Automation and Family: Marriage, Divorce, and Fertility Rates

Honors Thesis

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I exploit variation in the job composition of US local labor markets to determine how automation affects familial outcomes from 1980 to 2019 and look at employment, marriage, divorce, and fertility rates as outcomes. Following previous work, I use historical prevalence of routine jobs to measure exposure to automation. I find that individuals susceptible to automation are more likely to become unemployed from 2000 to 2010; however, from 2010 to 2019 these individuals are more likely to become employed and work comparatively more hours. Fertility rates correlate with marriage rates; the results show higher fertility and marriage rates from 1990 to 2000 in local labor markets susceptible to automation, but this trend shifts from 2000 to 2019 as fertility and marriage rates become relatively lower. Moreover, I find that women in areas most susceptible to female-specific automation are more likely to experience lower marriage rates and are simultaneously are more likely to leave the labor force. This finding is correlated with higher fertility rates for women but is not correlated with the fertility rates of men, which may suggest that many women susceptible to automation are becoming single mothers and dropping out of the labor force.

I. Introduction

Two of the biggest forces impacting labor markets in recent decades have been automation and international trade. Autor, Dorn, and Hanson (2019) study the effects of Chinese trade shocks on familial outcomes such as marriage and fertility and overall find that trade shocks found to reduce relative male earnings reduce marriage and fertility rates for men and raise the share of mothers who were unwed and living below the poverty line. However, adverse shocks to female employment result in relatively higher marriage rates.

While many researchers contribute to a large literature detailing labor market consequence of automation, to my knowledge there does not yet exist literature that details the potential familial consequences of automation, such as marriage, divorce, and fertility rates. This is of particular importance given automation's ever-increasing relevance in that global marketplace, with worldwide revenue due to automation is expected to grow by 15% from 2019 to 2021.[1] Such a study is incredibly relevant given the astonishing and rapid technological advances that have occurred in recent decades and will no doubt continue to occur in the decades to come. As the deployment of technology through automation becomes a cheaper source of labor for companies than the employment of workers, we must consider the potential implications.

Labor force displacement as a result of automation is debatable. Some scholars would argue that workers displaced by automation will find new jobs and prosper from the opportunities that arise from the advancement of very technology that initially displaced them. On the contrary, others would argue that technological automation will create mass unemployment that cannot easily be remedied. I expect the actual effect of automation to fall somewhere in the middle of the two theories—it may take a few decades for the initial displacement to be alleviated by the creation of new jobs.

Automation traditionally replaces labor in "middle-skilled" occupations, characterized by repetitive, routine tasks. This can lead to income inequality and employment polarization through greater concentration in both the upper- and lower-class jobs as middle class jobs disappear. Familial consequences may arise due to this change in labor markets. These consequences may also differ between men and women given that employment changes because of Chinese trade shocks affected men and women differently. Because men have traditionally assumed the role of breadwinners for their families, when they become displaced from the labor market, they may become less attractive as a potential marriage partner. However, when women become displaced from their jobs, they may be more likely to engage in marriage and become homemakers and caregivers of children. This theory derives from Becker (1973), which suggests that shocks to

[1] https://www.statista.com/statistics/257170/global-automation-market-revenue-by-end-market/

employment of the lower-earning spouse (which historically has been women) allows for increased gender-based specialization in the household. However, as societal norms and gender equality progress, this theory may decrease in relevance.

Overall, I find that both men and women in commuting zones more susceptible to automation (CZSAs hereafter) are displaced from routine-task labor at higher rates from 1980 to 2019. This shift is most prevalent from 1990 to 2010. From 2000 to 2010, unemployment rates for men and women are comparatively higher in CZSAs and both genders report working less hours during this decade when looking at commuting zones affected by gender-specific automation shocks. From 2010 to 2019, men and women affected by automation are more likely to become employed, and as one would expect, both reportedly work more hours during this decade. As a result, there is a large shift into abstract-task labor from 2000 to 2019 for both men and women in CZSAs (examples of abstract-task roles are those in managerial, professional, and technical occupations). Marriage rates are comparatively higher in CZSAs from 1990 to 2000 but lower between 2000 and 2019. As expected, fertility rates correlate with marriage rates; fertility rates are relatively higher from 1990 to 2000 and fall between 2000 and 2019 in CZSAs. As such, the combination of comparatively greater employment in abstract-task labor from 2000 to 2010 and higher employment rates from 2010 to 2019 likely contributes to the relatively lower marriage and fertility rates from 2000 to 2019. If both men and women in CZSAs are more likely to be employed in higher paying jobs with longer hours from 2000 to 2019, marriage unions may be less likely and fertility rates may be comparatively lower as well. When exploring how automation affects men and women differently, my results show that women in CZSAs experience higher fertility rates from 2000 to 2019 (as compared to women in CZs not susceptible to automation, or CZNSAs), whereas men in CZSAs experience comparatively lower fertility rates over the same period. The higher female fertility rates coincide with women leaving the paid labor force from 1980 to 2010 and may suggest that many of these women in CZSAs are single mothers staying home to take care of children, since men in the same CZSAs do not experience the same comparatively high fertility rates and do not drop out of the labor force at the same rates. However, further analysis would be required to definitively conclude this, and this is beyond the current scope of this paper.

II. *Literature Review & Theory*

Autor, Dorn and Hanson (2019) analyze the gender-specific employment effects of Chinese-US trade shocks on marriage, fertility, and child living circumstances. The study finds that "a fall in relative economic stature of men [due to trade shocks] …reduces the prevalence of marriage, while a decline in women's economic opportunities has the opposite effect." These two trends are also seen through fertility rates: improvements in men's labor market are associated with an increase in fertility, while improvements in women's labor markets are associated with the opposite.

Autor, Dorn and Hanson (2015) show that because of automation, a reduction in routine-occupation employment for women largely translates to an overall decline in the share participating in the labor force. Moreover, Autor, Dorn and Hanson (2015) also find that as men move out of routine-occupation roles, there is an increase in male employment in abstract roles, which are roles that generally offer higher pay than routine roles and cannot readily be automated. Both of these trends might correlate with higher fertility rates in CZSAs if one parent is able to stay home and take care of children while the other parent earns comparatively more than in previous years.

