Robots, Marriageable Men, Family, and Fertility *

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Abstract

Robots have radically changed the demand for skills and the role of workers in production. This phenomenon has replaced routine and mostly physical work of blue collar workers, but it has also created positive employment spillovers in other occupations and sectors that require more social interaction and managing skills. This study examines how the exposure to robots and its heterogeneous effects on the labor market opportunities of men and women affected demographic behavior. We focus on the United States and find that in regions that were more exposed to robots, gender gaps in income and labor force participation declined, reducing the relative economic stature of men. Regions affected by intense robot penetration experienced also an increase in both divorce and cohabitation and a decline –albeit non-significant– in the number of marriages. While there was no change in the overall fertility rate, marital fertility declined, and there was an increase in nonmarital births. Our findings provide support to the hypothesis that changes in labor market structures that affect the absolute and relative prospects of men may reduce their marriage-market value and affect marital and fertility behavior.

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1 Introduction

Millions of workers across the world feel the increasing pressure and fear of machines replacing their jobs. Artificial intelligence (AI), machine learning, robots, and the Internet have already transformed the nature of jobs and will continue to change our labor markets rapidly. The debate on the effects that the development of robotics and automation will have on the future of jobs has been lively (Brynjolfsson and McAfee, 2014; Autor et al., 2015; Graetz and Michaels, 2018; Dauth et al., 2019; Frey and Osborne, 2017; Acemoglu and Restrepo, 2020). However, despite the growing interest in the labor market effects of automation, we know very little about how these structural economic changes are reshaping key life-course choices. Previous studies investigated the effects of labor market shocks on fertility and family formation. Our study adds to this literature by examining how the exposure to robots and its effects on relative gender economic opportunities and the declining economic stature of blue collar male workers have affected demographic behavior (Shenhav, 2020; Schaller, 2016; Kearney and Wilson, 2018; Matysiak et al., 2020; Wilson, 1996). Unlike economic recessions or other temporary labor market shocks, the adoption of robots and automation systems permanently change the economic prospects of individuals, and thus, are likely to have long-lasting effects on family and fertility behavior.

We focus on the United States (US) context and exploit the information on marriage, cohabitation, divorce, marital, and non-marital fertility drawn from the American Community Survey (ACS) data covering the 2005 to 2016 period. We construct a measure of regional exposure to robots following Acemoglu and Restrepo (2020) and using data from the International Federation of Robotics (IFR). The adoption of robots could be correlated with other demographic trends within an industry or a local labor market. To mitigate the concern, we rely on variation in the historical sectoral distribution of employment across commuting zones.[1] combined with national changes in the adoption of robots across industries over time. Furthermore, we instrument the latter with the industry-level spread of robots in Europe. This variation should capture the exogenous trends in automatability of certain sectors driven by the advancements in the technological

[1] Commuting zones are geographical units corresponding to regional labor markets characterized by intense daily commuting of workers, as defined by David and Dorn (2013)

frontier, which are plausibly independent of the US demographic trends.

Using this empirical strategy, we investigate the effects of this shock on the absolute labor market outcomes of men and women, on the relative gender-gaps, on the marriage market, and fertility. The analysis of labor market outcomes shows that robot exposure had differential effects on the labor market opportunities of men and women: one standard deviation increase in robot exposure penalized to a larger extent employment and earnings of men. This, in turn, reduced the gender income gap by 4.2% and the gender gap in labor force participation by 2.1%, pointing at a reduction of both the absolute and relative value of men and at a greater bargaining power of women. Consistently with these labor market effects, commuting zones that were more exposed to robot penetration experienced a reduction –albeit non-significant– in the marriage rate and a statistically significant increase in divorce and cohabitation. A one standard deviation increase in robot exposure was associated with a 1% reduction in the marriage rate, a 9% increase in divorces, and a 10% increase in cohabitations. While we find a null effect of robots on the overall fertility, this result masks substantial heterogeneous effects. Indeed, we show that commuting zones that were more exposed to robots' penetration exhibit a 12% reduction in marital fertility and a 15% increase in the nonmarital fertility rate.

We discuss the typical challenges of a Bartik-type instrumental variable approach (Goldsmith-Pinkham et al., 2020), and reassuringly, we document no evidence of significant pre-trends in the outcomes of interest. The electronics sector has, by far, the highest Rotemberg weight throughout the period under investigation. We show that the results are substantially unchanged when removing the electronics sector or controlling for area-specific trends across quartiles of the share of employment in the electronics sector. Furthermore, as the automotive sector was driving the adoption of robots in the period under study, we show that our results are robust to the inclusion of specific time trends across areas with different initial shares of automotive sector employment. Finally, we show that our results are robust to controlling for differential exposure to trade liberalization.

Overall, our findings suggest that a decrease in the relative marriage-market value of men may be a relevant transmission mechanism of the impact of robot penetration on marriage and marital fertility rates (Shenhav, 2020; Schaller, 2016; Autor et al., 2019; Kearney and Wilson, 2018).

The rest of the paper is organized as follows. Section 2 reviews the relevant literature on technology, gender-specific labor demand shocks, marital behavior and fertility, and discusses the conceptual framework. Section 3 describes the data used and explains our empirical strategy. Results are presented in Section 4. Section 5 includes a set of robustness checks and heterogeneity analyses. Section 6 concludes.

2 Technology, Gender-Specific Labor Demand Shocks, Marital Behavior and Fertility

Our study contributes to three important strands of the literature analyzing family and fertility choices. First, many seminal papers have documented the massive impact of technology on family and fertility decisions. Previous literature shows how the advancements in contraceptive technology played a major role in the radical change in reproductive patterns during the past century, that is, the "Second Demographic Transition" (Lesthaeghe, 2010) and favored human capital investments and labor force participation of women (Goldin and Katz, 2002; Bailey, 2006). An additional dimension of technological change affecting the role of women within the household includes the diffusion of household appliances in the US between 1930 and 1950, which was a key driver of the increase in the labor market participation of women during that period and beyond (Greenwood et al., 2005; de V. Cavalcanti and Tavares, 2008). The technological progress in the medical field, such as the improvement in maternal and infant health, also plays an important role. This medical progress has allowed women to reconcile work and motherhood, thereby contributing to an increase in their fertility rate and participation in the labor market (Albanesi and Olivetti, 2016). Recently, technological change has also taken the form of the "digital revolution." Many studies have analyzed the impact of broadband Internet on a large array of demographic and health outcomes, including marriage decisions (Bellou, 2015), fertility behavior (Billari et al., 2019; Guldi and Herbst, 2017), bodyweight (DiNardi et al., 2017), and sleep (Billari et al., 2018). Both Bailey and DiPrete (2016) and Greenwood et al. (2017) provide comprehensive surveys of the literature modelling female labor force participation, marriage, divorce, fertility, and the role of technological changes and economic opportunities in determining life-course choices. Our study contributes to this discussion by focusing on a more recent wave of technological change—the development of robotics and automation—that, instead of directly affecting fertility and family choices, might disrupt them by profoundly changing employment opportunities for both women and men.

Second, our study adds to the literature on the decline in the relative and absolute marriage-value of men, and more generally, of partnership formation. In his classical framework, Becker (1973) predicts that a reduction in the gender wage gap would reduce the marriage option value for women because of a reduced scope for intra-household specialization. While Becker focused on the role of relative income, in the sociological literature, William Julius Wilson argued that the absolute fall in the economic stature of men due to the decline in the US blue-collared employment reduced the value of marriage for women, and thus, affected partnership formation and fertility (Wilson et al., 1986; Wilson, 1987, 1996). Testing these hypotheses empirically has proven to be a challenging task because of the many confounding factors that could be correlated both with male economic opportunities as well as other trends in marriage and family formation behavior. Yet, a handful of studies have attempted to shed light on the causal effects of labor market shocks on marital and fertility behavior. Black et al. (2003) provided empirical support to Wilson's thesis that the availability of high-paying manufacturing jobs for low-skilled workers may be an important contributor to explain trends in marriage markets and fertility behavior. Exploiting the effects of the Appalachian coal boom (the 1970s) and bust (the 1980s), they provide evidence that the expansion in high-wage jobs for low-skilled workers increased marriage rates and reduced the incidence of female-headed households. In a follow-up paper, Black et al. (2013) show that the coal boom also led to an increase in fertility within marriage and a decrease in the non-marital birth rate. Kearney and Wilson (2018) examined the effects of the more recent fracking boom and found that while the positive shock to the income of low-skilled men led to higher fertility, marital patterns were not affected. Changes in social norms may explain the differences for the observations by Black et al. (2013) examining coal boom and bust of the 1970s and 1980s. Consistent with Becker's model, Schaller (2016) documents that while improvements in the men's labor market conditions are associated with increases in fertility rates, improvements in the women's labor market conditions have smaller negative effects. Further support to the predictions of the Becker's model of household specialization is provided by Autor et al. (2019), who examine how the gender-specific components of labor market shocks induced by the increased competition with international manufacturing imports affected the relative economic stature of men versus women, and in turn, marital and fertility behavior. They find that—consistent with the prediction of the Becker's model of household specialization—a negative shock to male's earnings reduced marriage and fertility. In a related work, Shenhav (2020) uses gender-specific shocks and gender differences in occupational choice to predict changes in relative gender earnings, demonstrating that a higher female-to-male wage ratio increases the quality of women's mates, reduces marriage rates, and raises the number of hours worked by women. These results are also consistent with previous evidence by Watson and McLanahan (2011) who find that low-income men are less likely to be married if they live in a high-income metropolis, and that half of the marriage gap between high- and low-income men is determined by relative—rather than absolute—income. Watson and McLanahan (2011) suggest that low-income couples' decisions to marry are affected by their expectation of achieving a certain economic status, which, in turn, is determined relative to the income of their reference group. We offer two main contributions to this literature. To the best of our knowledge, this is the first study to provide empirical evidence of the effects of robots' penetration on marital and fertility choices. Second, we examine the differential effect of robots on the labor market opportunities of men and women—and thus, the impact on both the absolute economic outcomes of men and their relative marriage-market value—as the potential mechanism. Similar to the observations by Autor et al. (2019) when analyzing the relative exposure to import penetration, men are more likely to be employed in industries exposed to robot penetration. We thus expect that employment opportunities and earnings may decrease in these male-dominated sectors. At the same time, there is evidence that the increase in productivity triggered by robotization has translated into increases in employment opportunities in the service sector (Dauth et al., 2019). Contrary to manufacturing jobs, service jobs tend to be more gender-neutral and require interpersonal and social skills for which women might have a comparative advantage. These dynamics are likely to impact both the absolute and relative economic stature of men negatively.

In a Beckerian type model (Shenhav, 2020; Bertrand et al., 2016), as the difference between the income of the household and the income of the single woman erodes, the pecuniary gains from marriage decline. Similarly, as female relative wage increases, the child-rearing gains to marriage decline because of higher returns to labor market activity. More women may choose to remain single to pursue their career and higher relative wages. Unmarried couples may respond to these incentives by choosing less costly forms of commitment (i.e., cohabitation). Married couples may be induced to divorce in the face of lower returns to marriage. Consistent with previous evidence on the importance of relative gender earnings in marital and fertility behavior (Shenhav, 2020; Watson and McLanahan, 2011; Schaller, 2016), we, therefore, expect that reduced economic stature of men may lead to a reduction in marriages and an increase in divorce and cohabitation rates. These effects may contribute to a decline in marital fertility but potentially lead to an increase in nonmarital fertility (Autor et al., 2019; Black et al., 2013). As in Autor et al. (2019), our empirical setting does not allow us to distinguish between the role of relative economic stature within the couple (Becker hypothesis) and the role of men's (women's) absolute economic stature (Wilson hypothesis). As the adoption of robots generates both an absolute fall in the employment and earnings of men and a decline in their relative economic stature, we cannot cleanly distinguish between the two hypotheses.

The third strand of the demographic literature on which we build our work focuses on the effects of economic downturns and uncertainty on fertility choices. Several studies have documented fertility declines following economic recessions and rising unemployment rates (Cherlin et al., 2013; Sobotka et al., 2011; Özcan et al., 2010; Lanzieri, 2013). More recent studies have focused on the latest "Great Recession" and have confirmed previous findings on the pro-cyclicality of fertility (Goldstein et al., 2013; Currie and Schwandt, 2014; Matysiak et al., 2020). Recent work shows that exposure to robots may increase economic uncertainty following the dynamics of economic recessions. Acemoglu and Restrepo (2020) find significant negative effects of robot exposure on wages and employment. In an earlier study, Graetz and Michaels (2018) used variation in the adoption of industrial robots across six industries in different countries to estimate the effects of automation on productivity and wages. They find that robots had positive effects on productivity and wages, but negatively affected the employment of low-skilled workers. Dauth et al. (2019) estimate that robots accounted for almost 23% of the overall decline in manufacturing employment in Germany between 1994 and 2014, although this loss was offset by the jobs created in the service sector. Anelli et al. (2019) show that the structural economic changes induced by robotization in Europe have increased both actual and perceived economic uncertainty of individuals, which, in turn, have boosted voting for nationalist and radical right parties. While robotization generates effects on employment and wages that are potentially similar to those of an economic recession, it does have peculiar characteristics that differ from classical economic downturns. For instance, there is evidence that the impact of the increased economic uncertainty triggered by economic recessions on fertility is the result of both lower completed fertility rates (i.e., quantum) and postponement of fertility decisions (i.e., tempo) (Orsal and Goldstein, 2010; Comolli and Bernardi, 2015). Therefore, part of the temporary fall in total fertility rates determined by economic downturns is not translated into lower completed fertility rates but is "recuperated" after the end of the economic downturns. This phenomenon is strictly connected to the cyclical nature of economic recessions. Unlike economic recessions, the economic uncertainty caused by robotization of industrial production is not cyclical in nature and is likely to change the economic prospects of the affected workers permanently. It is costly and implausible for adults and young adults displaced by robots to retrain and become complementary to this new technology. Therefore, it is unclear a priori whether we should expect the effect of robotization on family choices and fertility to be comparable to those of standard economic recessions.

