A Quantitative Theory of the New Life Cycle of Women's Employment

Lidia Cruces*

Click here for most recent version

January 6, 2023

Abstract

"A new life cycle of women's labor force participation has emerged" Goldin and Mitchell (2017). Compared to previous cohorts, the employment profile of American college-educated married women born after the mid-1950s is flatter and higher with no hump but with a dip in the middle between ages 30-39. At the same time, these younger cohorts have delayed births, but their completed fertility rate has increased. I develop a quantitative theory to explain the changes in college-educated women's employment and fertility decisions across cohorts. First, I provide reduced-form evidence of a positive correlation between fertility and employment decisions. Second, I build a life-cycle model of labor supply and fertility decisions. My estimates indicate that the marginal returns to experience of college-educated married women increased by 46 percent. Although on-the-job accumulation of experience plays a crucial role in generating employment shifts and birth delays, the model does not generate an increase in the total fertility rate in the absence of infertility treatments. Thus, to understand why college-educated married women's life-cycle employment profiles and fertility decisions are changing, both factors must be considered.

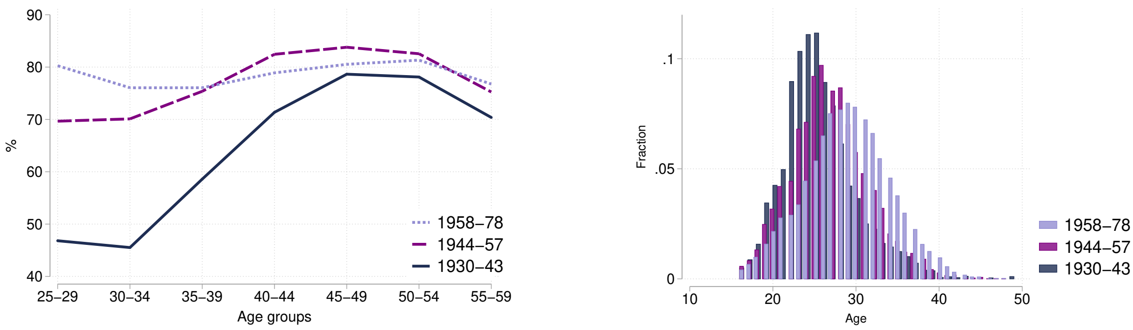
JEL Codes— J21, J13, J24.

Keywords: Female employment, Life cycle, Fertility, Returns to experience.

* University Carlos III, Madrid. **Email:** lcruces@eco.uc3m.es
Throughout this process, I have received invaluable support and guidance from Luisa Fuster, my advisor. I would also like to thank Árpád Ábrahám, Jaime Alonso, Manuel Amador, Mariacristina De Nardi, Andrés Erosa, Timothy J. Kehoe, Matthias Kredler, Víctor Ríos-Rull, Javier Rodríguez-Román, Clara Santamaría, Felix Wellschmied and Emircan Yurdagul for countless discussions that have improved this paper substantially. I thank all the participants of the Macro reading groups at the Universidad Carlos III, the Trade and the Macro-Micro Workshops at the University of Minnesota and the Vigo workshop of Dynamic Macroeconomics for their advice and helpful suggestions. The development of this study has been greatly enhanced by conversations with Marta Cota, Marta Morazzoni, Henry Redondo, Nicolò Ruso, and Katherina Thomas.

1 Introduction

In the United States, recent cohorts of college-educated married women have experienced dramatic changes in their employment profiles and fertility decisions, as shown in Figure 1. The employment profile of cohorts born before the fifties was initially flat and rose steeply after age 30. In contrast, the employment rate of women born after the mid-1950s started at a much higher level and fell sharply until reaching a plateau between ages 30-40, at approximately 75 percent (see Figure 1a). At the same time, younger cohorts have delayed births, but their completed fertility rate has increased (see Figure 1b). These observations motivate the following questions: why do college-educated women delay childbirth and work so much when they are young? Why does the employment rate remain low after age 30 and then flatten for a decade? How can these women have more children if they become mothers later in life? Why don't we see these changes in behavior among non-college-educated married women?



(a) Employment rates

(b) Mother's age at first birth

Figure 1: Female age-profile of employment and mother's age at first birth

Source: March CPS-ASEC microdata (1963-2019) and CPS June Fertility Supplement (1976-2018).
Notes: The sample includes ever-married women with at least a college education. For the mother's age at first birth, I restricted the sample to women older than 16.

In this paper, I develop a quantitative theory to provide a unified explanation for the changes across cohorts of employment and fertility decisions of college-educated women. I build a life-cycle model of labor supply and fertility decisions. Children are costly in goods and mother's time. Women face an increasing risk of being infertile as they age. In turn, this induces women to become mothers early in their lives, reducing their labor supply until their children are grown and less expensive. In the model, labor market experience implies higher wages in the future, and the returns to experience are higher for younger women. Returns to experience increase the opportunity cost of being a young mother and induce highly productive women to work hard when young and to postpone births. In my model, two changes in the economic environment trigger the shift in employment and fertility decisions of younger college-educated married women. First, the increase in returns to experience, especially at younger ages, encourages these women to work more at the beginning of their lives and postpone having children, which can decrease their total number of children. Second, the availability of infertility treatments for younger cohorts lowers the opportunity cost of delaying fertility because of the increased chances of becoming a mother as they age. I find that accumulation of experience explains the higher employment rate at younger ages and the delay in fertility. Despite this, in the absence of infertility treatments, the model does not generate the increase in the total fertility rate we observe in the data. It is, therefore, important to consider both drivers when analyzing the employment and fertility decisions of young college-educated married women.

The first part of my analysis is empirical. First, I document and compare the life-cycle profiles of employment and fertility decisions for three cohorts of college-educated married women using the Annual Social and Economic supplement to the Current Population Survey (CPS-ASEC) microdata (1963-2019). The first includes those born between 1930-43, the second between 1944-57, and the third from 1958-78. I refer to these cohorts as Old, Middle, and Young, respectively. Women in the Young cohort appear to be planning a lifelong career. Compared to women in the Middle cohorts, their employment rate between ages 25-29 is 14.3% higher, and at the same time, they delay children by three years. This causes a dip in labor supply between ages 30-39 (see Figure 1). Goldin and Mitchell (2017) named this drop in employment at age 30 the "sagging-middle". Despite delaying fertility, patterns in the data suggest that the total fertility rate of women in the Young cohort increased by 4.2% in comparison with women in the Middle cohort.[1]

Second, I show reduced-form evidence of a correlation between the sagging middle effect and fertility decisions. Using the CPS-ASEC microdata (1963-2019), I estimate the probability of being employed for college-educated married women. While the probability of being employed at ages 30-34 and 35-39 is 3.56 and 2.89 percent points smaller, respectively, than those at ages 25-29, once I introduce fertility controls in the regression, the probability becomes positive and statistically significant. These results imply that children are responsible for the decrease in employment among women in their thirties.

Third, I provide evidence of two exogenous explanations leading to the sagging middle effect and the fertility changes of the Young cohort. On the one hand, using the Panel Study of Income Dynamics (PSID) data, I find that college-educated married women born between 1958-1978 have higher returns to experience, especially at younger ages. In particular, returns to experience increased by 46%, relative to women born between 1944-57. Thus, there is

[1]This is why Goldin (2021) says that these women "have it all: career and family".

an economic incentive to postpone fertility. On the other hand, there is an increase in the probability of women having children when old, thanks to Assisted Reproductive Technology (ART).[2] The empirical literature has exploited that coverage of infertility treatments is mandatory for some states in the United States. They find that in those states, the mandate significantly increases first birth rates for women over 35 and that it increases the probability that women delay fertility (Schmidt (2007), Buckles (2007) and Machado and Sanz-de Galdeano (2015)). Moreover, the presence of this law is correlated with increased labor force participation for women ages 25-34 and decreased participation for women ages 35-44 (Buckles, 2007). Finally, they affect disproportionally older and highly-educated women (Bitler and Schmidt, 2012). These findings suggest that ART might have influenced career and family trade-offs in favor of postponing births, increasing fertility rates, and higher employment rates earlier in life.

This evidence suggests a link between the increase in returns to experience and the availability of infertility treatments with the employment and fertility decisions of Young cohorts. In the second part of my paper, I develop a quantitative life-cycle model of married individuals. Women choose their labor supply, fertility, consumption, and accumulate on-the-job experience. The husband's earnings have a deterministic age profile and a stochastic component. Children are costly in goods and in the mothers' time. Households can substitute only partially mothers' time with market childcare when mothers work outside the home. Each period, women face a fertility probability that decreases with age.

I calibrate the model to match the life-cycle profile of employment, hours worked, and fertility decisions of women born between 1944-1957, the Middle cohort. The model replicates well the main features of the data. It generates an inverted U shape in employment, the average age at first birth, and the distribution of households by the number of children. I run two experiments to quantify the extent to which the new employment and fertility trends can be explained by gains in returns to experience and ART. In the first experiment, I consistently increase the returns to experience in the model with the returns to experience that I estimate using PSID data of the Young cohort. As a result, women increase their employment rate by 13% between ages 25-29 relative to the baseline economy, which is 3.2 percentage points lower than in the data. Moreover, these women delay having their first child by 0.92 years. Their first child is born at an average age of 29.3, which is similar to the average age of 28.9 in the data. Yet the model predicts that the total fertility rate will drop by 15%, whereas the data show an increase of 4%. This motivates the second experiment, where I increase the returns to experience and introduce ART. To capture the increase in the

[2] ART includes all fertility treatments in which either eggs or embryos are handled outside a woman's body.

total fertility rate we observe in the data, I calibrate the increase in the fertility probabilities after age 30. In this case, women postpone births, but their overall employment rate increases by less than in the first experiment. This is partly because more women have two and three children, which decreases employment relative to the results in the first experiment. Overall, the employment rate is largely in line with the data of the Young cohort in this experiment. My results suggest that an increase in returns to experience, especially at younger ages, can qualitatively account for both the increase in employment before age 30, the flat employment profile between ages 30 and 39, and the delay in fertility. Although on-the-job accumulation of experience plays a crucial role, the model does not generate an increase in the total fertility rate in the absence of infertility treatments. Therefore, it is essential to combine both factors to explain the new shape of the age profile of employment and the changes in fertility decisions of the Young cohort.

The contributions I make are both empirical and theoretical. My empirical contributions are two. I contribute to the main paper that illustrates the new employment life-cycle profile of college-educated married women Goldin and Mitchell (2017) by providing reduced-form evidence of a correlation between the new employment profile and fertility decisions. Furthermore, I have also documented a new fact: these women are changing not only their employment profiles but also their work hours throughout their lives. There is a sagging middle effect in employment and hours worked. Second, I contribute to the literature on returns to experience by estimating them by cohort groups and by focusing on college-educated married women. Theoretically, this paper is the first attempt to link increasing returns to experience with fertility decisions under conditions of infertility treatment availability. Studies analyzing the impact of higher returns to experience typically focus on labor market outcomes rather than modeling fertility (Olivetti, 2006) and (Attanasio et al., 2008). Thus, this is the first paper to address the effects of higher returns to experience on fertility outcomes, such as the delay in births and the increase in the total fertility rate.

The rest of the paper is organized as follows. In Section 2, I position my paper in the context of the existing literature. In Section 3, I document the main changes in the labor market across cohorts in the U.S. In Section 4, I propose a set of potential explanations behind the change in women's behavior. In Section 5, I introduce the model. In Section 6, I carefully specify the calibration methodology. In Section 7, I analyze the calibration results. In Section 8, I disentangle the effect of each factor in shaping employment and fertility decisions. In Section 9, I discuss why the proposed explanations have minor impacts on non-college-educated women in the U.S. Finally, in Section 10, I conclude.

2 Literature Review

The paper contributes to different strands of the literature. First, it contributes to the literature on the drivers of changes in female labor force participation, employment, and work hours over time in the US economy. A vast majority of papers have analyzed the causes behind the sharp increase in the female employment rate. These explanations include the power of the contraceptive pills (Goldin and Katz, 2002), the electricity revolution (Greenwood et al., 2005), the relative change in returns to experience compared with the men's (Olivetti, 2006), the decrease in the gender wage gap (Jones et al., 2015), the infant formula (Albanesi and Olivetti, 2016) and the reduction in the child care cost (Sánchez-Marcos and Bethencourt, 2018), among many others.

Despite the literature having well-analyzed the female labor market increase over time, less research has been done on the new employment profile of recent cohorts of women in the US. To the best of my knowledge, Goldin and Mitchell (2017) are the first to document a "sagging middle" in the labor force participation of American college-educated women. According to their study, younger cohorts accumulate more work experience than previous cohorts, especially at a younger age. In addition, they show that a significantly higher proportion of these women work at least 80 percent of the time between the ages of 25 and 54. In addition, they conduct event studies in which they determine that, unlike previous cohorts, college-educated women's labor force participation does not fully recover ten years after the birth of their first child. Finally, they demonstrate that an increase in the age at which the first child is born is correlated with increased participation during the 25-34 year interval, but decreased participation during the 35-44 year interval. Despite this, their analysis does not demonstrate a correlation between the sagging middle effect in employment and women's fertility choices.[3] Moreover, their analysis does not address the underlying factors responsible for the observed sagging middle in employment and fertility trends together. In addition, their study focuses on the extensive margin, whereas I also provide evidence of a sagging middle effect in the intensive margin. In this line, Buttet and Schoonbroodt (2013) build a life-cycle model of endogenous female labor supply to quantitatively explain why the employment profile of married women in the US born between 1940 and 1960 is flatter. They exogenously evaluate the role of the decrease and delay in births, the increase in relative wages of women to men, and the decline in childcare costs. They find that the relative wages explain 67% of the flatter life-cycle profile of employment.

