Robots, Labor Markets, and Family Behavior*

Massimo Anelli†
Bocconi University, CESifo and IZA

Osea Giuntella
University of Pittsburgh and IZA‡

Luca Stella
Bocconi University and IZA§

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Abstract

Robots have radically changed the demand for skills and the role of workers in production at an unprecedented pace, with little scope for human capital adjustments. This has affected the job stability and the economic perspectives of large parts of the population in all industrialized countries. Recent evidence on the US labor market has shown negative effects of robots on employment and wages. In this study, we examine how exposure to robots and its consequences on job stability and economic uncertainty have affected individual demographic behavior. To establish this relationship, we use data from the American Community Survey and the International Federation of Robotics and we adopt an empirical strategy that relies on regional industry specialization before the advent of robots combined with the growth of robot adoption by industry. We first document the differential effect of robots on the labor market opportunities of men and women. We find that in regions that were more exposed to robots, the gender-income and labor-force-participation gaps declined. We then show that US regions affected by intense robot penetration experienced a decrease in new marriages, and an increase in both divorce and cohabitation. While there was no change in overall fertility rate, marital fertility declined, and there was an increase in out-of-wedlock births. Our findings are consistent with the hypothesis that the changes in labor markets triggered by robot adoption increased uncertainty, reduced the relative marriage-market value of men, and the willingness to commit for the long term.

JEL Codes: J12, J13, J21, J23, J24

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†Carlo F. Dondena Centre for Research on Social Dynamics and Public Policy, Bocconi University. Email: massimo.anelli@unibocconi.it

‡University of Pittsburgh. Email: osea.giuntella@pitt.edu.

§Carlo F. Dondena Centre for Research on Social Dynamics and Public Policy, Bocconi University. Email: luca.stella@unibocconi.it

1 Introduction

Million of workers across the world feel the growing 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 rapidly change our labor markets. 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., 2018; Frey and Osborne, 2017; Acemoglu and Restrepo, 2019). However, despite the growing interest on the labor market effects of automation, we know very little about how these structural economic changes are reshaping life-course choices. Our paper fills this gap in the literature, by examining how the exposure to robots and its consequences on job stability and economic uncertainty have affected individual demographic behavior. We focus on the US labor market and base our analysis on American Community Survey (ACS) data covering years from 2005 to 2016. We construct a measure of regional exposure to robots following Acemoglu and Restrepo (2019), and using data from the International Federation of Robotics (IFR). These data track the change by economic sector in the operational stock of "industrial robots", fully autonomous, multipurpose machines that are automatically controlled, do not need a human operator and can be re-programmed to perform several tasks.[1] These robots can easily replace human operators in most industrial production activities that require "reaching and handling" actions.

Over the last three decades, the stock of these operational industrial robots in the US increased by more than five times (see Figure 1). In 2016, robot sales increased by 16% reaching a new peak for the fourth year in a row. This surge is driven by the increase in electrical/electronics industry. Yet, the automotive industry still accounts for the highest share of industrial robots. Between 2011 and 2016, the average robot sales increase was at 12% per year. This continued growth was pushed by the trend to automate production as a way to strengthen American industries and keep manufacturing in the US. Just since 2005, and despite the slow-down caused by the great recession, the number of robots per thousand worker grew from 1.3 to 2.4 (see Figure 2). We construct a measure of robots penetration in US labor markets by exploiting the

[1] Machinery developed and programmed to accomplish a specific task in the production chain (e.g., dedicated assembly equipment or automated storage and retrieval systems) would thus not be considered robots.

variation in the distribution of industrial employment across commuting zones (i.e. geographical units corresponding to regional labor markets characterized by intense daily commuting of workers) combined with changes in the adoption of robots across industries over time. Figure 3 maps the intensity of robots penetration by commuting zone between 2004 and 2016. To mitigate the concern that the adoption of robots could be correlated with other demographic trends within an industry or a commuting zone, we use the industry-level spread of robots in advanced economies other than the US as an instrument for the adoption of robots in the US. In this way, we only exploit the variation resulting from industries that exhibited an increase in the use of robots in other advanced economies. This variation should capture the exogenous trends in automatability of certain sectors driven by advancements of the technological frontier, which are plausibly independent of US demographic trends. We support this claim by showing the absence of significant correlation between robot exposure in advanced economies other than the US and pre-robotization trends in marital and fertility patterns.

Using this empirical strategy, first we show that robot exposure had differential effects on the labor market opportunities of men and women. We find that a one standard deviation increase in robot exposure reduced the gender income gap by 4% and the gender gap in labor force participation by 2%. We then turn to investigate the effects of this labor market shocks on the marriage market and fertility. We find that commuting zones that were more exposed to robot penetration experienced a reduction in marriage rate and an increase in divorce and cohabitation. A one standard deviation increase in robot exposure was associated with a 4% reduction in the marriages, a 5% increase in divorces, and a 13% increase in cohabitations. All these effects are significant at the 1% level. While we find a null effect of robots on overall fertility, this result masks substantial heterogeneous effects on fertility. Indeed, we show that commuting zones that were more exposed to robots penetration exhibit a 15% reduction in marital fertility and a 20% increase in the rate of children born out-of-wedlock.

Overall, our findings suggest that a decrease in the relative marriage-market value of men and the greater labor market uncertainty may be a relevant transmission mechanisms of the impact of robot penetration on marriage and marital fertility rates.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature on technology, economic uncertainty and fertility, and presents a theoretical framework. Section 3 describes the data used and explains our empirical strategy. Results are presented in Section 4, followed by concluding remarks in Section 5.

2 Literature Review and Theoretical Framework

Our paper contributes to three important strands of the demographic literature. First, many seminal papers have documented the massive impact of technology on family and fertility choices. For instance, the literature shows how the advancements in contraceptive technology have played a major role in the radical change in reproductive patterns in the past century, i.e., 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 increase their fertility 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 impacts 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), body weight (DiNardi et al., 2017), and sleep (Billari et al., 2018). Our paper contributes to this discussion, by focusing on a more recent wave of technological change, i.e., the development of robotics and automation, that instead of playing a facilitating role for fertility and family choices, is a potential source of disruption for them.