If automation leads to higher fertility rates and greater male employment in abstract roles, it may also lead to lower divorce rates and higher marriage rates in CZSAs. Women who have dropped out of the labor force to work in the home after being displaced from their routine roles may have less bargaining power to divorce their husbands, given that they are no longer being paid for their labor, as seen through the Nash bargaining model as explained by Binmore et al (1986). This is reasonable to assume, as it is in line with the findings of Blau et al (2000), in that worse female labor markets and better male labor markets both correlate with higher marriage rates. The predicted decrease in divorce rates in CZSAs might suggest that a higher percentage of women are remaining in unhappy marriages because they are financially dependent on their husband, as a result of losing their jobs to automation. Although marriage satisfaction is not measurable, this potential implication should not be ignored.

Given that I analyze data from multiple decades (1980 to 2019), the effect of automation may change over time, especially in recent decades if new job market opportunities arise from the very technology that initially created job displacement. The use of data from more recent years is a key advantage for this study in relation to potentially similar studies or Autor's previous work. Moreover, previous studies detailing the effects of automation focus on labor force effects, so I add to the existing literature by focusing instead on the impacts on families through marriage, divorce, and fertility rates.

III. Data

Following Dorn, Autor, and Hanson (2015), I use decennial census data from 1980 to 2000 as well as ACS data for 2007 to 2019 from IPUMS, collapsed from the individual level into commuting zones (CZs) to approximate local labor markets. In doing so, I compare outcomes in

CZs that are likely to be affected by automation at different rates, given the relative proportion of individuals working in routine-task roles. As such, I specifically compare the CZ share of employment in occupations within the top third of routine task intensity[2] (CZSAs) to the CZs share of employment within the bottom two-thirds (CZNSAs). A commuting zone's initial share of employment in routine-task roles is a good proxy for automation, as jobs with a large proportion of routine-tasks are more likely to be replaced by automation. The geographical sorting of data was achieved by connecting county groups (in 1980) and PUMAs (public use microdata areas, from 1990 to 2019) to respective CZs, using Autor and Dorn's 2013 crosswalk files. These CZs were initially constructed by Tolbert and Sizer (1996), by analyzing county-level data to create 741 clusters of counties that have strong commuting ties within the cluster but weak commuting ties between the clusters. Following Autor and Dorn (2013), I use 722 of these CZs, which span across the continental United States.

I also use another one of Autor and Dorn's datasets (2013), which takes occupation codes and attributes values of 0-10 for the share of routine, manual, and abstract labor of each job. To determine the degree to which CZs have exposure to routine-task employment, I use Dorn's crosswalk file to sort individual occupational codes from the Dictionary of Occupational Titles into three categories: abstract-task, routine-task, and manual-task labor.

I specifically look at employment, marriage, divorce, and fertility rates. Thus, I create dummy variables for these outcomes (and create gendered versions of these variables as well) and collapse the data down from the individual level down to the commuting zone level to compute the average rate for each commuting zone. I then create variables that measure the change in rates

[2] Routine Task Intensity (RTI) is fully described on pages 7-8.

per decade for each variable, by commuting zone, by subtracting the previous decade's rate from the current decade of focus and will do this across all years.[3]

IV. Empirical Strategy

I analyze the impact of automation (in general, as well as gender-specific automation shocks) on marriage, divorce, and fertility rates. I leverage variation across CZs using share of routine jobs at beginning of the period, to approximate a commuting zone's likelihood of being exposed to automation. In accordance with Autor and Dorn (2013), I focus on changes in routine-task employment across 722 CZs that approximate local labor markets, of which span across the continental United States.

First, I create a dummy variable that indicates whether a given individual's "score" is considered within the top third of routine-task occupations. This is necessary, as occupations that mostly consist of routine tasks are the most susceptible to become automated. In doing so, when I collapse the data at the commuting zone level, each commuting zone has a ranking based on the prevalence of individuals in that commuting zone that engage in routine employment.

Like Autor, Dorn, and Hanson (2019) I categorize labor into three categories: routine-task, abstract-task, and manual-task labor. Routine-task jobs are those that are repetitive in nature and are thus most susceptible to automation, such as in retail, production, and clerical roles. Abstract-task roles encompass those in managerial, professional, and technical occupations, whereas

[3] Specifically, I use data from the following years: 1980, 1990, 2000, 2007, 2012, and 2019. I had intended to use 2010 in order to continue the trend of using the decennial census, but instead chose to weigh 2007 and 2012 in equal proportions (each makes up 50%) to create a pseudo-2010. This was intentional because 2010 was during the heat of the Great Recession, which could have otherwise clouded my results had I included it. So, taking an average of 2007 and 2012, which occurred before and after the Great Recession, respectively, seemed more appropriate. Moreover, I use 2019 instead of 2020 because 2020 data was not yet available at the onset of this project and also because the COVID-19 pandemic may have clouded results.

manual-task roles include those in craft, mechanics, agricultural, and service occupations. To determine the degree of routinization for any given occupation, I follow Autor and Dorn in using their measure of routine-task intensity, as defined by:

$$RTI_k = \ln(T^R_{k,1980}) - \ln(T^M_{k,1980}) - \ln(T^A_{k,1980}),$$

where $T^R{}_k$, $T^M{}_k$, and $T^A{}_k$ are the routine, manual, and abstract-task inputs for each occupation k, as of 1980. In accordance with Autor and Dorn, I define routine occupations as those that fall within the top third of the routine-task intensity scale. At the commuting zone level, this translates to the routine employment share measure (RSH_{jt}), which is a fraction that shows the relative routine-task commuting zone employment at the beginning of the period:

$$RSH_{jt} = \left[\sum_{k=1}^{K} L_{jkt} \times 1(RTI_k > RTI^{P66})\right]\left(\sum_{k=1}^{K} L_{jkt}\right)^{-1}.$$

Here, L_{jkt} is the employment in occupation k in commuting zone j at time t, while the $1(RTI_k > RTI^{P66})$ is the indicator function that takes a value of one if the occupation is within the top 33 percent of routine occupations but takes a zero otherwise. I also create gender-specific routine employment share measures—the construction is mostly the same, except it includes an indicator function that is specific to an individual's gender. For the female version, $L_{jkt} \times 1(RTI_k > RTI^{P66})$ is multiplied by one if the individual is female and zero if the individual is male. For the male version, $L_{jkt} \times 1(RTI_k > RTI^{P66})$ is multiplied by one if the individual is male and zero if the individual is female.