Second, I also contribute to the literature examining possible causes behind aggregate

[3] This is because they only consider households with children in this exercise

labor force participation leveling off in the late 1990s. They range from changes in women's beliefs about the long-run payoff from working (Fernández, 2013), the convergence of information across regions (Fogli and Veldkamp, 2011), a retreat in egalitarian gender role attitudes, and the rebound in traditional gender role attitudes (Fortin, 2015), the lack of "family-friendly" policies (Blau and Kahn, 2013), a crowding-out effect in the labor market as they were replaced by college-educated men who used to work in blue-collar occupations (Duran-Franch, 2021) or growth in earnings inequality for women married to highly educated and high-income husbands (Albanesi and Prados, 2022). I contribute to this literature from a different angle. In particular, I introduce a life-cycle model to evaluate the extent to which changes in returns to experience and infertility treatments explain the change in the women's participation rate over the life cycle for the recent cohorts. Understanding the incentives women face to work over the life cycle, especially its recent shifts, is crucial to comprehending the overall stagnation.

Finally, this paper also contributes to the literature building structural life-cycle models of labor supply decisions of married individuals and fertility decisions to understand the interaction between them. Key contributions to this literature are Moffitt (1984), Caucutt et al. (2002), Francesconi (2002), Erosa et al. (2002), Da Rocha and Fuster (2006), Sheran (2007), among others. While fertility decisions play an important role in these papers, their primary focus is on labor market outcomes, returns to experience, and understanding the gender wage gap. My paper contributes to the most recent papers modeling fertility and labor supply decisions where the conflict between career-family is explicitly introduced. In this vein, Adda et al. (2017) estimate a dynamic life-cycle model of labor supply, fertility, and savings, incorporating occupational choices with specific wage paths and skill atrophy that vary over the career. They quantify the career cost of children when women drop out of the labor market due to childcare. In contrast, my focus is on understanding the causes of the postponement of births and the decline in employment between 30 and 39 years of age. Eckstein et al. (2019) also estimate a life-cycle model of individual and household decisions regarding education, employment, marriage, divorce, and fertility. Similar to them, I show the relevant role of birth technology on career and family choices—they model contraception technologies, whereas I consider infertility treatments.

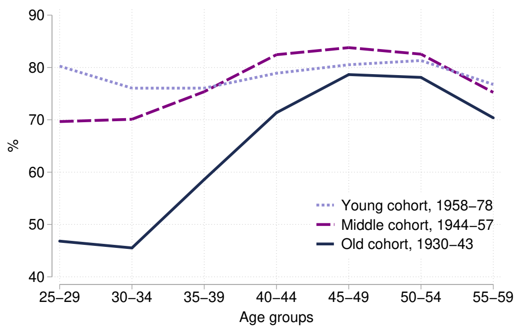
3 Facts to Explain

In this section, I provide empirical evidence about three facts. First, college-educated married women born after 1958 have a different life-cycle employment profile. This profile shows a sagging between the ages of 30-39. Further, I show that these women delay births compared to previous cohorts and have more children than those born in the 1940s-mid-1950s. Second, I demonstrate that the decrease in employment between ages 30-39 correlates with changes in fertility decisions. Third, I show that this new employment profile is a particular feature of college-educated married women.

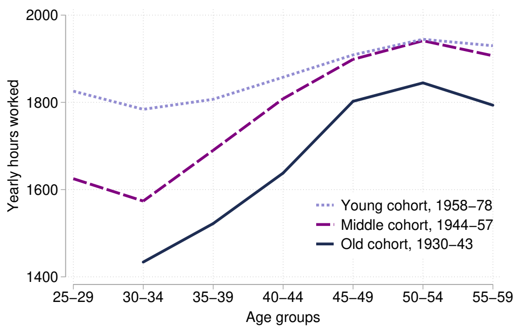
3.1 New life-cycle profile of employment

Data sources and sample. The primary datasets are the Current Population Census March, and the June Fertility Supplements extracted from the IPUMS for 1962-2019 and 1976-2018, respectively. I construct synthetic birth cohorts following Goldin and Mitchell (2017).[4] In particular, I restrict attention to three cohorts: the first includes those born between 1930-43, the second between 1944-57, and the third between 1958-78. I refer to these cohorts as Old, Middle, and Young, respectively. The sample consists of college-educated married individuals aged between 25-54.

Results. Figure 2 shows the employment rate and weekly hours worked for college-educated married women who belong to three different cohorts: Old, Middle, and Young.



(a) Employment rates



(b) Yearly working hours

Figure 2: Female life-cycle profile of employment and hours worked

Source: CPS-ASEC microdata, March, 1963 to 2019.
Notes: The sample includes ever-married women aged 25-59 with at least a college education. The variable yearly working hours is computed as the product of last year's weeks and the usual hours worked per week last year.

The Old cohort includes women born between 1930-43. Most of these women become mothers in their twenties and have, on average, 2.5 children. Their employment rate is 48% between ages 25-30. After childbearing, these women increase their labor market attachment and reach an employment rate of almost 80% at the age of 45-49. Therefore, the average

[4]Synthetic birth cohort is similar to cohort analysis, but instead of using successive observations of the same group of people, you treat the population's age distribution as if it were a cohort passing through time.

woman in the Old group has a *family and then a job* (Goldin, 2021).

The Middle cohort includes women born between 1944-57. Unlike the Old cohort, they decide to get on the career track first at the expense of delaying births. These women have their first kid at the age of 26.7, and they have, on average, 1.9 children. Consequently, 27% of them never have a kid. Their employment rate is higher than the previous groups, but the life-cycle shape remains similar. They have a constant employment rate of 70% between the ages of 25-34 and an increase after that. In the 45-49 age group, it is 82%. Thus, the average woman in the Middle group has a *career and then a family* (Goldin, 2021).

Finally, the Young group includes women born between 1958-78. They continue delaying fertility. They have their first child at the age of 29. Despite this, on average, they have more children than the Middle cohort. Even though we cannot observe the completed fertility for all the cohorts included in this group, the average fertility rate increases to 1.98.[5] The employment rate is similar on average between the Middle and the Young cohorts; however, over the life cycle, it is not. Women in the Young cohort have a higher employment rate between ages 25-29, dropping from the labor market and reducing the hours worked between ages 30 and 39, compared to the Middle cohort. This decline in the labor market attachment has long-lasting effects. Their employment rate and hours worked do not differ from the Middle cohort after age forty. As a result, the average woman in the Young group has it all: *career and family* (Goldin, 2021). In what follows, I examine the link between the postponement in births, the fertility increase, and the drop in employment between ages 30-39 for college-educated married women in the Young cohort.

3.2 Evaluating the sagging-fertility relationship

In the previous section, I suggested a correlation between female employment sagging in the 30-39 age group and the delay and increase in fertility for the Young cohort. To identify the role of children in the decision to be employed between ages 30-39 compared to ages 25-29, I estimate the probability of being employed as follows:

$$Prob(E_{it}) = \beta_0 + \sum_{j=1}^{6} \beta_j \text{Agegrpj}_{it} + \beta_6 X_{it} + u_{it}, \quad (1)$$

where E_{it} is 1 if the individual i at time t is employed and 0 otherwise. I consider 6 age groups of 4-year age bins starting at age 25, Agegrpj.[6] The omitted age group in the regression is

[5]See Doepke et al. (2022) for a detailed review of the literature showing that the negative correlation between income and fertility has reversed.

[6]Age groups from 1 to 6 correspond to the age intervals 25-29,30-34,35-39,40–44,45-49,50-54, respectively.

Agegrp1, corresponding to ages 25-29. In the regression, I introduce a set of individual-level control variables, X_{it}, including the state where each member of the household was born, the husband's worker characteristics and education, wave identifiers, fertility characteristics, and u_{it} is the remaining unobserved heterogeneity. I estimate equation (1) through a Logit regression and compute the marginal effects.

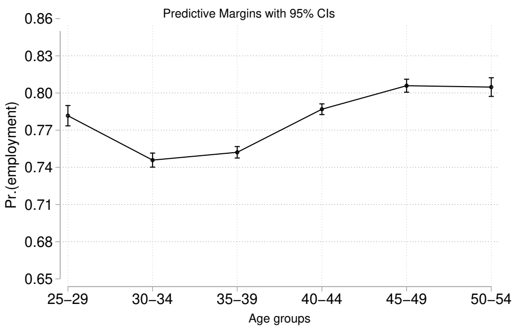
Variables. The dependent variable in the model is employment status, which indicates if the individual is employed or not. To construct this variable, I consider an individual employed if she/he is in the labor force and the employment status is "at work", "has a job, not at work last year", or "Armed forces". On the contrary, an individual is not employed if she/he is in the labor force as "Unemployed". I differentiate two groups of controls. First, demographic controls include the individual's age group, the individual's native indicator, equal to one if the individual was born in U.S. territory, an indicator for college education, and a dummy when children live in the household. Second, the employment husband's characteristics include an indicator for a full-time-full-year worker, an indicator for the worker being a private, public or self-employed employee, and the pre-tax wage and salary income in logs. I consider that the individual is full-time full-year if she/he answers that she/he was a full-time worker and worked at least 50 weeks the previous calendar year.

Methodology. To understand the role of fertility on employment decisions, I run the regression in equation (1) for four model specifications. Model (I) does not control by fertility decisions, while Models (II-IV) do. The differences between these last three are the set of controls I include. In the Appendix, Table B.1 shows the marginal effects of each control variable on the probability of being employed for those college-educated married women in the Young cohort group. The coefficients of interest are $\beta_2 - \beta_6$.[7] The interpretation of them is the following: if they are negative (positive), it means that the probability of being employed is lower (higher) in those age groups compared to the age group 25-29.

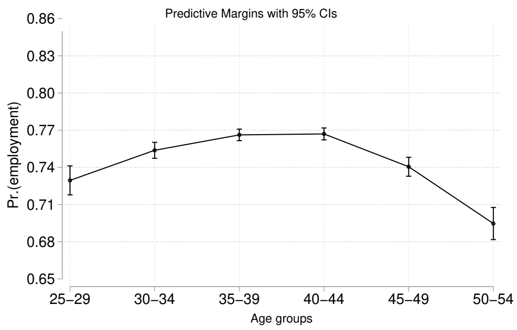
Results. The main result is the following: While the probability of being employed at ages 30-34 and 35-39 is 3.56 and 2.89 percent points smaller than those at ages 25-29 in Model (I), once I control for the presence of a child in the household, the number of children and the age of the youngest child, Model (IV), the probability becomes positive and statistically significant. In particular, the probability of being employed increases by 2.46 and 3.7 percent points for the 30-34 and 35-39 age groups compared to the 25-29. This implies that children

[7] Table B.2 and B.3 show the results for Models (I) and (IV), respectively, for the Young, Old and Middle cohorts.

are the main driving force behind the lower employment rate between ages 30-39. To illustrate this result, Figure 3 plots the predicted employment probability by age of Model (I) in Figure 3a and Model (IV) in Figure 3b. Only the first model predicts a sagging middle effect because once fertility decisions are considered, there is no sagging middle effect.



(a) Not fertility controls



(b) Fertility controls

Figure 3: Marginal effects for college-educated women in Young cohort

Source: CPS-ASEC microdata, March, 1963 to 2019.
Notes: The sample includes ever-married women with at least a college education.

I confirm these findings by showing two population subgroups' employment and hours worked life-cycle profiles. First, the shape is similar between the Middle and Young cohorts of women without children (see Figure A.1 in the Appendix). Second, the sagging middle effect is more pronounced in households with more kids and a higher postponement in births. This is the case, for instance, of college-educated women married to college-educated men. The Young cohort has 0.13 kids more, and they have them on average two years later compared to college-educated women married to non-college-educated men.[8] For the later group, their shape displays a sagging middle effect, but it recovers faster, and the dip is less pronounced (see Figure A.2 in the Appendix).

3.3 The sagging middle effect is prevalent for college-educated married women

Despite providing evidence that college-educated married women have changed their employment profiles, I have not explained why this story is about married women with college degrees. Only those individuals exhibit a sagging middle effect in their employment profiles. To provide evidence for this, I compare three measures for labor market outcomes (employment, hours worked, and participation) for different sub-samples of the population. First, for non-college-educated married women, each line is above its predecessor, and there is no

[8] Table B.5 displays the evolution in the average number of children in the household and the average age at which college-educated women have their first kid through the education of their husbands.

sagging middle effect (see Figure A.3 in the Appendix). Second, for non-married-college-educated women, no clear patterns can be derived from this analysis (see Figure A.4 in the Appendix). Third, for college-educated married men, the life cycle shows the same pattern across cohorts (see Figure A.5 in the Appendix). Interestingly, a lower fraction of these men from the Young cohort are employed; however, this new phenomenon is out of the scope of the paper.[9]

Lastly, as a robustness check, I run the same regressions in Equation 1 for married women who are not college graduates. The sagging middle effect is not present for these women, even in Model (I). Figure A.6 shows their predicted employment by age.

4 Potential Drivers

In this section, I provide detailed empirical evidence to support my theory. First, I demonstrate that college-educated women born after the mid-1950s experienced greater returns to experience, particularly at younger ages. Second, I present historical evidence from the empirical literature suggesting that Assisted Reproductive Technology influenced women's decisions regarding employment and fertility in a way consistent with the behavior of women in the Young cohort.

4.1 Returns to experience

My analysis relies on data from the Panel Survey of Income Dynamics (PSID), a longitudinal survey of a representative sample of the American population. The University of Michigan runs the PSID, which has been conducted annually since 1968 and biennially since 1997. For my analysis, I used data from 1968 to 2015. My main argument for higher returns to experience for the Young cohort compared to women in the Middle cohort is based on three pieces of evidence: full-time workers' earnings have a steeper age profile, experience provides greater marginal returns, and higher returns to experience are associated with greater returns at a young age. Finally, I discuss and compare my findings with those of the literature.