The second strand of the demographic literature upon which we build our work focuses on the effects of economic downturns and uncertainty on fertility choices. Several works have documented fertility declines following economic recessions and rising unemployment rates (Cherlin et al., 2013; Sobotka et al., n.d.; Özcan et al., 2010; Lanzieri, 2013). More recent studies have focused on the latest "Great Recession" and have confirmed previous findings on the procyclicality of fertility (Goldstein et al., 2013; Currie and Schwandt, 2014; Matysiak et al., 2018). By decreasing employment and wage prospects of current workers, robotization increases economic uncertainty. Moreover, workers who have not yet been directly affected by robots and perspective workers might also feel that their current or future job opportunities are threatened by robots, and thus perceive higher future economic uncertainty. As shown by Comolli (2017), individual sentiment's about their future financial situation – even when there is no current impact – is highly correlated with fertility decisions. Robotization is therefore likely to impact fertility choices of a portion of population larger than just individuals directly displaced by robots. Given the increase in actual and/or perceived economic uncertainty triggered by robotization, we expect robots to impact fertility in a similar way as economic recessions, certainly we expect the relation to go in the same direction. However, there is evidence that the impact of the increased economic uncertainty on fertility is the result of both a lower completed fertility rates –"quantum"– and a postponement of fertility decisions – "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. Contrary to economic recessions, the economic uncertainty caused by the process of industrial production robotization is not cyclical in nature and has a longer-run impact. It is costly and unlikely for adults and young adults displaced by robots to retrain so to become complementary to this new technology. Therefore, the economic uncertainty triggered is likely to permanently change the economic prospects of the affected workers (or the perceived economic prospects of threatened individuals). In this respect, the scope of the negative impact of robots on fertility and family choices could thus potentially be larger than that of economic recessions.

Third, our paper speaks to the literature on the decline of the relative marriage-value of men and more generally of partnership formation. By replacing manufacturing jobs that have been traditionally male-dominated, robotization has certainly concentrated its negative effects on male workers. At the same time, there is evidence that the increase in productivity trigger by robotization have translated into increases in employment opportunity in the service sector (Dauth et al., 2018). 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.

Overall, the distributional impact of robotization might have penalized men substantially more than women. This can in turn lower the relative value of men in the partnership formation process and boost the degree of economic independence of women. Ample literature has focused on the effects of the decline of manufacturing employment on partnership formation and fertility (Wilson et al., 1986; Wilson, 1987, 1996; Dorn et al., 2017). These studies theorize how the reduced working opportunities for blue-collar workers has impacted the pool of adult men with secure jobs and wages and reduced marriage value for women. Also Becker (1973) proposes a theoretical framework in which a reduction in the gender wage gap should reduce the marriage option value for women because of a reduced scope for intra-household specialization. More recent papers have focused on the effect of relative wage on women's spouse quality, marriage and labor supply. Shenhav (2016) shows that a higher relative wage increases the quality of women's mates, reduces marriage and raises women's hours worked. Schaller (2016) documents how the heterogeneity in the responsiveness of fertility to gender-specific shocks. While improvements in men's labor market conditions are associated with increases in fertility rates, improvements in women's labor market conditions have smaller negative effects. 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 on the role of technological changes and economic opportunities in determining life-course choices.

Finally, our paper builds upon the recent economic literature on the effects of technology and globalization on labor markets and to studies linking labor demand shocks to marriage and fertility outcomes (Ananat et al., 2013; Kearney and Wilson, 2017). Acemoglu and Restrepo (2019) 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 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. (2018) estimate that robots accounted for almost 23% of the overall decline of manufacturing employment in Germany between 1994 and 2014, but this loss was offset by the jobs created in the service sector. Anelli et al. (2019) shows 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. There is also increasing evidence that the labor market shocks induced by the exposure to imports from China and Mexico negatively impacted the marriage opportunities of men, with consequences on fertility rates and the rate of out-of-wedlock childbearing (Dorn et al., 2017). The effects of robot penetration on labor market have been shown to be independent from other labor market shocks (trade, ICT and the decline of routine jobs etc.). We contribute to this literature, by providing for the first time empirical evidence of the effects of robots penetration on marital decision-making and fertility choices and by examining the differential effect of robots on the labor market opportunities of men and women as the potential mechanism, which may affect the relative marriage-market value of men and women. Moreover, 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 (2019), 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.

3 Data and Methods

To document the relationship between robot exposure and demographic outcomes, we merge data from two main sources: the International Federation of Robotics (IFR) and the American Community Survey (ACS).

3.1 Robots Data

The data on the stock of robots by industry, country and year come from the International Federation of Robotics (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 (2019) for the US, Dauth et al. (2017) for

Germany, Giuntella and Wang (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). Basically, industrial robots are fully autonomous machines that are automatically controlled, do not need a human operator and can be programmed to perform 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, since they cannot be programmed to perform other tasks, require a human operator, or both.

However, the IFR robot data present some limitations. First, 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), including, for instance, food and beverages, textiles, wood and furniture, paper, plastic and chemicals, glass and ceramics, basic metals, metal products, metal machinery, electronics, automotive, other vehicles, and other manufacturing industries. For nonmanufacturing sectors, data on the operational stock of robots are restricted to six broad categories, namely, agriculture, forestry and fishing, mining, utilities, construction, education, research and development, and other non-manufacturing industries (e.g., services and entertainment). Furthermore, approximately a third of robots are not classified. Following Acemoglu and Restrepo (2019), we allocate unclassified robot in the same proportion as in the classified data. An additional limitation of the IFR data is the lack of the geographical information on the within-country distribution of robots (i.e., the smallest geographical unit is the country). Figure 1 documents the change in the stock of industrial robots in Europe and the US over the last 25 years. As evident from the figure, the use of industrial robots has been stably increasing in Europe and in the US. Similarly, Figure 2 displays the rapid growth of US robots per thousand workers since 2005. Overall, the pattern that emerges is that despite the slow-down 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, since their adoption in a plant in a given regional labor market affects employment opportunities for all individuals that can potentially commute to that factory to work. Focusing on smaller geographical unit would introduce substantial measurement error

3.2 American Community Survey

The American Community Survey (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 millions per year). A number of 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 aggregate-level analyses. Finally, our dataset contains information on individuals' labor market behavior, such as their income and employment. Since we expect that robot exposure will 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 and year level, the level of variation of our robot exposure measure. 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. The average fertility rate in a given commuting zone and year is about 6% (3.4% marital fertility and 2% out-of-wedlock fertility). The proportion of married and divorced people is 41% and 10%, respectively. Approximately, 4% of individuals are cohabiting. The average income by

[2] 2005 is the first year in which demographic outcomes were collected in the ACS data.

commuting zone and year is $23,388, roughly 75% of individuals are in the labor force and 69% are employed.

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 index ct denotes a commuting zone c in a given year t. Y_{ct} represents one of our outcomes of interest, i.e., marriage, divorce, cohabitation, fertility (i.e., overall, marital and out-of-wedlock), 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 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 commuting zone-level demographic controls, such as the share of women and the average age. The model 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 the family behavior. Finally, ϵ_{ct} represents an idiosyncratic error term. Throughout the analysis, we cluster standard errors by commuting zone.