Finally, by focusing on the period 2005–2016, we provide new evidence on the effects of robots on the US labor market outcomes relative to the study by Acemoglu and Restrepo (2020), which considered the pre-recession period. A longer-term perspective on the effects of robotization allows us to capture the long-term economic and human capital adjustments, which might counteract the short-term negative impact estimated by Acemoglu and Restrepo (2020).

3 Data and Methods

To document the relationship between robot exposure and demographic outcomes, we merge data from two main sources: the ACS and IFR.

3.1 American Community Survey

The ACS is an ongoing survey conducted annually by the US Census Bureau since 2000. The survey gathers information previously contained only in the long form of the decennial census, such as ancestry, citizenship, educational attainment, income, language proficiency, migration, disability, employment, and housing characteristics. It collects information on approximately

295,000 households monthly (or 3.5 million per year). Several features of the ACS data make them particularly attractive for the present analysis. First, they collect information on household structure, marital status, fertility in the previous year, and the number of children. We use this information to create our main outcomes of interest. Second, the large sample sizes of the ACS allow us to conduct analyses at the granular geographical level. Finally, our dataset contains information on individuals' labor market behavior, such as their income and employment. Given that we expect robot exposure to affect the labor market outcomes, these variables enable us to shed some light on the potential mechanisms through which robot exposure affects marital and fertility behavior.

Our working sample is constructed as follows. We consider the survey years 2005–2016 and restrict attention to individuals aged 16–50 during the years in which outcomes were measured.[2] We then aggregate the data at the commuting zone[3] and year level, the level of variation in our measure of exposure to robots. We obtain a final longitudinal sample containing 7,410 commuting zone-year observations resulting from 741 commuting zones.

Table A.1 in the Appendix reports descriptive statistics on the main variables used in the analysis at the commuting zone-level. The fertility rate is derived by dividing the number of women reporting a birth in the previous year by the number of women aged between 16 and 50 residing in a commuting zone in a given year. To measure (non-)marital fertility rate, we restrict the numerator to (un)married women reporting a birth in the previous year, while we keep the denominator constant. The effect estimated on these two outcomes has the advantage of capturing both the increase/decrease in (non-)marital fertility due to the changing family formation patterns and the one induced by the change in fertility rates within married and unmarried women. In the Appendix (see Table A.2), we replicated our analysis, focusing either only on the fertility rates within (un)married women or using the share of births born to married or unmarried women. Results are consistent with our baseline measure.

The average fertility rate in a given commuting zone and year is about 6% (3.4% marital fertility and 2% nonmarital fertility). One of the limitations of the ACS data is that we do not have information on the number of people married or divorced in the previous year for the

[2] 2005 is the first year in which demographic outcomes were collected in the ACS data.
[3] Commuting zones can be regarded as local labor market areas.

entire period under investigation. Thus, we can only analyze changes in the share of married and divorced individuals over time. The proportion of married and divorced people is 41% and 10%, respectively. Approximately, 4% of individuals are cohabiting.[4] The average income by commuting zone and year is $23,388, roughly 75% of individuals are in the labor force, and 69% are employed.

3.2 Robots Data

The data on the stock of robots by industry, country, and year are sourced from the IFR, a professional organization of robot suppliers established in 1987 to promote the robotics industry worldwide. Specifically, the IFR conducts an annual survey among its members collecting information on the number of robots that have been sold in a given industry and country. This survey reports data on the stock of robots for 70 countries over the period from 1993 to 2016, covering more than 90% of the world robots market. This dataset has been employed before by Acemoglu and Restrepo (2020) for the US, Dauth et al. (2019) for Germany, Giuntella et al. (2019) for China, Anelli et al. (2019) for Europe, and by Graetz and Michaels (2018) in a cross-country analysis. The IFR data provide the operational stock of "industrial robots," which are defined as "automatically controlled, reprogrammable, and multipurpose machines" (IFR, 2016). In practice, these industrial robots are autonomous machines not operated by humans that can be programmed for several tasks, such as welding, painting, assembling, carrying materials, or packaging. Single-purpose machines, such as coffee machines, elevators, and automated storage systems are, by contrast, not robots in this definition, because they cannot be programmed to perform other tasks, require a human operator, or both.

However, the IFR robot data present some limitations. First, the information on the number of industrial robots by sectors is limited to a sub-sample of countries for the period 1990–2003. For example, the IFR dataset for the US provides details on the industry background only since 2004, although we do have information on the total stock of industrial robots in the US since 1993. Second, while the information is broken down at the industry-level, industry classifications are coarse. Within manufacturing, we have data on the operational stock of robots for 13 industrial sectors (roughly at the three-digit level), namely, food and beverages (1), textiles (2), wood and

[4]Cohabitation is defined as living with an unmarried partner.

furniture (3), paper (4), plastic and chemicals (5), glass and ceramics (6), basic metals (7), metal products (8), metal machinery (9), electronics (10), automotive (11), other vehicles (12), and other manufacturing industries (13). For non-manufacturing sectors, data on the operational stock of robots are restricted to six broad categories, namely, agriculture, forestry and fishing (1), mining (2), utilities (3), construction (4), education, research and development (5), and other non-manufacturing industries (e.g., services and entertainment) (6). Furthermore, approximately a third of the robots are not classified. Following Acemoglu and Restrepo (2020), we allocate the unclassified robots in the same proportion as in the classified data. An additional limitation of the IFR data is the lack of geographical information on the within-country distribution of robots (i.e., the smallest geographical unit for which robot data are available is at the country level). To construct a metric of robot penetration in the US labor market, we follow Acemoglu and Restrepo (2020) and use the variation in the pre-existing distribution of employment across commuting zones and industries to redistribute the number of robots by sectors across commuting zones (see Section 3.3 for further details). The pattern that emerges is that despite the slowdown caused by the Great Recession, the number of robots per thousand workers has rapidly increased between 2005 and 2016, going from 1.3 to 2.4 robots per thousand workers (+78%).

We aggregate our measure of exposure to robots at the commuting zone-level because their adoption in a plant in a given regional labor market affects employment opportunities of all individuals that can potentially commute to that factory to work. Focusing on a smaller geographical unit would introduce substantial measurement errors.

3.3 Empirical Strategy

To examine how robot exposure affects the family behavior, we estimate the following linear regression model:

$$Y_{ct} = \alpha + \beta(\text{Exposure to Robots})^{US}_{c,t-2} + \lambda X_{ct} + \tau_t + \eta_c + +\epsilon_{ct} \tag{1}$$

where the subscript ct denotes a commuting zone c in a given year t. Y_{ct} represents one of our outcomes of interest, including, for instance, marriage, divorce, cohabitation, fertility (i.e., overall, marital and nonmarital fertility), the logarithm of income, labor force participation, and employment. Our variable of interest is $(\text{Exposure to Robots})^{US}_{c,t-2}$, which represents the exposure to robots of a community zone c at time $t-2$. We decided to lag the exposure to robots by two years because, in the questionnaire, women are asked whether they had a child in the previous year. Therefore, a time lag of two years allows us to account for the additional time individuals may need to adjust their life-course choices in response to robot exposure. X_{ct} is a set of time-varying, commuting zone-level demographic controls, such as the share of women, and the proportion of individuals under the age of 25.[5] The model in Equation (1) contains survey year fixed effects (τ_t) to account for possible trends in our outcomes. We also include a full set of commuting zone fixed effects (η_c) to control for unobservable time-invariant differences across commuting zones that may affect family behavior. Finally, ϵ_{ct} represents an idiosyncratic error term. Throughout the analysis, we cluster standard errors by commuting zone.[6]

To construct a metric of robot penetration in the US labor market, we follow Acemoglu and Restrepo (2020), and thus, exploit the variation in the pre-existing distribution of employment across commuting zones and industries, and multiply it by the national level evolution in the number of robots across industries. Because most of the rise in industrial robots in the US occurred after 1990, we choose 1990 as the baseline year. In practice, we compute the ratio of robots to employed workers in industry i at the national level and multiply it by the commuting zone's baseline employment share in sector i and then sum separately for each community zone, over all sectors. Formally, our measure of exposure to robots is constructed as follows:

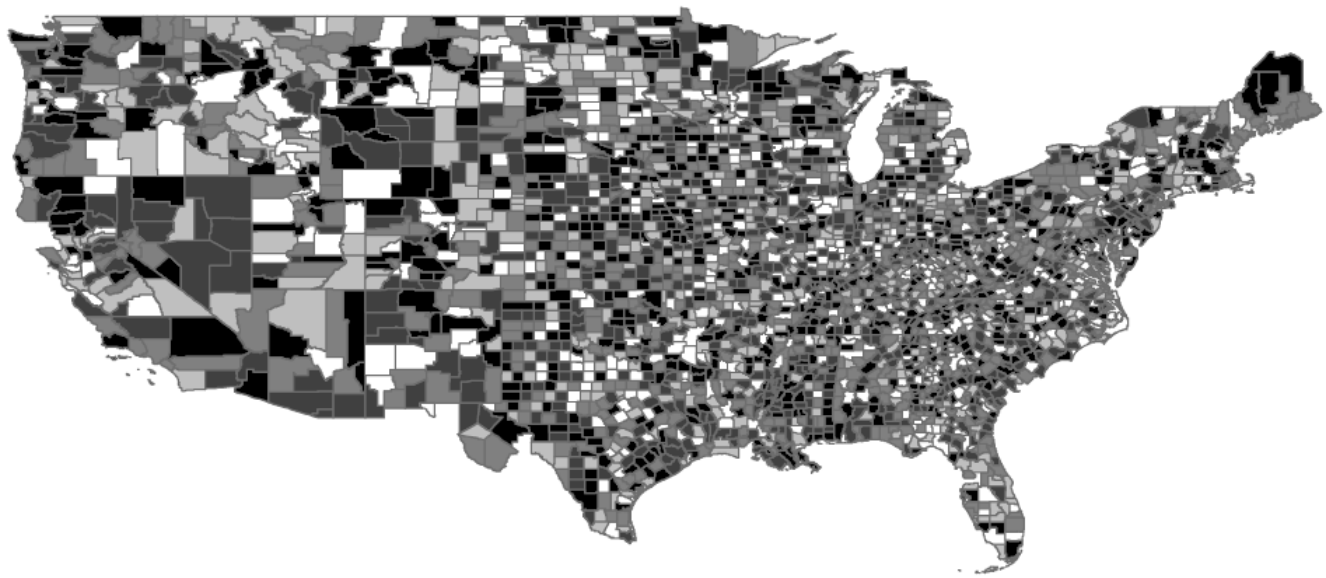
$$\text{Exposure to Robots}^{US}_{c,t-2} = \sum_{i \in I} l^{1990}_{ci} \left(\frac{R^{US}_{i,t-2}}{L^{US}_{i,1990}} \right) \tag{2}$$

where l^{1990}_{ci} denotes the 1990 distribution of employment across industries and commuting zones; $R^{US}_{i,t-2}$ identifies the stock of robots in the US across industries in year $t-2$; and $L^{US}_{i,1990}$

[5] While we report the results obtained controlling for differential exposure to trade penetration across commuting zones in the Appendix, in our baseline specification, we do not control for the impact of the trade shock because both Acemoglu and Restrepo (2020) and Anelli et al. (2019) show that the trade shock is orthogonal to the adoption of robots for both the US and Europe. The main reason for this orthogonality is that industries that strongly robotized production processes were generally industries that did not offshore production. Thus, commuting zones that historically specialized in offshorable production (e.g. furniture) were mostly hit by the trade shock, while commuting zones that historically specialized in industries that were later not subject to offshoring (e.g., food processing) were mostly hit by robot adoption.

[6] Constructing the standard errors by bootstrapping results over commuting zones as in Goldsmith-Pinkham et al. (2020) does not substantially alter the significance of the estimated coefficients (see Table A.3 in the Appendix).

Figure 1: Industrial Robots across the US, $\Delta_{2004-2016}$



Notes - Data are drawn from the International Federation of Robotics. While we use county-level boundaries, the variation in our measure of robot exposure is at the commuting zone level.

represents the total number of individuals (in thousands) employed in sector i in 1990.

Figure 1 illustrates the intensity of robot penetration across commuting zones between 2004 and 2016 based on the above metric.[7] While the increase in the use of industrial robots was widespread across the US, Figure 1 depicts the substantial variation in the penetration of robots across commuting zones and over time. Our analysis leverages these variations in exposure to robots across commuting zones and over time.

