level of education is 3, which corresponds to upper secondary education. As h moves away from the middle of the interval, it reaches a threshold, in absolute terms, above which the value of waiting becomes lower compared to the blue line. The gray line reports the result when the increase in displacement is greater than the increase in productivity. In this case, the range of individuals who experience an increase in the postponement value is larger. On the contrary, when the increase in productivity surpasses the increase in displacement (red line), the range shrinks. ■

[6] By plugging C^* in Equation (9), we also get the constant: $A = \frac{1}{(\frac{\beta}{\beta-1}R)^{\beta}}R(1-\frac{\beta}{\beta-1})$.

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The section that follows aims at testing this last proposition (which is in turn a consequence of Proposition 1).

4 Empirical evidence

The variable that captures the level of robot exposure is based on the one used by Acemoglu and Restrepo (2020) for the US. This section describes its construction, along with the identifying assumptions behind it. It then reports the data sources and the summary statistics of the variables used in the analysis. Finally, the fixed-effect model is described, followed by the Two-Stages Least Squares specification that addresses possible endogeneity concerns.

4.1 Identification and predictor variables

The explanatory variable is identified at the level of European regions (NUTS2) and is meant to represent how much a regional labor market is exposed to the advancements in industrial robotics. This follows other works, i.e. Acemoglu and Restrepo (2020), Anelli et al. (2021), Chiacchio et al. (2018), and Dauth et al. (2017), in which it is assumed that the distribution of robots within industries is uniform across all 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 adaptation to Europe of the variable on robot exposure follows Chiacchio et al. (2018). The baseline year is set to 1995, which is the year after which most of the rise in industrial robotics in Europe began (see Figure 2), and the earliest year in the time series of Eurostat regional database. Because 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 in employment outcomes. The measure of exposure in a given industry is computed by multiplying the regional baseline employment share in the region with 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 robotics:

$$Exposure_{rt} = \sum_i \frac{Empl_{ir}^{1995}}{Empl_r^{1995}} \frac{StockRobots_{ict}^c}{Empl_{ic}^{1995}}. \tag{15}$$

$Empl_{ir}^{1995}$ represents the number of employed workers in industry i and region r, and $Empl_r^{1995}$ is the total employment in the region. $\frac{StockRobots_{ict}^c}{Empl_{ic}^{1995}}$ denotes the amount of robots per employed worker in the country in industry i.

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The aggregation of data does not allow to evaluate separately the demographic outcomes of different education-cohorts of individuals. To circumvent 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 primary, secondary, and tertiary education with the yearly average in the other European regions. Specifically, let us define the following three indicators:

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

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

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

Hence, the operator $\mathbb{1}^e$, where $e \in \{\text{L, M, H}\}$, takes value 1 if the share of e-skilled women in region r at year t is greater than the average of such share of all the regions in the Eurostat dataset in year t.

4.2 Data

The dataset used to examine the relation between industrial robotics and fertility timing is obtained by merging data from the International Federation of Robotics (IFR) and Eurostat. It is an unbalanced panel, with information on 59 regions, in 7 European countries[7], for 18 years (2000-2018). The following paragraphs describe the sources and report the descriptive statistics of the variables of interest.

4.2.1 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

[7]Austria, Finland, Germany, Netherlands, Slovakia, Spain, and Sweden. The results are robust to the exclusion of each country one-by-one, which reassures on the possibility that one of the 7 countries is driving the effects.

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other words, industrial robots are machines that are fully autonomous (do not require a human operator in order to work), automatically controlled, and can be programmed to perform repetitive tasks.

The dataset has some limitations. Sectoral data for the United States are provided only since 2004. Moreover, while the division of the manufacturing industries is very detailed, the stocks of robots referred to the other sectors are aggregated. Another limitation stands in the fact that 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. Furthermore, the smallest geographical unit in the dataset is the country. Therefore, information on the within-country distribution of the stocks of robots is missing.

Figure 2 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 US and starting from 1995 in Europe. Since then, it has been constantly increasing, with a little slow-down during the Great Recession period.

4.2.2 Labor, demographics, and education

Historical data on employment, used to construct the explanatory variable along with the stocks of robots from the IFR, come from the Structural Business Statistics (SBS) Eurostat database, which breaks down information on regional employment to the sectoral (NACE) level. These data refer to the year 1995. Whereas information on employment in the manufacturing sectors is sufficiently rich, the other industries have many missing observations. Hence, employment in the agriculture and fishery industries is integrated using the Annual Regional Database of the European Commission's Directorate General for Regional and Urban Policy (ARDECO) database, which contains time-series on labor for EU regions. All the other sectors are considered together as the difference between the employment in all industries, minus the employment in manufacturing, agriculture and fishery. We end up with information on 11 different manufacturing industries[8] at the 2-digits level and the two other industries at the 1-digit level. Notice, however, that industrial robotics interests almost entirely (around 99%) the manufacturing sector.

The variables on demographics and education are gathered from the Eurostat regional database, starting from 2000. It contains regional total, as well as age-specific, fertility rates. The variables which 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-

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

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4 represents people with 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.

4.2.3 Summary statistics

Table 1 shows the descriptive statistics of the main variables used in the analysis. A line separates those that are used on the right-hand side (above) and on the left-hand side (below) of the regression model.

Concerning education, on average, medium-educated individuals represent around half of the population, whereas low- and high-skilled ones are approximately one-fourth each. There is high heterogeneity in such shares between observations. For the share of women with primary and tertiary education, the standard deviation is around half of the mean. This is probably due to the trend of decrease in the first case, and of increase in the second. The use of the yearly, instead of the overall, average in constructing the indicators in Section 4.1 avoids that their values are due to such time trends. The within standard deviation for the shares of women with primary and tertiary schooling level are a fifth of the overall one.

As for demographics, the median age of the female population is 42 years old on average. Because of the skewness in population size, the logarithm is taken and reports a mean of 14.

The outcome variables are the mean age at first birth and fertility rates for different age cohorts. The first birth happens usually at the age of 30, with a standard deviation of around one year and a half overall, and half a year within. The mean fertility rate is 1.54. Age-specific fertility rates are shown for the range 20 to 40 years old women. The mean reaches the maximum of 0.107 at the age of 30, and decreases in a bell-shaped pattern when the age approaches 20 and 40.