Following Acemoglu and Restrepo (2019), we exploit the variation in the pre-existing distribution of industrial employment across commuting zones and use the evolution in the amount of robots across industries to construct a measure of robots penetration in the US labor market. We choose our baseline to be 1990, since most of the rise in industrial robots in the US took place after 1990. By relying on pre-existing industrial composition of commuting zones before the increase in the adoption of robots, we focus on historical differences in the specialization of US commuting zones in different industries, and avoid any mechanical correlation or mean reversion with changes in overall or industry-level employment outcomes. To measure the exposure to robots for a commuting zone, 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 over all sectors. Formally:

$$\text{Exposure to robots}_{c,t-2}^{US} = \sum_{i \in I} l_{ci}^{1990} (\frac{R_{i,t-2}^{US}}{L_{i,1990}}) \tag{2}$$

where l_{ci}^{1990} identifies the 1990 distribution of employment across industries and commuting zones; $R_{i,t}^{US}$ denotes the stock of robots in the US by sector in year $t-2$; and $L_{i,1990}$ represents the total number of individuals employed (in thousands) in sector i in 1990. Figure 3 shows the intensity of robots penetration across commuting zones between 2004 and 2016 based on the above metric. While the increase in the use of industrial robots was widespread across the US, Figure 3 documents substantial variation in the penetration of robots across commuting zones and over time. In our analyses, we will leverage these variations in exposure to robots across commuting zones and over time.

To address the concerns of confounding factors that may be correlated with both the industry-level spread of robots in the US and demographic and labor market outcomes, we rely on the identification strategy proposed by Acemoglu and Restrepo (2019) and exploit the industry-level spread of robots in other economies, which are meant to proxy improvements in the world technology frontier of robots. In particular, we use the average industry-level spread of robots in the nine European countries that are available in the IFR data over the same period of time.[3] Thus, we exploit only the variation resulting from industries that exhibited an increase in the use of robots in these other economies. Our instrument for the adoption of robots in the US is formally defined as follows:

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

where the sum runs over all industries in the IFR data, l_{ci}^{1970} is the 1970 share of commuting zone c employment in industry i, as computed from the 1970 Census, and $(p30(\frac{R_{i,t-2}^{Other}}{L_{i,1990}})$ represents the 30th percentile of robot usage among European countries in industry i and year $t-2$.

[3] These European countries include Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden, and the United Kingdom.

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

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

where $\sum_{i \in I} l_{ci}^{1990}(\frac{R_{i,t-2}^{US}}{L_{i,1990}})$ is instrumented with $[\sum_{i \in I} l_{ci}^{1970}(p30(\frac{R_{i,t-2}^{Other}}{L_{i,1990}}))]$, the industry-level robot from other economies (i.e., 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.2 shows that the adoption of robots in Europe is strongly correlated with robot exposure in the US. With a first stage F-statistic of 607 (reported at the bottom of Table 5), our instrument easily passes conventional thresholds for strong instruments. Figure 4 confirms the relevance of the instrument.

Before presenting our main results, we provide some preliminary visual evidence about the reduced-form relationship between our instrument (i.e., robot exposure in Europe) and the demographic outcomes. In practice, we plot the long-run 2005-2016 change in our demographic outcomes in each commuting zone against the long-run 2005-2016 change in robot exposure as measured by our instrument. Figure 5 considers the relationship between the instrument and marital behavior. Overall, Figure 6 indicates that robot exposure in Europe is negatively associated with marriage, whereas it is positively associated with divorce and more weakly with cohabitation. Figure 6 illustrates the link between our instrument and fertility behavior. We distinguish between overall fertility, marital fertility and out-of-wedlock fertility. While there is no correlation between robot usage in Europe and overall fertility, this lack of association masks stark heterogeneity between marital and out-of-wedlock fertility patterns. It appears that the pattern of marital fertility is negatively influenced by the adoption of robots in Europe, whereas the opposite holds for out-of-wedlock fertility.

4 Main Results

In this section, we present our main empirical results. First, we measure the impact of robotics on economic uncertainty of all workers and separately for women and men. We then explore the impact of industrial robots on marital behavior. Finally, we estimate the effects of robots on fertility choices.

4.1 Effects on Labor Market Outcomes

The logical mapping of the effect of robot exposure on demographic behavior requires to first show the relationship between specific labor market outcomes and demographic outcomes in our data, and then estimate the impact of robot exposure on those labor market outcomes. For instance, we expect a clear negative effect of robots on labor market outcomes to translate into a negative impact on fertility. At the same time, we expect that differences in the labor market impact of robots on women and men may affect the marriage market and the willingness to take up long-run commitment, such as marriage or fertility.

In Tables 1, 2 and 3, we show the impact of income, labor force participation and employment on marital and fertility behavior in descriptive OLS regressions. Specifically, Table 1 displays the results of OLS regressions of income on our outcomes: marriage, divorce, cohabitation, overall fertility, marital fertility and out-of-wedlock fertility. We find that higher annual income is associated with higher incidence of marriages and cohabitations (see columns 1 and 3) and a lower divorce probability (see column 3). Interestingly, while marriage is positively associated with income of both men and women, divorce is positively and significantly correlated with women income and negatively correlated with the gender gap. Higher income is also weakly, positively associated with higher overall fertility (see column 4), strongly positively associated with marital fertility (see column 5), and strongly negatively correlated with out-of-wedlock fertility (see column 6).

Table 1 also shows that the higher the gap between male and female income, the higher the marital fertility (see column 5), and the lower the out-of-wedlock fertility (see column 6). Table 2 contains the corresponding OLS estimates of labor force participation and Table 3 those of employment. Both overall labor force participation and employment are not surprisingly positively correlated with marriage while only employment is negatively and significantly correlated to divorce probability. When looking at differential associations for men and women, the higher labor force participation of women is positively and significantly associated to higher divorce rates. Consistently, higher levels of gender gap in labor force participation (as well as in employment probability) is negatively associated with divorce probability. In columns 4-6 of Tables 2 and 3 we turn to fertility behavior: while both overall labor force participation and employment appear to have weak or null association with fertility choices in our data, there are stark association patterns of the gender gap in labor force participation and employment with fertility. More specifically, the higher the gap between women and men in labor force participation and employment, the higher the marital fertility (see column 5), and the lower the out-of-wedlock fertility (see column 6).

Overall, this preliminary evidence on the relationship between labor market outcomes, marital behavior, and fertility suggests that a potential negative impact of robots on income (Acemoglu and Restrepo, 2017; Dauth et al., 2018) should reduce marital fertility and favor out-of-wedlock fertility, while the impact on overall fertility is more uncertain, depending on which of the two types of fertility effect prevails. We do not expect, instead, changes in overall labor force participation and employment to affect overall fertility in a specific direction. The preliminary analysis also highlights the importance of studying the impact of robots on labor market outcomes separately for men and women. While lower income for both men and women are predicted to decrease marital fertility and increase out-of-wedlock fertility, changes in labor force participation for men and women have effects of opposite signs on fertility. This is consistent with the idea that higher income (and thus more economic security) is beneficial to fertility independently of its source, while the decision of women to participate (or to increase participation) might reduce fertility. Finally, our preliminary evidence shows a clear relationship pattern between the gender gap in all three labor market outcomes and fertility. If robots lower the gender gaps in income, labor force participation and employment by substituting workers in the male-dominated manufacturing sector and boosting the creation in more gender-neutral service sectors (as discussed in our theoretical framework), we should expect a drop in marital fertility and an increase in out-of-wedlock fertility.