While this measure of exposure to robots can be considered already as a Bartik instrument per se—given that most of its variation relies on employment shares measured well before the advent of automation—some concerns about the endogeneity of the stock R_i^{US} of robots in the US may still arise. For instance, there may exist confounding factors correlated with both the industry-level adoption of robots in the US and family or fertility behavior. To address these potential concerns, we robustify our measure of exposure as proposed by Acemoglu and Restrepo (2020). We use the industry-level robot installations in other economies, which are meant to proxy

[7] While the borders of geographical units in the map refer to counties, coloring refers to the commuting zone variation. This is because commuting zones either correspond to counties or are a sum of counties. Hence, all counties within a commuting zone in the map will share the same color gradient and robot penetration measure.

improvements in the world technology frontier of robots, as our instrument for the adoption of robots in the US. Specifically, we use the average robot exposure at the industry-level in the nine European countries that are available in the IFR data over the same period.[8] Therefore, we leverage only the variation in the increase in robot adoption across industries of other countries. Formally, our instrument for the adoption of robots in the US can be written in the following form:

$$\text{Exposure to Robots}_{c,t-2}^{IV} = \sum_{i \in I} l_{ci}^{1970} \left(\frac{R_{i,t-2}^{p30,EU}}{L_{i,1990}^{EU}} \right) \tag{3}$$

where the sum runs over all industries available in the IFR data, l_{ci}^{1970} represents the 1970 share of employment in commuting zone c and industry i, as calculated from the 1970 Census, and $\frac{R_{i,t-2}^{p30,EU}}{L_{i,1990}^{EU}}$ denotes the 30th percentile of robot exposure among the above-mentioned European countries in industry i and year $t-2$.[9] [10]

A concern with our identification strategy is that our estimates may reflect specific trends in sectors that may be playing a primary role in our identifying variation. These sectors may have been subject to specific economic trends, and this may confound our estimates and cast doubts on a causal interpretation of our results. To partially alleviate this concern, we first show that marital behavior and fertility rates are largely uncorrelated with future trends in the adoption of robots in Europe (i.e., our instrumental variable) and if anything some of the outcomes were trending in the opposite direction. Second, we follow Goldsmith-Pinkham et al. (2020), and find that the electronics sector plays a predominant role in driving the variation of the instrument (i.e., it has, by far, the highest Rotemberg weight in the identification). In our robustness analyses, we show that reassuringly, the results are substantially unchanged when removing the stock of robots in the electronics sector from the computation of the robot exposure measure or controlling for specific time trends across areas with different initial employment shares in the electronics industry.[11] Similarly, we show that results are unchanged when controlling for specific time

[8] France, Denmark, Finland, Italy, Germany, Norway, Spain, Sweden, and the United Kingdom.

[9] Following Acemoglu and Restrepo (2020), we used the 30th percentile as the US robot adoption closely follow the 30th percentile of the EU robot adoption distribution.

[10] We use the 1970 share of employment following Acemoglu and Restrepo (2020). However, using 1990 as a base year yields similar results.

[11] In practice, we include as controls interactions of year dummies with quartiles of the share of employment in the electronics sector as of 1990.

trends across areas with different initial employment shares in the automotive sector, which is by far the leading sector in terms of industrial robots' adoption.

Model (1) is estimated using two stage least squares (2SLS), and the first stage regression is given by:

$$\sum_{i \in I} l_{ci}^{1990} \left(\frac{R_{i,t-2}^{US}}{L_{i,1990}^{US}}\right) = \pi_0 + \pi_1 \left[\sum_{i \in I} l_{ci}^{1970} \left(\frac{R_{i,t-2}^{p30,EU}}{L_{i,1990}^{EU}}\right)\right] + \gamma X_{ct} + \delta_t + \sigma_c + v_{ct} \tag{4}$$

where $\sum_{i \in I} l_{ci}^{1990}(\frac{R_{i,t-2}^{US}}{L_{i,1990}^{US}})$ is instrumented with $[\sum_{i \in I} l_{ci}^{1970}(\frac{R_{i,t-2}^{p30,EU}}{L_{i,1990}^{EU}})]$, the industry-level robot exposure of other countries (i.e., the above-mentioned European countries). X_{ct}, δ_t, σ_c, and v_{ct} are defined in the same way as in Model (1).

The first stage regression presented in Table A.4 shows that the adoption of robots in Europe is strongly correlated with robot exposure in the US. With a first stage F-statistic of 605 (reported at the bottom of Tables 1, 2 and 3), our instrument easily passes conventional thresholds for strong instruments. Figure 2 confirms the relevance of the instrument.

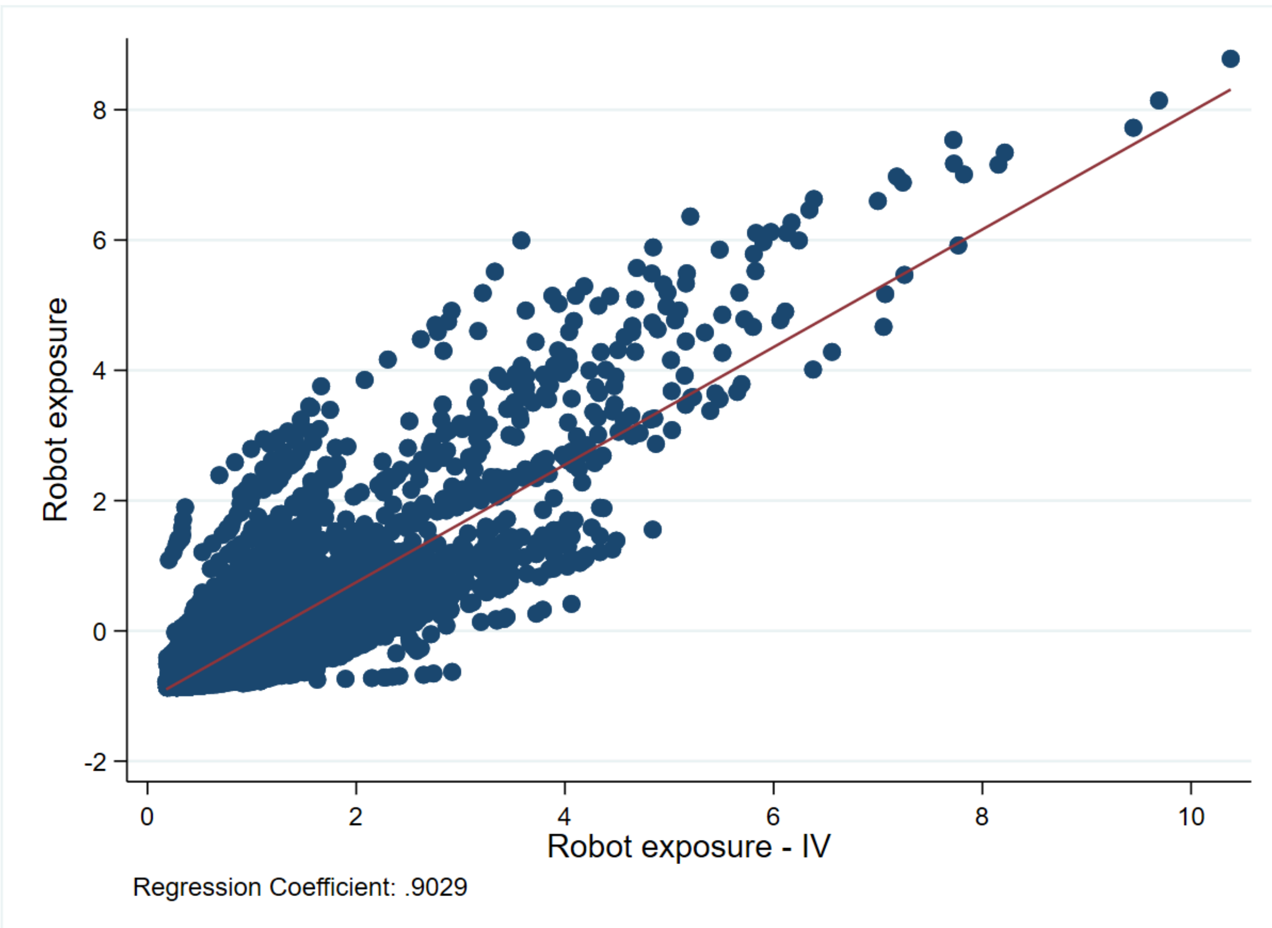
4 Main Results

In this section, we present our main empirical results. First, we document the impact of robotics on labor market outcomes, focusing on the heterogeneity for women and men and the effect on the gender gap. We then explore the impact of industrial robots on marital behavior. Finally, we estimate the effects of robots on fertility choices.

4.1 The Differential Effects of Robots on the Labor Market Opportunities of Women and Men

As a first step to explore the effects of robots on demographic behavior, we document its impact on labor market outcomes, its differential effects on men and women and thus on gender gaps. Importantly, while Acemoglu and Restrepo (2020) focus on the onset of robotics up to the Great Recession (1993–2007 period) and show negative effects on employment and wages,

Figure 2: First Stage: Robot Exposure in the US and Europe



Notes - Data are drawn from the International Federation of Robotics.

we think it is important to extend their analysis by focusing on the recent decades to document whether the pre-2008 dynamics have persisted also in later years, those for which we are going to study demographic outcomes.

In Table 1, we rely on the identification strategy presented in Section 3.3 to estimate the impact of robot exposure on three labor market indicators: income, labor force participation, and employment.[12] Columns 1–3 in Panel A illustrate the impact of robot exposure on income and present an OLS specification (see column 1), a reduced form one (see column 2), and the 2SLS estimation (see column 3). Focusing on the IV estimate of column 3, a one standard deviation increase in robot exposure (1.90 robots per 1,000 workers) decreases income by 4.2%. The effect for the IV estimate is larger than the one for the OLS estimate. This is not surprising because we expect the OLS estimates to be biased downward by the pro-cyclicality of robot adoption, that is, more robots are installed in periods of economic growth, which, in turn, is also associated with better labor market outcomes, on average. Columns 4–9 report a positive effect on labor force participation and employment. These results are consistent with empirical evidence showing that robots reduce employment in traditional well-paid manufacturing sectors but boost employment—through productivity spillovers—in service sectors with lower income and slower career progression (Dauth et al., 2019). Importantly, with respect to Acemoglu and Restrepo (2020), our results suggest that contrary to the earlier periods, the overall effect of robotics on US employment might have turned positive in the recent years, while the negative impact on income appears robust in both the short- and long-run.[13]

In Panel B of Table 1, we turn to study the effect of robot exposure on labor market outcomes separately for men and women and the gender gap in those same outcomes. Columns 1–3 show that the effect of robots on male income (-5.8%, see column 2) is substantially larger than that on female income (-1.6%, see column 1). This drives the gender income-gap (defined as the ratio between male and female income) down by 4.2% in areas that were more exposed to robot penetration.[14] In columns 4–6, we provide the corresponding results of robot exposure on labor force

[12]As detailed in the Empirical Strategy section, in each regression, we include a set of commuting zone-level demographic controls, year dummies, and commuting zone FEs.

[13]A similar pattern has been observed by Bloom et al. (2019) when analyzing the effects of trade on labor market outcomes and by David and Dorn (2013) when expanding the analysis to the post-recession period .

[14]Our results on the gender income-gap complement recent empirical evidence by Aksoy et al. (2019) for European countries. In the context of Eastern European countries with higher baseline levels of gender inequality, the authors find that automation has increased the gender earning gap with this effect driven by middle-skill workers. This

Table 1: Effects of Robot Exposure on Labor Market Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. var.:		Income			Labor force participation			Employment	
Panel A: Full sample									
	OLS	Reduced form	2SLS	OLS	Reduced form	2SLS	OLS	Reduced form	2SLS
Robot exposure	-0.017*		-0.042***	0.008***		0.009***	0.030***		0.034***
	(0.009)		(0.011)	(0.003)		(0.003)	(0.003)		(0.004)
Robot exposure - IV		-0.024***			0.005***			0.019***	
		(0.006)			(0.002)			(0.002)	
Mean of dep. var.	23,390	23,390	23,390	0.750	0.750	0.750	0.685	0.685	0.685
Std. dev. of dep. var.	4,824	4,824	4,824	0.060	0.060	0.060	0.073	0.073	0.073
First stage F-statistic			605			605			605
Observations	7,410	7,410	7,410	7,410	7,410	7,410	7,410	7,410	7,410
Panel B: Split by gender and gender ratio – 2SLS Estimates									
	Females	Males	M/F Gender Ratio	Females	Males	M/F Gender Ratio	Females	Males	M/F Gender Ratio
Robot exposure	-0.016	-0.058***	-0.042***	0.018***	0.001	-0.023***	0.037***	0.032***	-0.008
	(0.012)	(0.014)	(0.011)	(0.004)	(0.004)	(0.008)	(0.004)	(0.005)	(0.008)
Mean of dep. var.	18,250	28,320	1.567	0.723	0.776	1.075	0.664	0.704	1.063
Std. dev. of dep. var.	3,913	6,260	0.248	0.062	0.068	0.078	0.073	0.082	0.088
First stage F-statistic	605	605	605	605	605	605	605	605	605
Observations	7,410	7,410	7,410	7,410	7,410	7,410	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

participation. The estimates reported in columns 4 and 5 reveal significant differences between male and female labor force participation. Robot exposure has a relatively small impact on male labor force participation. Conversely, an increase in robot exposure has a positive and highly significant effect on female labor force participation. As a result, the gender gap in labor force participation decreases by 2.1% (with respect to the mean) in response to more robot adoption in the US (see column 6). Finally, the effect on the gender gap in employment is negative, although not statistically significant (see column 9).