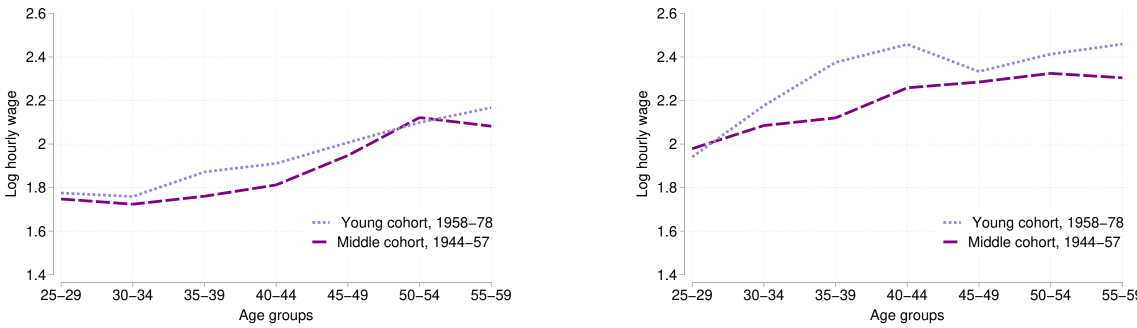
Steeper wage profile of earnings for full-time workers. I use the panel structure of the PSID to construct a dataset where I restrict attention to married women for whom I have observed their labor market outcomes since age 25. I divide these women into two categories: almost full-time workers and all-sample workers. The first includes women who work full-time at least 80% of the time they are on the panel.[10] The second does not make

[9]See Juhn and Potter (2006), Krueger (2017) or Abraham and Kearney (2020) for an explanation of the decrease in employment to population ratio in the U.S.

[10]I consider that an individual is a full-time worker if she works at least 1500 hours.

this restriction; therefore, it includes all women who work regardless of their hours.

Figure 4 plots the median real log-hourly wage for all sample and full-time married women workers as a function of age for the Middle and the Young cohorts. A steeper wage profile suggests larger returns to experience. The difference between the all-sample-workers (left panel) and almost full-time-workers (right panel) shows that the former has lower returns to experience than the latter. Moreover, this Figure also shows that women in the Young cohort have higher returns to experience than those in the Middle cohort. This conclusion comes from two features. First, the hourly wage difference between the all-sample workers and almost-full-time workers is higher for the Young cohort. Second, almost full-time workers in the Young cohort display a steeper earnings profile than the Middle cohort. This finding provides the first evidence of a higher effect of experience on earnings, especially for young individuals.



(a) All-sample-workers

(b) Almost full-time-workers

Figure 4: Real median log hourly wages for all sample and most-time full-time workers.

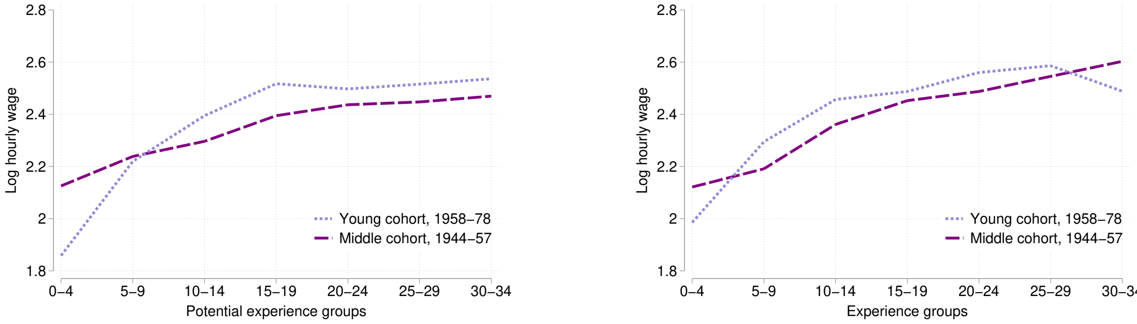
Source: PSID, 1968 to 2015.
Sample: married women.
Notes: I use the 1968 family weight. Almost full-time workers imply that they work at least 80% of the time as full-time workers through the panel. I consider an individual a full-time worker if she works at least 1500 hours.

Steeper experience-wage profiles. The second piece of evidence shows differences between the two cohort groups regarding experience-wage profiles. To do so, I use the couples dataset and restrict attention to college-educated married workers. I construct two different variables for the experience. First, potential experience is defined as the number of years that have elapsed since a worker finished schooling or turned 18, whichever is smaller.[11] Second, actual experience is constructed with the family question about the number of years the head and the spouse have worked full-time since they were 18.[12]

[11] As in Lagakos et al. (2018), I define potential experience as experience = age - schooling - 6 for individuals with 12 or more years of schooling and as experience = age- 18 for individuals with fewer than 12 years of schooling.

[12] In the Appendix, I make a detailed description of the construction of these variables. Specifically how I overcome issues with missing data.

Figure 5 shows the experience-wage profiles for these two experience measures. The main conclusion is that women in the Young cohort experience a much steeper experience-wage profile. Specifically, the wage growth between the first two groups of experience is higher in the Young cohort than in the Middle one. Thus, it is more likely that those women delay fertility to accumulate enough experience compared to the Middle cohort, for whom the difference is smaller.



(a) Potential experience

(b) Actual experience

Figure 5: Real median log hourly wages

Source: PSID, 1968 to 2015.
Notes: The sample includes college-educated married women. I use the 1968 family weight.

To complement the previous findings, I run a Mincer regression for each cohort group of college-educated married women. I regress log hourly wages on a constant, experience and experience squared. Table 1 shows the coefficients of such regressions. According to this analysis, women in the Young cohort experience higher returns to experience than those in the Middle cohort. The coefficient for experience is 3 pp higher. Experience squared, however, also has a higher coefficient, suggesting that as women accumulate experience, they will have more similar returns to those of the Middle cohort. Figure 6 shows the average marginal effect of one extra year of experience for a given level of experience stock. After eight years of labor market experience, marginal returns of experience for the Young cohort become not statistically different from the Middle cohort. It is important to note that the sample of women who have worked more than 16 years for the Young cohort is smaller than for the Middle cohort. Overall, the average rate of return to a year of experience among the Middle cohort is 2%, while it is 3.43% for the Young cohort, i.e., it is 70% higher for the Young cohort.

Higher returns to experience when young. Finally, I demonstrate that the higher returns to experience are particularly higher at younger ages. First, I regress the daily log income on age, experience, and its interactions (treated as continuous variables). Table 2

Table 1: Mincer regression for college-educated married women by cohort

	Middle cohort	Young cohort
Experience	0.0311***	0.0625***
	(0.004)	(0.006)
Experience^2	-0.000413***	-0.00154***
	(0.000)	(0.000)
Constant	1.974***	1.875***
	(0.030)	(0.030)
Observations	5278	3629
R-squared	0.0427	0.0640

Standard errors in parentheses
Source: PSID 1968-2015
Sample: College-educated married women
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

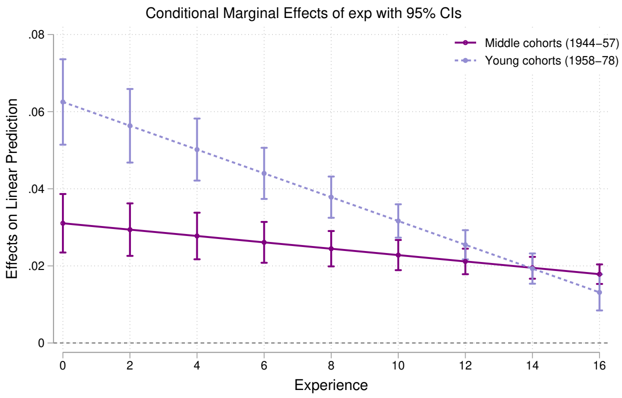


Figure 6: Average marginal effect of experience from Table 1

shows the coefficients of these two regressions. From this table, it is clear that the coefficient of experience is greater for the Young cohort. Moreover, I plot in Figure 7 the average marginal effect of experience at different ages. It indicates that the marginal returns to experience are greater for the Young cohort before age 30. Secondly, I run a Mincer regression where I control by an age dummy equal to one if the worker's age is younger than 30, experience, experience squared, and their interactions. Table 3 shows the results of this estimation. The coefficient of interest is the interaction between the age dummy and the experience. This shows that the marginal effect of experience on log-hourly wages is positive and significant for the Young cohort, while for the Middle one, there are no differences. This is suggestive evidence that Young cohorts are profiting from an increase in the returns to experience when young. The results of the last regression have been robust to the inclusion of more control variables, including the number of children, the husband's job characteristics, experience, and education, the use of only one regression for women born in the Young cohort, and eliminating the squared term of experience. See Tables B.6, B.7 and B.8 in the

Appendix.

Table 2: Mincer regression for college-educated married women by cohort

	Middle cohort	Young cohort
Age	0.0102***	0.0333***
	(0.002)	(0.003)
Experience	0.0497***	0.0931***
	(0.005)	(0.010)
Age × Experience	-0.000716***	-0.00204***
	(0.000)	(0.000)
Constant	1.639***	0.968***
	(0.078)	(0.089)
Observations	5420	3704
R-squared	0.0437	0.0809

Standard errors in parentheses

Source: PSID 1968-2015

Sample: College-educated married women

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

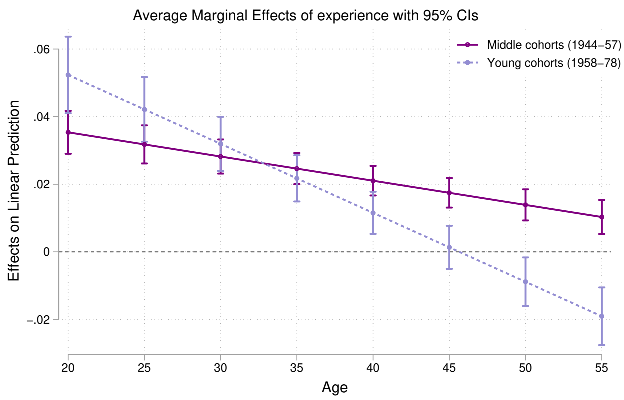


Figure 7: Average marginal predicted effect of experience

Table 3: Mincer regression for college-educated married women by cohort and age group

	Middle cohort	Young cohort
Age dummy (< 30)	-0.0843	-0.529***
	(0.059)	(0.070)
Experience	0.0279***	0.0281***
	(0.005)	(0.008)
Age dummy (< 30) $\times$ Experience	-0.0124	0.135***
	(0.010)	(0.024)
Experience^2	-0.000391**	-0.000644*
	(0.000)	(0.000)
Age dummy (< 30) $\times$ Experience^2	0.000190	-0.0130***
	(0.001)	(0.002)
Constant	2.035***	2.171***
	(0.048)	(0.057)
Observations	5420	3704
R-squared	0.0433	0.0800

Standard errors in parentheses
Source: PSID 1968-2015
Sample: College-educated married women
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Discussion My hypothesis is those college-educated women born after the mid-1950s increase their employment rate at younger ages because of increased returns to experience. In addition, greater returns to experience at younger ages motivate women to delay fertility because children impose a time cost for mothers reducing their labor supply. This mechanism is in line with Olivetti (2006). She shows that between the 1970s and 1990s, women's returns to experience increased more than men's, which helps explain a significant portion of the increase in female employment. Nonetheless, she does not attempt to make the relationship between postponing births and increasing returns to experience. The positive effect of fertility delay on wages is in line with the empirical findings. Amuedo-Dorantes and Kimmel (2005) find that college-educated mothers experience a wage boost of about 4 percent compared to their non-college-educated counterparts. They point to selecting more family-friendly jobs for mothers as the leading explanation. Moreover, they find that college-educated women additionally enhance a wage boost by 13 percent when delaying fertility. This could suggest that women accrue the maximum benefit to their human capital investment by postponing fertility. Miller (2011) shows that motherhood delay leads to a substantial increase in earnings of 9% per year of delay, an increase in wages of 3%, and an increase in work hours of 6%.

4.2 Assisted Reproductive Technology (ART)

Assisted Reproductive Technology (ART) is defined by the Centers for Disease Control and Prevention (CDC) as "all treatments or procedures that include the handling of human eggs or embryos to help a woman become pregnant". The main type of ART is *in vitro* fertilization (IVF), and the first successful procedure in the United States was in 1981. The availability of ART significantly changed women's reproductive lives, as it increased the chances of becoming a mother at older ages. However, like in many European countries, infertility treatments are relatively new, costly, and many insurance plans do not cover them. According to Hamilton and McManus (2012), each attempt of IVF treatment typically entails a cost of $10,000 to $15,000 to the patient, with a probability of success around 25-30%.[13]

Despite this, in the United States, 17 states have passed legislation requiring insurance companies to cover varying degrees of infertility treatment since the 1980s, and a few states mandate IVF coverage specifically. In some states, however, this coverage is restrictive and not available to everyone.[14] Hamilton and McManus (2012) showed that insurance mandates for IVF increased both treatment access and reduced the aggressiveness of the procedure.

The empirical literature has exploited the variation in ART coverage across states to show how infertility treatments affect women's employment and fertility decisions, among other outcomes. Buckles (2007) shows that the presence of this law is correlated with increased labor force participation for women ages 25-34 and decreased participation for women ages 35-44. Buckles (2007) and Machado and Sanz-de Galdeano (2015) demonstrate that the coverage of these services increased the probability that women delay fertility. Schmidt (2007) shows that these mandates significantly increase first birth rates for women over 35. Moreover, as discussed in Moreno-Maldonado and Santamaria (2022), the mandate's effect on the delay of parenthood went above the increase in the utilization rates. ART can incentivize women to postpone fertility, even if they don't use them in the end. Additionally, it changed women's perceptions of its effectiveness.

ART availability generates similar employment and fertility decisions to those of married women with a college degree in the Young cohort. Since this technology is recent, it can only affect the employment and fertility decisions of women in the Young cohort.[15] Further evidence of this is the fact that these mandates disproportionately affect older and college-educated women (Bitler and Schmidt, 2012). For instance, Abramowitz (2017)

[13] See Bitler and Schmidt (2012) for an analysis of the cost of different infertility services.

[14] Arkansas, Connecticut, Delaware, Hawaii, Illinois, Louisiana, Maryland, Massachusetts, Montana, New Hampshire, New Jersey, New York, Ohio, Rhode Island, and West Virginia are among the states that require insurers to cover diagnosis and treatment for infertility. However, of those 17 states, two states require insurers to offer coverage for infertility diagnosis and treatment: California and Texas.