Regarding the predictors, Table 2 reports the summary statistics of the robot exposure variable and the three indicators. The observations in the panel reduce from approximately 3600 to 978 for the variable "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 reaches a maximum of 12, which corresponds to 6 times its mean. Robustness checks are going to take outliers into account. Figure 3 shows a map of Europe with four different levels of the variable in 2018 for the regions contained in the dataset. According to the available data, Germany appears as the most exposed country and the Netherlands as the least. There is heterogeneity in Spain, with the north being much exposed, contrary to the south. Similarly, in Sweden, the north and the south witness a low and high exposure to robots, respectively. The only region in Finland for which the sample has

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information has a low level of automation. There is high spatial heterogeneity in Austria. In Slovakia the level gradually decreases approaching the northeast.

Figure 4 plots the evolution over time of the average exposure to robots in the dataset from 2004[9] to 2018. The graph suggests an exponential evolution. We witness a unitary increase in the variable (1.3 to 2.3) from 2004 to 2013. The value is approximately 3.3 in 2018, which suggests that the time range needed 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", 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 conventionally refers to the fact that technological progress, in general, tends to be exponential.

With the observations reduced to the 995 involved in the regression models (such that the value for the robot exposure is not missing), $\mathbb{1}^M$ and $\mathbb{1}^H$ take value one for half of the regions, while $\mathbb{1}^L$ is so for 38% of them. The positive within standard deviations suggest that the same region may experience different values of the indicators over time.

4.3 Fixed-effect model

The analysis proposed in this section is based on the intuition that the effect of robotics on fertility decisions depends on the level of schooling of an individual. In the baseline regression model, the exposure variable interacts with the three indicators described in Section 4.1. It takes the form:

$$\begin{aligned} Y_{rt} = \alpha + \beta_L(\mathbb{1}^L_{rt} * Exposure_{rt}) + \beta_M(\mathbb{1}^M_{rt} * Exposure_{rt}) + \beta_H(\mathbb{1}^H_{rt} * Exposure_{rt}) + \\ + \beta_{exp} Exposure_{rt} + \rho_L \mathbb{1}^L_{rt} + \rho_M \mathbb{1}^M_{rt} + \rho_H \mathbb{1}^H_{rt} + \gamma X_{rt} + \mu_r + \lambda_t + \varepsilon_{rt}, \quad (16) \end{aligned}$$

where 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 outcomes. 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. X_{rt} is a matrix of demographic control variables, specifically, the median age of the female population and 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 on the level of regional education is equal to one. Proposition 2 makes it reasonable to expect that $\beta_L < 0$, $\beta_M > 0$, and $\beta_H < 0$.

[9]Due to missing values, the variable is very discontinuous from 2000 to 2003.

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Notice that Equation (16) may suffer from collinearity issues. Clearly, the three indicators 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. Hence, the model is estimated both by including all the three interaction terms and by including them one-by-one, i.e. by estimating:

$$Y_{rt} = \alpha + \beta_e(\mathbb{1}^e_{rt} * Exposure_{rt}) + \beta_{exp}Exposure_{rt} + \rho_e\mathbb{1}^e_{rt} + \gamma X_{rt} + \mu_r + \lambda_t + \varepsilon_{rt}, \qquad (17)$$

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

As of the effects solely due to exposure and education, the overall average change in Y due to a unitary increase in the exposure to robots is given by $\beta_{exp} + \beta_e$, i.e. the effect concerning regions with $\mathbb{1}^e = 0$ plus the effect linked to regions where $\mathbb{1}^e = 1$. Similarly, being a region with $\mathbb{1}^e = 1$ is associated with a change in the outcome by $\rho_e + \beta_e$.

4.3.1 Two-Stages 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 as both the automation of jobs and innovation. As aging creates a shortage of middle-aged workers specialized in manual production tasks, firms that operate in countries that are undergoing faster aging tend to employ more automation of labor.

To address endogeneity, Acemoglu and Restrepo (2020) exploited the spread of robots in Europe as a proxy for automation in the US. I adopt a symmetrical strategy and construct an instrument for the explanatory variable using the stock of robots in the US. The instrumental variable is defined as follows:

$$Exposure^{IV}_{rt} = \sum_i \frac{Empl^{1995}_{ir}}{Empl^{1995}_r} \frac{StockRobots^{US}_{it}}{Empl^{US,1995}_i}, \qquad (18)$$

where $StockRobots^{US}_{it}$ represents the stock of robots used in industry i at year t, in the United States, and $Empl^{US,1995}_i$ denotes the employment in industry i in the United States[10].

When using the Two-Stages Least Squares (2SLS) approach, we need to assume that the instrument is correlated with the endogenous variable and that its effect on the outcome is only indirect, through the endogenous variable. Let us first estimate the following equation

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

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in order to assess the existence of a relation between the instrumented and instrumental variables:

$$Exposure_{rt} = \pi_0 + \pi_1 Exposure_{rt}^{IV} + \mu_r + \lambda_t + \varepsilon_{rt}. \tag{19}$$

The result of model 19 is reported in Table 3, which shows a statistically significant coefficient for π_1. An additional unit in the instrument corresponds to an increase by 0.664 units in $Exposure$, with the probability of the effect being null below 1%.

Tables 9 and 11 show the Kleibergen and Paap (2006) Wald rk F-statistics for each specification of Equation 17. This measure of F-statistic is used to test for weak instruments in models with multiple endogenous regressors where standard errors are robust to heteroskedasticity or clustered. Stock and Yogo (2005) provide critical values for the Cragg and Donald (1993) F-statistic, which is used in case of multiple endogenous variables, when errors are assumed to be independent and identically distributed. Critical values for F-statistics when the assumption of independent and identical distribution fails are instead missing. In any case, the three Kleibergen-Paap F-statistics always remain higher than the conventional critical value of 10.

5 Results

In this section, the results of the model described in Section 4.3, are reported. First, the statement of Proposition 2 is empirically tested, using the regional mean age at first birth as the outcome. This is followed by some robustness checks and the 2SLS results. Finally, the consequences of automation on both total and age-specific fertility rates are discussed. This allows to understand whether a quantum effect overlaps with the tempo one.

5.1 Mean age at first birth

This section reports the findings on the relation between the regional exposure to robots and the mean age of women when they have the first birth.