While I am solely interested in the routine employment share in a given commuting zone and how it may change over time due to automation, the current construction of RSH_{jt} may also incorporate other unobserved shifts that could impact a CZ's routine occupation share through other means than automation. Autor and Dorn acknowledge this and provide the example of a hypothetical “cyclical spike in demand for a CZ’s manufacturing outputs, which draws low-skilled workers temporarily from services into manufacturing” (Autor and Dorn, 2013). This would inflate RSH_{jt} for the start of the period and would bias the OLS estimate of β_1 in the previous equation by allowing a positive relationship to form between the start of the period *RSH* and subsequent changes in *RSH* that are not related to automation.

As such, I follow Autor and Dorn (2013) in creating an instrument that isolates long-run, partially fixed element of the routine occupation share. $E_{i,j,1950}$ is the employment share of industry i in commuting zone j in 1950 and $R_{i,-j,1950}$ is the routine occupation share among workers in industry i in 1950 across all US states, excluding the state(s) the commuting zone is in. The product of these two variables summed across industries is the predicted value of routine employment share in each CZ, based on the local industry composition in 1950 and the structure of industries in nationally in 1950:

$$\widetilde{RSH}_j = \sum_{i=1}^{I} E_{i,j,1950} \times R_{i,-j,1950}.$$

Because this instrument is created three decades prior to the rapid computerization of the 1980’s, I expect it should be correlated with long-run routine occupation share (RSH) but uncorrelated with other coexistent changes unrelated to automation.

However, I also acknowledge the 1950 instrument’s limitations given that it is nearly 70 years from 2019, which is when our dataset concludes. A lot can change in 70 years, so the 1950 instrument has limited applicability to more recent years of the data. As such, I create a second instrument using 1980 as a base year instead of 1950. The 1980 instrument cannot be used as an instrument in the year 1980 but may serve as a more effective instrument between 1990 to 2019. In this study, unless otherwise specified, I use the 1980 instrument.

Further, I wanted to explore how automation that targets men and women differently (male-specific or female-specific automation) might affect our outcome variables for both men and women. As such, I created a gender specific IV strategies using 1980 as the base year, outlined as:

$$\widetilde{RSH}_{F,j} = \sum_{i=1}^{I} F_{i,j,1980} \times E_{i,j,1980} \times R_{i,-j,1980}$$

and

$$\widetilde{RSH}_{M,j} = \sum_{i=1}^{I} (1 - F_{i,j,1980}) \times E_{i,j,1980} \times R_{i,-j,1980}.$$

Like the non-gendered instrument, $E_{i,j,1980}$ is the employment share of industry *i* in commuting zone *j* in 1980 and $R_{i,-j,1980}$ is the routine occupation share among workers in industry *i* in 1980 across all US states, excluding the state that includes commuting zone *j*. The product of these two variables is the predicted value of routine employment share in each CZ, solely dependent on the local industry composition in 1980 and the structure of industries in nationally in 1980. For the female instrument, I include $F_{i,j,1980}$, which is the share of women in industry *i* in commuting zone *j* in 1980. The male instrument is similar, except I multiply the predicted value of routine employment share in each CZ by $(1 - F_{i,j,1980})$.

Estimation Equation

I now shift to the impact of automation on local labor markets. In further accordance with Autor and Dorn, I construct the following estimation equation:

$$\Delta Y_{jkt} = \gamma_t + \beta_1 RSH_{jt} + X'_{jt}\beta_2 + \delta_k + e_{jkt}.$$

Here, the dependent variable ΔY_{jkt} shows the decadal change in an outcome of interest, which might be the employment-, unemployment-, non-participation-, marriage-, divorce-, or fertility-to-population rate for adults aged 16 to 64, in commuting zone j in decade t and census division k. The main independent variable is RSH_{jt}, which is the CZ-level, start of the decade routine employment share. The independent variable is instrumented in the 2SLS models through the use of the 1980 predicted routine share instrument, described on page 9. In some instances, I use the gender specific RSH_{jt} independent variables. Moreover, I also include time-period fixed effects γ_t, census division indicators δ_k that allow for employment trends to differ across divisions, and my control variables X_{jt} that account for beginning of decade demographics.[4] These regressions are weighted by the CZ share of the total US mainland population at the start of a period and standard errors are clustered by state.

V. Results

One standard deviation for the routine share of all individuals is around 3 percentage points and this remains consistent across decades. For men specifically, one standard deviation is close to 3.5 percentage points and for women one standard deviation is close to 2.5 percentage points. Thus, I multiply 3 points by the coefficient on my outcome of interest to better contextualize and analyze my findings, and I refer to this as a "one unit automation shock." Moreover, given that the 1980 predicted routine share instrument is preferred over the 1950 version, I only analyze from 1990 to 2019 when referring to my 2SLS results given that the 1980 instrument is not applicable in the decade from 1980 to 1990.

[4] These demographics include race as well as share of individuals that are college educated and foreign born.

Employment Status

The results suggest relatively lower employment from 1980 to 2010—this effect is greatest from 2000 to 2010 as a one-unit automation shock predicts lower employment by 1.65%. I calculate this by multiplying -0.551 (found in the fourth row of the second column in Table 4) by 0.03 (a one-unit automation shock). This is reflected by a relatively higher share not participating in the labor force (from 1980 to 2010) as well as a higher share of unemployed (from 2000 to 2010). From 2000 to 2010, a one-unit automation shock predicts higher unemployment by 0.82% and a higher share not participating in labor force by 0.83%.

I find that from 1980 to 2010, women are more likely to shift from being employed to not participating in the labor force. This shift is quite large, as a one-unit automation shock for women is associated with a 1.01% relative decrease per decade in the share of women employed and an average relative increase in the share not participating in the labor force by 0.81%. Moreover, from 2000 to 2010, I also predict relatively higher women's unemployment—a one-unit automation shock for women predicts relatively lower employment by 1.52%, relatively higher unemployment by 0.70%, and a relatively higher share of those not participating in the labor force by 0.82%. From 2010 to 2019, this trend reverses and women are more likely to become employed instead of not participating in the labor force/being unemployed, although this shift is not very large or statistically significant—a one-unit automation shock predicts relatively higher employment of 0.16%.