[15] Women in the Middle cohort were years old at least when ART treatments were available and

employs duration and competing risks analyses, exploiting the exogeneity of mandates, to document that mandates are associated with delayed marriage and childbearing at younger ages and an increased likelihood of marriage and motherhood at ages 30 and older, but only for college graduate women.

In a nutshell, in this section, I have shown that the employment decrease between ages 30-40 for college-educated married women in the US correlates with the delay in births and the increase in the number of children. Two potential drivers might explain these employment and fertility trends. The increase in the returns to experience, especially at younger ages, might have created an economic incentive for women to work more when in their twenties and postpone births. Besides, the importance of higher returns to experience at younger ages is accentuated by the fact that assisted reproductive technologies have decreased the incidence of infertility among women as they age. Taking these factors into account, I developed the life-cycle model I will introduce in the following section.

5 The Life-Cycle Model

This section describes the model I develop to explain the new life-cycle profile of women's labor supply. The economic environment consists of a discrete-time life-cycle model of married individuals who never divorce. Women make labor supply, fertility, and consumption decisions. There is on-the-job experience accumulation. The model reflects women's main trade-offs when making career and fertility decisions. There are monetary and time costs associated with becoming a mother. In addition to childcare services, women also suffer wage losses due to interruptions in their labor market participation. The model hinders women's earnings growth because there is no experience accumulation if they do not participate in the labor market.

5.1 Demographics

Each household is composed of a wife and a husband, $g = \{f, m\}$, who never divorce. I assume that both spouses are of the same age and face the same deterministic lifespan. They enter the economy at the age of $j = 1$, corresponding to age 25, and they die at age $j = J$, which is age 55 in reality. As one model period is one year, $J = 31$.

Between ages $j \in [1, \bar{J}]$, the wife decides whether she wants to have an additional child. I denote this decision by $b_{j+1} \in \{0, 1\}$. Each woman can have a maximum of three children, and I denote the total number of children by $N_j \in \{0, 1, 2, 3\}$. Regardless of her decision

($b_{j+1} = 1$), she gives birth with probability $p^j(N_j)$. This probability is a function of age to capture increasing infertility with age. It is also a function of the number of children already in the household.

After being born, children age stochastically.[16] They belong to four different groups: newborns n_0, babies n_1, school-age children n_2 or teenagers n_3. These stages differ in the cost children impose on mothers as they age and the utility they derive from them. Newborns and babies entail the same consumption, leisure, and childcare costs. However, newborns provide extra utility for mothers who stay at home. School-age children continue to impose consumption and leisure costs, although quantitatively not identical to those imposed by newborns and babies. Moreover, I assume that there is a universal public provision of school, and thus, school-age children do not impose childcare costs. Finally, those in the fourth stage, teenagers/young adults, are not costly. The exact mathematical form all these costs take and the functional form of the utility of children are discussed in subsections 5.3 and 5.6.

I denote by $\mathbf{n_j} = \{n_{0j}, n_{1j}, n_{2j}, n_{3j}\}$ the vector indicating the number of children of each type, and hence $N_j = n_{0j} + n_{1j} + n_{2j} + n_{3j}$ is the total number of children in the household of age j. A newborn becomes a baby with a probability equal to one next period. A baby becomes a school-age child, and a school-age child becomes a teen with probabilities λ_1 and λ_2, respectively. The teenage/young adult stage is absorbing: once a child reaches this stage, it remains there. I denote this structure by $\mathbf{n_{j+1}} = \Lambda(\mathbf{n_j}, b_{j+1})$[17].

5.2 Time allocation

Each individual is endowed with one unit of time. I assume that husbands always work full-time. On the contrary, women make fertility, market work, and consumption decisions. Thus, women are the sole decision-makers in the household.

Each period, besides their fertility decision, women decide their labor supply decision (h_j^f). I model the extensive and intensive margins of market work. Thus women decide between participating or not in the labor market, and if they do so, they decide between becoming part-time or full-time workers. I refer to these three labor market statuses as $h_j^f \in \{0, pt, ft\}$, respectively.

[16] Da Rocha and Fuster (2006) and Guner et al. (2020a) also assume stochastic aging of children to reduce the number of state variables.

[17] See appendix C.1 for the exact functional form this structure takes.

5.3 The cost of children

Children are costly in the mother's time. The cost increases with the number of kids but decreases with the child's age. In particular, the time cost associated with having children is:

$$\tau_j^f(\mathbf{n_j}) = \begin{cases} \zeta_1(n_{0j}+n_{1j}) & \text{if } (n_{0j}+n_{1j})>0 \\ \zeta_2 n_{2j} & \text{if } (n_{0j}+n_{1j})=0 \text{ and } n_{2j}>0 \\ 0 & \text{if } (n_{0j}+n_{1j}+n_{2j})=0 \end{cases}, \tag{2}$$

where $\zeta_1 > \zeta_2$. As a result of this functional form, a woman who is taking care of newborns and babies is also able to take care of school-aged children without incurring any additional time.

In addition to time costs, children are costly in terms of goods. First, mothers who work need to buy childcare services in the market for newborns, babies, and school-age children. These childcare services are proportional to the labor status of the mother. In particular, I assume that the following function describes the childcare services:

$$s_j(\mathbf{n_j}) = \begin{cases} (\kappa_1(n_{0j}+n_{1j})+\kappa_2(n_{2j}))\bar{Y}_j & \text{if } h_j^f = ft \\ 0.5(\kappa_1(n_{0j}+n_{1j})+\kappa_2(n_{2j}))\bar{Y}_j & \text{if } \mathrm{h}_j^f = pt \end{cases}, \tag{3}$$

where $\bar{Y}_j$ denotes the average household income. Second, children are costly because they deflate consumption, $\Psi(\widetilde{N_j})$. I denote by $\widetilde{N_j} = n_{0j}+n_{1j}+n_{2j}$ the number of costly children in the household at age j. Note that young adults do not incur time or goods costs.

5.4 Experience and Earnings Dynamics

Household income is the sum of the husband's and wife's labor earnings. Earnings of each individual of gender g at period j, is the product of labor productivity z_j^g and the hours worked in the market h_j^g :

$$w_j^g = z_j^g h_j^g. \tag{4}$$

The husband's labor productivity, z_j^m, is a function of age because I assume they always work full-time. However, females' productivity, z_j^f, depends on their experience accumulation at age j, x_j^f. The wage processes are:

$$\ln\left(z_j^m\right) = \eta_0^m + \eta_1^m j + \eta_2^m j^2 + u_i^m + v_j^m,$$
$$\ln\left(z_j^f\right) = \eta_0^f + \eta_1^f x_j^f + \eta_2^f \left(x_j^f\right)^2 + u_i^f + v_j^f, \tag{5}$$

where $u_i^g \sim N\left(-\frac{\sigma_{u^g}^2}{2}, \sigma_{u^g}^2\right)$ is a fixed effect at birth, and v_j^g is a persistent productivity shock. Both wives and husbands receive uncorrelated shocks v_j^f and v_j^m, which evolve stochastically over time according to an AR(1) process:

$$\begin{aligned} v_j^m &= \rho v_{j-1}^m + \xi_j^m \\ v_j^f &= \rho v_{j-1}^f + \xi_j^f \end{aligned} \quad \text{with} \begin{bmatrix} \xi_j^m \\ \xi_j^f \end{bmatrix} \sim N\left(\begin{matrix} -\frac{\sigma_{\xi^m}^2}{2} \\ -\frac{\sigma_{\xi^f}^2}{2} \end{matrix}, \begin{bmatrix} \sigma_{\xi^m}^2 & 0 \\ 0 & \sigma_{\xi^f}^2 \end{bmatrix} \right), \; v_0^m = v_0^f = 0. \tag{6}$$

I assume that when the wife works full-time, she accumulates one year of experience. However, if she works part-time, she accumulates half-year experience. She keeps the same experience if she does not work. Thus, female experience in the labor market accumulates as follows:

$$x_{j+1}^f = F(x_j^f, h_j^f) = \begin{cases} x_j^f + 1 & \text{if } h_j^f = ft \\ x_j^f + 0.5 & \text{if } h_j^f = pt \\ x_j^f & \text{if } h_j^f = 0 \end{cases} . \tag{7}$$

5.5 The government

The government collects taxes from labor income, and the tax's revenue is simply wasted. The tax function is

$$T(Y_j) = \left(1 - \lambda Y_j^{-\tau}\right) Y_j \tag{8}$$

where τ measures the degree of progressivity, λ is the average level of taxation and Y_j is the total household income. This functional form allows for negative tax rates, and thus it incorporates the Earned Income Tax Credit (EITC).

5.6 Preferences

Each period the household receives utility from consumption (c_j), leisure (l_j^f), and children ($\mathbf{n_j}$). Each child deflates consumption, $\Psi(\widetilde{N}_j)$, and implies a time cost that reduces leisure, $\tau_j^f(\mathbf{n_j})$. In addition, mothers derive utility from the number of costly children they have, $\widetilde{N}_j$, and the value of staying at home when the child is a newborn, υ. Based on this, we can formulate the per-period utility function as follows:

$$U_j(c_j, l_j^f, \mathbf{n_j}) = \alpha_c \frac{\left(\frac{c_j}{\Psi(\widetilde{N_j})}\right)^{1-\gamma_c} - 1}{1-\gamma_c} + \alpha_l \frac{(l_j^f)^{1-\gamma_l} - 1}{1-\gamma_l} + \alpha_n \frac{\left(1+\widetilde{N_j}\right)^{1-\gamma_n} - 1}{1-\gamma_n} \tag{9}$$
$$- \chi \mathbb{1}_{N_j>0} + \upsilon \mathbb{1}_{n_{0j}=1} \mathbb{1}_{h_j^f=0},$$

where χ is a fixed disutility of motherhood. This parameter captures either preference over not being a mother or other costs associated with motherhood that are not modeled. Anticipating the calibration, χ is crucial for the extensive margin of fertility (i.e. remaining childless or becoming a mother), while α_n and γ_n are important for the intensive margin (having 1, 2, or 3 children).

5.7 Budget and time constraints

The per-period budget constraint restricts the consumption in the household and expenditure on childcare activities to be equal to the sum of net household income. It is described by:

$$c_j + s_j(\mathbf{n_j}) = Y_j - T(Y_j), \tag{10}$$

where the household's income is the sum of both partners' labor income, i.e., $Y_j = w_j^f + w_j^m$. Regarding the time constraint, it restricts the sum of the time allocated to work, childbearing, and leisure to be equal to the endowment of time:

$$h_j^f + \tau_j^f(\mathbf{n_j}) + l_j^f = 1. \tag{11}$$

5.8 The household problem

I use a recursive formulation to describe the household's problem. The vector of state variables is given by the age, the experience accumulation of the wife, the vector of children by age, and the income shocks, $\mathbf{S} = \{x^f, \mathbf{n}, v^m, v^f\}$. Women decide how much to consume (c), how much to work (h^f), and whether to give birth or not next period (b'). The decision problem of a female at age j is given by:

$$V_j\left(x^f, \mathbf{n}, v^m, v^f\right) = \max_{b' \in B(j,\mathbf{n}), c, h^f \in \{0, pt, ft\}} \left\{U\left(c, \mathbf{n}, h^f\right) + \beta E\left[V_{j+1}\left(x'^f, \mathbf{n}', v'^m, v'^f\right) \middle| \mathbf{n}, v^m, v^f\right]\right\}$$

subject to

$$c + s(\mathbf{n}) = Y - T(Y)$$

$$w^f = z^f h^f$$

$$w^m = z^m h^m$$

$$h^f + \tau^f(\mathbf{n}) + l^f = 1$$

$$x'^f = F(x^f, h^f)$$

$$\mathbf{n}' = \Lambda_j(\mathbf{n}, b')$$

Equations 5, 6

where the expectation is taken over the number of kids in each category and the productivity shocks. The choice set for the birth decision is defined as:

$$B(j, \mathbf{n}) = \begin{cases} \{0,1\} & \text{if } N < 3 \text{ and } j < \bar{J} \\ \{0\} & \text{otherwise.} \end{cases}$$

6 Calibration

I calibrate the model using a two-step strategy to match the data for college-educated married women born between 1944 and 1957. In the first step, I use data to estimate the parameters that can be identified outside the model. Table 4 shows the value of these parameters. In the second step, I calibrate the remaining parameters to match the labor market life-cycle patterns and fertility decisions observed in the data. Although parameters and moments do not have a one-to-one mapping, I discuss how certain moments can provide information about some parameters.

6.1 First step

Timing. The length of the model period corresponds to one calendar year. I only model two life stages. The first stage in life corresponds with the working periods when women are fertile. I assume that women begin their life at age 25, $j = 1$, and they are fertile until age 43, $j = \bar{J} = 19$. During this first stage, they face a fertility probability that decreases

Table 4: Calibration: Exogenous Parameters

Parameter	Value	Meaning	Source
Demographics			
J_f	19	Last fertile period	See text
J	35	Last model period	See text
Λ_1	0.2	Probability from baby to school-age children	See text
Λ_2	0.1	Probability from school-age children to teenager	See text
Utility			
ψ	$1.5 + 0.3(n_0 + n_1 + n_2)$	Equivalence scale	OECD
Income			
η_0^m	0.692		
η_1^m	0.078	Regression log wage on age and age2 (men)	
η_2^m	-0.001		
σ_{ξ^m}	0.173	Standard deviation of income shock	
ρ^m	0.946	Persistance of income shock	PSID
σ_{ξ^f}	0.185	Standard deviation of income shock	
ρ^f	0.886	Persistance of income shock	
σ_{u^m}	0.220	Standard deviation of fixed effect for husbands	
σ_{u^f}	0.213	Standard deviation of fixed effect for wifes	
λ	2.915		Borella et al. (2022)
τ	0.107		Borella et al. (2022)

with the woman's age and the number of children.[18] The second stage corresponds with the periods $j \in [\bar{J}+1, J]$ when women are no longer fertile, but their children are still newborns, babies, or school-age children. The last period corresponds to the extreme case when the woman gives birth at the last fertile age, $j = \bar{J}$, and this child becomes a teenager, i.e., $J = 36$.[19]

I model four types of children according to their age: newborns (aged 0-1), babies (aged 1-5), school-age children (aged 5-14), and teenagers (+14). Children qualify as newborns for only one period, and they age deterministically, i.e. with probability one, a newborn at period j will be a baby at period $j+1$. However, transitioning from baby to school-age child and from school-age child to teenager is stochastic. The transition probabilities are $\lambda_1 = 0.2$ and $\lambda_2 = 0.1$, respectively. That is, in expectation, a child spends 4 years as a baby and ten years of school age.