In Table A.5 in the Appendix, we build an empirical bridge between the labor market evidence and family formation/fertility decisions, by documenting the association of income, labor force participation, and employment gender gaps with marital and fertility behavior in cross-commuting zone, fixed-effect (FE) regressions. This descriptive evidence shows that higher male to female gaps are positively associated with higher marriage and marital fertility rates and negatively associated with divorce and nonmarital fertility rates. Despite its descriptive nature, it is reassuring that this empirical evidence is consistent with the classical Becker model of household specialization and with recent evidence by Schaller (2016).

This first set of results captures three main dynamics triggered by the consequences of automation: first, the absolute economic stature of men as measured by income has been substantially lessened; second, women have seen an improvement in their employment opportunities; third, the relative economic position of men relative to women has substantially declined. All three impacts might reduce the gains from household specialization, reduce the pecuniary and child-rearing gains to marriage (Shenhav, 2020), increase the divorce "threat point" (Lundberg and Pollak, 1996), and therefore increase divorce, with a potential consequential shift from marital towards nonmarital fertility.

4.2 Effects on Marital Behavior

In Table 2, we test whether it is the case that, by reducing labor market gender gaps, robot exposure tend to lessen the value of marriage (Wilson, 1987; Becker et al., 1974), relying on the identification strategy described in the Empirical Strategy section. Panel A displays the results for marriage, whereas Panels B and C report the estimates for divorce and cohabitation, respectively.

suggests that the impact of automation on the gender gap may be context-specific.

In Panel A, the OLS (see column 1) and the reduced-form (see column 2) estimates suggest that one standard deviation increase in robot exposure (1.90 robots per 1,000 workers) decreases the probability of being married by 0.5% relative to the mean outcome. The 2SLS estimate in column 3 presents a larger coefficient, although not statistically significant.

When considering divorce rates and cohabitation as the dependent variable (see Panels B and C, respectively), we find a positive relationship. The 2SLS coefficient shows that a one standard deviation increase in robot exposure leads to a 9% increase in divorce (see column 3 of Panel B) and to a 10% increase in the likelihood of cohabitation (see column 3 of Panel C).[15]

Consistent with the evidence on absolute and relative economic opportunities of men and women, these results show that the consequences of automation have impacted marriage on both the extensive (returns to marriage) and intensive (intra-marriage bargaining) margin. With respect to the extensive margin, women compare their potential income in a married household with their income as single women (Shenhav, 2020). As their relative wage increases, the pecuniary and child-rearing gains to marriage decline, and hence the woman's threshold for acceptable husband quality rises. In this framework, these dynamics lead to fewer marriages and higher-quality husbands among those that do marry. This prediction is consistent with our evidence of a negative, albeit not precisely estimated, effect on marriage (see column 3 of Panel A of Table 2) and a larger negative, precisely estimated, effect obtained among women aged 30+ (see Tables A.6–A.8 in the Appendix). We also test the prediction on the effects on matching quality and find that among married and cohabiting couples, robot exposure leads to an increase in the share of women married or cohabiting with a higher-educated partner (see Table A.9 in the Appendix). This effect is particularly large for cohabitation (+20% with respect to the mean), suggesting an overall increase in the quality of women's mates (Shenhav, 2020). Our results for cohabitation also suggest that the exposure to the shock may yield unmarried couples to opt for less costly forms of commitment. Regarding the intensive margin, the increase in divorces in response to the automation shock are consistent with a rise in the "threat-point" of divorce (Lundberg and Pollak, 1996) – i.e., the maximum available utility outside of marriage –, thereby

[15] The fact that our IV coefficients are slightly larger in magnitude compared to the OLS ones suggests once again that the potential endogenous bias was driven by the pro-cyclicality of robot adoption, namely, more robots are installed during periods of economic growth, which is likely correlated with a higher (lower) incidence of marriage (divorce) relative to economic downturns.

Table 2: Effects of Robot Exposure on Marital Behavior

	(1) OLS	(2) Reduced form	(3) 2SLS
Panel A: Dep. var.: Marriage			
Robot exposure	-0.002		-0.004
	(0.003)		(0.004)
Robot exposure - IV		-0.002	
		(0.002)	
Mean of dep. var.	0.412	0.412	0.412
Std. dev. of dep. var.	0.061	0.061	0.061
First stage F statistic			605
Panel B: Dep. var.: Divorce			
Robot exposure	0.007***		0.009***
	(0.002)		(0.002)
Robot exposure - IV		0.005***	
		(0.001)	
Mean of dep. var.	0.098	0.098	0.098
Std. dev. of dep. var.	0.021	0.021	0.021
First stage F statistic			605
Panel C: Dip. var.: Cohabitation			
Robot exposure	0.001		0.004***
	(0.001)		(0.001)
Robot exposure - IV		0.003***	
		(0.001)	
Mean of dep. var.	0.039	0.039	0.039
Std. dev. of dep. var.	0.012	0.012	0.012
First stage F statistic			605
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

increasing the intra-marriage bargaining power of women, triggered by the improved earnings and employment opportunities of women relative to men.

One natural concern is that when jobs disappear because of robots, people might move away to find new jobs or people who would have moved might not any more. As certain types of individuals might be better able/more likely to adjust on this margin, this could change the composition of the population. Therefore, we re-estimated our baseline regression restricting the analysis to individuals who did not change the place of residence in the previous year (see Table A.10 in the Appendix), and to individuals who currently reside in their state of birth (see Table A.11 in the Appendix). Results remain substantially unchanged, suggesting that our findings are not driven by compositional effects. Similarly, including controls for the share of individuals changing residence with respect to the previous year or for the share of individuals who were born in their current state of residence does not significantly affect the results (see Tables A.12 and A.13 in the Appendix, respectively).

While the inclusion of CZ FEs does control for the time-invariant differences across commuting zones, one remaining source of concern about our regression specification is linked to the possibility that robot adoption was somehow correlated with (or the result of) pre-existing trends in family outcomes. To dispel this concern, we test whether the change in robot adoption captured by our IV is correlated with commuting zone trends in demographic outcomes that occurred before the advent of robotics. Data on demographic outcomes are drawn from the 1980 and 1990 US Census. The results of this analysis are reported in Table 4. If anything, 1980–1990 trends in marital behavior were opposite to the patterns observed between 2005 and 2016 (see columns 1–3). Furthermore, the coefficients are all relatively small and statistically significant only for cohabitation (see column 3).[16]

4.3 Effects on Fertility Behavior

In Table 3, we analyze the impact of automation on fertility behavior. We focus on women because the ACS surveys only women on whether they had a child in the previous year.

Panel A considers overall fertility as the outcome. We estimate that the effect of robot expo-

[16]As shown in Figure A.1 in the Appendix, already in the 1990s there was a positive trend in the adoption of industrial robots across the US. For this reason, we considered pre-trends for the years 1980-1990.

Table 3: Effects of Robot Exposure on Fertility Behavior

	(1) OLS	(2) Reduced form	(3) 2SLS
Panel A: Dep. var.: Overall Fertility			
Robot exposure	-0.001		0.000
	(0.002)		(0.002)
Robot exposure - IV		0.000	
		(0.001)	
Mean of dep. var.	0.059	0.059	0.059
Std. dev. of dep. var.	0.018	0.018	0.018
First stage F statistic			605
Panel B: Dep. var.: Marital Fertility			
Robot exposure	-0.002**		-0.004**
	(0.001)		(0.001)
Robot exposure - IV		-0.002**	
		(0.001)	
Mean of dep. var.	0.033	0.033	0.033
Std. dev. of dep. var.	0.013	0.013	0.013
First stage F statistic			605
Panel C: Dep. var.: Nonmarital Fertility			
Robot exposure	0.001		0.003**
	(0.001)		(0.001)
Robot exposure - IV		0.002**	
		(0.001)	
Mean of dep. var.	0.019	0.019	0.019
Std. dev. of dep. var.	0.011	0.011	0.011
First stage F statistic			605
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

sure on the overall fertility rate is zero. However, these zero fertility effects may mask important heterogeneity along two dimensions of fertility behavior: marital and nonmarital fertility.

Indeed, Panels B and C document opposite trends for marital and nonmarital fertility. Specifically, column 1 of Panel B reports the relationship between our measure of robot exposure across commuting zones and the share of married women reporting that they had a child in the past year. According to the OLS and reduced-form specification (see columns 1 and 2), a one standard deviation increase in the exposure to robots is associated with a 6% decrease in marital fertility with respect to the mean outcome (0.034). The 2SLS estimate in column 3 is larger than the OLS and reduced-form estimates in absolute value, suggesting that the exposure to robot penetration may be negatively correlated with unobserved determinants of marital fertility. A one standard deviation increase in the exposure to robots decreases marital fertility in the previous year by 12% or .3 standard deviations. This effect is consistent with the changes observed in marital behavior discussed in the previous section.

Panel C examines the impact of robot exposure on nonmarital fertility. The OLS and reduced-form estimates imply that a one standard deviation increase in robot exposure raises nonmarital fertility by 5% and 10%, respectively (see columns 1 and 2), although the former effect is not precisely estimated. The 2SLS estimate is larger in absolute value and indicates that a one standard deviation increase in robot exposure leads to a 15% increase in nonmarital fertility (see column 3). In Table A.2, we replicated the analysis using alternative metrics for marital and non-marital fertility, that is, focusing either only on the fertility rates within (un)married women or using the share of births born to married or unmarried women. Panel A replicates our baseline results as reference. In Panel B, we calculated the fertility rate among married (see column 2) and unmarried women (see column 3). The results show that the change in the number of births from (un)married women is not driven only by the changing number of women getting married or divorcing (see Table A.2, Panel B). Following Autor et al. (2019) and Kearney and Wilson (2018), we also replicated our analysis using the share of all births from married and unmarried women as outcomes (see Table A.2, Panel C). The estimated effects are substantially similar with respect to our baseline.

Similar to what observed for marriage patterns, estimates are robust to restricting the analysis to individuals who did not change the place of residence in the previous year (see Table A.14 in the Appendix) or to individuals who currently reside in their state of birth (see Table A.15 in the Appendix). Results are also unchanged when we include controls for the share of individuals changing residence with respect to the previous year or for the share of individuals who were born in their current state of residence (see Tables A.16 and A.17, respectively).

Reassuringly, columns 4–6 of Table 4 further corroborate the causal interpretation of the estimates, because 1980–1990 trends in fertility behavior are not correlated with exposure to robots, as measured by our IV. Specifically, there is no evidence of pre-trends in marital fertility, and, if anything, a negative (opposite) trend in nonmarital fertility.

5 Robustness Checks and Heterogeneity Analyses

5.1 Robustness Checks

In this section, we conduct several robustness checks. First, we show that the 2SLS results obtained using a long-difference specification tend in the same direction and remain statistically significant (see Table A.18 in the Appendix). In practice, we regress the change in our outcomes between 2005-07 and 2014-16 on the change in robot exposure over the same period. We find that a one standard deviation increase in robot exposure reduces the gender income gap by 0.126 standard deviations, the labor force participation gap by 0.129 standard deviations, and the gender gap in employment by 0.119 standard deviations (see, respectively, columns 1 to 3 of Panel A). Turning to marital behavior, a one standard deviation increase in robot exposure is associated with a 0.064 standard deviations reduction in the marriage rate, a 0.098 standard deviations increase in divorces, and a 0.061 standard deviations increase in cohabitations (see, respectively, columns 1 to 3 of Panel B). Considering fertility behavior, robot exposure leads to a 0.083 standard deviations reduction in marital fertility and a 0.164 standard deviations increase in nonmarital fertility (see, respectively, columns 2 to 3 of Panel C). Using this long-difference approach, we also demonstrate that the 2SLS results are unchanged when controlling for pre-trends from 1980-1990 in the respective outcome of interest (see Table A.19 in the Appendix).

Second, to address the concern that our identification may be subject to differential trends experienced by some industries driving the results, and to better understand the source of variation underlying our identification strategy, we calculated the Rotemberg weights by sector and

Table 4: Pre-trends Analysis: Effects of Robot Exposure (IV) on Marital and Fertility Change 1980-1990

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	Marriage	Divorce	Cohabitation	Overall fertility	Marital fertility	Nonmarital fertility
Robot exposure - IV	0.001	-0.001	-0.001***	0.000	0.000	-0.001*
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Mean of dep. var.	-0.054	0.019	0.019	-0.017	-0.028	0.005
Std. dev. of dep. var.	0.023	0.009	0.006	0.011	0.015	0.008
Observations	741	741	741	741	741	741

Notes - Data on demographic outcomes are drawn from the 1980 and 1990 US Census. Robust standard errors are reported in parentheses. All models include CZ-level demographic and economic characteristics. These include the share of individuals under the age of 25, the share of females, the share of people in the labor force, the share of unemployed, the share of employed, average income, average education, and the poverty rate.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

year following the methodology described in Goldsmith-Pinkham et al. (2020). Table A.20 in the Appendix presents these weights averaged by sector throughout the period under study, and indicates that the electronics industry has, by far, the highest Rotemberg weight in the identification, with an average weight of 0.32 throughout the period under investigation (ranging between 0.07 and 0.76).[17] We first show that our main results for marital and fertility behavior are robust to the exclusion of the stock of robots in the electronics sector from the computation of the robot exposure measure (see Tables A.21 and A.22 in the Appendix). Second, we show that the estimates are similar to the baseline specification (see Tables 2 and 3) when controlling for differential trends across commuting zones in different quartiles of the 1990 share of employment in the electronics sector (see Tables A.23 and A.24 in the Appendix). Third, we show no evidence of a significant correlation between the change in the outcomes between 1980 and 1990 and the share of employment in the electronics industry in 1970 (see Panel A of Table A.25 in the Appendix). Additionally, as the automotive sector was still by far the largest robot adopter in the US, we conduct similar tests for the automotive sector, and overall confirm our main results (see Tables A.26, A.27, and Panel B of Table A.25 in the Appendix). These findings lend further support to a causal interpretation of the effect of robot exposure on marital and fertility behavior.