The employment shifts for men are much less clear and do not show incredibly strong patterns across decades. Table 4 shows male employment increasing from 1980 to 2000 although this shift is very small and not statistically significant. From 2000 to 2010, men affected by automation are more likely to shift out of employment into unemployment or not participating in the labor force—a one-unit automation shock predicts relatively lower employment by 1.78% and relatively higher unemployment and share not participating in the labor force by 0.94% and 0.84%, respectively. From 2010 to 2019, men affected by automation are more likely to become employed—a one-unit automation shock predicts an increase in employment for men by 0.51%.

Hours Worked

With regards to hours worked, the results are noisy and generally not statistically significant for the 2SLS regressions. From 1990 to 2000, both the OLS and 2SLS results predict that women worked fewer hours while men worked more when impacted by automation. This is likely because women susceptible to automation are more likely drop out of the labor force, thus we might expect them to have worked fewer hours. The OLS results predict that individuals affected by automation worked fewer hours per year from 2000 to 2010. From 2010 to 2019, the OLS estimates predict a relative increase in number of hours worked per year as a result of automation.

When looking specifically hours worked by gender and by whether the automation is male- or female-specific, the results become more convoluted. Specifically for individuals in areas susceptible to male-specific automation, the 2SLS results suggest that men work comparatively more hours from 1990 to 2000 and from 2010 to 2019, although this is only statistically significant from 1990 to 2000. On the contrary, the exact opposite is true for women in in areas susceptible to male-specific automation, as they work comparatively fewer hours from 1990 to 2000 and from 2010 to 2019.

For individuals in areas susceptible to female-specific automation, only the decade from 1990 to 2000 is statistically significant when looking at the 2SLS results. Interestingly, in these areas, men are more likely to work more hours from 1990 to 2010 as compared to men in areas not affected by automation, whereas women are more likely to work comparatively less hours during the same time. From 2010 to 2019 this trend reverses, as women affected by automation are more likely to work more hours than their counterparts not affected by automation, whereas men affected by automation are more likely to work less hours.

Overall, from 2000 to 2010 unemployment for both men and women is comparatively higher in CZSAs, which is likely why both genders reportedly work fewer hours during this time. This trend changes from 2010 to 2019 during when both men and women affected by automation are more likely to become employed, hence the relatively higher number of hours worked for both men in women in commuting zones affected by gender-specific automation.

Occupation Group

As previously stated, automation traditionally replaces routine-task oriented middle-class work, and as a result, may push some workers into either lower-skilled manual occupations or higher-skilled abstract work. Thus, I might expect employment polarization through greater concentration in both the lower-skilled manual and higher-skilled abstract roles as middle-skilled routine labor disappears. With regards to the movements between occupation groups overall, both men and women move out of routine task labor from 1980 to 2019. This shift out of routine-task labor is greatest from 1990 to 2000 and from 2000 to 2010, during which a one-unit automation shock predicts lower routine-task employment of 1.10% and 1.79%, respectively. I calculate this by multiplying -0.367 and -0.595 (found in the eighth and ninth rows of the first column in Table 6, respectively) by 0.03 (a one-unit automation shock). From 1980 to 2010 there are relatively small shifts into manual-task labor, with a one-unit automation shock predicting higher manual-task labor employment of 0.13% for all years. Comparatively, there is a relatively large shift into abstract-task labor from 2000 to 2010, with a one-unit automation shock predicting higher abstract-task employment of 1.67%.

For men, there is a significant shift into abstract labor from 2000 to 2010 and a smaller, but still significant, shift into manual labor from 1980 to 1990 and from 2010 to 2019. As such, a one-unit automation shock predicts a 1.82% increase into abstract labor for men from 2000 to 2010 as well as a 0.83% increase in manual labor employment from 2010 to 2019.

For women there is a similar pattern to men, with a shift into abstract-task labor from 2000 to 2019 and shift into manual-task labor from 1990 to 2010. A one-unit automation shock predicts an increase in abstract employment by 1.48% from 2000 to 2010 and 0.62% from 2010 to 2019. Moreover, a one-unit automation shock predicts a shift into manual-task labor from 1990 to 2000 and from 2000 to 2010 by 0.22% and 0.40%, respectively.

Marriage

Overall, marriage rates are comparatively higher in CZSAs from 1990 to 2000, although this changes from 2000 to 2019 when marriage rates become lower in CZSAs. This is statistically significant for the 2SLS results from 1990 to 2010. A one-unit automation shock predicts a relatively higher marriage rate of 0.41% from 1990 to 2000 and a relatively lower marriage rate of 0.56% from 2000 to 2010. For 1990 to 2000, I calculate 0.41% by multiplying 0.137 (found in the first row of the first column in Table 7B) by 0.03 (a one-unit automation shock). The OLS results largely reflect the 2SLS results from 1990 to 2010. From 2010 to 2019, the 2SLS estimate suggests a very small relative decrease whereas the OLS suggests a small increase, and neither are statistically significant—as such, the effect from 2010 to 2019 is likely very small overall.

The gender-specific results regarding marriage rates are less clear. The 2SLS results are generally not statistically significant and the effect sizes are rather small, and across decades there are many instances in which the OLS results contradict the 2SLS results. The OLS results suggest that male and female marriage rates are relatively lower in CZSAs from 1980 to 1990 although this effect is small—a one-unit automation shock predicts lower marriage rates by 0.03% for women and 0.28% for men. However, marriage rates are comparatively higher for both genders from 1990 to 2000 (a one-unit automation shock predicts higher marriage rates of 0.40% for women and 0.09% for men from 1990 to 2000). For women, marriage rates are comparatively lower from 2000 to 2010 and higher from 2010 to 2019, a predicted 0.48% lower from 2000 to 2010 and a predicted 0.23% higher from 2010 to 2019. The opposite is true for men, as a one-unit automation shock predicts higher marriage rates by 0.06% from 2000 to 2010 and comparatively lower by 0.11% from 2010 to 2019.