In Table 4, we move to exploring the direct effect of robot exposure on our three labor market outcomes: income, labor force participation and employment. We use the identification strategy described in the Empirical Strategy section. Panel A Columns 1-3 show the impact of robot exposure on income estimated with our OLS specification (Column 1), by regressing our outcome directly on our instrumented exposure (Column 2) and with our two-stage-least-square estimation (Column 3). Focusing on the IV estimate of Column 3, we find that a 1 standard deviation increase in robot exposure decreases income by 6.8 percent. The effect for the IV estimate is marginally larger than for the OLS estimate. This is not surprising since we expect the OLS estimates to be biased downward by the pro-ciclicality of robot adoption, that is more robots are installed in period of economic growth, which are also associated with better labor market outcomes on average. Columns 4-6 show instead no effect of robot exposure on labor force participation, while Columns 7-9 report a positive effect on 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., 2018). Our positive employment estimate complements the empirical evidence in Acemoglu and Restrepo (2017). While their work focus on the on-set of robotics up to the great recession (1993-2007 period), our evidence captures the impact of robotics on the more recent period (2005-2016), including the years of post-recession economic recovery. Our results thus 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 in the long run.

On the one hand, based on our evidence on the effects of robot exposure on overall labor market outcomes, it is hard to predict the effect of robot exposure on fertility: while we should expect a large negative impact on income to reduce fertility for workers, the increase in employment – albeit small in magnitude – might reduce economic uncertainty for those who gained employment. On the other hand, the evidence on the heterogenous effects of robot exposure on labor market outcomes by gender has clear and interesting predictions.

In Table 4 Panel B, we therefore turn to studying the effect of robot exposure on labor market outcomes separately for men, women and for the gender gap in those same outcomes. Columns 1-3 show that the effect of robots on male income (-8.3%, see column 2) is substantially larger than that on female income (-4.3%, see column 1). This drives the gender income-gap (defined as the ratio between male and female income) down by 4% in areas that were more exposed to robots penetration.[4] In Columns 4-6, we provide the corresponding results of robot exposure on labor force participation. The estimates reported in columns 4 and 5 reveal significant differences between male and female labor force participation. Robot exposure has a negative - albeit not statistically significant - 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% in response to more robot adoption in the US (see column 6). Finally, also the effect on the gender gap in employment is negative, although not statistically significant. These results on the gender gap together with the empirical evidence of 1 -3 deliver clear predictions about the effect of robot exposure on fertility: we should expect a clear negative effect on marital fertility and a positive one for out-of-wedlock fertility. The expected effect on overall fertility is, however, less clear. In the next sections, we test these predictions on fertility, by first focusing on partnership formation as a complementary outcome of our analysis on fertility.

4.2 Effects on Marital Behavior

As described in our theoretical framework section, a decrease in gender gaps should reduce the value of marriage (Wilson, 1987; Becker, 1973). In Table 5 we therefore test the impact of robot exposure on partnership formation, relying on the same identification strategy used for labor market outcomes. Panel A displays the results for marriage, whereas Panel B and C report the estimates for divorce and cohabitation, respectively. As detailed in the Empirical Strategy section, in each regression we include a set of commuting zone-level demographic controls, year and commuting zone fixed effects. The OLS estimate presented in column 1 suggests that one standard deviation increase in robot exposure decreases the probability of being married by 3.2% relative to the mean outcome. In line with the visual evidence (see Figure 5), we detect a negative and highly-significant reduced-form relationship between the robot adoption in Europe

[4]Our results on the gender income-gap differ from recent empirical evidence by Aksoy et al. (2019) for European countries. The authors find that automation has driven the gender earning gap up in Eastern European countries with high baseline levels of gender inequality and that the effect is driven by middle-skill workers. This suggests that the significant negative impact on the gender gap we find may be context specific.

and marriage.[5] The 2SLS estimate in column 3 implies that one standard deviation increase in robot exposure reduce marriage by 4%, confirming the negative impact of robot penetration on marriage. The fact that our IV coefficient is slightly larger in magnitude compared to the OLS coefficient suggests once again that the potential endogenous bias was driven by the prociclicality of robot adoption, that is more robots are installed during periods of economic growth, which are likely correlated with a higher incidence of marriage relative to economic downturns.

When considering instead divorce rates as the dependent variable (see Panel B) we find a positive relationship. The 2SLS coefficient shows that a one standard deviation increase in robot exposure leads to a 5% increase in divorce (see column 3 of Panel B). Considering cohabitation (see Panel C), we find that robot adoption also increases the likelihood of cohabitation.[6] In particular, a one standard deviation increase in robot exposure implies a 13% increase in cohabitation (see column 3 of Panel C). These results are consistent with the hypothesis that the uncertainty of the labor markets and the reduced value of men in the marriage market may have reduced the willingness to a long-run commitment, such as the marriage. They are also highly consistent with the marital and out-of-wedlock fertility patterns presented in the following section.

While the inclusion of CZ fixed effects 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 thus test whether the change in robot adoption captured by our instrumental variable is correlated with commuting zone trends in demographic outcomes that took place already before the advent of robotics. Data on demographic outcomes are drawn from the 1980 and 1990 US Census. We find that the 1980-1990 trends in marital behavior were, if anything, opposite to the patterns observed between 2005 and 2016 (see Table 7, columns 1-3). Furthermore, the coefficients are all relatively small, and statistically significant only for cohabitation (see column 3). Overall, these results lend support to a causal interpretation of the effect of robot exposure on marital behavior.

[5] Notice that relative to Figure 5 the estimated regression has the advantage of exploiting yearly variation and to control for commuting zone fixed effects.

[6] Cohabitation is defined as the likelihood of living with an unmarried partner.

4.3 Effects on Fertility Behavior

In Table 6, 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 exposure on overall fertility rate is very close to zero. However, these zero fertility effects may mask important heterogeneity along two dimensions of the fertility behavior: marital and out-of-wedlock fertility.