Fourth, we show that our results are largely unchanged when controlling for exposure to trade penetration. To measure trade penetration, we followed Pierce and Schott (2020), and computed exposure to Chinese imports by looking at the difference between tariff rates set by the Smoot-Hawley Tariff Act and the corresponding NTR (normal trade relations) tariffs. In 2000, the US passed a bill granting normal trade relations to China. This trade liberalization affected differentially US regions depending on their industry structure. A larger difference between the non-NTR rates and the NTR rates implied a larger potential for Chinese exporters increasing import competition for US producers in a given sector. Consistent with Pierce and Schott (2020), we calculated the commuting zone-level exposure to import penetration using the labor-share-weighted average NTR gaps of the industries active within a commuting zone in 1990. We then interacted this commuting zone-level measure of exposure to trade with year dummies. Reassuringly, in Table A.28 in the Appendix we obtain similar 2SLS results for marital and fertility

[17] Instead, all the other industries play a less relevant role in the identification, with the average weights being below 0.05.

behavior relative to the benchmark specification (see Tables 2 and 3). As a further check, in Table A.29 in the Appendix we demonstrate that our 2SLS results are robust to the inclusion of time-specific trends interacted with the 1990 share of employment in total manufacturing.

Another relevant concern is that our estimates may be capturing the effect of the different implementation of family and reproductive policies over time across the US. To dispel this concern, we include in our analysis a large array of state-year control variables for various policies related to access to family planning services. Specifically, we used the data constructed by Myers (2021) including the following state and year-level policies: mandatory delay for abortion, which indicates whether a state requires a mandatory delay for women seeking abortions; parental-involvement laws, which measures the fraction of a year that a parental involvement law for minors seeking abortion was in place, where parental involvement is defined as a requirement of notification and/or consent; mandated insurance coverage for contraception, which requires that private insurance plans that cover prescription drugs also provide coverage for any FDA-approved contraceptive; emergency contraception available, which indicates whether a state permitted over-the-counter access to emergency contraception; medicaid expansion, which indicates that a state has expanded Medicaid eligibility for family planning services; and the poverty threshold for family planning Medicaid expansion eligibility. In column 1 of Tables A.30 and A.31, we show that the 2SLS results for marital and fertility behavior are robust to the inclusion of the above-mentioned controls for family policies. In addition, we collected contextual information on abortion rules (i.e., TRAP laws) from the work by Jones and Pineda-Torres (2020), and added them to our model. As shown in column 2 of Tables A.30 and A.31, the results remain substantially unaffected by this inclusion. Finally, in column 3 we added to our model controls for both family policies and TRAP laws, and obtained remarkably similar estimates compared to those obtained in the baseline specification. Taken together, this evidence suggests that our results are not distorted by family policies that happened during the sample period under investigation.

5.2 Heterogeneity Analyses

In what follows, we present some heterogeneity analyses along several dimensions. First, we explore the heterogeneity of the effects by age groups (see Tables A.6– A.8 in the Appendix). Taken together, we find evidence that the effect of robot exposure on marital fertility is mainly driven by older individuals (i.e., 30-50 years old), while the effect on nonmarital fertility is larger (in absolute value) among younger age groups (i.e., younger than 30 years old).[18]

Second, we examine whether the adoption of robots differentially affected fertility choice on the extensive and on the intensive margin. Panels A and B of Table A.32 in the Appendix suggest that the fertility effects are present both on the extensive – defined as the likelihood of having a first child– and on the intensive margin– defined as the likelihood of having a second or higher-order child. The impact of robots on nonmarital fertility is fairly similar on the extensive and on the intensive margin (+17% vs. +14% with respect to the mean). At the same time, the effects on marital fertility are marginally stronger on the extensive rather than on the intensive margin: a one standard deviation increase in robot exposure increases marital fertility on the extensive margin by 17% compared to a 11% increase on the intensive margin. In Panel C of Table A.32, we further explored the effect of robot exposure on the intensive margin of fertility by considering the number of children as the dependent variable. In line with the evidence above, we find a negative effect on marital fertility and a positive effect on nonmarital fertility. We also explored the heterogeneity of the results on marital behavior by the presence of children and age of the youngest child (see Table A.33 in the Appendix). If anything, the presence of children is associated with a larger negative effect on marriage (see Panel A). Similarly, we detect a slightly larger effect on divorce among families with children, although the impacts tend to be smaller (in absolute value) among families with younger children (see Panel B). The positive effects of exposure to robots on cohabitation tend to be instead slightly higher among families with children, regardless of the child's age (see Panel C). These results suggest that the shocks induced by robot exposure may both reduce the propensity to marriage and the propensity

[18]We note that the effects may vary by cohort. Older cohorts may be more entrenched in their career and further along on the lifecycle when robots come on the scene. While it would be interesting to examine the heterogeneity of the effects by birth cohorts, our data–and the limited window of time for which we have information on robots' adoption–does not allow us to isolate cohort from age effects. Future research using longer panels may shed further light on this point.

divorce, but increase cohabitation.

Third, in Table A.34 in the Appendix, we examine completed fertility, which reflects the actual number of children per woman measured after the reproductive age (i.e., aged 45 and older). We find consistent evidence of a significant negative effect of robot exposure on marital fertility and a positive effect on nonmarital fertility. Our estimates reveal that a one standard deviation increase in robot exposure is associated with a 3.7% reduction in the number of children among married women, and a 21% increase in the number of children among unmarried women. Because our dataset does not contain information on marital histories and we lack longitudinal data, these results should be interpreted with caution. However, these estimates are suggestive that robot exposure did not only affect period fertility rates but also completed (or cohort) fertility. Taken together, in response to robot exposure, the short-term changes in period fertility result in a long-term effect on completed fertility, signalling a limited role for recuperation effects in the long-run.

Fourth, combining information available in our dataset on women's fertility, marital status, and cohabitation, we constructed two additional measures of fertility: nonmarital fertility among women who are not married but are cohabiting, and nonmarital fertility among women who are neither married nor cohabiting. In Table A.35 in the Appendix, we explore the differential fertility effects between unmarried but cohabiting and unmarried not cohabiting women using these two measures of fertility as alternative outcome variables. We find that the effect of robots on nonmarital fertility is largely driven by unmarried women who are not cohabiting (see column 3). This result is consistent with the findings of previous work analyzing the impact of economic shocks on fertility and finding an increase in the fraction of children living in single-headed households (Autor et al., 2019; Black et al., 2003).

Finally, we investigated the effects of robot exposure among same-sex couples (see Table A.36 in the Appendix). Previous studies suggest that specialization may be less pronounced in same-sex couples (Badgett, 2009; Jepsen and Jepsen, 2015; Giddings et al., 2014). Thus, the implications of automation for same-sex couples may be very different compared to those obtained in hetero-sexual couples. Restricting attention to same-sex couples, we estimate a close to null effect on fertility behavior, and no significant impact on divorce and cohabitation (see Panel A). Interestingly, we detect a negative and significant impact of robot exposure on same-sex marriages (see column 1). As shown in Table A.37, this negative effect is larger among male same-sex marriages, which may be consistent with men being less likely to commit given their exposure to worse labor market conditions. However, given the small fraction of same-sex couples in our sample (approximately 1% throughout the period), we do not think that much can be inferred from this specific result. Excluding same-sex couples from our sample yields substantially identical results relative to the benchmark specification (see Panel B). Furthermore, we demonstrate that our 2SLS results for marital and fertility behavior are unchanged when controlling for the timing of the introduction of legal same-sex marriages across US states (see Panel C).[19]

6 Conclusion

The impact of automation, robots, and artificial intelligence on labor markets has produced fundamental shifts in our daily lives. A handful of pioneering studies have examined the impact of robots on labor markets (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018). Yet, we know little about how these labor market shocks may affect gender differences in labor market opportunities, and, in turn, family and fertility decisions. This study estimates the impact of exposure to industrial robots on life-course choices, such as marriage, divorce, cohabitation, and fertility. In areas that were more exposed to robot penetration, marriage rates decreased, while divorce rates and cohabitation increased. We then show that exposure to robots reduced marital fertility but increased nonmarital fertility. Looking at potential mechanisms, we show that robot penetration has different effects on the labor market opportunities of men and women, reducing the gender gap in income. Male income fell at a substantially higher rate than female income, decreasing the gender income gap. Moreover, robot exposure has increased female labor force participation significantly while leaving the labor force participation of men unchanged.

While our empirical setting does not allow us to distinguish between the role of absolute (Wilson hypothesis) and relative income (Becker hypothesis), we argue that robots have both worsened the absolute economic stature of men as measured by their earning opportunities, and lowered the relative position of men on the marriage market. This, in turn, has contributed to reducing women's willingness to long-term commitments, such as marrying. At the same time,

[19] We draw data on the variation in the timing of legalization of same-sex marriage across states relying on the works by Hansen et al. (2020); Carpenter and Sansone (2021).

the lower marriage-market value of men has increased the value of nonmarital fertility options for women and the share of children born to single-headed households.

Given the concerns that cohabitation may reduce children's well-being (Manning, 2015), developing more encompassing family policies that cover married and cohabitating couples more homogenously could be an effective response to the implications of robotics on life-course choices. Future research exploiting longitudinal data or matched employer-employee data may shed further light on these mechanisms and the impact of automation on children's well-being as well as trying to distinguish the Becker hypothesis on relative economic stature from the Wilson's thesis emphasizing men's absolute economic stature.

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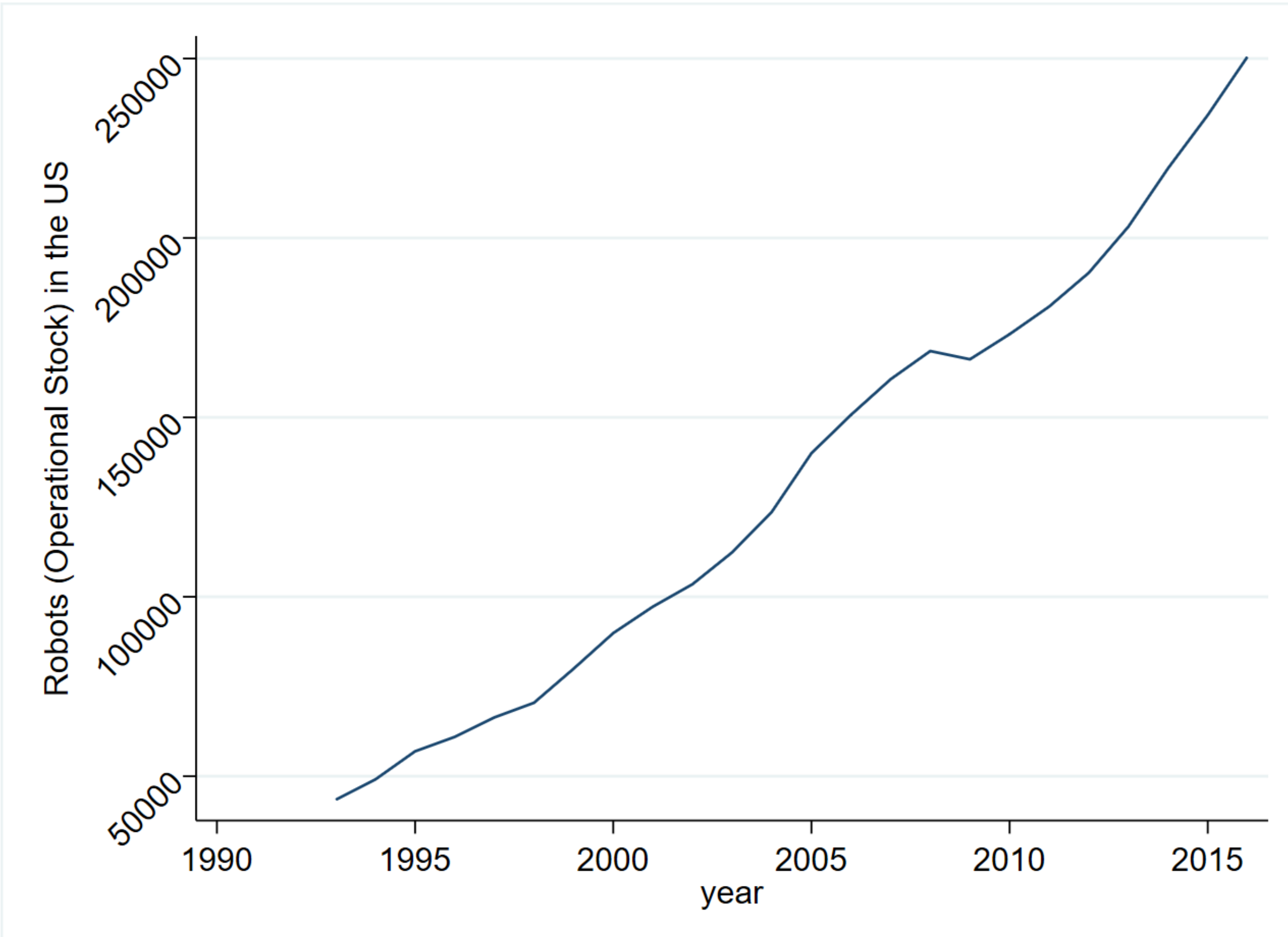
Appendix A: Supplemental Figures and Tables

Figure A.1: Evolution of the Stocks of Robots, 1993-2016



Notes - Data are drawn from the International Federation of Robotics over the period 1993-2016.