In CZs most susceptible to female-specific automation, the 2SLS results suggest relatively lower marriage rates for women from 1990 to 2019, whereas men experience relatively higher marriage rates from 1990 to 2000 and from 2010 to 2019. The effect for both genders is greatest from 2010 to 2019, where a one-unit automation shock for women and men respectively predicts relatively lower marriage rates for women by 7.20% and relatively higher marriage rates for men by 4.06%.

In CZs most susceptible to male-specific automation, the 2SLS results suggest comparatively lower marriage rates for women from 1990 to 2000 and from 2010 to 2019 (although this effect is small), and relatively higher marriage rates from 2000 to 2010. Men experience relatively lower marriage rates for men from 2000 to 2019. For both groups, this effect is most significant from 2000 to 2010, during which a one-unit automation shock would predict relatively higher marriage rates for women of 1.13% and relatively lower marriage rates for men of 0.84%.

Overall, women in CZs affected by female-specific automation shocks experience comparatively lower marriage rates, especially in comparison to women in commuting zones most susceptible to male-specific automation. This is interesting and not expected given that our results contradict those of Autor, Dorn, and Hanson (2019): they find that a decline in women's labor market opportunities generally increases the prevalence of marriage.

Divorce

Overall, divorce rates are lower each decade from 1990 to 2019 in CZSAs and this is statistically significant in each decade, except for from 2000 to 2010. The 2SLS coefficients are similar in magnitude to the OLS coefficients from 1990 to 2010. Using the 2SLS results, the greatest effect is from 2010 to 2019 in that a one-unit automation shock predicts a relatively lower divorce rate by 0.38%. I calculate this by multiplying 0.128 (found in the first row of the third column in Table 8B) by 0.03 (a one-unit automation shock).

For CZs most susceptible to male-specific automation, the 2SLS results show that from 1990 to 2019, a one-unit automation shock predicts relatively higher divorce rates for men and relatively lower rates for women. This effect is strongest from 2010 to 2019—a one-unit automation shock predicts comparatively lower divorce rates by 3.72% for women and relatively higher divorce rates for men by 1.94%. These results are not necessarily what I would expect in that they seem uncorrelated with marriage rates. However, given that men affected by automation are more likely to move into manual-task employment during this time, this may suggest that men become less attractive as marriage partners, thus resulting in a comparatively higher divorce rate for men in CZs susceptible to male-specific automation due to a potential downgrade in employment for men.

For women in CZs affected by female-specific automation, there is a similar pattern from 1990 to 2010 in that divorce rates are higher for women and lower for men. However, from 2010 to 2019, this shifts and divorce rates for women become relatively higher whereas divorce rates for men become relatively lower. The greatest effect is from 2010 to 2019 in that a one-unit automation shock predicts comparatively higher divorce rates for women by 4.71% and comparatively lower divorce rates for men by 3.14%. These results from 2010 to 2019 are the exact opposite of what I find in CZs susceptible to male-specific automation. Given that women affected by automation from 2010 to 2019 are more likely to move into abstract-task employment, women may feel that their relative value in the marriage market has increased due to their employment shift into likely higher-paying roles—this may encourage certain women to divorce their husbands if they are now financially independent and feel that they may be better on their own.

Fertility

In CZSAs, the OLS and 2SLS results suggest higher fertility rates from 1990 to 2000, but this trend shifts from 2000 to 2019 as fertility rates become relatively lower. These results are statistically significant for each decade. Overall, as one might expect, these results positively correlate with the 2SLS estimates for marriage, which predict relatively higher marriage rates from 1990 to 2000 and relatively lower marriage rates from 2000 to 2019. This trend is the strongest from 1990 to 2010 during which a one-unit automation shock predicts a comparatively lower fertility rate of 1.01% from 1990 to 2000 and a relatively higher rate of 1.01% from 2000 to 2010.

For 1990 to 2000, I calculate 1.01% by multiplying 0.338 (found in the first row of the first column in Table 9B) by 0.03 (a one-unit automation shock). This shift from higher to lower fertility rates that occurs starting in 2000 may be due in-part to labor market changes during that time. From 2010 to 2019, there is a shift into employment for both men and women susceptible to automation. As such, a one-unit automation shock predicts a higher rate of employment for men and women by 0.51% and 0.16%, respectively. Moreover, from 2000 to 2019, men and women affected by automation move out of routine-task employment and into abstract-task employment—this trend is the most prevalent from 2000 to 2010 during which a one-unit automation shock predicts a relatively higher employment in abstract-task roles of 1.82% for men and 1.48% for women. If both men and women are more likely to employed in abstract-task employment roles that are potentially more demanding than their previous roles, I might expect fertility rates to decrease as well. A combination of comparatively greater employment in abstract-task labor from 2000 to 2010 higher employment rates from 2010 to 2019 might contribute to the relatively lower fertility rates from 2000 to 2019.

For CZs most susceptible to male-specific automation, the IV results suggest that women overall experience higher fertility rates from 2000 to 2019, whereas men experience lower rates over the same period—this is not statistically significant for any decade. Although the effects are opposite according to gender, the magnitude of the results are similar. A one standard deviation increase in routine share predicts relatively higher fertility for women of 3.74% and relatively lower fertility rates for men of 3.03% from 2000 to 2010. The same holds true from 2010 to 2019, although the magnitude of the effect for both men and women is slightly smaller.

For CZs susceptible to female-specific automation, very similar results to those found in CZs most susceptible to male-specific automation. As such, these results suggest that fertility rates are more affected by automation in general and are not as affected by which gender is specifically affected by the automation. The relatively higher fertility rates for women in CZSAs is likely due to women leaving the paid labor force from 1980 to 2010. There are not similarly high fertility rates for men in CZs susceptible to automation which may suggest that many of these women in CZs susceptible to automation are single mothers. However, further analysis would be required to conclude this, as this is beyond the current scope of this paper.

VI. Conclusion

Overall, I find that both men and women affected by automation are displaced from routine-task labor from 1980 to 2019. From 2000 to 2010, unemployment for men and women affected by automation is comparatively higher, and both genders report working less hours during this decade when looking at commuting zones affected by gender-specific automation shocks; this switches from 2010 to 2019 as men and women are more likely to become employed and both genders work more hours during this decade. This suggests that from 2000 to 2010, automation negatively affected the labor force and replaces jobs, creating mass unemployment in areas most susceptible to automation. However, from 2010 to 2019, individuals that initially experienced displacement by automation saw employment growth, which suggests that they were able to retrain themselves and benefit from new opportunities that arose from the very technology that created the initial displacement.