Table 4 reports the results of the regression formalized by Equation (16), in the first column, and by Equation (17), in the last three columns. As for the first, the coefficients related to the interaction terms have signs consistent with Proposition 2. While the statistical significance is above the conventional levels 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. The loss of significance in the first specification may hence be driven by collinearity. The coefficients obtained with the specification of Equation (16) suggest that, on average, medium-education

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regions experience an increase by 0.1 years (or equivalently, by multiplying by 12, 1.26 months) in mean age at birth, when a robot per thousand worker (with respect to the 1995 employment distribution) is added. Low-education regions, instead, experience a reduction by around 3 months. Looking at Columns (2), (3), and (4) (estimated with Equation (17)), the magnitudes correspond to around 4.5 months for low-education regions, and 3 months and a half (more than half the within standard deviation) for the medium- and high-education cases. To get an idea on the magnitude of such effects, let us consider again the Moore's law, mentioned in Section 4.2.3, and Figure 4. If we were in 2004, we would need around 9 years to witness a unitary increase in exposure to robots, hence a change in fertility timing by around 4 months. If we were in 2013, we would need approximately 5 years to have another unitary increase in robots adoption, and such an interval of years is likely to reduce over time.

The effects of being in a region where the share of women with a certain level of education is relatively high are obtained by summing two coefficients: the one linked to the interaction term and the one linked to the indicator. Again, the non significance of the effects in Column (1) is likely to be driven by collinearity. Column (2) reports that a region with a high share of women with low schooling experiences an anticipation of fertility by -0.376+0.154=-0.222 years. The medium-skill indicator is associated with an anticipation of 0.276-0.378=-0.052 years in Column (3). Hence, the postponement effect, due to the combination of being in a local labor market with a high level of automation and with a relatively high number of medium-skilled women, appears to outperform their tendency to anticipate fertility. High-skill regions witness an increase in age at birth by -0.292+0.399=0.107 years (Column (4)). The tendency of highly educated women to postpone fertility is well known in the literature (Glick et al. (2015), Rindfuss and John (1983)). The results in Column (4) suggests that the anticipation effect due to automation looks greater than the postponement purely driven by high education.

Straightforwardly, the relation between age at birth and median age of the female population tends to be positive. Finally, the higher the population, the lower the age at birth, despite the significance levels do not exclude that the correlation is actually null. This is likely to be driven by the positive relation, at the aggregate level, between completed fertility and age at first birth (Beaujouan and Toulemon (2021)). The within R-squared is almost 35% in the first columns, around 30% in the second one, and around 25% in the last two.

5.1.1 Robustness and Two-Stages Least Squares

The following robustness and endogeneity checks have the aim of reassuring that the baseline effects do not dramatically change after some modifications to the specification, and that

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they are not subject to endogeneity. The robustness checks take into account the possibility that the results may be actually due to the indicator functions, that fertility outcomes shall actually be observed after some time with respect to the predictors, and that the coefficients may be driven by specific sectors or by outliers in the data. The Two-Stages Least Squares reduces the concerns due to the reverse causality between demography and the adoption of robots, as found by Acemoglu and Restrepo (2021).

Table 5 reports the results obtained by dropping the indicators and interacting the exposure variable with the share of women with primary, secondary, and tertiary education instead. 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 and with statistical significance lower than the conventional levels in all the three cases. 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 estimation. The effects are statistically significant at the 99% in the first two cases, and at the 95% in the last. A percentage point increase in the share of women with primary education, combined with the addition of a robot per thousand workers, decreases the mean age at first birth by 0.00866 years. The reduction is -0.00563 when the interaction regards tertiary education. By interacting the predictor with the secondary education share, the mean age increases by 0.0093. The coefficients of the education shares in the last three columns still suggest a positive relation between schooling and the age at first birth, which can be obtained by summing the effect of the interaction with the one of the education share. There is an average decrease of -0.0128 years for a one percentage point increase in the share of women with primary education (Column (2)). Column (3) reports a decrease by -0.0114 when the share of women with secondary education increases by 1%. An increase in the share with tertiary education is instead associated with an increase in the mean age at first birth by 0.0142.

Another check is provided by accounting for the possibility that life-course decisions are observed after some time. This is pursued by lagging the dependent variable forward by one year. Results are reported in Table 6. The signs of the effects are unchanged in all the four specifications, and the statistical significance remains above the 99% level. The magnitudes in Columns (2), (3), and (4) amount to around 0.3 in absolute terms, and hence still corresponding to half of the within standard deviation.

In Table 7, the vehicles sector is dropped from the exposure variable and added in isolation as a control. This aims at ensuring that the effects of the explanatory variable are not driven by the automobile industry, which has adopted much more robots than any other industry[11].

[11]See Figure 2 in Acemoglu and Restrepo (2020), which compares the 1993-2007 increase in the penetration of robots in the automotive sector, in both the European and American labor market, with the one in the

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Not only the direction of the effects remain consistent, but they seem actually much stronger. In Column (1), the preponement reported for low- and high-skill regions amounts to almost 0.3 years. The effect for the middle-skill cohort, instead, is not statistically significant at the conventional levels. When the interactions are considered in isolation, the coefficients are higher than the baseline ones amounting to approximately half a year, or equivalently, one within standard deviation.

Finally, the results in Table 8, obtained by dropping observation for which the level of exposure is greater than 5, reassures that the previous effects are not driven by outliers. The signs and the levels of statistical significance remain unchanged, and the magnitude of the effects are almost the same as the baseline ones.

Results obtained from the Two-Stages Least Squares regression are reported in Table 9, to address the possibility that the results are biased due to the reverse causality between demographic changes and automation. As in the baseline estimation, the changes in fertility timing amount to approximately half the within standard deviation.

Overall, the checks can be interpreted as bolstering the intuition provided in Section 3.

5.2 Fertility rates

A last consideration regards the effect of automation on fertility rates. The effect results 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 robots exposure, with the usual four specifications. In Column (1), the only significant effect (at the 99%) is shown for the cohort of middle-skill regions, with an increase in total fertility by 0.06. Again, the remaining three columns suffer less from collinearity. Columns (2) shows that fertility is reduced by 0.039 (two fifth of the within standard deviation) in regions with a high number of women with primary education, with a 95% significance level. Column (3) confirms the increase in fertility for middle-skilled labour markets, while still no effect is found for the high-education cohort.