Indeed, Panels B and C document opposite trends for marital and out-of-wedlock fertility. Specifically, column 1 of Panel B reports the OLS 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. A one standard deviation increase in the exposure to robots (1.90) is associated with a 10% decrease in marital fertility with respect to the mean outcome (0.037). The reduced-form coefficient displayed in column 2 is very similar to the OLS estimate, suggesting that a one standard deviation increase in robot adoption as measured using data from European countries decreases marital fertility by approximately 6% relative to the mean outcome (see column 2), equivalent to .2 standard deviations. The 2SLS estimate in column 3 is larger than the OLS estimate in absolute value, suggesting that the exposure to robots 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 15%, or .37 standard deviations.

Panel C examines the impact of robot exposure on out-of-wedlock fertility. The OLS and reduced-form estimates imply that a one standard deviation increase in robot exposure raises out-of-wedlock fertility by 10% (see columns 1 and 2). The 2SLS estimate is larger in absolute value and indicates that a one standard deviation increase in robot exposure leads to a 20% increase in out-of-wedlock fertility.

Reassuringly, columns 4-7 of Table 7 further corroborate the causal interpretation of the estimates, since the 1980-1990 trends in fertility behavior are not correlated with exposure to robots, as measured by our instrumental variable. Specifically, we find no evidence of pre-trends in marital fertility, and, if anything, a negative (opposite) trend in out-of-wedlock fertility.

5 Conclusion

The impact of automation, robots and artificial intelligence on labor markets is likely to produce fundamental shifts on our daily lives. A handful of pioneering studies has examined the impact of robots on labor markets (Acemoglu and Restrepo, 2019; Graetz and Michaels, 2018). Yet, we know little about the ways in which 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. We show that robots penetration has different effects on the labor market opportunities of men and women, reducing the gender-gap in income. Robot penetration has substantially lowered income, but had small positive effects on overall employment rates. Importantly, our analysis shows that the impact on economic uncertainty was highly heterogenous across gender. Male income fell at substantially higher rate than female income, decreasing the gender income gap. Moreover, robot exposure has increased female labor force participation substantially, while leaving the labor force participation of men unchanged. These effects contribute to explain the impact of robot penetration on family formation and fertility outcomes. We find that in areas that were more exposed to robots penetration, marriage rate decreased, while divorce rates and cohabitation increased. We then show that exposure to robots reduced marital fertility, but increased the fraction of children born out-of-wedlock.

We argue that robots have increased uncertainty associated with the labor market conditions for most workers and has substantially lowered the economic value of men on the marriage market. This in turn has contributed to reduce willingness to long-term commitments, such as marrying. At the same time, the lower value of men has increased the value of out-of-wedlock fertility options for women and the probability that children grow-up in cohabitating households.

Given the concerns that cohabitation may reduce children's well-being (Manning, 2015), developing more encompassing family policies that cover more homogenously married and cohabitating couples could be a natural response to the effects of robotics on life-course choices. Future research exploiting longitudinal data or matched employer-employee data may shed further light on these mechanisms and on the impact of children's well-being.

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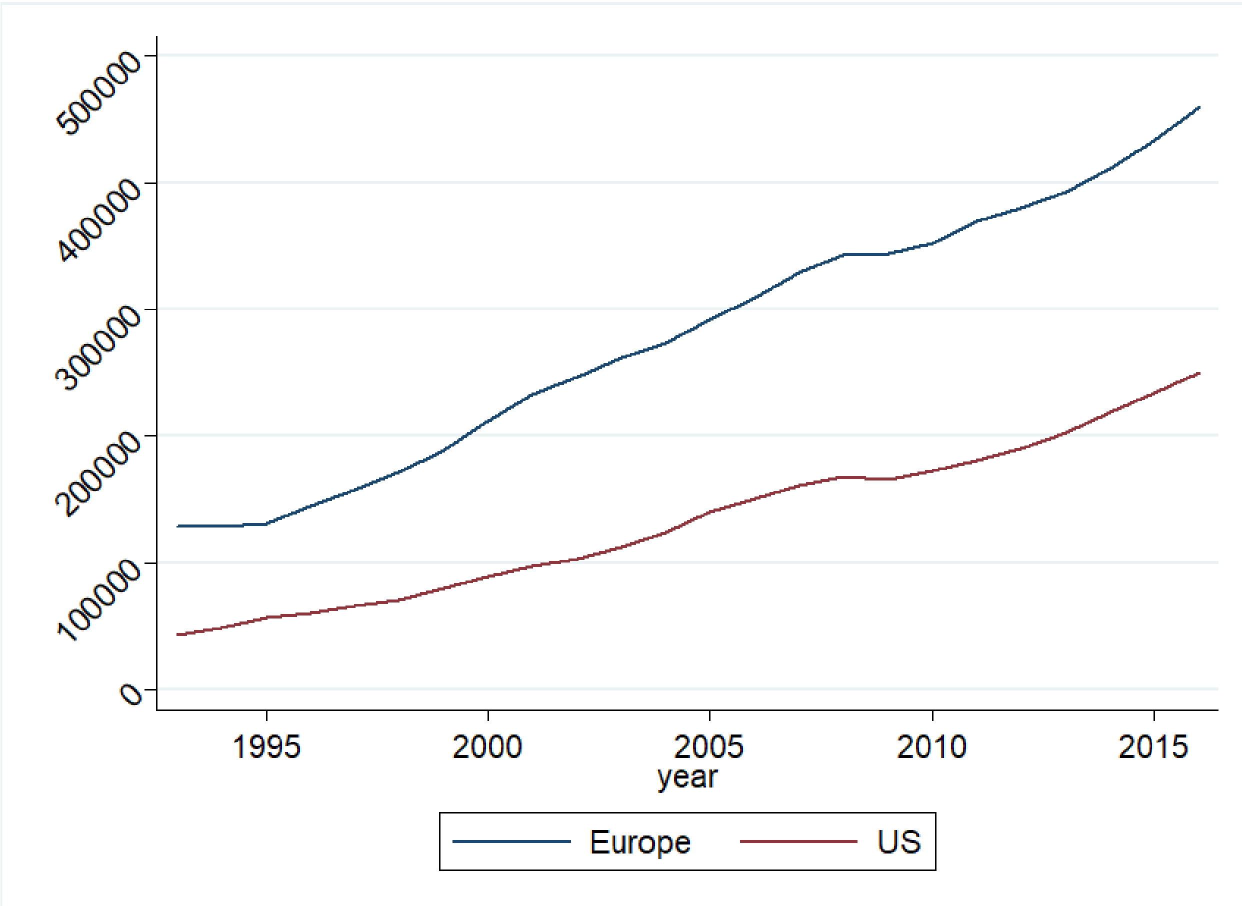
Figures