Moreover, fertility rates correlate with marriage rates, and the results show higher fertility and marriage rates from 1990 to 2000 for individuals affect by automation, but this trend shifts from 2000 to 2019 as fertility and marriage rates become relatively lower. The combination of comparatively greater employment in abstract-task labor from 2000 to 2010 and higher employment rates in general from 2010 to 2019 likely contributes to the relatively lower marriage and fertility rates from 2000 to 2019. If both men and women affected by automation are more likely to be employed in higher paying jobs with longer hours from 2000 to 2019, marriage unions may be less likely, and fertility rates may be comparatively lower as well.

Interestingly, my results for marriage contradict previous work by Autor, Dorn, and Hanson (2019). I predict that women in CZs susceptible to female-specific automation are more likely to experience lower marriage rates and are simultaneously are more likely to leave the labor force, whereas Autor, Dorn, and Hanson find that a decline in women's labor market opportunities (due to the Chinese trade shocks) generally increases the prevalence of marriage for women. Furthermore, the results show that from 2010 to 2019, men in CZs affected by automation are more likely to become employed and are also more likely to work in higher-paying, abstract-task roles. However, I do not see higher marriage rates for men during this decade, which further differs from the findings of Autor, Dorn, and Hanson, who find that positive labor market shocks for men generally result in higher marriage rates for men. This may suggest that there is a difference in the cultural attitudes regarding marriage between the individuals affected by Chinese trade shocks and the individuals affected by automation.

I also discover that from 1980 to 2010, women susceptible to automation are more likely drop out of the labor force, and this shift is rather significant and correlated with higher fertility rates for women but is not correlated with the fertility rates of men. This might suggest that many women susceptible to automation are becoming single mothers and dropping out of the labor force, but further analysis is needed to prove this connection.

VII. Tables

Table 1A—First Stage Estimates for Routine Occupation Share

(Dependent variable: Routine occupation share in CZs in indicated years)

	1980-1990	**1990-2000**	**2000-2010**	**2010-2019**
1950 Industry Mix Measure	0.449***	0.310***	0.252***	0.208***
	(0.0438)	(0.0429)	(0.0460)	(0.0475)
Controls	YES	YES	YES	YES
Observations	722	722	722	722
R-squared	0.788	0.720	0.598	0.481

Notes. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 1B—First Stage Estimates for Routine Occupation Share

(Dependent variable: Routine occupation share in CZs in indicated years)

	1980-1990	**1990-2000**	**2000-2010**	**2010-2019**
1980 Industry Mix Measure	1.166***	0.909***	0.767***	0.632***
	(0.0358)	(0.0356)	(0.0477)	(0.0561)
Controls	YES	YES	YES	YES
Observations	722	722	722	722
R-squared	0.961	0.909	0.815	0.669

Notes. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 2—Routine Employment Share (RSH_{jt}) Mean and Standard Deviation

	Mean			Standard Deviation		
	All	**Men**	**Women**	**All**	**Men**	**Women**
All Years	0.295	0.192	0.412	0.030	0.036	0.026
1980-1990	0.283	0.167	0.421	0.034	0.040	0.030
1990-2000	0.289	0.182	0.408	0.030	0.034	0.026
2000-2010	0.300	0.202	0.409	0.027	0.035	0.022
2010-2019	0.310	0.217	0.411	0.027	0.033	0.028

Table 3A—Computer Adoption and Task Specialization within CZs, 1980-2019

(Dependent variable: 10 x annual change in employment share of routine occupations)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	All Workers	College	Noncollege	Age<40	Age≥ 40
Share of Routine Occs	-0.264***	-0.154***	-0.302***	-0.283***	-0.237***
	(0.0305)	(0.0271)	(0.0249)	(0.0276)	(0.0376)
R-squared	0.352	0.454	0.488	0.241	0.352

Notes. N = 2,888 for all columns (722 CZ x 4 years). All Regressions include controls for decade and state fixed effects. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 3B—Computer Adoption and Task Specialization for Men within CZs, 1980-2019

(Dependent variable: 10 x annual change in employment share of routine occupations)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	All Workers	College	Noncollege	Age<40	Age≥ 40
Share of Routine Occs	-0.187***	-0.119***	-0.216***	-0.234***	-0.128***
	(0.0239)	(0.0259)	(0.0151)	(0.0245)	(0.0294)
R-squared	0.945	0.186	0.353	0.303	0.230

Notes. N = 2,888 for all columns (722 CZ x 4 years). All Regressions include controls for decade and state fixed effects. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 3C—Computer Adoption and Task Specialization for Women within CZs, 1980-2019

(Dependent variable: 10 x annual change in employment share of routine occupations)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	All Workers	College	Noncollege	Age<40	Age≥ 40
Share of Routine Occs	-0.415***	-0.241***	-0.423***	-0.407***	-0.431***
	(0.0378)	(0.0323)	(0.0382)	(0.0307)	(0.0496)
R-squared	0.437	0.529	0.265	0.313	0.393

Notes. N = 2,888 for all columns (722 CZ x 4 years). All Regressions include controls for decade and state fixed effects. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are in line with those used by Autor and Dorn (2013). * Robust standard errors in parenthesis. ** p<0.01, ** p<0.05, * p<0.10

Table 4—Effect of Exposure to Routine-biased Technological Change on Employment Status among Working Age Population, 1980-2019: 2SLS Estimates

(Dependent variable: 10x annual change in employment share of routine occupations)