Table 11 reports what happens when the Two-Stages Least Squares approach is used.

other industries.

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The effect for low-education regional markets appears to have been due to endogeneity, as the coefficients in Columns (1) and (2) have no appreciable statistical significance and inconsistent signs. The increase in fertility for medium-education ones remains consistent with Table 10, despite being the effect shown in Column (3) lower by 0.015, with a 90% significance level. The results found for the high educations regions is controversial, as it is positive with the three interactions included together, but turns negative when the interaction is isolated.

All considered, the only effect which can be considered consistent is the increase in fertility in contexts with a prevalence of medium-educated women. This is likely to be due to the reduction in opportunity cost of bearing children such a cohort of workers, who bear the most of the negative employment effects of automation.

The following section sheds more light on the fertility dynamics by considering the tempo and the quantum effects simultaneously.

5.3 Age-Specific Fertility rates

To have a clearer view about how robotics change demographic dynamics, age-specific fertility rates are used as new dependent variables in Equation (17). β_L, β_M, and β_H follow an S-shaped path in the plots shown in Figures 5, 6, and 7, where the horizontal axes represent the age cohorts. In low-skill regions (Figure 5), the correlation is positive at the age of 20. The coefficient increases and reaches a peak, corresponding to 0.0057, for the cohort of 23-years old women. It becomes negative after the age of 27 and reaches the minimum at 31, with a magnitude, in absolute terms, of 9/11 the within standard deviation. It then stabilizes to zero at 39 years.

High-skill regions (Figure 7) follow a similar path to the low-skill case. The positive effect is almost stable from the age of 20 to 25, with a coefficient of approximately 0.005. It then drops and turns negative after the age of 27. It reaches a negative peak of -0.0084 at the age of 32. After that, it slowly approaches zero.

In the middle-education case (Figure 6), the correlation is slightly negative at the beginning of the reproductive life, with an almost constant value of -0.003. It turns positive at 27 and experiences a fast increase until the age of 31, with a coefficient of almost 0.01 (10/11 the within standard deviation). After the peak, it slowly reduces and reaches a level close to zero at age 40. As suggested by Table 10, the positive effect of robotics on fertility prevails on the negative one. Contrary to the cases of low- and high-education regions, where there is a pure anticipation effect, in medium-skill regions the postponement of childbearing appears to overlap with an increase in the optimal family size, with the additional children being

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born at the end of the reproductive life.

These S-shaped relations between robot exposure and age-specific fertility can be interpreted as strenghtening the preponement and postponement mechanisms suggested by the effects on the regional mean age at first birth.

6 Conclusion

The progress in industrial automation is having a great impact on the labor market and on the life-course decisions of individuals. While many pioneering studies are examining the consequences of robotics on employment, there is not much work about the link between such labor market changes and family behavior. This paper analyses how industrial robotics affect fertility choices, specifically regarding the timing parents decide to bear children.

The mechanism behind such a relation is suggested by a model where children are considered as an irreversible investment, which the cost corresponds to the losses in terms of career opportunities due to child-bearing. It is assumed that the automation of labor can both increase, especially for non-routine workers, and decrease, particularly for routine workers, the opportunity cost of the parent. An increase in the expectations about the impact of robots on jobs is shown to result in the desire to anticipate fertility for individuals at the extremes of the education distribution and to postpone it for those in the middle.

A fixed-effect model, that uses European panel data at the regional level, gives empirical support to the above statement by interacting a measure of exposure to industrial robotics with three indicators about the level of education in a region. The analysis suggests a positive relation between automation and the mean age at first birth in areas with many individuals with secondary education. It is instead negative in contexts with many individuals with primary and tertiary education. This tempo effect is reflected in the correlation between robotics and age-specific fertility rates. In low- and high-education regions, the relation is positive at the beginning of the reproductive life and slowly decreases until it turns negative. The contrary happens for medium-education regions. From a policy perspective, these results suggest that family policies are likely to be more effective at the beginning of the reproductive life in labor markets with a prevalence of low- or high-skilled workers, and later where medium-skilled workers are prevalent.

Given the huge influence that the progress in technology has on the labor market, the consequence in terms of life-course decisions shall not be ignored. Future research may encompass the limitations of this study due to the aggregation of data, and provide a more holistic theoretical view of how labor automation affects the choices of a family.

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Tables

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Within Std. Dev.	Min.	Max.	N
% fem pop with ISCED0-2	28.68	15.156	5.831	2.7	86	3635
% fem pop with ISCED3-4	45.68	15.749	3.218	7.600	78.400	3650
% fem pop with ISCED5-8	25.733	10.503	5.200	6.100	63.9	3642
Population	1815278.93	1559330.723	88534.29	25706	12210524	3657
Log Population	14.107	0.843	0.0365	10.154	16.318	3657
Median age fem pop	42.217	3.269	1.747	31.9	52.8	3657
Mean age at first birth	29.735	1.398	0.608	24.7	33	3575
Tot. fertility rate	1.536	0.258	0.104	0.86	2.69	3575
Fertility rate Y20	0.036	0.019	0.007	0	0.125	3540
Fertility rate Y21	0.043	0.019	0.007	0.008	0.127	3540
Fertility rate Y22	0.049	0.019	0.008	0.009	0.129	3540
Fertility rate Y23	0.057	0.02	0.008	0.011	0.128	3540
Fertility rate Y24	0.066	0.021	0.009	0.013	0.145	3540
Fertility rate Y25	0.076	0.022	0.009	0.018	0.153	3540
Fertility rate Y26	0.086	0.023	0.008	0.026	0.182	3540
Fertility rate Y27	0.095	0.024	0.008	0.036	0.171	3540
Fertility rate Y28	0.102	0.025	0.008	0.038	0.199	3540
Fertility rate Y29	0.106	0.025	0.009	0.051	0.192	3540
Fertility rate Y30	0.107	0.024	0.010	0.045	0.206	3540
Fertility rate Y31	0.104	0.025	0.011	0.039	0.181	3540
Fertility rate Y32	0.097	0.024	0.012	0.03	0.167	3540
Fertility rate Y33	0.088	0.023	0.012	0.025	0.164	3540
Fertility rate Y34	0.078	0.022	0.011	0.02	0.16	3540
Fertility rate Y35	0.067	0.02	0.011	0.015	0.131	3540
Fertility rate Y36	0.056	0.018	0.010	0.012	0.133	3540
Fertility rate Y37	0.044	0.015	0.009	0.007	0.09	3540
Fertility rate Y38	0.034	0.013	0.007	0.005	0.088	3540
Fertility rate Y39	0.026	0.01	0.006	0.004	0.078	3540
Fertility rate Y40	0.018	0.008	0.005	0	0.063	3540

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

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Table 2: Summary statistics of the main explanatory variables.