I assume that women's labor force participation can take three values: $h^f \in \{0, 0.2, 0.4\}$, where $h^f = 0$ means no participation, and $h^f = 0.2$ and $h^f = 0.4$ stand for part-time and full-time work, respectively. The individual's endowment of discretionary time is 5200 hours per year. I consider 16 hours per day, 6 days per week, and 52 weeks per year of discretionary time. A full-time job represents an average of 40 working hours per week, and I assume that

[18]The National Center for Health Statistics estimates that in 2015-19, 14.6% of married women between the ages of 15-29 have impaired fecundity (i.e., who are not surgically sterile, and for whom it is difficult or impossible to get pregnant or carry a pregnancy to term). This number increases to 27.3% and 43.3% when women are in the age range of 30-39 and 40-49, respectively.

[19]In this case, the child is a newborn at age $\bar{J}+1$ and transitions to a teenager 16 years after. If at period $j-1$, the child is not a teenager, the transition to this status occurs with probability one next period.

part-time workers supply half of the hours. Therefore, full-time workers spend 0.4 of the time endowment in the labor market, while part-time workers spend 0.2 of it.

Wages. To estimate the parameters in the wage equations, I use the Panel Study of Income Dynamics (PSID) data from 1968 to 2015. In particular, I make the same specification for the annual process for log hourly wages as Erosa et al. (2016a):

$$\ln(z_{ij}^g) = \eta^g x_j^g + u_i^g + \nu_j^g + \lambda_j^g, \tag{12}$$

where $\ln(z_{ij}^g)$ represents the observed annual log hourly wage of individual i of gender g, at age j in the data, x_j^m and x_j^f represents a second-order polynomial in age and experience, respectively, η^g is the vector of coefficients, $u_i^g \sim N\left(-\frac{\sigma_{u^g}^2}{2}, \sigma_{u^g}^2\right)$ is a fixed effect determined at birth, $\lambda_j^g \sim N\left(-\frac{\sigma_{\lambda,g}^2}{2}, \sigma_{\lambda,g}^2\right)$ is interpreted as measurement error and ν_j^g follows a first-order autoregressive process:

$$\begin{array}{l} v_j^m = \rho v_{j-1}^m + \xi_j^m \\ v_j^f = \rho_{j-1}^{v}{}^f + \xi_j^f \end{array} \text{ with } \begin{bmatrix} \xi_j^m \\ \xi_j^f \end{bmatrix} \sim N\left(\begin{matrix} -\frac{\sigma_{\xi^m}^2}{2} \\ -\frac{\sigma_{\xi^f}^2}{2} \end{matrix}, \begin{bmatrix} \sigma_{\xi^m}^2 & 0 \\ 0 & \sigma_{\xi^f}^2 \end{bmatrix} \right), \; v_0^m = v_0^f = 0. \tag{13}$$

For women, I only take the income shock's standard deviation, the income shock's persistence, and the fixed effect's standard deviation as the parameters estimated in the data. The η^f coefficients in the equation 12 are calibrated in the second step to generate some targets regarding the wage gap data. For the numerical solution, I approximate the auto-regressive vector of persistent stochastic shocks for the woman and her partner with a discrete-valued Markov chain using the method proposed by Tauchen (1986) and Tauchen and Hussey (1991).[20] For the fixed effect, instead of discretizing the process, I make a simplifying assumption to reduce the number of state variables. In particular, I assume that the variance of the normal distribution from where the individual draws the realization of the shock is higher for the first period. In the first period, the individual draws a realization of the shock $v_j^g \sim N\left(-\frac{\sigma_{\xi^g}^2}{2}, \sigma_{\xi^g}^2 + \sigma_{u,g}^2\right)$ while from the second period onwards is $v_j^g \sim N\left(-\frac{\sigma_{\xi^g}^2}{2}, \sigma_{\xi^g}^2\right)$. This assumption generates a higher variance in the first periods and, thus, more heterogeneity in the persistent shock. Moreover, while I assume the existence of a transitory shock to estimate the wage process, λ_j^g, I do not model it. In Table 4, I list the values of the parameters driving the stochastic process for labor productivity in the baseline economy.

[20] I use five values for the persistent shock.

Tax function. I take the estimations of λ, and τ from Borella et al. (2022). Using the PSID data from 1968 to 2015, they estimate these two by regressing the logarithm of after-tax household income on a constant and on the logarithm of pre-tax household income by year, and household type. They provide estimates for single and married households. In this paper, I use their estimates for couples in the year 1982.

6.2 Second step

I calibrate the remaining 22 parameters to match 22 data statistics. Table 5 reports the values of these calibrated parameters that correspond to the female income process, preference parameters, the pregnancy probabilities, the time cost of children, and the childcare cost. These parameters are selected to target the following data moments that correspond to married women with a college education and belonging to the Middle cohort:

- 1–3. The proportion of households with zero, one, two, and three children or more.
- 4. The mother's age at her first child's birth.
- 5. The spacing between the first and the second child.
- 6–7. Childcare expenditure as a fraction of average household income for children between 0-5 and 5-15.
- 8–13. Employment rates between the ages of 25 and 54 by four-year age groups.
- 14. The initial gender wage gap between spouses.
- 15–16. The coefficient of experience and experience squared.
- 17–18. The employment rate and the share of full-time for women who do not have children.
- 19–20. The employment rate and the share of full-time for women who are mothers.
- 21–22. The employment rate and percentage of full-time workers among mothers who have a child between the ages of 0 and 5 and those who have a child between the ages of 5 and 14.

Despite the calibration process implying that all parameters affect all moments, I discuss which parameters provide more information about particular moments.

Table 5: Calibration: Endogenous Parameters

Parameter	Value	Parameter	Value
Preferences		*Income*	
β	0.910	η_0^f	2.165
γ_c	0.500	η_1^f	0.046
γ_l	0.520	η_2^f	-0.0012
γ_n	0.645	*Pregnancy probability*	
α_c	0.205	$p^{25-29}(0)$	0.7
α_l	0.330	$p^{30-34}(0)$	0.25
α_n	0.360	$p^{35-39}(0)$	0.15
χ	0.190	$p^{40-43}(0)$	0.08
ν	0.600	$p^j(1)$	0.88*$p^j(0)$
Children		$p^j(2)$	0.4*$p^j(0)$
ζ_1	0.060		
ζ_2	0.020		
κ_1	0.081		
κ_2	0.058		

Female earnings. I calibrate η_0^f to match the initial gender wage gap between ages 25-29. The remaining parameters in the earnings equation of women are calibrated by an indirect inference approach. I simulate individual data from the model, I construct the experience accumulation as in the data, and then I run the same Mincer regression as in the data but on model-generated data. I choose η_1^f and η_2^f so that the estimated coefficient of experience and experience squared in the model-generated data equals its analog in the PSID.

Preferences. The utility weights $(\alpha_c, \alpha_l, \alpha_n)$ and the curvatures $(\gamma_c, \gamma_l, \gamma_n)$ are crucial to targeting the female employment rate for childless women, for mothers, and the desire to be a mother for some women, respectively. The direct disutility of being a mother (χ) helps to target the share of women with zero children. The utility of being at home whenever the child is a newborn (ν) is informative about the share of full-time workers of mothers with children between 0-5.

Finally, the discount factor (β) is calibrated to match the age at with women have their first child. This parameter is in the range of the standard values in the literature.[21]

Pregnancy probability. I parametrize fertility probability with 6 parameters as in Erosa et al. (2016b). The first four $(p^{25-29}(0), p^{30-34}(0), p^{35-39}(0), p^{40-43}(0))$ capture the decrease in the changes a woman has to get pregnant as she gets older. The remaining two parameters $(p^j(1), p^j(2))$ measure how difficult it is for a mother to give birth to another child once she

[21] For example Da Rocha and Fuster (2006) and Attanasio et al. (2008) assume a discount factor of 0.96 and 0.98, respectively.

has already given birth to one and two children. All these parameters are selected to match the share of women with 1, 2, and 3 or more children in the model, the age at which women have their first child, and the spacing between children. Furthermore, these pregnancy probabilities are crucial to matching the employment profile of mothers throughout their life. Figure 8 shows the pregnancy probabilities as a function of age for women with zero, one, and two children.

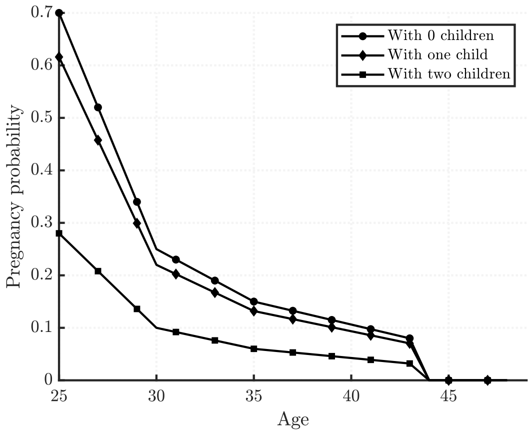


Figure 8: Pregnancy probability as a function of age

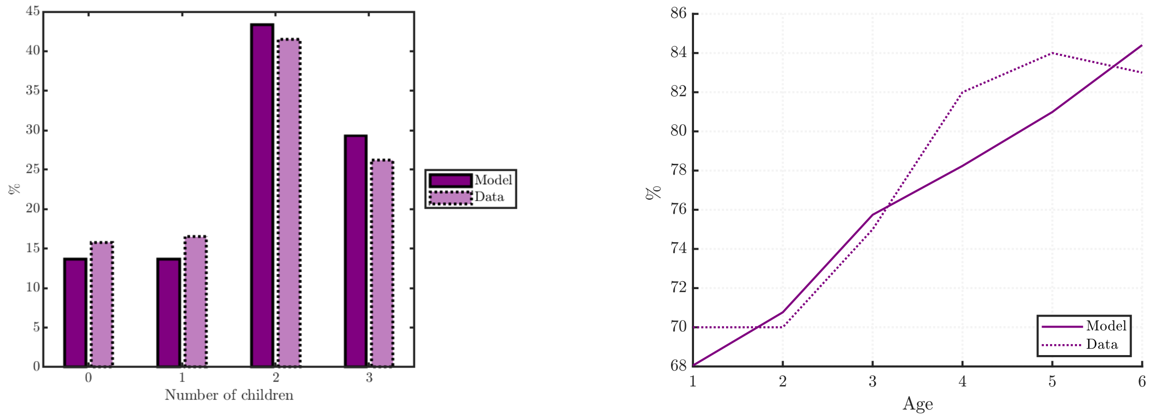
Time cost of children. The time mothers spend with their children is chosen to match the impact children have on women's labor supply. I match two moments: the difference in the share of full-time workers first between mothers of children younger than 5 years old and mothers of children of ages 5-14 and, second, between mothers and non-mothers.

Out-of-pocket childcare costs. I assume that the childcare cost for part-time working mothers is half of those who work full-time. Moreover, I calibrate this κ_1 and κ_2 to match the childcare cost implied by children aged between 0-4 and 5-14 in the data. To this end, I use the U.S. Bureau of Census data from the Survey of Income and Program Participation (SIPP) to compute childcare costs.[22] The Census estimates the average childcare payments of working mothers who make childcare payments for the sample period 1993-2011. I compute the average payment for college-educated mothers by the child's age. A child between the ages of 0 and 4 costs about 8 % of the average household income, while it is 5% for children aged between 5 and 14. Hence I calibrate κ_1 and κ_2 so that it generates a cost of 8% and 5% in the household income, respectively.

[22] Guner et al. (2020b), and Hannusch et al. (2019) also use these childcare cost estimates.

7 Calibration Results

The Baseline economy is intended to replicate the behavior of college-educated women who marry and belong to the 1944-57 birth cohort. The model replicates reasonably well all the targeted moments in the calibration. Figure 9a compares the distribution of households regarding the number of children in the model and the data. The model generates a difference of -0.02, -0.03, 0.02, and 0.03 between the fraction of women with 0, 1, 2, and 3 children in the model and the data, respectively.



(a) Distribution of children

(b) Employment rate

Figure 9: Calibration results: female employment rate and distribution of households by the number of kids.

The age at first birth is 1.9 years later in the model than in the data. Children are costly in goods, and since households cannot borrow nor save, they need to postpone births by more in the model. This effect is stronger among women who are endowed with higher initial labor productivity. This delay in births impacts the spacing between children. As the average age is larger in the model, the spacing is shorter because women who aim to have two or three children need to have them together enough to avoid ending up having fewer kids than their desired number due to the pregnancy probabilities. As a result, the model displays that the spacing is of 1.33 years, while in the data, it is 2.99.

Figure 9b shows the employment rate for six age groups in the model and the data. While the increasing profile of employment is well captured in the model, there are two features that my model can not reproduce. First, the model does not match a flat age profile of employment between ages 25 and 34. This is a sign of the model underestimating either the cost of having a child, which would induce more women to stay at home when they become mothers, or either the value of staying at home should increase to generate more mothers willing to take off from the labor market when their child is young. The second feature that my model does not capture is the concave shape, especially after age 40. Consequently, modeling human capital depreciation is necessary to discourage women from working when they take long breaks from the labor market to take care of their children. Despite this, the model displays a good fit regarding the share of women who work and the proportion of them working full-time for three different women: childless women, mothers, and mothers with young children (0-5), see Table 6. There is a greater likelihood of childless women being in the labor market and working full-time than mothers. Furthermore, being a mother of a child between 0-5 discourages even more labor force participation. Because women receive a value of staying at home only when the child is young, and because mothers in the labor market must pay childcare expenses, 62.2% of these women choose to work, and among them, 64.1% are part-time workers.