VARIABLES	All	Male	Female	Non-College	College	Young	Old
Share Employed							
All Years	-0.159***	-0.0505	-0.285***	-0.209***	-0.158***	-0.117**	-0.220***
1980-1990	-0.0189	0.052	-0.116**	-0.0796	-0.0519	0.0389	-0.108**
1990-2000	-0.14***	0.0779	-0.384***	-0.0423	-0.243***	-0.0858	-0.167***
2000-2010	-0.551***	-0.593***	-0.508***	-0.774***	-0.196**	-0.673***	-0.431***
2010-2019	0.111*	0.169**	0.0545	0.135**	0.0606	0.0975	0.113
Share Unemployed							
All Years	0.0187	0.0349*	0.0022	0.0449**	0.00215	-0.000286	0.0342***
1980-1990	-0.0297	-0.0236	-0.0376*	-0.0249	-0.0176	-0.0691**	0.022
1990-2000	-0.0191	-0.0342	-0.00216	-0.0246	-0.0051	-0.0312	-0.0104
2000-2010	0.274***	0.313***	0.234***	0.35***	0.154***	0.33***	0.214***
2010-2019	-0.086***	-0.078***	-0.093***	-0.118***	-0.0523**	-0.107***	-0.062***
Share not in labor force							
All Years	0.140***	0.0156	0.283***	0.164***	0.156***	0.117***	0.186***
1980-1990	0.0486	-0.0284	0.153***	0.105**	0.0695*	0.0303	0.0862**
1990-2000	0.159***	-0.0437	0.386***	0.0669	0.248***	0.117**	0.177***
2000-2010	0.277***	0.279***	0.273***	0.424***	0.0424	0.343***	0.217**
2010-2019	-0.0256	-0.0908	0.0385	-0.0169	-0.00829	0.00985	-0.0518

Notes. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, Census geographical region dummies, and state and decade fixed effects. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are in line with those used by Autor and Dorn (2013). *** p<0.01, ** p<0.05, * p<0.10

Table 5A—Effect of Exposure to Routine-biased Technological Change on Hours Worked among Working Age Population, 1980-2019: OLS Estimates

(Dependent variable: 10 x annual change in hours worked)

	1980-1990	1990-2000	2000-2010	2010-2019
Share Routine Occs	378.9***	-12.89	-1,734***	460.7***
	(121.9)	(95.87)	(231.8)	(160.9)
Observations	722	722	722	722

Notes. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are largely in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 5B—Effect of Exposure to Routine-biased Technological Change on Hours Worked among Working Age Population, 1990-2019: 2SLS Estimates

(Dependent variable: 10 x annual change in hours worked)

	1990-2000	2000-2010	2010-2019
Share Routine Occs	-63.01	-2,514***	475.1**
	(136.5)	(358.6)	(232.2)
Observations	722	722	722

Notes. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are largely in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 5C—Effect of Exposure to Routine-biased Technological Change on Hours Worked among Working Age Population in CZs Affected by Male-Specific Automation, 1990-2019: 2SLS Estimates

(Dependent variable: 10 x annual change in hours worked)

	1990-2000	2000-2010	2010-2019
Female Share Routine Occs	-4,661*	648.6	-9,129
	(2,820)	(4,437)	(13,946)
Male Share Routine Occs	3,859**	-2,897	5,921
	(1,935)	(2,730)	(8,104)
Observations	722	722	722

Notes. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are largely in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 5D—Effect of Exposure to Routine-biased Technological Change on Hours Worked among Working Age Population in CZs Affected by Female-Specific Automation, 1990-2019: 2SLS Estimates

(Dependent variable: 10 x annual change in hours worked)

	1990-2000	2000-2010	2010-2019
Female Share Routine Occs	-5,080*	-11,436	7,093
	(2,622)	(7,079)	(11,343)
Male Share Routine Occs	2,666	5,195	-3,868
	(1,852)	(4,368)	(6,624)
Observations	722	722	722

Notes. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are largely in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 6—Effect of Exposure to Routine-biased Technological Change on Employment by Occupation Group among Working Age Population, 1980-2019: 2SLS Estimates

(Dependent variable: 10-year change in share of working age population employed in specific occupation group)

VARIABLES	All	Male	Female	Non-College	College	Young	Old
Primary Task: Abstract							
All Years	0.0459	0.0499	0.0342	0.0892	0.0149	0.0738	0.024
1980-1990	-0.00234	0.0183	-0.0263	-0.0103	-0.0272	0.0276	-0.0175
1990-2000	-0.0297	-0.0354	-0.0291	-0.0516*	-0.0227	-0.0432	-0.0217
2000-2010	0.555***	0.606***	0.494***	0.583***	0.328***	0.563***	0.515***
2010-2019	0.121*	0.0461	0.206***	0.0917**	0.12*	-0.0339	0.284***
Primary Task: Routine							
All Years	-0.305***	-0.257***	-0.35***	-0.337***	-0.191***	-0.340***	-0.286***
1980-1990	-0.259***	-0.224***	-0.292***	-0.246***	-0.217***	-0.271***	-0.249***
1990-2000	-0.367***	-0.392***	-0.338***	-0.439***	-0.238***	-0.437***	-0.297***
2000-2010	-0.595***	-0.474***	-0.704***	-0.693***	-0.264**	-0.767***	-0.415***
2010-2019	-0.127***	-0.14**	-0.113	-0.159***	-0.134**	0.032	-0.311***
Primary Task: Manual							
All Years	0.0442**	0.0752***	0.0174	0.0729**	0.0155	0.0648***	0.0413**
1980-1990	0.0469***	0.0883***	0.00408	0.0873***	-0.0137	0.0299	0.112***
1990-2000	0.00707	-0.0641	0.0725**	-0.00417	0.00868	0.0445	-0.00208
2000-2010	0.0656*	0.0119	0.132***	-0.00276	0.0934	0.0995	0.0381
2010-2019	0.137***	0.277***	-0.0154	0.27***	0.0355	0.239***	0.0445

Notes. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, Census geographical region dummies, and state and decade fixed effects. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are in line with those used by Autor and Dorn (2013). *** p<0.01, ** p<0.05, * p<0.10

Table 7A—Effect of Exposure to Routine-biased Technological Change on Marriage Status among Working Age Population, 1980-2019: OLS Estimates
(Dependent variable: 10 x annual change in share married)

	1980-1990	1990-2000	2000-2010	2010-2019
Share Routine Occs	-0.0657*	0.116***	-0.0521	0.0191
	(0.0331)	(0.0350)	(0.0773)	(0.0481)
Observations	722	722	722	722

Notes. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are largely in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 7B—Effect of Exposure to Routine-biased Technological Change on Marriage Status among Working Age Population, 1990-2019: 2SLS Estimates
(Dependent variable: 10 x annual change in share married)