Variable	**Mean**	**Std. Dev.**	**Within Std. Dev.**	**Min.**	**Max.**	**N**
Exposure to Robotics	2.038	1.634	0.751	0	12.06	995
$\mathbb{1}^L$	0.381	0.486	0.158	0	1	995
$\mathbb{1}^M$	0.506	0.5	0.207	0	1	995
$\mathbb{1}^H$	0.502	0.5	0.19	0	1	995

Table 3: Correlation of Robot Exposure IV with Robot Exposure in the EU

Dependent variable:	*Exposure*
$Exposure^{IV}$	0.664***
	(0.121)
Constant	1.257***
	(0.0676)
Observations	937
Within R-squared	0.3635

*** 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.

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

	(1)	(2)	(3)	(4)
Mean age at first birth	Equation (16)	Equation (17)	Equation (17)	Equation (17)
$\mathbb{1}^L * Exposure$	-0.265***	-0.376***		
	(0.0633)	(0.0390)		
$\mathbb{1}^M * Exposure$	0.105*		0.276***	
	(0.0555)		(0.0528)	
$\mathbb{1}^H * Exposure$	-0.0713			-0.292***
	(0.0672)			(0.0591)
$Exposure$	-0.0885	0.0230	-0.260***	0.0372
	(0.0709)	(0.0325)	(0.0686)	(0.0335)
$\mathbb{1}^L$	0.0773	0.154***		
	(0.0676)	(0.0563)		
$\mathbb{1}^M$	-0.0604		-0.378***	
	(0.0990)		(0.111)	
$\mathbb{1}^H$	0.175			0.399***
	(0.115)			(0.116)
Median age fem pop	0.0728	0.133***	0.0375	0.00962
	(0.0491)	(0.0437)	(0.0460)	(0.0452)
Log population	-0.244	0.0589	-0.733	-1.028
	(0.743)	(0.707)	(0.784)	(0.762)
Observations	963	963	963	963
Within R-squared	0.351	0.306	0.263	0.243

*** 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.

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Table 5: Effect of robot exposure on mean age at first birth. Robustness check: Interaction between exposure and share of women with primary, secondary and tertiary education.

	(1)	(2)	(3)	(4)
Mean age at first birth	Equation (16)	Equation (17)	Equation (17)	Equation (17)
$Share\, low\, educ * Exposure$	0.0710	-0.00866***		
	(0.0659)	(0.00252)		
$Share\, med\, educ * Exposure$	0.0849		0.00929***	
	(0.0660)		(0.00157)	
$Share\, high\, educ * Exposure$	0.0752			-0.00563**
	(0.0664)			(0.00253)
$Exposure$	-8.035	0.109**	-0.547***	0.187**
	(6.625)	(0.0445)	(0.103)	(0.0755)
$Share\, low\, educ$	-0.0284	0.0215***		
	(0.207)	(0.00704)		
$Share\, med\, educ$	-0.0448		-0.0207***	
	(0.206)		(0.00725)	
$Share\, high\, educ$	-0.0131			0.0198**
	(0.211)			(0.00880)
Observations	963	963	963	963
Within R-squared	0.291	0.186	0.258	0.15

*** 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 log population, and the median age of women in the region.

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Table 6: Effect of robot exposure on mean age at first birth. Robustness check: Outcome lagged forward by one year.

	(1)	(2)	(3)	(4)
Mean age at first birth at $t+1$	Equation (16)	Equation (17)	Equation (17)	Equation (17)
$\mathbb{1}^L * Exposure$	-0.201***	-0.331***		
	(0.0703)	(0.0506)		
$\mathbb{1}^M * Exposure$	0.115		0.257***	
	(0.0770)		(0.0486)	
$\mathbb{1}^H * Exposure$	-0.0799			-0.275***
	(0.0950)			(0.0587)
Observations	964	964	964	964
Within R-squared	0.318	0.281	0.259	0.243

*** 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 level of exposure to robots, the education indicators, the 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: Drop vehicles sector.

	(1)	(2)	(3)	(4)
Mean age at first birth	Equation (16)	Equation (17)	Equation (17)	Equation (17)
$\mathbb{1}^L * Exposure^{no\,vehicles}$	-0.287***	-0.499***		
	(0.108)	(0.0580)		
$\mathbb{1}^M * Exposure^{no\,vehicles}$	0.0987		0.393***	
	(0.0792)		(0.0915)	
$\mathbb{1}^H * Exposure^{no\,vehicles}$	-0.271**			-0.524***
	(0.112)			(0.0691)
Observations	963	963	963	963
Within R-squared	0.364	0.296	0.279	0.31

*** 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 level of exposure to robots, the education indicators, the log population, the median age of women in the region, and the exposure to robots in the vehicles sector.

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

	(1)	(2)	(3)	(4)
Mean age at first birth	Equation (16)	Equation (17)	Equation (17)	Equation (17)
$\mathbb{1}^L * Exposure$	-0.270***	-0.376***		
	(0.0637)	(0.0429)		
$\mathbb{1}^M * Exposure$	0.107*		0.269***	
	(0.0566)		(0.0567)	
$\mathbb{1}^H * Exposure$	-0.0718			-0.285***
	(0.0697)			(0.0664)
Observations	911	911	911	911
Within R-squared	0.329	0.282	0.238	0.215

*** 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 level of exposure to robots, the education indicators, the log population, and the median age of women in the region.

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Table 9: Effect of robot exposure on mean age at first birth. 2SLS estimation.