Table A.1: Descriptive Statistics - Commuting Zone-Year Observations: 7,410

	Mean	Std. dev.	Min	Max
Panel A: Outcome variables				
Fertility	0.059	0.018	0.003	0.160
Marital fertility	0.034	0.014	0	0.117
Nonmarital fertility	0.020	0.012	0	0.084
Married	0.412	0.061	0.214	0.662
Divorced	0.099	0.021	0.037	0.187
Cohabiting	0.040	0.012	0.005	0.110
Income	23,388	4,824	12,105	51,834
Labor Force Participation	0.750	0.060	0.534	0.907
Employed	0.685	0.073	0.434	0.871
Panel B: Covariates				
Robot exposure	1.841	1.963	0.123	20.508
Robot exposure - IV	1.233	0.935	0.244	10.815
Age under 25	0.289	0.037	0.166	0.555
Female	0.489	0.018	0.391	0.557

Notes - Data are drawn from the American Community Survey and the International Federation of Robotics over the period 2005-2016.

Table A.2: Effects of Robot Exposure on Fertility Behavior - Alternative Outcomes (2SLS Estimates)

	(1)	(2)	(3)
		Panel A: Baseline Specification	
Dep. var.:	Overall fertility	Marital fertility	Nonmarital fertility
Robot exposure	0.000	-0.004**	0.003**
	(0.002)	(0.001)	(0.001)
Mean of dep. var.	0.059	0.033	0.019
Std. dev. of dep. var.	0.018	0.013	0.011
First stage F statistic	605	605	605
		Panel B: Fertility Rates Among Married and Unmarried Women	
Dep. var.:	Overall fertility	Marital fertility rate	Nonmarital fertility rate
Robot exposure	0.000	-0.009***	0.010***
	(0.002)	(0.003)	(0.003)
Mean of dep. var.	0.059	0.075	0.049
Std. dev. of dep. var.	0.018	0.025	0.028
First stage F statistic	605	605	605
		Panel C: Share of Births	
Dep. var.:	Overall fertility	Share of births born to married mothers	Share of births born to unmarried mothers
Robot exposure	0.000	-0.045***	0.029**
	(0.002)	(0.014)	(0.014)
Mean of dep. var.	0.059	0.572	0.326
Std. dev. of dep. var.	0.018	0.154	0.145
First stage F statistic	605	605	605
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.3: Effects of Robot Exposure on Labor Market Outcomes, Marital and Fertility Behavior, Bootstrapped Standard Errors – 2SLS Estimates

	(1)	(2)	(3)
Dep. var.:	Robot exposure Coefficient	Standard *p*-value	Corrected *p*-value
Income - M/F gender ratio	-0.042	0.003	0.007
Labor force participation - M/F gender ratio	-0.023	0.003	0.003
Employment - M/F gender ratio	-0.008	0.299	0.324
Marriage	-0.004	0.354	0.350
Divorce	0.009	0.000	0.000
Cohabitation	0.004	0.000	0.000
Overall fertility	0.000	0.803	0.829
Marital fertility	-0.004	0.011	0.008
Nonmarital fertility	0.003	0.015	0.013
Observations	7,410		

Notes - The table reports the coefficient of robot exposure derived by regressions of the outcome listed in in each row on robot exposure. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects. Standard *p*-values as well as bootstrapped *p*-values are reported.

Table A.4: First Stage: Effects of Robot Exposure IV on Robot Exposure

	(1)
Dep. var.:	Robot exposure
Robot exposure - IV	0.564***
	(0.023)
Mean of dep. var.	-0.054
Std. dev. of dep. var.	0.944
Observations	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models include CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.5: Effects of Labor Market Status on Marital and Fertility Behavior - Fixed-Effect Estimates

Dep. var.:	(1) Marriage	(2) Divorce	(3) Cohabitation	(4) Fertility Overall	(5) Fertility Marital	(6) Fertility Nonmarital
Income - M/F Gender Ratio	0.026***	-0.014***	-0.001	-0.001	0.003**	-0.003**
	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
LFP - M/F Gender Ratio	0.052***	-0.017***	0.000	0.012***	0.018***	-0.009***
	(0.006)	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)
Employment - M/F Gender Ratio	0.051***	-0.018***	-0.001	0.006*	0.013***	-0.007***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Mean of dep. var.	0.412	0.098	0.039	0.059	0.033	0.019
Std. dev. of dep. var.	0.061	0.021	0.012	0.018	0.013	0.011
Observations	7,410	7,410	7,410	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.6: Effects of Robot Exposure on Marital Behavior, by Age Group – 2SLS Estimates

	(1) Marriage	(2) Divorce	(4) Cohabitation
Panel A: Individuals aged 16-29			
Robot exposure	0.009*	0.002	-0.001
	(0.005)	(0.001)	(0.002)
Mean of dep. var.	0.175	0.023	0.044
Std. dev. of dep. var.	0.057	0.013	0.018
Panel B: Individuals aged 30-50			
Robot exposure	-0.013**	0.013***	0.008***
	(0.006)	(0.004)	(0.001)
Mean of dep. var.	0.588	0.154	0.036
Std. dev. of dep. var.	0.069	0.029	0.013
Panel C: Individuals aged 15-44			
Robot exposure	-0.014***	0.003*	0.005***
	(0.005)	(0.002)	(0.001)
Mean of dep. var.	0.353	0.076	0.041
Std. dev. of dep. var.	0.058	0.020	0.013
Panel D: Individuals aged 15-19			
Robot exposure	0.007***	0.001**	0.001
	(0.002)	(0.000)	(0.001)
Mean of dep. var.	0.008	0.001	0.007
Std. dev. of dep. var.	0.013	0.003	0.011
First stage F statistic	605	605	605
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.7: Effects of Robot Exposure on Fertility Behavior, by Age Group – 2SLS Estimates

	(1) Overall fertility	(2) Marital fertility	(4) Nonmarital fertility
Panel A: Individuals aged 16-29			
Robot exposure	0.004	-0.002	0.006**
	(0.004)	(0.003)	(0.003)
Mean of dep. var.	0.093	0.044	0.040
Std. dev. of dep. var.	0.036	0.025	0.025
Panel B: Individuals aged 30-50			
Robot exposure	-0.002	-0.005***	0.002**
	(0.002)	(0.001)	(0.001)
Mean of dep. var.	0.035	0.026	0.004
Std. dev. of dep. var.	0.015	0.013	0.005
Panel C: Individuals aged 15-44			
Robot exposure	0.003	-0.003*	0.004***
	(0.002)	(0.002)	(0.001)
Mean of dep. var.	0.069	0.039	0.023
Std. dev. of dep. var.	0.021	0.016	0.014
Panel D: Individuals aged 15-19			
Robot exposure	0.008**	0.000	0.005*
	(0.003)	(0.001)	(0.003)
Mean of dep. var.	0.028	0.004	0.023
Std. dev. of dep. var.	0.029	0.009	0.027
First stage F statistic	605	605	605
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.8: Effects of Robot Exposure on Fertility Behavior, by Age Group – 2SLS Estimates

	(1) Overall fertility	(2) Marital fertility	(3) Nonmarital fertility
	Panel A: Individuals aged 30-40		
Robot exposure	0.000	-0.005*	0.002
	(0.004)	(0.003)	(0.002)
Mean of dep. var.	0.064	0.048	0.008
Std. dev. of dep. var.	0.028	0.025	0.011
	Panel B: Individuals aged 41-50		
Robot exposure	0.002*	0.000	0.001***
	(0.001)	(0.001)	(0.000)
Mean of dep. var.	0.007	0.004	0.001
Std. dev. of dep. var.	0.009	0.006	0.002
First stage F statistic	605	605	605
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.9: Effects of Robot Exposure on Match Quality in Couples – 2SLS Estimates

Dep. var.: Spouse Education, Relative to Own	(1) More	(2) More among married	(3) More among cohabiting
Robot exposure	0.011**	0.008	0.048***
	(0.005)	(0.005)	(0.016)
Mean of dep. var.	0.188	0.184	0.232
Std. dev. of dep. var.	0.0378	0.0386	0.131
First stage F statistic	605	605	605
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.10: Effects of Robot Exposure on Marital Behavior - Restricting to Individuals who did not Change Residence in the Previous Year

	(1) OLS	(2) Reduced form	(3) 2SLS
Panel A: Dep. var.: Marriage			
Robot exposure	-0.003		-0.009*
	(0.004)		(0.004)
Robot exposure - IV		-0.005*	
		(0.003)	
Mean of dep. var.	0.452	0.452	0.452
Std. dev. of dep. var.	0.068	0.068	0.068
First stage F statistic			599
Panel B: Dep. var.: Divorce			
Robot exposure	0.007***		0.008***
	(0.002)		(0.002)
Robot exposure - IV		0.005***	
		(0.001)	
Mean of dep. var.	0.095	0.095	0.095
Std. dev. of dep. var.	0.020	0.020	0.020
First stage F statistic			599
Panel C: Dep. var.: Cohabitation			
Robot exposure	-0.001		0.002
	(0.001)		(0.001)
Robot exposure - IV		0.001	
		(0.001)	
Mean of dep. var.	0.031	0.031	0.031
Std. dev. of dep. var.	0.011	0.011	0.011
First stage F statistic			599
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.11: Effects of Robot Exposure on Marital Behavior - Restricting to Individuals who Reside in the Same State as the Place of Birth

	(1) OLS	(2) Reduced form	(3) 2SLS
Panel A: Dep. var.: Marriage			
Robot exposure	-0.002		-0.003
	(0.004)		(0.005)
Robot exposure - IV		-0.001	
		(0.003)	
Mean of dep. var.	0.389	0.389	0.389
Std. dev. of dep. var.	0.072	0.072	0.072
First stage F statistic			600
Panel B: Dep. var.: Divorce			
Robot exposure	0.006***		0.007***
	(0.002)		(0.002)
Robot exposure - IV		0.004***	
		(0.001)	
Mean of dep. var.	0.094	0.094	0.094
Std. dev. of dep. var.	0.023	0.023	0.023
First stage F statistic			600
Panel C: Dep. var.: Cohabitation			
Robot exposure	0.002*		0.004***
	(0.001)		(0.001)
Robot exposure - IV		0.002***	
		(0.001)	
Mean of dep. var.	0.038	0.038	0.038
Std. dev. of dep. var.	0.013	0.013	0.013
First stage F statistic			600
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.12: Effects of Robot Exposure on Marital Behavior - Controlling for the Share of Individuals Changing Residence

	(1) OLS	(2) Reduced form	(3) 2SLS
Panel A: Dep. var.: Marriage			
Robot exposure	-0.002		-0.003
	(0.003)		(0.004)
Robot exposure - IV		-0.002	
		(0.002)	
Mean of dep. var.	0.412	0.412	0.412
Std. dev. of dep. var.	0.061	0.061	0.061
First stage F statistic			605
Panel B: Dep. var.: Divorce			
Robot exposure	0.007***		0.009***
	(0.002)		(0.002)
Robot exposure - IV		0.005***	
		(0.001)	
Mean of dep. var.	0.098	0.098	0.098
Std. dev. of dep. var.	0.021	0.021	0.021
First stage F statistic			605
Panel C: Dep. var.: Cohabitation			
Robot exposure	0.001		0.004***
	(0.001)		(0.001)
Robot exposure - IV		0.002***	
		(0.001)	
Mean of dep. var.	0.039	0.039	0.039
Std. dev. of dep. var.	0.012	0.012	0.012
First stage F statistic			605
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), commuting zone and year fixed effects, and include the share of people who remained in the same house in the previous year.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.13: Effects of Robot Exposure on Marital Behavior - Controlling for the Share of Individuals Residing in their State of Birth

	(1) OLS	(2) Reduced form	(3) 2SLS
Panel A: Dep. var.: Marriage			
Robot exposure	-0.002		-0.003
	(0.003)		(0.004)
Robot exposure - IV		-0.002	
		(0.002)	
Mean of dep. var.	0.412	0.412	0.412
Std. dev. of dep. var.	0.061	0.061	0.061
First stage F statistic			605
Panel B: Dep. var.: Divorce			
Robot exposure	0.007***		0.009***
	(0.002)		(0.002)
Robot exposure - IV		0.005***	
		(0.001)	
Mean of dep. var.	0.098	0.098	0.098
Std. dev. of dep. var.	0.021	0.021	0.021
First stage F statistic			605
Panel C: Dep. var.: Cohabitation			
Robot exposure	0.001		0.005***
	(0.001)		(0.001)
Robot exposure - IV		0.003***	
		(0.001)	
Mean of dep. var.	0.039	0.039	0.039
Std. dev. of dep. var.	0.012	0.012	0.012
First stage F statistic			605
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), commuting zone and year fixed effects, and include the share of people whose current state of residence is the same as their state of birth.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.14: Effects of Robot Exposure on Fertility Behavior - Restricting to Individuals who did not Change Residence in the Previous Year