Figure 1: Industrial Robots in the US and Europe

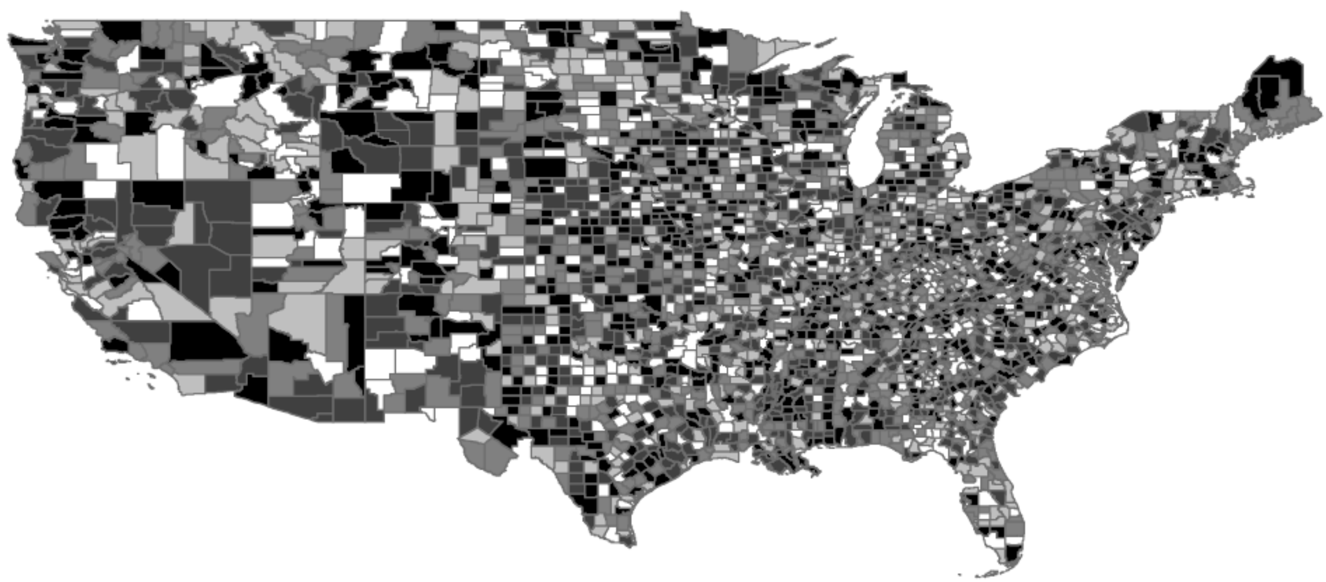


Notes - Data are drawn from the International Federation of Robotics.

Figure 2: Robots per 1000 workers in the US

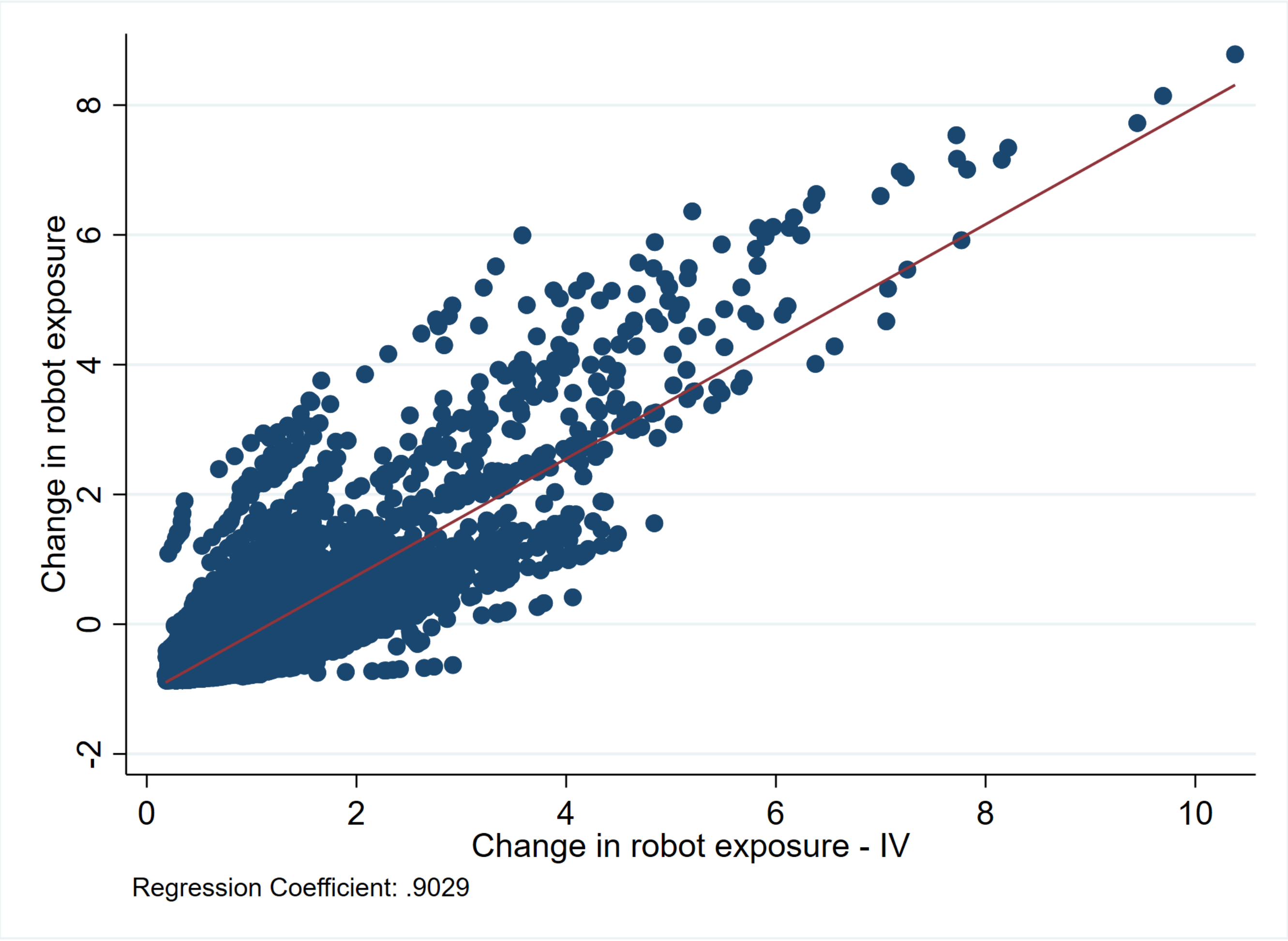
Notes - Data are drawn from the International Federation of Robotics.