Mean age at first birth	(1) Equation (16)	(2) Equation (17)	(3) Equation (17)	(4) Equation (17)
$\mathbb{1}^L * \widehat{Exposure}$	-0.154*	-0.301***		
	(0.0881)	(0.0674)		
$\mathbb{1}^M * \widehat{Exposure}$	0.0955		0.258***	
	(0.0778)		(0.0714)	
$\mathbb{1}^H * \widehat{Exposure}$	-0.0948			-0.291***
	(0.119)			(0.0782)
Observations	908	908	908	908
KP F-Stat	15.904	30.455	29.318	23.685
R-squared	0.309	0.267	0.245	0.234

*** 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 level of exposure to robots, the education indicators, the log population, and the median age of women in the region.

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Table 10: Effect of robot exposure on Total Fertility Rates. Baseline estimation.

	(1)	(2)	(3)	(4)
Total Fertility Rate	Equation (16)	Equation (17)	Equation (17)	Equation (17)
$\mathbb{1}^L * Exposure$	0.000817	-0.0389**		
	(0.0211)	(0.0165)		
$\mathbb{1}^M * Exposure$	0.0640***		0.0522***	
	(0.0207)		(0.0133)	
$\mathbb{1}^H * Exposure$	0.0175			-0.0315
	(0.0284)			(0.0205)
Observations	963	963	963	963
Within R-squared	0.277	0.222	0.264	0.216

*** 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 level of exposure to robots, the education indicators, the log population, and the median age of women in the region.

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Table 11: Effect of robot exposure on Total Fertility Rates. 2SLS estimation.

Total Fertility Rate	(1) Equation (16)	(2) Equation (17)	(3) Equation (17)	(4) Equation (17)
$\mathbb{1}^L * \widehat{Exposure}$	0.0241	-0.0116		
	(0.0208)	(0.0219)		
$\mathbb{1}^M * \widehat{Exposure}$	0.105***		0.0371*	
	(0.0173)		(0.0210)	
$\mathbb{1}^H * \widehat{Exposure}$	0.0773***			-0.00626
	(0.0241)			(0.0213)
Observations	908	908	908	908
KP F-Stat	15.904	30.455	29.318	23.685
R-squared	0.239	0.214	0.267	0.209

*** 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 level of exposure to robots, the education indicators, the log population, and the median age of women in the region.

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Figures

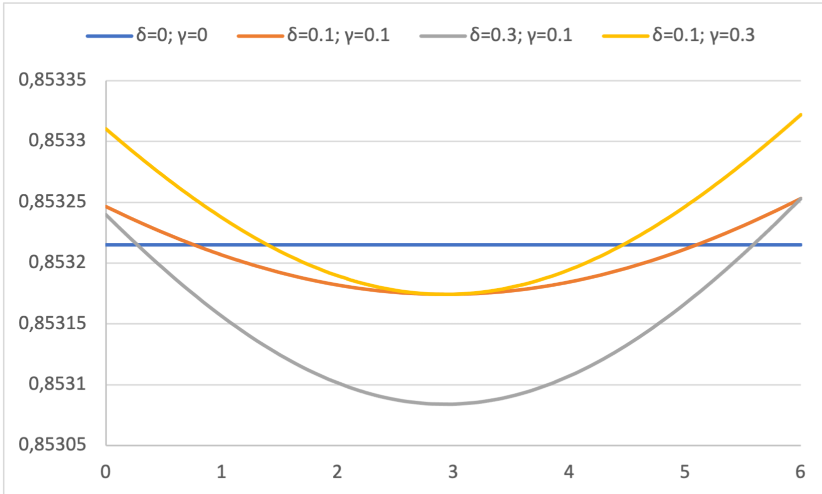

Figure 1: Approximated values of $\frac{\beta}{\beta-1}$ (on the vertical axis) for different levels of h (on the horizontal axis). $\sigma = 0.05$, $\rho = 0.99$, $\lambda = 0.01$.

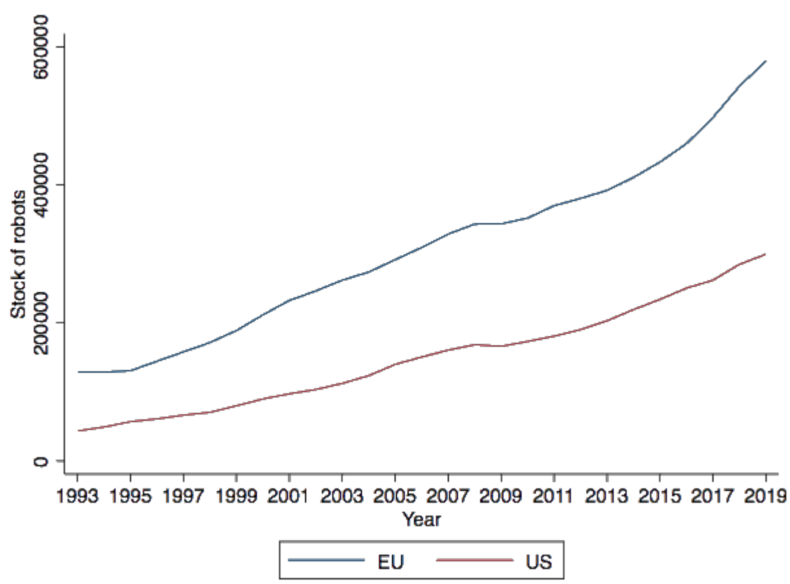

Figure 2: Evolution of the stock of industrial robots in Europe and the US from 1993 to 2019.