	(1) OLS	(2) Reduced form	(4) 2SLS
Panel A: Dep. var.: Overall Fertility			
Robot exposure	-0.002		-0.001
	(0.002)		(0.002)
Robot exposure - IV		-0.001	
		(0.001)	
Mean of dep. var.	0.053	0.053	0.053
Std. dev. of dep. var.	0.017	0.017	0.017
First stage F statistic			599
Panel B: Dep. var.: Marital Fertility			
Robot exposure	-0.005***		-0.006***
	(0.001)		(0.002)
Robot exposure - IV		-0.004***	
		(0.001)	
Mean of dep. var.	0.033	0.033	0.033
Std. dev. of dep. var.	0.014	0.014	0.014
First stage F statistic			599
Panel C: Dep. var.: Nonmarital Fertility			
Robot exposure	0.003***		0.004***
	(0.001)		(0.001)
Robot exposure - IV		0.002***	
		(0.001)	
Mean of dep. var.	0.015	0.015	0.015
Std. dev. of dep. var.	0.011	0.011	0.011
First stage F statistic			599
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.15: Effects of Robot Exposure on Fertility Behavior - Restricting to Individuals who Reside in the Same State as the Place of Birth

	(1) OLS	(2) Reduced form	(4) 2SLS
Panel A: Dep. var.: Overall Fertility			
Robot exposure	0.002		0.006**
	(0.002)		(0.002)
Robot exposure - IV		0.003**	
		(0.001)	
Mean of dep. var.	0.060	0.060	0.060
Std. dev. of dep. var.	0.021	0.021	0.021
First stage F statistic			600
Panel B: Dep. var.: Marital Fertility			
Robot exposure	-0.003*		-0.003*
	(0.002)		(0.002)
Robot exposure - IV		-0.002*	
		(0.001)	
Mean of dep. var.	0.032	0.032	0.032
Std. dev. of dep. var.	0.015	0.015	0.015
First stage F statistic			600
Panel C: Dep. var.: Nonmarital Fertility			
Robot exposure	0.004***		0.007***
	(0.001)		(0.002)
Robot exposure - IV		0.004***	
		(0.001)	
Mean of dep. var.	0.022	0.022	0.022
Std. dev. of dep. var.	0.015	0.015	0.015
First stage F statistic			600
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.16: Effects of Robot Exposure on Fertility Behavior - Controlling for the Share of Individuals Changing Residence

	(1) OLS	(2) Reduced form	(4) 2SLS
Panel A: Dep. var.: Overall Fertility			
Robot exposure	-0.001		0.000
	(0.002)		(0.002)
Robot exposure - IV		0.000	
		(0.001)	
Mean of dep. var.	0.059	0.059	0.059
Std. dev. of dep. var.	0.018	0.018	0.018
First stage F statistic			605
Panel B: Dep. var.: Marital Fertility			
Robot exposure	-0.002*		-0.004**
	(0.001)		(0.001)
Robot exposure - IV		-0.002**	
		(0.001)	
Mean of dep. var.	0.033	0.033	0.033
Std. dev. of dep. var.	0.013	0.013	0.013
First stage F statistic			605
Panel C: Dep. var.: Nonmarital Fertility			
Robot exposure	0.001		0.003**
	(0.001)		(0.001)
Robot exposure - IV		0.002**	
		(0.001)	
Mean of dep. var.	0.019	0.019	0.019
Std. dev. of dep. var.	0.011	0.011	0.011
First stage F statistic			605
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), commuting zone and year fixed effects, and include the share of people who remained in the same house in the previous year.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.17: Effects of Robot Exposure on Fertility Behavior - Controlling for the Share of Individuals Residing in their State of Birth

	(1) OLS	(2) Reduced form	(4) 2SLS
Panel A: Dep. var.: Overall Fertility			
Robot exposure	-0.001		0.001
	(0.002)		(0.002)
Robot exposure - IV		0.000	
		(0.001)	
Mean of dep. var.	0.059	0.059	0.059
Std. dev. of dep. var.	0.018	0.018	0.018
First stage F statistic			605
Panel B: Dep. var.: Marital Fertility			
Robot exposure	-0.002**		-0.004**
	(0.001)		(0.001)
Robot exposure - IV		-0.002**	
		(0.001)	
Mean of dep. var.	0.033	0.033	0.033
Std. dev. of dep. var.	0.013	0.013	0.013
First stage F statistic			605
Panel C: Dep. var.: Nonmarital Fertility			
Robot exposure	0.001		0.003**
	(0.001)		(0.001)
Robot exposure - IV		0.002**	
		(0.001)	
Mean of dep. var.	0.019	0.019	0.019
Std. dev. of dep. var.	0.011	0.011	0.011
First stage F statistic			605
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), commuting zone and year fixed effects, and include the share of people whose current state of residence is the same as their state of birth.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.18: Long-Difference Specification: Effects of Robot Exposure on Labor Market Outcomes, Marital and Fertility Behavior – 2SLS Estimates

	(1)	(2)	(3)
	Panel A: Labor Market Outcomes - M/F gender ratio		
Dep. var.:	Income	Labor Force Participation	Employment
Robot exposure	-0.126***	-0.129***	-0.119***
	(0.035)	(0.034)	(0.034)
First stage F statistic	604	604	604
Observations	741	741	741
	Panel B: Marital Behavior		
Dep. var.:	Marriage	Divorce	Cohabitation
Robot exposure	-0.064*	0.098**	0.061*
	(0.036)	(0.041)	(0.036)
First stage F statistic	604	604	604
Observations	741	741	741
	Panel C: Fertility Behavior		
Dep. var.:	Overall fertility	Marital fertility	Nonmarital fertility
Robot exposure	0.039	-0.083**	0.164***
	(0.031)	(0.034)	(0.035)
First stage F statistic	604	604	604
Observations	741	741	741

Notes - Robust standard errors are reported in parentheses. All models control for baseline CZ-level demographic and economic characteristics. These include the average age, the share of females, the share of women and men in the labor force, and the share of employed.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.19: Long-Difference Specification: Effects of Robot Exposure on Marital and Fertility Behavior - Including Controls for Pre-trends (from 1980-1990) – 2SLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	Marriage	Divorce	Cohabitation	Overall fertility	Marital fertility	Nonmarital fertility
Robot exposure	-0.074**	0.121***	0.045	0.046	-0.064*	0.160***
	(0.037)	(0.041)	(0.037)	(0.031)	(0.034)	(0.035)
First stage F statistic	599	603	613	586	584	607
Observations	741	741	741	741	741	741

Notes - Robust standard errors are reported in parentheses. All models control for baseline CZ-level demographic and economic characteristics. These include the average age, the share of females, the share of women and men in the labor force and the share of employed. All models further include controls for pre-trends (from 1980-1990) in the outcome of interest.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.20: Rotemberg Weights

Sector	Rotemberg Weight
Electronics	0.32
Basic metal	0.05
Metal machinery	0.02
Paper float	0.02
Construction	0.02
Automotive	0.01
Metal product	0.01
Glass	< 0.01
Plastic	< 0.01
Other vehicles	< 0.01
Textile	< 0.01
Education	< 0.01
Food	< 0.01
Agriculture	< 0.01
Mining	< 0.01
Wood	< 0.01
Electricity	< 0.01
Other	< 0.01
Other manufacturing	< 0.01

Notes - We calculated Rotemberg weights by year and sector. Here we report the average weight of each sector throughout the period of the analysis.

Table A.21: Effects of Robot Exposure on Marital Behavior – Excluding Robots in the Electronics Sector

	(1) OLS	(2) Reduced form	(3) 2SLS
	Panel A: Marriage		
Robot exposure	-0.004		-0.004
	(0.004)		(0.004)
Robot exposure - IV		-0.002	
		(0.002)	
Mean of dep. var.	0.412	0.412	0.412
Std. dev. of dep. var.	0.061	0.061	0.061
First stage F statistic			588
	Panel B: Divorce		
Robot exposure	0.008***		0.009***
	(0.002)		(0.002)
Robot exposure - IV		0.005***	
		(0.001)	
Mean of dep. var.	0.098	0.098	0.098
Std. dev. of dep. var.	0.021	0.021	0.021
First stage F statistic			588
	Panel C: Cohabitation		
Robot exposure	0.002**		0.005***
	(0.001)		(0.001)
Robot exposure - IV		0.003***	
		(0.001)	
Mean of dep. var.	0.039	0.039	0.039
Std. dev. of dep. var.	0.012	0.012	0.012
First stage F statistic			588
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects. All models exclude the stock of robots in the electronics sector from the computation of the robot exposure measure. *Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.22: Effects of Robot Exposure on Fertility Behavior – Excluding Robots in the Electronics Sector

	(1) OLS	(2) Reduced form	(4) 2SLS
Panel A: Overall Fertility			
Robot exposure	-0.002		0.001
	(0.002)		(0.002)
Robot exposure - IV		0.000	
		(0.001)	
Mean of dep. var.	0.059	0.059	0.059
Std. dev. of dep. var.	0.018	0.018	0.018
First stage F statistic			588
Panel B: Marital Fertility			
Robot exposure	-0.003**		-0.004**
	(0.001)		(0.001)
Robot exposure - IV		-0.002**	
		(0.001)	
Mean of dep. var.	0.033	0.033	0.033
Std. dev. of dep. var.	0.013	0.013	0.013
First stage F statistic			588
Panel C: Nonmarital Fertility			
Robot exposure	0.001		0.003**
	(0.001)		(0.001)
Robot exposure - IV		0.002**	
		(0.001)	
Mean of dep. var.	0.019	0.019	0.019
Std. dev. of dep. var.	0.011	0.011	0.011
First stage F statistic			588
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects. All models exclude the stock of robots in the electronics sector from the computation of the robot exposure measure. *Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.23: Effects of Robot Exposure on Marital Behavior – Including Controls for Specific Time Trends by Initial Share of Employment in the Electronics Sector

	(1) OLS	(2) Reduced form	(3) 2SLS
Panel A: Marriage			
Robot exposure	-0.010**		-0.010*
	(0.004)		(0.006)
Robot exposure - IV		-0.005*	
		(0.003)	
Mean of dep. var.	0.412	0.412	0.412
Std. dev. of dep. var.	0.061	0.061	0.061
First stage F statistic			438
Panel B: Divorce			
Robot exposure	0.006***		0.006**
	(0.002)		(0.002)
Robot exposure - IV		0.003**	
		(0.001)	
Mean of dep. var.	0.098	0.098	0.098
Std. dev. of dep. var.	0.021	0.021	0.021
First stage F statistic			438
Panel C: Cohabitation			
Robot exposure	0.004***		0.008***
	(0.001)		(0.001)
Robot exposure - IV		0.004***	
		(0.001)	
Mean of dep. var.	0.039	0.039	0.039
Std. dev. of dep. var.	0.012	0.012	0.012
First stage F statistic			438
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), commuting zone and year fixed effects, and include specific time trends across areas in different quartiles of the initial share of employment in the electronics sector. In practice, we include controls interacting year dummies with quartiles of the share of employment in the electronics sector as of 1990. *Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.24: Effects of Robot Exposure on Fertility Behavior – Including Controls for Specific Time Trends by Initial Share of Employment in the Electronics Sector

	(1) OLS	(2) Reduced form	(4) 2SLS
Panel A: Overall Fertility			
Robot exposure	-0.005**		-0.001
	(0.002)		(0.002)
Robot exposure - IV		-0.001	
		(0.001)	
Mean of dep. var.	0.059	0.059	0.059
Std. dev. of dep. var.	0.018	0.018	0.018
First stage F statistic			438
Panel B: Marital Fertility			
Robot exposure	-0.003**		-0.004**
	(0.001)		(0.002)
Robot exposure - IV		-0.002**	
		(0.001)	
Mean of dep. var.	0.033	0.033	0.033
Std. dev. of dep. var.	0.013	0.013	0.013
First stage F statistic			438
Panel C: Nonmarital Fertility			
Robot exposure	-0.001		0.001
	(0.001)		(0.001)
Robot exposure - IV		0.001	
		(0.001)	
Mean of dep. var.	0.019	0.019	0.019
Std. dev. of dep. var.	0.011	0.011	0.011
First stage F statistic			438
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), commuting zone and year fixed effects, and include specific time trends across areas in different quartiles of the initial share of employment in the electronics sector. In practice, we include controls interacting year dummies with quartiles of the share of employment in the electronics sector as of 1990. *Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.25: Relationship between the Share of Employment in the Automotive and Electronics in the US in 1970 and Marital and Fertility Change 1980-1990 – OLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	Marriage	Divorce	Cohabitation	Overall fertility	Marital fertility	Nonmarital fertility
Panel A: Share of Employment in the Electronics Industry in 1970						
Share of employment in the electronics sector in 1970	0.000	-0.001**	-0.000	-0.001	-0.001	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Mean of dep. var.	-0.054	0.019	0.018	-0.016	-0.027	0.004
Std. dev. of dep. var.	0.023	0.009	0.006	0.011	0.015	0.008
Observations	741	741	741	741	741	741
Panel B: Share of Employment in the Automotive Industry in 1970						
Share of employment in the automotive sector in 1970	0.000	-0.000	-0.001***	-0.000	0.000	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean of dep. var.	-0.054	0.019	0.018	-0.016	-0.027	0.004
Std. dev. of dep. var.	0.023	0.009	0.006	0.011	0.015	0.008
Observations	741	741	741	741	741	741

Notes - Data on demographic outcomes are drawn from the 1980 and 1990 US Census. Robust standard errors are reported in parentheses. All models include CZ-level demographic and economic characteristics. These include the share of individuals under the age of 25, the share of females, the share of people in the labor force, the share of unemployed, the share of employed, average income, average education, and the poverty rate.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.26: Effects of Robot Exposure on Marital Behavior - Including Controls for Specific Time Trends by Initial Share of Employment in the Automotive Sector.