Figure 3: Industrial Robots across US Commuting Zones, $\Delta_{2004-2016}$



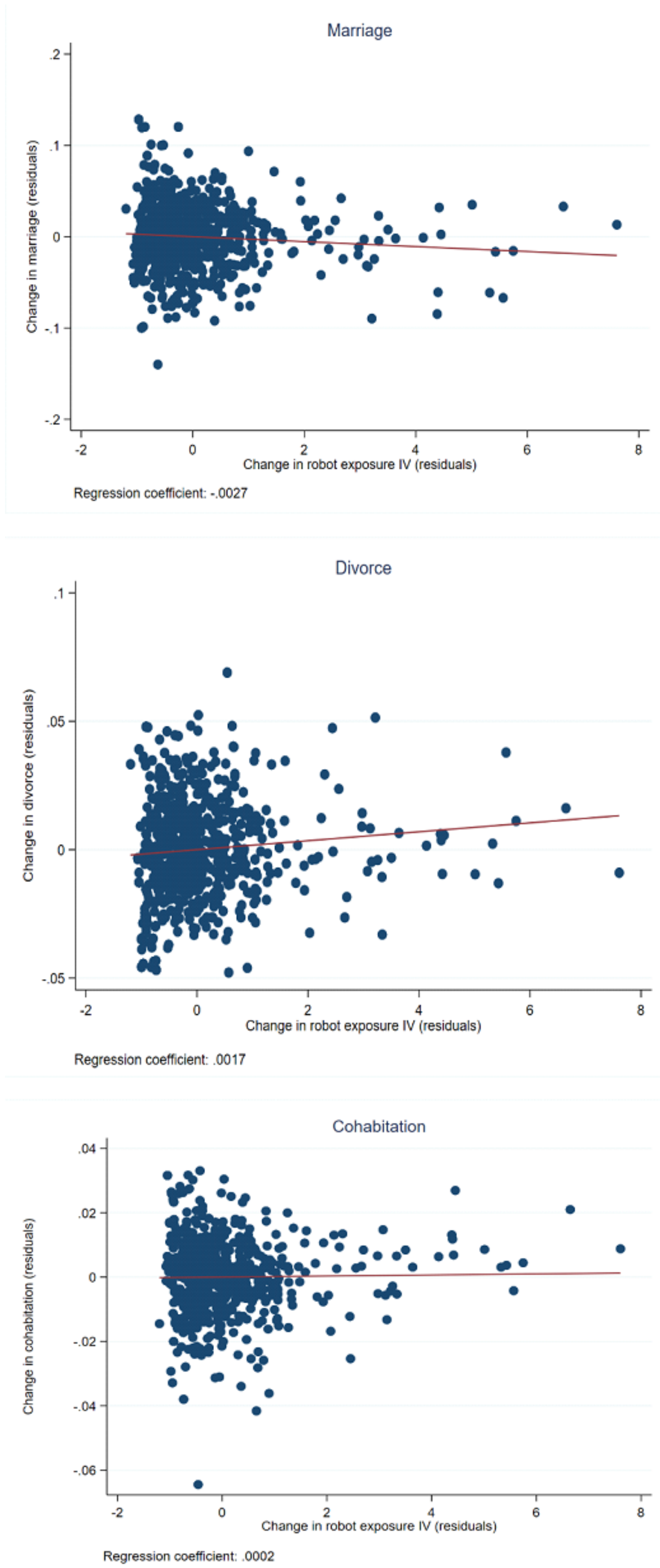
Notes - Data are drawn from the International Federation of Robotics.

Figure 4: First Stage: Change in Robot Exposure in the US and Exposure to Robots in Europe



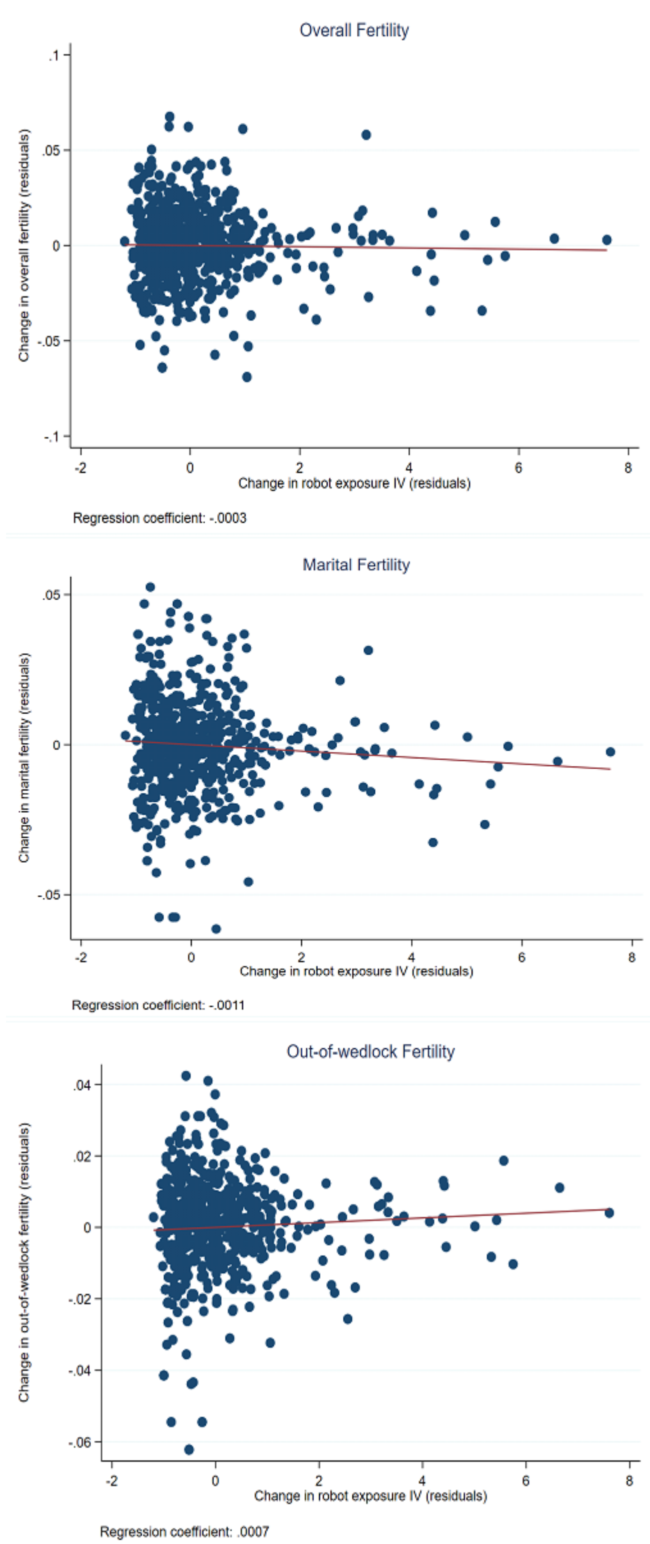
Notes - Data are drawn from the International Federation of Robotics.

Figure 5: Reduced Form: Change in Marital Behavior and Robot Exposure (IV) - Residuals



Notes - Data on robot penetration are drawn from the International Federation of Robotics. Data on marital behavior are drawn from the American Community Survey (2005-2016).