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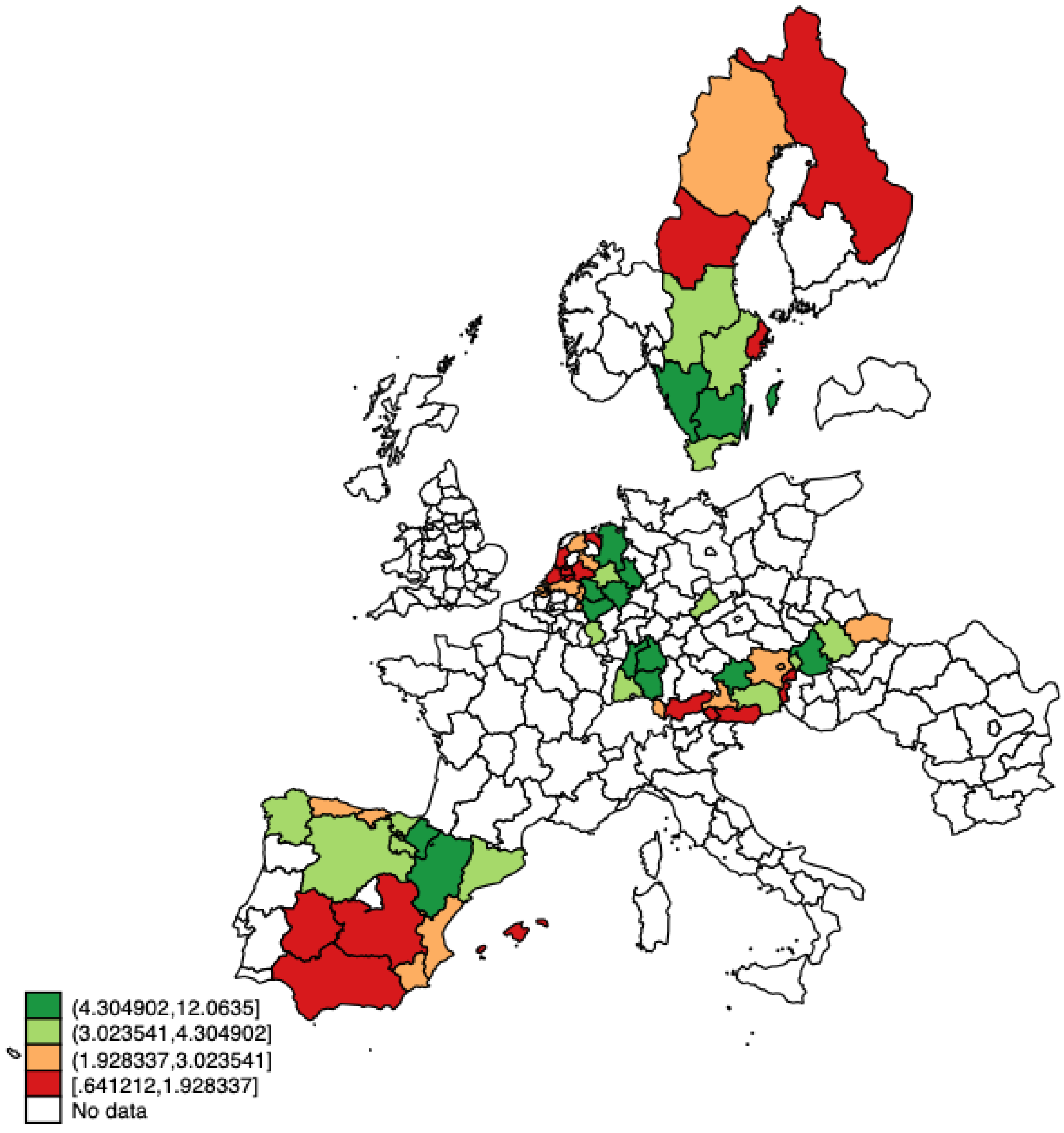

Figure 3: 2018 regional levels of the robot exposure variable.

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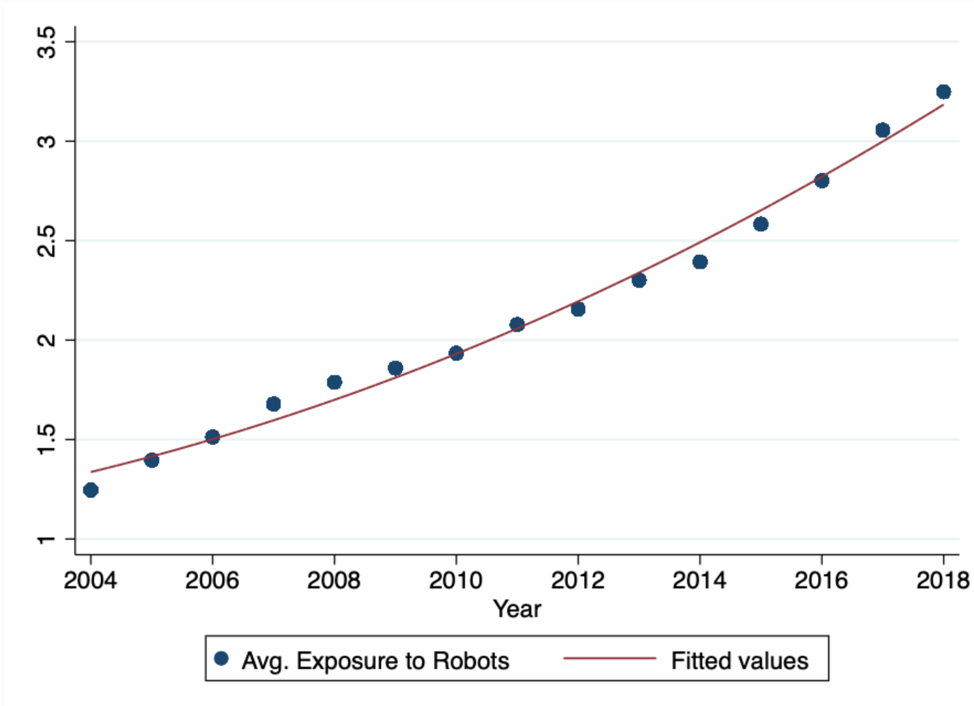

Figure 4: Evolution of average exposure to robots in Europe over time.