Table 6: Calibration results: female employment rate of mothers and non-mothers

	Model baseline	**Data baseline**	**Difference**
Employment childless	0.916	0.870	-0.046
Full-time childless	0.676	0.690	0.014
Employment mothers	0.738	0.730	-0.008
Full-time mothers	0.469	0.470	0.001
Employment mothers, child 0-5	0.622	0.580	-0.042
Full-time mothers, child 0-5	0.359	0.310	-0.049

The model replicates well the initial wage gap we observe in the data between ages 25-29. The difference in earnings between men and women who are full-time workers in my model is 8.7%, while the difference in data is 7.6%. Moreover, when regressing log hourly wages of women on a constant, experience and experience squared in the simulated data from the model, it generates very similar coefficients for the last two when compared with the regression on PSID data, see Table 7.

Even though the model does not explicitly target the intensive margin in the labor market, the model replicates the share of women who work full-time after the age of 40, when few women have children, see Table 8.

8 Quantitative Experiments

The purpose of this section is to quantify the employment and fertility effects of two exogenous changes affecting the choice between having kids and a career: higher marginal returns to experience and the availability of Assisted Reproductive Technology. For this reason, I conduct two exercises. First, I calibrate the parameter that measures the marginal returns to experience to generate the increase we observe in the data. Second, I additionally calibrate

Table 7: Calibration results: Mincer regression for college-educated women

	Data baseline	Model baseline
Experience	0.0282***	0.0275***
	(0.003)	(0.000)
Experience^2	-0.000449 ***	-0.000458***
	(0.000)	(0.000)
Constant	2.087***	2.2241***
	(0.023)	(0.003)
Observations	3894	178159
R-squared	0.0567	0.0688

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Data baseline: Middle cohort, PSID 1968-2015

Model baseline: simulated data

Table 8: Calibration results, untargeted moments

	Model baseline	**Data baseline**	**Difference**
% full-time workers at ages 40-44	0.643	0.600	-0.043
% full-time workers at ages 45-49	0.651	0.640	-0.011
% full-time workers at ages 50-54	0.657	0.650	-0.007

an increase in the probability of a woman getting pregnant after the age of 30. Lastly, I discuss how each factor contributes to the sagging middle effect, the postponement of births, and the increase in the total fertility rate observed in the data for the Young cohort.

8.1 Experiment 1: Increase in returns to experience

Measuring the exogenous change across cohorts. I follow two steps to calculate the difference in returns to experience between the Middle and Young cohorts. First, I run a Mincer regression of log hourly wage on experience and experience squared for these two cohort groups. In this regression, the coefficient of experience increases from 0.028 to 0.041; see Table B.9 in the Appendix. Second, I run the regression for individuals younger than 30 years old. In this case, the coefficient for experience is not significant and equal to 0.00554 for the Middle cohort, while it is statistically significant and equal to 0.0865 for the Young cohort, see Table B.10 in the Appendix. Thus, returns to experience are not only greater overall for the Young cohort, but also they have an experience premium when they work when young compared to women in the Middle cohort.

In light of these two findings, in Experiment 1, I recalibrate the coefficient of experience η_1^f to match the overall increase in the returns to experience, and, second, I change the accumulation of experience for the Young cohort. As only for this group of cohorts, individuals younger than 30 receive an experience premium, I modified the equation 7 in the model in the following way:

$$x^f_{j+1} = F(x^f_j, h^f_j) = \begin{cases} x^f_j + 1 + \pi & \text{if } h^f = ft \quad \& \quad j \leq 6 \\ x^f_j + 1 & \text{if } h^f = ft \quad \& \quad j > 6 \\ x^f_j + 0.5 & \text{if } h^f = pt \\ x^f_j & \text{if } h^f = 0. \end{cases} \tag{14}$$

where individuals younger than 30 receive an experience premium of π when they work full-time. I also calibrate π to generate the increase in the coefficient for experience in the sample of individuals younger than 30. This assumption makes a direct link between female wage growth and birth delays. Women who become mothers at the beginning of their careers and do not work full-time are penalized.

Table 9 shows the calibration results and matched moments. Women in the Young cohort experience similar returns to experience compared to the data in the new economy. In the Appendix, Table B.11 shows all the coefficients of the two Mincer regressions in the data and the simulated data from this experiment.

Table 9: Calibration results and targets in Experiment 1

Parameters	**Baseline model**	**Experiment 1**
η_1^f	0.046	0.050
π	0	1
Targets	**Experiment 1**	**Data Young cohort**
Marginal returns to experience	0.043	0.041
Marginal returns to experience < 30	0.096	0.086

Results. In this experiment, I compare two economies: the baseline economy, which replicates the Middle cohort, and the new economy, which aims to reflect the Young cohort's behavior. Table 10 shows the average employment and the share of full-time workers for all women, childless women, mothers, and mothers with young children. On average, the increase in returns to experience induces an increase in employment of 7.35 pp. Independent of their family status, women find it optimal to work more hours as the opportunity cost of being at home increases. In particular, the highest increase is coming from mothers. Women with children are more likely to participate in the labor market and do so more intensively, as the share of full-time workers also increased by 8.66 pp. Mothers want it all: to be in the labor market and have kids.

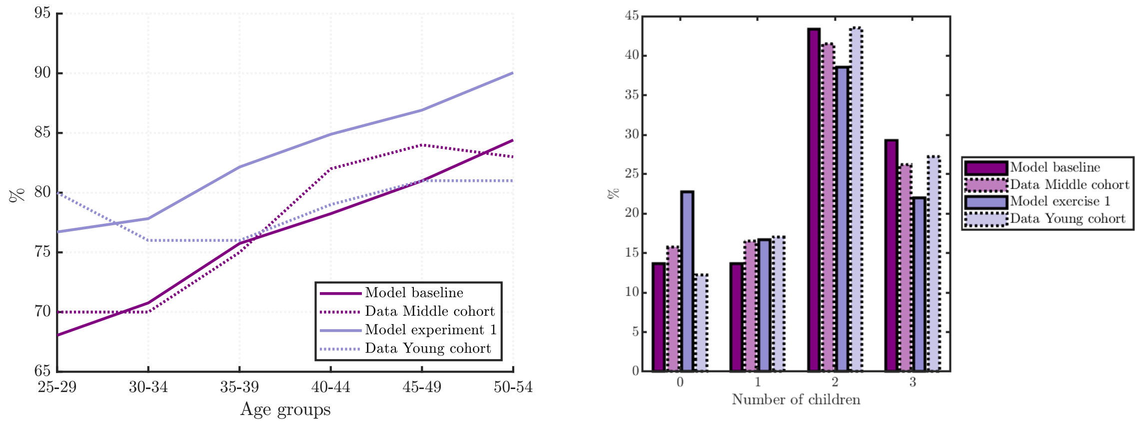
Table 10: Results of Experiment 1

	Baseline	Experiment 1	Difference (pp)
Employment rate	79.60%	86.96%	7.35
Employment childless	91.64%	94.61%	2.98
Full-time childless	67.61%	75.71%	8.09
Employment mothers	73.82%	80.12%	6.29
Full-time mothers	46.95%	55.60%	8.66
Employment mothers with a child 0-5	62.16%	71.32%	9.15
Full-time mothers with a child 0-5	35.89%	47.32%	11.43

Figure 10 plots the life-cycle profile of employment and the distribution of households by the number of children they have. This figure compares the Middle and the Young cohorts in the model with solid lines and the data with dotted lines. Panel A in Figure 10 shows how the employment profile of wives over the life cycle reacts to higher marginal returns to experience. According to this figure, the increase in returns to experience, especially when an individual is young, increases employment rates at all age groups, given the parameters of the baseline economy. The new economy reproduces the increase in employment at ages 25-29 that we observe in the data. Despite this, the model does not produce the sagging middle effect we observe in the data. From age 35 onwards, the employment rate increases until it reaches 89%. The model overpredicts employment rates in this new economy after 30 years of age.

The increase in returns to experience generates a postponement in the birth of the first child of 0.92 years. Postponing births caused the fertility rate to drop from 1.9 in the baseline to 1.6. Panel B in Figure 10 shows the share of women with 0, 1, 2, and 3 children. I compare four moments, the ones implied by the model and the data counterpart for the baseline (Middle cohort) and the new economy (Young cohort). In this new economy, the share of women who are not mothers increases from 13.7% to 22.8%. Moreover, the share of women with 1 child increases by 3 percentage points while the share of women with two and three children narrows by 4.8 and 7 percentage points, respectively. This result shows that increasing returns to experience, especially when young, hurts total fertility rates because women have fewer children and they have them later in life. However, this finding contradicts the behavior of women in the Young cohort. This suggests that women in this economy face a much stronger trade-off between career and family than the one observed for the Young cohort in the data.

On the labor supply side, in this paper, I find that the increase in returns to experience induces an increase in the employment rate of 7.35 percentage points on average. Moreover, it implies an increase in employment of women younger than 29 of 13%, which is similar



(a) Employment rate

(b) Distribution of children

Figure 10: Results Experiment 1

to the increase of 14% in the data. The results of this experiment on the labor supply are qualitatively in line with Olivetti (2006) and Attanasio et al. (2008). They also find that an increase in the returns to experience affects women's labor supply. However, these two papers abstract from modeling fertility decisions and model an increase in returns to experience without the age component that I emphasize in my counterfactual exercise. In this line, my findings are consistent with Caucutt et al. (2002). They use a dynamic general equilibrium model of family formation and investment in children to study the determinants of women's timing of births and labor supply decisions. Although women do not receive a return to labor market experience in the form of higher future wages in their model, they show that women's productivity (wages) delays fertility even when the labor market returns to work experience is zero. My paper complements the previous literature by quantifying how much a change in returns to experience across generations, especially when young, explains the delay in births we observe in the data.

Despite higher returns to experience increasing employment rates at younger ages and delaying births, this exogenous change does not fully explain women's behavior in the Young cohort. This new economy predicts a fall in the total fertility rate by 15%, while it actually rises by 4%. I then introduce ART to determine if ART, in conjunction with higher returns to experience, can generate a similar profile of employment and fertility decisions to the Young cohort.

8.2 Experiment 2: Increase in returns to experience and IVF technology

Measuring the increase in IVF technology. Given the new income process with higher returns to experience, I additionally change the fertility probabilities to capture the arrival of infertility treatments. It is unclear how much infertility treatments increase the likelihood of having a child. Moreover, most of the ART cycles performed in 2018 were performed on patients under the age of 35.[23] It is still true, however, that infertility increases with age.[24] Therefore, there is a trade-off between IVF technology being relevant for older women whose infertility probability is higher and IVF technology being majorly used by young women. As a result, I make a conservative assumption: I increase the probability of becoming pregnant for all age groups after age 30 at the same rate $\bar{\pi}$ to match the total fertility rate of the Young cohort.[25] Data shows that total fertility rises by 0.08 percent, reaching 1.98 percent, and I use this number as my target. Table 11 summarizes this experiment's parameters and targets.

Table 11: Calibration results and targets in Experiment 1

Parameters	**Baseline model**	**Experiment 2**
$\bar{\pi}$	0	0.06
Targets	**Experiment 2**	**Data Young cohort**
Total fertility rate	1.98	1.98

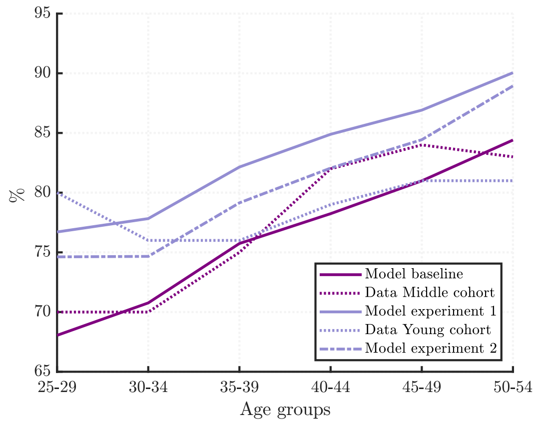
Results. Figure 11 presents the results of this experiment. IVF technology increases the probability of becoming a mother, when, biologically, women are less likely to get pregnant. Under this scenario, the total fertility rate of women in this economy increases by 0.09 compared to women in Experiment 1. When IVF technology is considered, the employment profile is much more similar to the data counterpart. In particular, the employment rate flattens out between ages 25-29 and only increases after this age, see Panel A. The postponement of births caused by higher returns to experience when young for women does not prevent women from forming a family. Indeed, the relaxation of the opportunity of cost of building a career when young, thanks to a greater probability of becoming pregnant when old, generates an increase in the share of women with three children of 7.4 percentage points in exercise 2 vs exercise 1.

Using IVF technology, new cohorts can relax the trade-off between building their professional career and having a family. Several studies have shown that career and family trade-off exist. For example, Bertrand et al. (2010) study MBA graduates from the University of Chicago's Booth School of Business, and they find that there is a big trade-off between career and family for US female top professionals. Although this is the case, recent papers like Shang

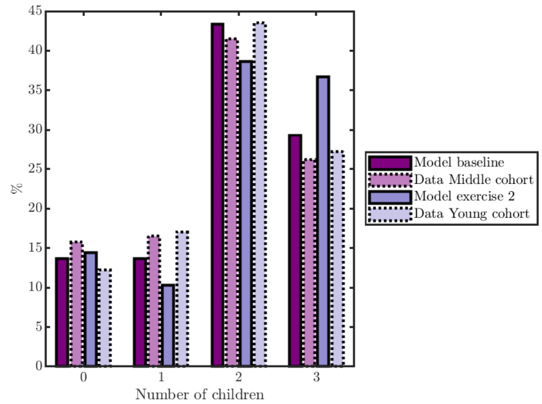
[23] This age group represented 37.2% of all cycles, compared to 22.7% among those aged 35–37, 19.6% among those aged 38–40, 9.4% among those aged 41–42, and 11.1% among those older than age 42.

[24] According to the National Survey of Family Growth, 12.6%, 22.1%, and 26.8% of women aged 15-29, 30-39, and 40-49 were infertile in 2015-2019.

[25] I assume that $\tilde{p}^{30-34}(0) = \bar{\pi} + p^{30-34}(0)$, $\tilde{p}^{35-39}(0) = \bar{\pi} + p^{35-39}(0)$ and $\tilde{p}^{40-43}(0) = \bar{\pi} + p^{40-43}(0)$.