	(1) OLS	(2) Reduced form	(3) 2SLS
Panel A: Dep. var.: Marriage			
Robot exposure	-0.006		-0.009
	(0.005)		(0.007)
Robot exposure - IV		-0.004	
		(0.003)	
Mean of dep. var.	0.412	0.412	0.412
Std. dev. of dep. var.	0.061	0.061	0.061
First stage F statistic			200
Panel B: Dep. var.: Divorce			
Robot exposure	0.003		0.006*
	(0.002)		(0.003)
Robot exposure - IV		0.002*	
		(0.001)	
Mean of dep. var.	0.098	0.098	0.098
Std. dev. of dep. var.	0.021	0.021	0.021
First stage F statistic			200
Panel C: Dep. var.: Cohabitation			
Robot exposure	0.003**		0.009***
	(0.001)		(0.002)
Robot exposure - IV		0.004***	
		(0.001)	
Mean of dep. var.	0.039	0.039	0.039
Std. dev. of dep. var.	0.012	0.012	0.012
First stage F statistic			200
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), commuting zone and year fixed effects, and include specific time trends across areas in different quartiles of the initial share of employment in the automotive sector. In practice, we include controls interacting year dummies with quartiles of the share of employment in the automotive sector as of 1990. *Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.27: Effects of Robot Exposure on Fertility Behavior - Including Controls for Specific Time Trends by Initial Share of Employment in the Automotive Sector.

	(1) OLS	(2) Reduced form	(4) 2SLS
Panel A: Dep. var.: Overall Fertility			
Robot exposure	-0.002		0.002
	(0.002)		(0.003)
Robot exposure - IV		0.001	
		(0.001)	
Mean of dep. var.	0.059	0.059	0.059
Std. dev. of dep. var.	0.018	0.018	0.018
First stage F statistic			200
Panel B: Dep. var.: Marital Fertility			
Robot exposure	-0.004**		-0.006**
	(0.002)		(0.002)
Robot exposure - IV		-0.002**	
		(0.001)	
Mean of dep. var.	0.033	0.033	0.033
Std. dev. of dep. var.	0.013	0.013	0.013
First stage F statistic			200
Panel C: Dep. var.: Nonmarital Fertility			
Robot exposure	0.001		0.004**
	(0.001)		(0.002)
Robot exposure - IV		0.002**	
		(0.001)	
Mean of dep. var.	0.019	0.019	0.019
Std. dev. of dep. var.	0.011	0.011	0.011
First stage F statistic			200
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), commuting zone and year fixed effects, and include specific time trends across areas in different quartiles of the initial share of employment in the automotive sector. In practice, we include controls interacting year dummies with quartiles of the share of employment in the automotive sector as of 1990. *Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.28: Effects of Robot Exposure on Marital and Fertility Behavior – Including Controls for Exposure to Trade – 2SLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	Marriage	Divorce	Cohabitation	Overall fertility	Marital fertility	Nonmarital fertility
Robot exposure	-0.004	0.008***	0.004***	-0.000	-0.004***	0.002**
	(0.004)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Mean of dep. var.	0.412	0.098	0.039	0.059	0.033	0.019
Std. dev. of dep. var.	0.061	0.021	0.012	0.018	0.013	0.011
First stage F statistic	589	589	589	589	589	589
Observations	7,410	7,410	7,410	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects. All models further include the CZ-level measure of exposure to trade (detailed in Section 5.1) interacted with year dummies.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.29: Effects of Robot Exposure on Marital and Fertility Behavior - Including Controls for Trends in the Manufacturing Sector – 2SLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	Marriage	Divorce	Cohabitation	Overall fertility	Marital fertility	Nonmarital fertility
Robot exposure	-0.004	0.008***	0.004***	-0.000	-0.004***	0.002**
	(0.004)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Mean of dep. var.	0.412	0.098	0.039	0.059	0.033	0.019
Std. dev. of dep. var.	0.061	0.021	0.012	0.018	0.013	0.011
First stage F statistic	590	590	590	590	590	590
Observations	7,410	7,410	7,410	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), commuting zone and year fixed effects, and include controls interacting year dummies with the share of employment in total manufacturing as of 1990.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.30: Effects of Robot Exposure on Marital Behavior– Including Controls for Family Policy Environment – 2SLS Estimates

	(1) Family controls	(2) TRAP laws	(3) Family controls and TRAP laws
Panel A: Dep. var.: Marriage			
Robot exposure	-0.004	-0.004	-0.004
	(0.004)	(0.004)	(0.004)
Mean of dep. var.	0.412	0.412	0.412
Std. dev. of dep. var.	0.061	0.061	0.061
First stage F statistic	639	619	647
Panel B: Dep. var.: Divorce			
Robot exposure	0.009***	0.009***	0.009***
	(0.002)	(0.002)	(0.002)
Mean of dep. var.	0.098	0.098	0.098
Std. dev. of dep. var.	0.021	0.021	0.021
First stage F statistic	639	619	647
Panel C: Dep. var.: Cohabitation			
Robot exposure	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)
Mean of dep. var.	0.039	0.039	0.039
Std. dev. of dep. var.	0.012	0.012	0.012
First stage F statistic	639	619	647
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects. Furthermore, column 1 includes controls for family policies (see Section 5.1 for details), column 2 adds TRAP laws, and column 3 includes controls for both family policies and TRAP laws.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.31: Effects of Robot Exposure on Fertility Behavior– Including Controls for Family Policy Environment – 2SLS Estimates

	(1) Family controls	(2) TRAP laws	(3) Family controls and TRAP laws
Panel A: Dep. var.: Overall Fertility			
Robot exposure	-0.001	0.000	-0.001
	(0.002)	(0.002)	(0.002)
Mean of dep. var.	0.059	0.059	0.059
Std. dev. of dep. var.	0.018	0.018	0.018
First stage F statistic	639	619	647
Panel B: Dep. var.: Marital Fertility			
Robot exposure	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)
Mean of dep. var.	0.033	0.033	0.033
Std. dev. of dep. var.	0.013	0.013	0.013
First stage F statistic	639	619	647
Panel C: Dep. var.: Nonmarital Fertility			
Robot exposure	0.003**	0.003**	0.002*
	(0.001)	(0.001)	(0.001)
Mean of dep. var.	0.019	0.019	0.019
Std. dev. of dep. var.	0.011	0.011	0.011
First stage F statistic	639	619	647
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects. Furthermore, column 1 includes controls for family policies (see Section 5.1 for details), column 2 adds TRAP laws, and column 3 includes controls for both family policies and TRAP laws.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.32: Effects of Robot Exposure on Fertility Behavior, Extensive and Intensive Margin – 2SLS Estimates

	(1) Overall fertility	(2) Marital fertility	(4) Nonmarital fertility
Panel A: Extensive Margin of Fertility (Share of Women Having at Least One Child)			
Robot exposure	0.001	-0.003***	0.003**
	(0.002)	(0.001)	(0.002)
Mean of dep. var.	0.0402	0.0174	0.0185
Std. dev. of dep. var.	0.0173	0.0101	0.0131
Panel B: Intensive Margin of Fertility (Share of Women Having More than One Child)			
Robot exposure	-0.002	-0.007***	0.004**
	(0.003)	(0.003)	(0.002)
Mean of dep. var.	0.102	0.0637	0.0289
Std. dev. of dep. var.	0.0288	0.0247	0.0172
Panel C: Intensive Margin of Fertility (Number of Children)			
Robot exposure	-0.000	-0.073***	0.055***
	(0.010)	(0.015)	(0.012)
Mean of dep. var.	1.019	1.556	0.374
Std. dev. of dep. var.	0.135	0.185	0.146
First stage F statistic	605	605	605
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.33: Effects of Robot Exposure on Marital Behavior, Conditioning on Children's Presence – 2SLS Estimates

	(1) Baseline	(2) Number of children=0	(3) Number of children>0	(4) Age of the youngest child<5	(5) Age of the youngest child<10	(6) Age of the youngest child<15
Panel A: Marriage						
Robot exposure	-0.004	0.006	-0.021***	-0.029***	-0.027***	-0.027***
	(0.004)	(0.004)	(0.005)	(0.008)	(0.007)	(0.006)
Mean of dep. var.	0.412	0.179	0.708	0.698	0.703	0.711
Std. dev. of dep. var.	0.061	0.045	0.065	0.086	0.074	0.0689
Panel B: Divorce						
Robot exposure	0.009***	0.007***	0.011***	0.006*	0.008**	0.010***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Mean of dep. var.	0.098	0.094	0.105	0.055	0.076	0.090
Std. dev. of dep. var.	0.021	0.026	0.024	0.027	0.026	0.0251
Panel C: Cohabitation						
Robot exposure	0.004***	0.002	0.006***	0.006*	0.006**	0.005***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.002)
Mean of dep. var.	0.039	0.033	0.048	0.063	0.056	0.051
Std. dev. of dep. var.	0.012	0.013	0.018	0.030	0.023	0.0202
First stage F statistic	605	605	605	605	605	605
Observations	7,410	7,410	7,410	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.34: Effects of Robot Exposure on Completed Fertility Behavior (as Measured by the Number of Children among Women aged 45-50) – 2SLS Estimates

	(1) Overall fertility	(2) Marital fertility	(3) Nonmarital fertility
Robot exposure	-0.010	-0.039*	0.081*
	(0.017)	(0.023)	(0.047)
Mean of dep. var.	0.905	1.064	0.373
Std. dev. of dep. var.	0.191	0.255	0.349
First stage F statistic	605	605	605
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.35: Effects of Robot Exposure on Nonmarital Fertility among Cohabiting and Non-cohabiting Women – 2SLS Estimates

	(1)	(2)	(3)
Dep. var.:	Nonmarital fertility	Nonmarital fertility - cohabiting women	Nonmarital fertility - non-cohabiting women
Robot exposure	0.003**	0.000	0.003**
	(0.001)	(0.000)	(0.001)
Mean of dep. var.	0.019	0.003	0.017
Std. dev. of dep. var.	0.011	0.004	0.011
First stage F statistic	605	605	605
Observations	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.36: Effects of Robot Exposure on Marital and Fertility Behavior among Same-Sex Couples – 2SLS Estimates

	(1) Marriage	(2) Divorce	(3) Cohabitation	(4) Overall fertility	(5) Marital fertility	(6) Nonmarital fertility
Panel A: Focusing on Same-Sex Couples						
Robot exposure	-0.001***	0.000	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean of dep. var.	0.001	0.001	0.002	0.000	0.000	0.000
Std. dev. of dep. var.	0.002	0.001	0.002	0.001	0.001	0.000
First stage F statistic	597	597	597	597	597	597
Panel B: Baseline that excludes Same-Sex Couples						
Robot exposure	-0.003	0.009***	0.004***	0.000	-0.004**	0.003**
	(0.004)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Mean of dep. var.	0.413	0.0982	0.0382	0.0595	0.0338	0.0196
Std. dev. of dep. var.	0.0616	0.0212	0.0119	0.0180	0.0136	0.0117
First stage F statistic	604	604	604	604	604	604
Panel C: Baseline that includes Legislation of Same-Sex Marriage						
Robot exposure	-0.003	0.009***	0.005***	0.000	-0.004***	0.003**
	(0.004)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
Mean of dep. var.	0.412	0.0986	0.0398	0.0594	0.0337	0.0196
Std. dev. of dep. var.	0.0612	0.0213	0.0120	0.0180	0.0135	0.0116
First stage F statistic	597	597	597	597	597	597
Observations	7,410	7,410	7,410	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.

Table A.37: Effects of Robot Exposure on Marital Behavior among Same-Sex Couples, by Gender – 2SLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
		Females			Males	
	Marriage	Divorce	Cohabitation	Marriage	Divorce	Cohabitation
Robot exposure	-0.001*	0.000	0.000	-0.002***	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mean of dep. var.	0.001	0.001	0.002	0.001	0.001	0.001
Std. dev. of dep. var.	0.003	0.002	0.002	0.002	0.001	0.002
First stage F statistic	597	597	597	597	597	597
Observations	7,410	7,410	7,410	7,410	7,410	7,410

Notes - Standard errors are reported in parentheses and are clustered at the commuting zone level. All models control for CZ-level demographic characteristics (share of individuals under the age of 25 and share of females), as well as commuting zone and year fixed effects. All models further include controls for legislation of same-sex marriage.
*Significant at 10 per cent; ** Significant at 5 per cent; ***Significant at 1 per cent.