Figure 6: Reduced Form: Change in Fertility Behavior and Robot Exposure (IV) - Residuals



Notes - Data on robot penetration are drawn from the International Federation of Robotics. Data on fertility behavior are drawn from the American Community Survey (2005-2016).

Tables

Table 1: Effects of Income on Marital and Fertility Behavior - OLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:					Fertility	
	Marriage	Divorce	Cohabitation	Overall	Marital	Out-of-wed
Income - All	0.095***	-0.009***	0.004**	0.005*	0.018***	-0.010***
	(0.006)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Income - Women	0.037***	0.009***	0.004***	0.004	0.008***	-0.004**
	(0.005)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Income - Men	0.074***	-0.013***	0.002	0.003	0.013***	-0.008***
	(0.004)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Income - Gender gap	0.025***	-0.014***	-0.001	-0.001	0.003**	-0.003**
	(0.003)	(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
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 (average age 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 2: Effects of Labor Force Participation on Marital and Fertility Behavior - OLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:					Fertility	
	Marriage	Divorce	Cohabitation	Overall	Marital	Out-of-wed
LFP - All	0.183***	-0.000	0.045***	0.006	0.009	-0.001
	(0.017)	(0.009)	(0.005)	(0.010)	(0.008)	(0.007)
LFP - Women	0.011	0.017**	0.023***	-0.011	-0.019***	0.012**
	(0.012)	(0.007)	(0.004)	(0.008)	(0.006)	(0.006)
LFP - Men	0.191***	-0.017**	0.026***	0.019**	0.030***	-0.013***
	(0.012)	(0.007)	(0.004)	(0.008)	(0.006)	(0.005)
LFP - Gender gap	0.063***	-0.014***	-0.000	0.011**	0.018***	-0.009***
	(0.006)	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)
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
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 (average age 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 3: Effects of Employment on Marital and Fertility Behavior - OLS Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:					Fertility	
	Marriage	Divorce	Cohabitation	Overall	Marital	Out-of-wed
Employment - All	0.206***	-0.026***	0.036***	-0.011	0.007	-0.016**
	(0.015)	(0.008)	(0.005)	(0.010)	(0.007)	(0.006)
Employment - Women	0.033***	0.006	0.022***	-0.015**	-0.015***	0.003
	(0.012)	(0.006)	(0.004)	(0.008)	(0.005)	(0.005)
Employment - Men	0.192***	-0.033***	0.020***	0.002	0.021***	-0.020***
	(0.010)	(0.006)	(0.004)	(0.007)	(0.005)	(0.004)
Employment - Gender gap	0.060***	-0.015***	-0.001	0.005	0.013***	-0.008***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
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
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 (average age 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 4: 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	-0.041***		-0.068***	0.003		0.004	0.023***		0.026***
	(0.010)		(0.013)	(0.003)		(0.004)	(0.003)		(0.004)
Robot exposure IV		-0.039***			0.002			0.015***	
		(0.008)			(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	0.0603	0.0603	0.0603	0.0730	0.0730	0.0730
First stage F-statistic			607.4			607.4			607.4
Observation	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 gap				
	Females	Males	Gender gap	Females	Males	Gender gap	Females	Males	Gender gap
Robot exposure	-0.043***	-0.083***	-0.040***	0.012***	-0.004	-0.021***	0.029***	0.023***	-0.009
	(0.013)	(0.016)	(0.014)	(0.004)	(0.005)	(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	2,480	0.0624	0.0687	0.0783	0.0730	0.0823	0.0889
First stage F-statistic			607.4			607.4			607.4
Observation	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 (average age 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 5: Effects of Robot Exposure on Marital Behavior

	(1) OLS	(2) Reduced form	(3) 2SLS
Panel A: Marriage			
Robot exposure	-0.013***		-0.016***
	(0.004)		(0.005)
Robot exposure - IV		-0.009***	
		(0.003)	
Mean of dep. var.	0.412	0.412	0.412
Std. dev. of dep. var.	0.0612	0.0612	0.0612
First stage F statistic			607.4
Panel B: Divorce			
Robot exposure	0.004**		0.005***
	(0.002)		(0.002)
Robot exposure - IV		0.003***	
		(0.001)	
Mean of dep. var.	0.0986	0.0986	0.0986
Std. dev. of dep. var.	0.0213	0.0213	0.0213
First stage F statistic			607.4
Panel C: Cohabitation			
Robot exposure	0.002*		0.005***
	(0.001)		(0.001)
Robot exposure - IV		0.003***	
		(0.001)	
Mean of dep. var.	0.0398	0.0398	0.0398
Std. dev. of dep. var.	0.0120	0.0120	0.0120
First stage F statistic			607.4
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 (average age 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 6: Effects of Robot Exposure on Fertility Behavior

	(1) OLS	(2) Reduced form	(3) 2SLS
Panel A: Overall Fertility			
Robot exposure	-0.000		0.001
	(0.002)		(0.002)
Robot exposure - IV		0.001	
		(0.001)	
Mean of dep. var.	0.0594	0.0594	0.0594
Std. dev. of dep. var.	0.0180	0.0180	0.0180
First stage F statistic			607.4
Panel B: Marital Fertility			
Robot exposure	-0.003***		-0.005***
	(0.001)		(0.001)
Robot exposure - IV		-0.003***	
		(0.001)	
Mean of dep. var.	0.0337	0.0337	0.0337
Std. dev. of dep. var.	0.0135	0.0135	0.0135
First stage F statistic			607.4
Panel C: Out-of-Wedlock Fertility			
Robot exposure	0.002**		0.004***
	(0.001)		(0.001)
Robot exposure - IV		0.002***	
		(0.001)	
Mean of dep. var.	0.0196	0.0196	0.0196
Std. dev. of dep. var.	0.0116	0.0116	0.0116
First stage F statistic			607.4
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 (average age 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 7: Placebo Test: 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	Out-of-wedlock fertility
Robot exposure IV	-0.001	0.000	-0.002***	-0.000	0.000	-0.001**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Mean of dep. var.	-0.0549	0.0195	0.0189	-0.0169	-0.0279	0.00482
Std. dev. of dep. var.	0.0237	0.00982	0.00656	0.0112	0.0156	0.00803
Observations	741	741	741	741	741	741

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

Appendix A: Supplemental Tables

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

	Mean	Standard deviation	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	32.620	0.894	27.786	34.987
Female	0.489	0.018	0.391	0.557

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

Table A.2: First Stage: Effects of Robot Exposure IV on Robot Exposure in the US

	(1)
Dep. var.:	Robot exposure
Robot exposure - IV	0.567***
	(0.023)
Mean of dep. var.	-0.0546
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 (average age adn 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.