(a) Employment rate



(b) Distribution of children

Figure 11: Results of Experiment 2

and Weinberg (2013) and Goldin and Katz (2008) indicate that highly educated women in the US have more children and work more.

8.3 Discussion

Returns to experience are key for understanding the age profile of employment for the Young cohort. The increased probability of being a mother when old plays a much smaller role in generating this new employment profile. However, fertility outcomes do not match observed data without infertility treatments. Quantitatively, I compare average employment rates, first birth ages, and total fertility rates in the data and those generated by the model to assess the contributions of these two complementary explanations. Table 12 summarizes the results.

Table 12: Changes in the data vs. model

	Data Young vs Middle	**Experiment 1 vs Baseline**	**Experiment 2 vs Baseline**
Employment rate 25-54	1%	8%	6%
Employment rate 25-29	14%	13%	10%
Employment rate 30-34	9%	10%	6%
Employment rate 35-39	1%	8%	4%
Employment rate 40-44	-4%	8%	5%
Employment rate 45-49	-4%	7%	4%
Employment rate 50-54	-2%	7%	5%
Mother's age first child	9%	3%	3%
Total fertility rate	4%	-15%	5%

The data shows that the employment rate for 25-54-year-old women who belong to the Young cohort is 1% higher than those women in the Middle cohort. Despite this overall minor increase in employment rates, the results of both experiments suggest a higher increase than what we see in the data. In Experiments 1 and 2, the employment rate increases by 8% and 6%, respectively. Therefore, both experiments overestimate the change in employment profiles over the life cycle, but the second experiment generates a much similar employment pattern over the life cycle. Regarding the postponement of births, the model generates a much smaller effect than we observe in the data. Compared to the data, the age at which women have their first child increases by 9%, while it is 3% in both experiments. However, only Experiment 2 results in a positive change in total fertility. In the absence of infertility treatments, an increase in returns to experience would result in a 15% decrease in fertility rates, contrary to the 5% increase we observe in the data. As a result of these two exercises, it is evident that returns to experience may play a key role in postponing births. Nonetheless, if infertility treatments had not been available, the fertility rate would have been lower than it is today.

Since the purpose of this paper is to quantify how much each exogenous factor, namely an increase in marginal returns to experience and ART, explains employment and fertility behavior among college-educated women born in the Young cohort, the following comparison is made. Table 13 shows the percentage difference between the Young cohort data and the experiments. The closer these differences to zero are, the more similar my model's economy is to the Young cohort's. Based on this exercise, it appears that the combination of the two factors generates behavior similar to that of the Young cohort.

Table 13: Deviation from the moments of the Young cohort

	Experiment 1 vs data Young cohort	**Experiment 2 vs data Young cohort**
Employment rate 25-54	6%	4%
Employment rate 25-29	-4%	-7%
Employment rate 30-34	2%	-2%
Employment rate 35-39	8%	4%
Employment rate 40-44	7%	4%
Employment rate 45-49	7%	4%
Employment rate 50-54	11%	10%
Mother's age first child	1%	1%
Total fertility rate	-19%	0%

9 Sensitivity Analysis: Why Only College-Educated Women?

The new employment life-cycle profile is a particular feature of college-educated married women. Figure 12 shows the employment rate of non-college-educated women over their life cycle. At age 20, women in the Young cohort have a higher employment rate than those in the Middle cohort. The employment rates of the Middle and Young cohorts do not become similar until they reach the age of 40. This sample of women does not show a sagging middle effect between the ages of 30-39, as do college-educated women.

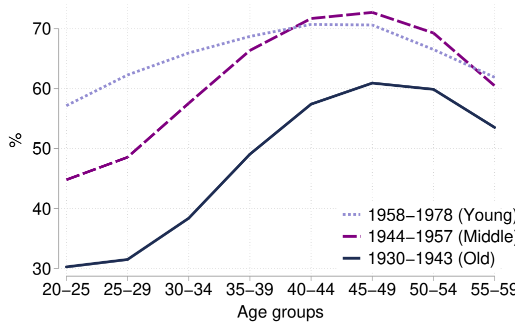


Figure 12: Employment rate of ever-married non-college educated women

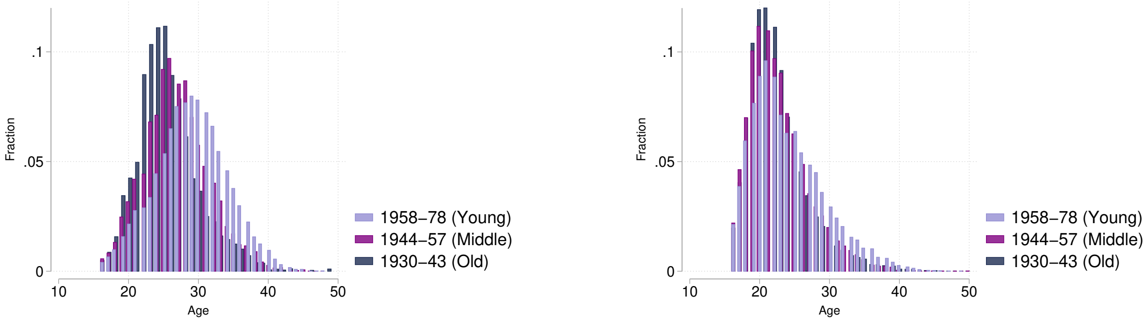
At the same time, fertility decisions also differ between college and non-college-educated women. Figure 13 shows the age distribution at first birth by cohort and education of the mother. The rise in maternal age for mothers with a college degree is substantial; we can observe how these curves shift to the right, implying an increase in the median age at which these women have their first child. In contrast, women with less education have increasingly delayed childbirth yet have not delayed it to the same extent. The average age at first birth increases by 4.25 and 1.43 for college and non-college women, respectively, between the Old and the Young cohorts. Thus, the delay in fertility has been predominant among women with more education.[26] Moreover, while the fertility rate increases by 8pp for college-educated women in the Young cohort compared to the Middle cohort, non-college-educated women keep decreasing the total fertility rate by 9 pp.[27] This section aims to answer the question: why do non-college-educated women behave differently?

In this paper, I show the relevant role of higher returns to experience and infertility treatments in generating employment and fertility changes for college-educated women. However, for non-college-educated women, it seems that the mechanism is not that intense. To understand why these two exogenous factors affect non-college-educated women by less, I first analyze the evolution of returns to experience for non-college-educated women. Second, I give several reasons differentiating college and non-college-educated women, which might be relevant to their employment and fertility decisions.

Returns to experience have also increased for non-college-educated women, yet to a

[26]See Yang and Morgan (2003) for a deeper analysis of postponement in births by education of the mother.

[27]See Table B.13 in the Appendix for comparison in the average number of children these two groups of women have as well as the average age at which they have their children.



(a) College **(b)** Non-college

Figure 13: Age distribution at first birth.

lower extent. Table 14 shows the results of a Mincer regression where I regress log hourly wages on experience and experience squared. I run this regression for different subsamples: for the Middle, for the Young cohort, and each of those differentiating between college and non-college-educated married women. This analysis shows that returns to experience have increased for all women, independent of their educational attainment. Moreover, in line with the findings for college-educated women, the returns to experience increase when we focus on individuals younger than 30 (see Table B.12 in the appendix). Despite returns to experience also being higher for those women, this increase is lower than the one for college-educated women. Therefore, the mechanism I highlight in this paper is also present: women have an economic incentive to work more when young and ultimately to postpone fertility. Despite this, the effect for those women is lower.

Table 14: Labor income process by cohort and education

	Middle	Middle, NC	Middle, C	Young	Young, NC	Young, C
Experience	0.0333***	0.0306***	0.0311***	0.0643***	0.0536***	0.0625***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.004)	(0.006)
Experience^2	-0.000413***	-0.000351***	-0.000413***	-0.00153***	-0.00104***	-0.00154***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.636***	1.482***	1.974***	1.594***	1.461***	1.875***
	(0.016)	(0.019)	(0.030)	(0.018)	(0.023)	(0.030)
Observations	18977	12504	5278	13633	8379	3629
R-squared	0.0521	0.0558	0.0431	0.0664	0.0704	0.0645

Standard errors in parentheses
Source: PSID 1968-2015
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The increase in the returns to experience for college-educated women could be driven by changes in the occupational structure. Erosa et al. (2017) document that workers in non-linear occupations work on average more hours, and the hourly wage is higher than workers in linear occupations.[28] Over time, the fraction of women working in non-linear

[28]Non-linear occupations constitute those occupations with the higher hours group.

occupations (mostly college-educated women) has increased. Changes in the sorting of college females across occupations might partly explain the increase in the returns to experience relative to non-college-educated women. In Figures A.8 and A.9 I provide evidence of a dramatic shift in the distribution of women towards occupations with a higher mean and lower dispersion of hours.

To understand why non-college-educated women postpone births by less than women with a college degree and why they do not have a sagging middle effect, I will propose a set of potential explanations. First, the slope of earnings is flatter for women with lower education.[29] This suggests that women might not find it a sufficient incentive to postpone fertility, even when the return to experience increases. Second, due to the rise in positive assortative mating, (Greenwood et al., 2014), less educated women are less likely to be married to a college-educated husband. Because of this, these women have a lower negative income effect on employment than women married to high-income earners. Finally, for women without a college degree, infertility treatments might not be as relevant as they are for those with one. Two reasons make these treatments less relevant to non-college-educated women's fertility and employment decisions: first, even with the postponement in births, these women have their kids very young and may not require them, and second, these treatments are very expensive and may not be affordable for women without a college degree. Based on Danish administrative data, Groes et al. (2017) finds an education gradient when it comes to IVF success.[30] It is possible that these disparities influence the opportunity cost of delaying childbearing differently among more and less educated women, which may affect fertility choices and labor market outcomes differently.

10 Conclusions

A new life cycle of college-educated married women's labor force participation emerged with cohorts born in the mid-1950s. Compared to previous cohorts, their employment profile is flatter and higher with no hump but with a dip in the middle between ages 30-39. In addition, younger cohorts of women are delaying births and increasing their fertility rates.

What brought about the change in women's work and fertility decisions? In this paper, I develop a quantitative theory to provide a unified explanation for the changes across cohorts of employment and fertility decisions of college-educated women. I build a life-cycle model of labor supply and fertility decisions. Children are costly in goods and mother's time. Women

[29] See Figure A.7 in the Appendix for a comparison in the life-cycle profile of earnings by education.

[30] In the first cycle of pregnancy, Groes et al. (2017) finds that women with a college degree are 24% more likely to deliver a live child than high school dropouts.

face an increased risk of being infertile as they age. These assumptions lead some women to have a low labor supply in their early years until their children grow up and become less expensive. In the model, labor market experience implies higher wages in the future, and the returns to experience are higher for younger women. These assumptions lead some young women to work hard in the market and delay children until later in life. I calibrate the model to match the life-cycle profile of employment, hours worked, and fertility decisions of women born between 1944-1957.

In my model, I assume that two changes in the economic environment trigger the shift in employment and fertility decisions of younger college-educated married women: higher returns to experience, especially at younger ages, and the arrival of Assisted Reproductive Technology (ART). Rising returns to work experience have increased the opportunity cost of career disruptions, especially at the beginning of their careers. Having a child at a young age entails lost wages at this stage and lower human capital accumulation in the long run. If returns to experience are high, women may prefer to postpone childbirth to later ages and invest in a career instead. It means that children will be born during those years when the returns to education materialize, and wages are high. While delaying births increase the risk of infertility, recent advances in ART reduced the risk of infertility, and thus postponing pregnancy has become less costly.

In the first experiment, I take the baseline economy and only increase the returns to experience. Unlike women in the baseline economy, these women have an economic incentive to postpone fertility and work more. As a result, women increase their employment rate between ages 25-29 by 13% and delay the arrival of their first child by 0.92 years. Even though these align with the data, the model predicts a 15% drop in total fertility. In the second experiment, not only do I increase the returns to experience, but I also introduce ART. In this case, women postpone fertility 0.4% less, and their overall employment rate increases by -2.1% less than in the first experiment. According to my findings, the sagging middle effect is primarily caused by higher returns to experience when young. Despite this, ART technology has increased the likelihood of getting pregnant at an older age, which is crucial to capturing the overall increase in fertility we observe. It is, therefore, essential to consider both drivers when analyzing the employment and fertility decisions of young college-educated married women.

This paper's results are very suggestive and provide a basis for further investigation. One key issue that I have ignored is income taxation in the U.S. The combination of progressive and joint taxation, where individuals are taxed at the household level, distorts the labor supply decisions of the secondary earner, usually women. It may significantly affect women's employment life-cycle profile, making it an important factor in determining the new profile. Currently, I am working on a policy experiment that removes joint taxation and expands the tax system to the individual level in an extension of this paper. This exercise aims to quantify the role of income taxation in generating long-lasting effects on the labor market. In particular, I aim to answer the following question: What is the impact of joint taxation on amplifying the sagging middle effect? [31]

[31] See section D the Appendix for a longer discussion of this issue.

References

Abraham, K. G. and Kearney, M. S. (2020). Explaining the decline in the us employment-to-population ratio: A review of the evidence. *Journal of Economic Literature*, 58(3):585–643.

Abramowitz, J. (2017). Assisted reproductive technology and women's timing of marriage and childbearing. *Journal of Family and Economic Issues*, 38(1):100–117.

Adda, J., Dustmann, C., and Stevens, K. (2017). The career costs of children. *Journal of Political Economy*, 125(2):293–337.

Albanesi, S. and Olivetti, C. (2016). Gender roles and medical progress. *Journal of Political Economy*, 124(3):650–695.

Albanesi, S. and Prados, M. J. (2022). Slowing women's labor force participation: The role of income inequality. Technical report, National Bureau of Economic Research.

Amuedo-Dorantes, C. and Kimmel, J. (2005). The motherhood wage gap for women in the united states: The importance of college and fertility delay. *Review of Economics of the Household*, 3(1):17–48.