	1990-2000	2000-2010	2010-2019
Share Routine Occs	0.137***	-0.185**	-0.0808
	(0.0422)	(0.0817)	(0.0740)
Observations	722	722	722

Notes. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are largely in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 7C—Effect of Exposure to Routine-biased Technological Change on Marriage Status among Working Age Population in CZs Affected by Male-Specific Automation, 1990-2019: 2SLS Estimates

(Dependent variable: 10 x annual change in share married)

	1990-2000	2000-2010	2010-2019
Female Share Routine Occs	-0.0497	0.375	-0.0406
	(0.342)	(0.774)	(1.108)
Male Share Routine Occs	0.102	-0.281	-0.0609
	(0.239)	(0.499)	(0.646)
Observations	722	722	722

Notes. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are largely in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 7D—Effect of Exposure to Routine-biased Technological Change on Marriage Status among Working Age Population in CZs Affected by Female-Specific Automation, 1990-2019: 2SLS Estimates

(Dependent variable: 10 x annual change in share married)

	1990-2000	2000-2010	2010-2019
Female Share Routine Occs	-0.324	-0.215	-2.400
	(0.331)	(0.588)	(4.419)
Male Share Routine Occs	0.401*	-0.140	1.353
	(0.231)	(0.371)	(2.575)
Observations	722	722	722

Notes. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are largely in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 8A—Effect of Exposure to Routine-biased Technological Change on Divorce Status among Working Age Population, 1980-2019: OLS Estimates
(Dependent variable: 10 x annual change in share divorced)

	1980-1990	1990-2000	2000-2010	2010-2019
Share Routine Occs	-0.0536***	-0.0938***	-0.0406	-0.0481*
	(0.0172)	(0.0201)	(0.0354)	(0.0253)
Observations	722	722	722	722

Notes. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are largely in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 8B—Effect of Exposure to Routine-biased Technological Change on Divorce Status among Working Age Population, 1990-2019: 2SLS Estimates
(Dependent variable: 10 x annual change in share divorced)

	1990-2000	2000-2010	2010-2019
Share Routine Occs	-0.0772***	-0.0315	-0.128**
	(0.0218)	(0.0325)	(0.0507)
Observations	722	722	722

Notes. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are largely in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 8C—Effect of Exposure to Routine-biased Technological Change on Divorce Status among Working Age Population in CZs Affected by Male-Specific Automation, 1990-2019: 2SLS Estimates

(Dependent variable: 10 x annual change in share divorced)

	1990-2000	2000-2010	2010-2019
Female Share Routine Occs	-0.175	-0.194	-1.240
	(0.253)	(0.323)	(2.377)
Male Share Routine Occs	0.0527	0.0729	0.646
	(0.184)	(0.198)	(1.399)
Observations	722	722	722

Notes. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are largely in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 8D—Effect of Exposure to Routine-biased Technological Change on Divorce Status among Working Age Population in CZs Affected by Female-Specific Automation, 1990-2019: 2SLS Estimates

(Dependent variable: 10 x annual change in share divorced)

	1990-2000	2000-2010	2010-2019
Female Share Routine Occs	-0.110	-0.0121	1.570
	(0.149)	(0.384)	(2.683)
Male Share Routine Occs	0.00612	0.00100	-1.047
	(0.0994)	(0.238)	(1.574)
Observations	722	722	722

Notes. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are largely in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 9A—Effect of Exposure to Routine-biased Technological Change on Fertility Rates among Working Age Population, 1980-2019: OLS Estimates
(Dependent variable: 10 x annual change in share of households with child under age of 5)

	1980-1990	1990-2000	2000-2010	2010-2019
Share Routine Occs	0.248***	0.286***	-0.287***	-0.105
	(0.0403)	(0.0333)	(0.0788)	(0.0720)
Observations	722	722	722	722

Notes. Fertility rates determined by the number of children under the age of five living in a household. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are largely in line with those used by Autor and Dorn (2013). *** p<0.01, ** p<0.05, * p<0.10

Table 9B—Effect of Exposure to Routine-biased Technological Change on Fertility Rates among Working Age Population, 1990-2019: 2SLS Estimates
(Dependent variable: 10 x annual change in share of households with child under age of 5)

	1990-2000	2000-2010	2010-2019
Share Routine Occs	0.338***	-0.337***	-0.170*
	(0.0364)	(0.0815)	(0.0980)
Observations	722	722	722

Notes. Fertility rates determined by the number of children under the age of five living in a household. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are largely in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 9C—Effect of Exposure to Routine-biased Technological Change on Fertility Rates among Working Age Population in CZs Affected by Male-Specific Automation, 1990-2019: 2SLS Estimates

(Dependent variable: 10 x annual change in share of households with child under age of 5)

	1990-2000	2000-2010	2010-2019
Female Share Routine Occs	0.337	1.245	0.887
	(0.299)	(1.067)	(1.889)
Male Share Routine Occs	0.0701	-1.010	-0.676
	(0.211)	(0.669)	(1.109)
Observations	722	722	722

Notes. Fertility rates determined by the number of children under the age of five living in a household. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are largely in line with those used by Autor and Dorn (2013). Robust standard errors in parenthesis. *** p<0.01, ** p<0.05, * p<0.10

Table 9D—Effect of Exposure to Routine-biased Technological Change on Fertility Rates among Working Age Population in CZs Affected by Female-Specific Automation, 1990-2019: 2SLS Estimates

(Dependent variable: 10 x annual change in share of households with child under age of 5)

	1990-2000	2000-2010	2010-2019
Female Share Routine Occs	0.338	1.093	0.654
	(0.291)	(0.939)	(1.632)
Male Share Routine Occs	0.0696	-0.970*	-0.498
	(0.201)	(0.588)	(0.966)
Observations	722	722	722

Notes. Fertility rates determined by the number of children under the age of five living in a household. All Regressions include controls for the start of the period share of Black individuals, Asian individuals, share of other minority races, share of population that is college educated, share of population that is foreign born, and Census geographical region dummies. Robust standard errors in parenthesis are clustered on state. Models are weighted by start of the period commuting zone share of the national population. These controls are largely in line with those used by Autor and Dorn (2013). *** p<0.01, ** p<0.05, * p<0.10

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