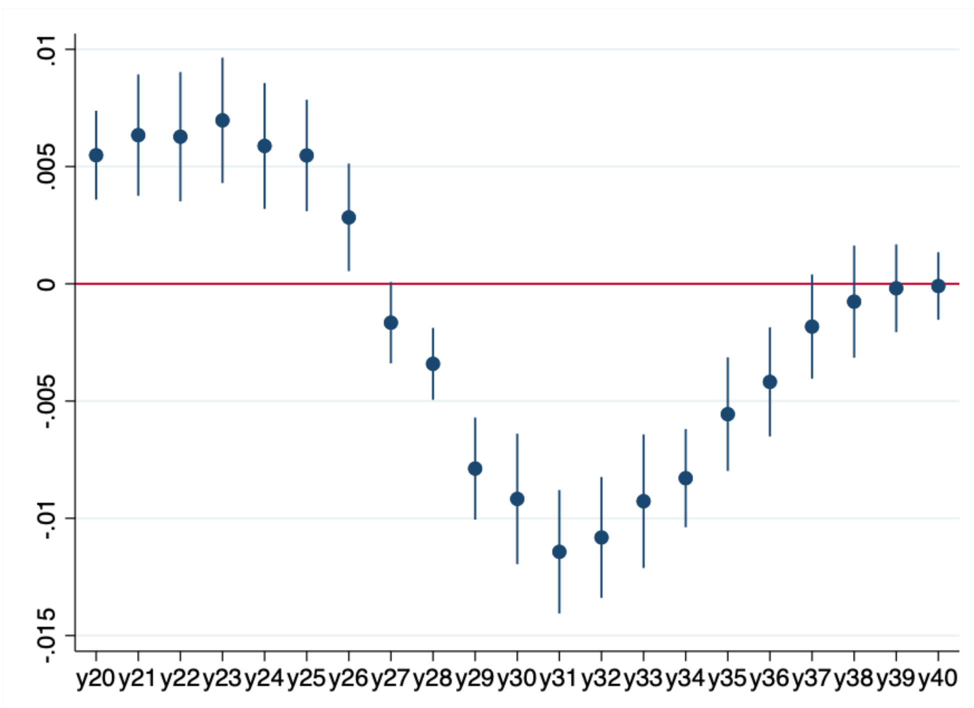

Figure 5: Coefficients β_L (on vertical axis) of Equation (17), where Y_{rt} represents age-specific fertility rates (on horizontal axis).

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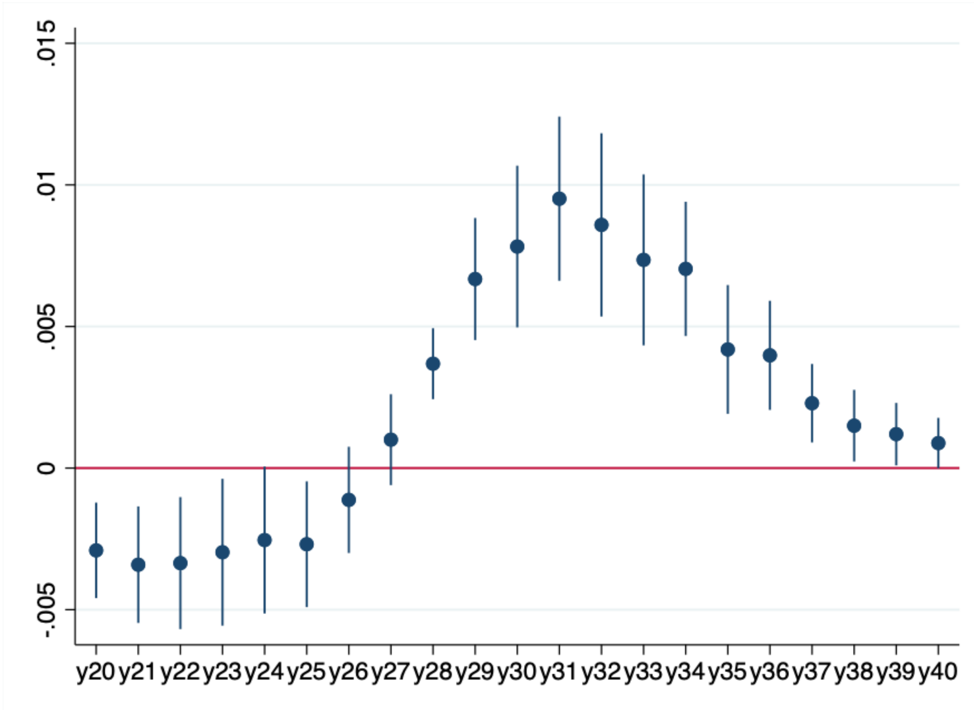

Figure 6: Coefficients β_M (on vertical axis) of Equation (17), where Y_{rt} represents age-specific fertility rates (on horizontal axis).

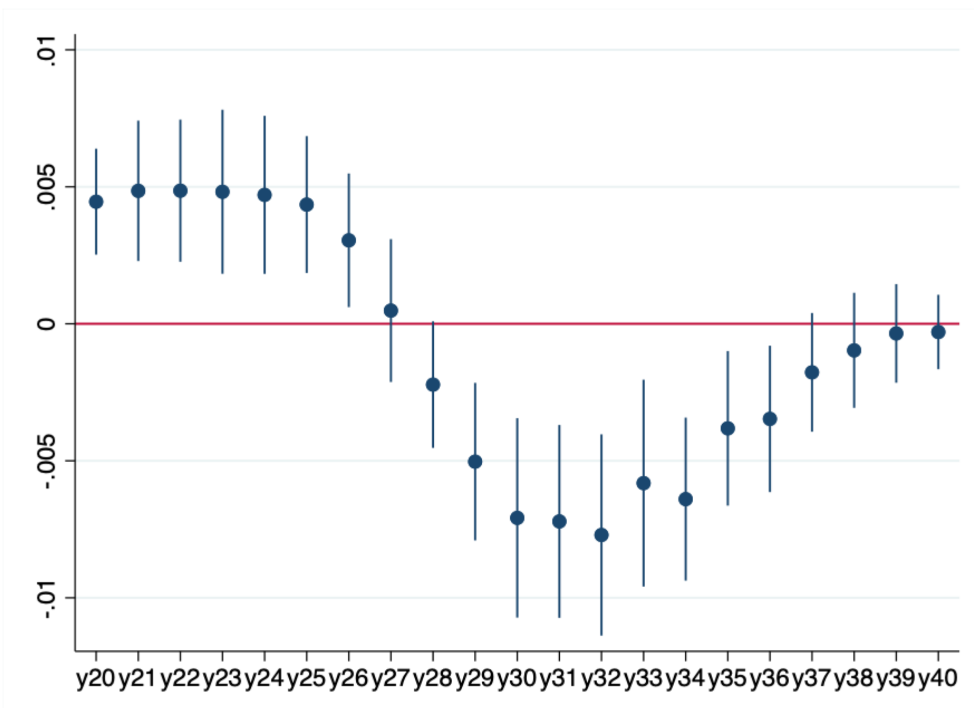

Figure 7: Coefficients β_H (on vertical axis) of Equation (17), where Y_{rt} represents age-specific fertility rates (on horizontal axis).

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