Attanasio, O., Low, H., and Sánchez-Marcos, V. (2008). Explaining changes in female labor supply in a life-cycle model. *American Economic Review*, 98(4):1517–52.

Bertrand, M., Goldin, C., and Katz, L. F. (2010). Dynamics of the gender gap for young professionals in the financial and corporate sectors. *American economic journal: applied economics*, 2(3):228–55.

Bick, A., Brüggemann, B., Fuchs-Schündeln, N., and Paule-Paludkiewicz, H. (2019). Long-term changes in married couples' labor supply and taxes: Evidence from the us and europe since the 1980s. *Journal of International Economics*, 118:44–62.

Bitler, M. P. and Schmidt, L. (2012). Utilization of infertility treatments: the effects of insurance mandates. *Demography*, 49(1):125–149.

Blau, F. D. and Kahn, L. M. (2013). Female labor supply: Why is the united states falling behind? *American Economic Review*, 103(3):251–56.

Borella, M., De Nardi, M., Pak, M., Russo, N., and Yang, F. (2022). U.s. taxes effective over time. Technical report, Working Paper.

Borella, M., De Nardi, M., and Yang, F. (2019). Are marriage-related taxes and social security benefits holding back female labor supply? Technical report, National Bureau of Economic Research.

Bronson, M. A. and Mazzocco, M. (2018). Taxation and household decisions: an intertemporal analysis. Technical report, Working Paper.

Buckles, K. (2007). Stopping the biological clock: Infertility treatments and the career-family tradeoff. *Boston University, Unpublished Manuscript*.

Buttet, S. and Schoonbroodt, A. (2013). An accounting exercise for the shift in life-cycle employment profiles of married women born between 1940 and 1960. *Journal for Labour Market Research*, 46(3):253–271.

Caucutt, E. M., Guner, N., and Knowles, J. (2002). Why do women wait? matching, wage inequality, and the incentives for fertility delay. *Review of Economic Dynamics*, 5(4):815–855.

Da Rocha, J. M. and Fuster, L. (2006). Why are fertility rates and female employment ratios positively correlated across oecd countries? *International Economic Review*, 47(4):1187–1222.

Doepke, M., Hannusch, A., Kindermann, F., and Tertilt, M. (2022). The economics of fertility: A new era. Technical report, National Bureau of Economic Research.

Duran-Franch, J. (2021). Oh, man! what happened to women? the blurring of gender-based occupational segregation.

Eckstein, Z., Keane, M., and Lifshitz, O. (2019). Career and family decisions: Cohorts born 1935–1975. *Econometrica*, 87(1):217–253.

Erosa, A., Fuster, L., and Kambourov, G. (2016a). Towards a micro-founded theory of aggregate labour supply. *The Review of Economic Studies*, 83(3):1001–1039.

Erosa, A., Fuster, L., Kambourov, G., and Rogerson, R. (2017). Hours, occupations, and gender differences in labor market outcomes. *NBER Working Paper Series*.

Erosa, A., Fuster, L., and Restuccia, D. (2002). Fertility decisions and gender differences in labor turnover, employment, and wages. *Review of Economic Dynamics*, 5(4):856–891.

Erosa, A., Fuster, L., and Restuccia, D. (2016b). A quantitative theory of the gender gap in wages. *European Economic Review*, 85:165–187.

Fernández, R. (2013). Cultural change as learning: The evolution of female labor force participation over a century. *American Economic Review*, 103(1):472–500.

Fogli, A. and Veldkamp, L. (2011). Nature or nurture? learning and the geography of female labor force participation. *Econometrica*, 79(4):1103–1138.

Fortin, N. M. (2015). Gender role attitudes and women's labor market participation: Opting-out, aids, and the persistent appeal of housewifery. *Annals of Economics and Statistics/Annales d'Économie et de Statistique*, (117/118):379–401.

Francesconi, M. (2002). A joint dynamic model of fertility and work of married women. *Journal of labor Economics*, 20(2):336–380.

Goldin, C. (2021). *Career and Family: Women's Century-Long Journey toward Equity.* Princeton University Press.

Goldin, C. and Katz, L. F. (2002). The power of the pill: Oral contraceptives and women's career and marriage decisions. *Journal of political Economy*, 110(4):730–770.

Goldin, C. and Katz, L. F. (2008). Transitions: Career and family life cycles of the educational elite. *American Economic Review*, 98(2):363–69.

Goldin, C. and Mitchell, J. (2017). The new life cycle of women's employment: Disappearing humps, sagging middles, expanding tops. *Journal of Economic Perspectives*, 31(1):161–82.

Greenwood, J., Guner, N., Kocharkov, G., and Santos, C. (2014). Marry your like: Assortative mating and income inequality. *American Economic Review*, 104(5):348–53.

Greenwood, J., Seshadri, A., and Yorukoglu, M. (2005). Engines of liberation. *The Review of Economic Studies*, 72(1):109–133.

Groes, F., Iorio, D., Leung, M. Y., Santaeulalia-Llopis, R., et al. (2017). Educational disparities in the battle against infertility: Evidence from ivf success. *Copenhagen Business School, Unpublished Manuscript.*

Guner, N., Kaya, E., and Sanchez-Marcos, V. (2020a). Labor market institutions and fertility. Technical report, Technical report, CEMFI Working paper.

Guner, N., Kaygusuz, R., and Ventura, G. (2012). Taxation and household labour supply. *The Review of economic studies*, 79(3):1113–1149.

Guner, N., Kaygusuz, R., and Ventura, G. (2020b). Child-related transfers, household labour supply, and welfare. *The Review of Economic Studies*, 87(5):2290–2321.

Hamilton, B. H. and McManus, B. (2012). The effects of insurance mandates on choices and outcomes in infertility treatment markets. *Health economics*, 21(8):994–1016.

Hannusch, A. et al. (2019). Taxing families: The impact of child-related transfers on maternal labor supply. *Unpublished Manuscript, Mannheim University.*

Iskhakov, F., Jørgensen, T. H., Rust, J., and Schjerning, B. (2017). The endogenous grid method for discrete-continuous dynamic choice models with (or without) taste shocks. *Quantitative Economics*, 8(2):317–365.

Jones, L., Manuelli, R., and McGrattan, E. (2015). Why are married women working so much ? *JODE - Journal of Demographic Economics*, 81(1):75–114.

Juhn, C. and Potter, S. (2006). Changes in labor force participation in the united states. *Journal of Economic Perspectives*, 20(3):27–46.

Krueger, A. B. (2017). Where have all the workers gone? an inquiry into the decline of the us labor force participation rate. *Brookings papers on economic activity*, 2017(2):1.

Lagakos, D., Moll, B., Porzio, T., Qian, N., and Schoellman, T. (2018). Life cycle wage growth across countries. *Journal of Political Economy*, 126(2):797–849.

Machado, M. P. and Sanz-de Galdeano, A. (2015). Coverage of infertility treatment and fertility outcomes. *SERIEs*, 6(4):407–439.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. In Zarembka, P., editor, *Frontiers in Econometrics*. Academic Press, New York.

Miller, A. R. (2011). The effects of motherhood timing on career path. *Journal of population economics*, 24(3):1071–1100.

Moffitt, R. (1984). Profiles of fertility, labour supply and wages of married women: A complete life-cycle model. *The Review of Economic Studies*, 51(2):263–278.

Moreno-Maldonado, A. and Santamaria, C. (2022). Delayed childbearing and urban revival.

Olivetti, C. (2006). Changes in women's hours of market work: The role of returns to experience. *Review of Economic Dynamics*, 9(4):557–587.

Sánchez-Marcos, V. and Bethencourt, C. (2018). The effect of public pensions on women's labor market participation over a full life cycle. *Quantitative Economics*, 9(2):707–733.

Schmidt, L. (2007). Effects of infertility insurance mandates on fertility. *Journal of health economics*, 26(3):431–446.

Shang, Q. and Weinberg, B. A. (2013). Opting for families: Recent trends in the fertility of highly educated women. *Journal of Population Economics*, 26(1):5–32.

Sheran, M. (2007). The career and family choices of women: A dynamic analysis of labor force participation, schooling, marriage, and fertility decisions. *Review of Economic Dynamics*, 10(3):367–399.

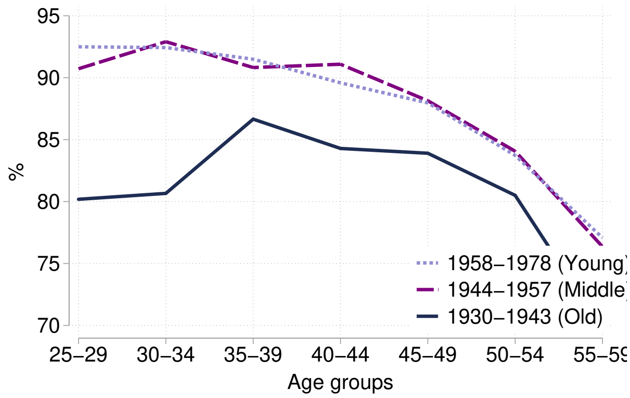
Tauchen, G. (1986). Finite state markov-chain approximations to univariate and vector autoregressions. *Economics Letters*, 20(2):177–181.

Tauchen, G. and Hussey, R. (1991). Quadrature-based methods for obtaining approximate solutions to nonlinear asset pricing models. *Econometrica*, 59(2):371–396.

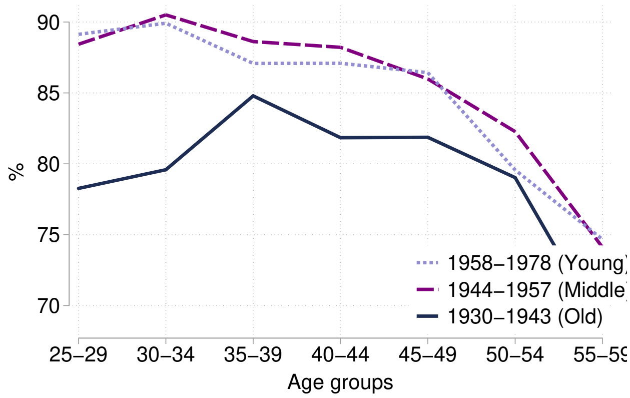
Yang, Y. and Morgan, S. P. (2003). How big are educational and racial fertility differentials in the us? *Social biology*, 50(3-4):167–187.

Appendices

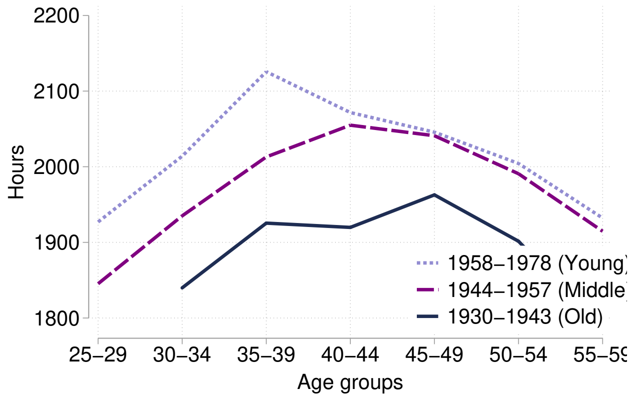
A Figures



(a) Labor force participation



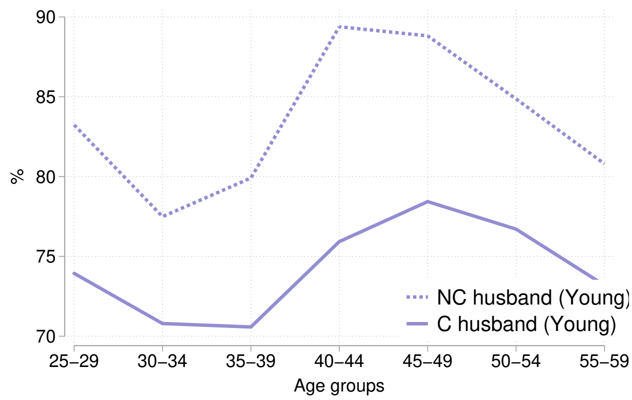
(b) Employment rate



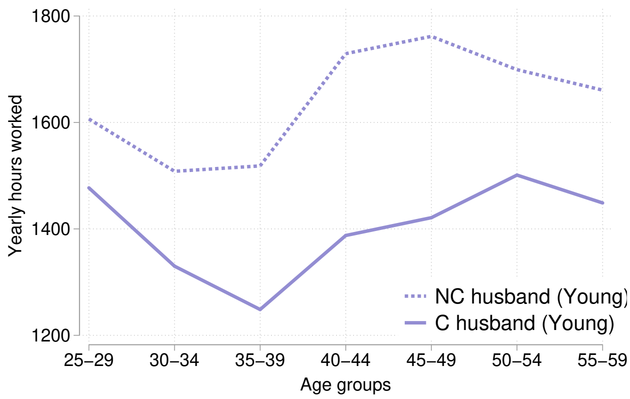
(c) Yearly working hours

Figure A.1: Not-mothers married college-educated female labor market outcomes.

Source: CPS-ASEC microdata, March, 1963 to 2019.
Notes: The sample includes married women aged 25-55 with a college education who do not have a child in the household. The variable yearly working hours is computed as the product of the weeks worked last year times the usual hours worked per week last year.



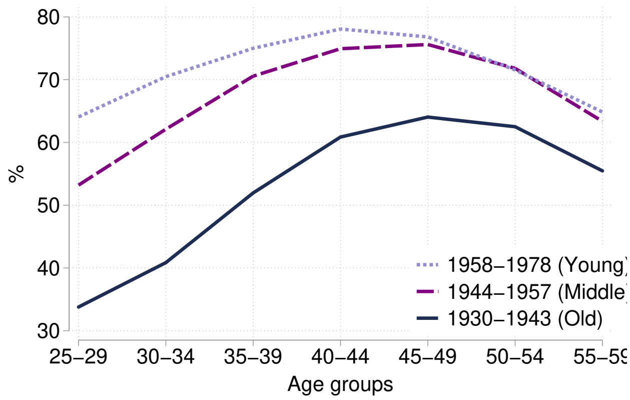
(a) Employment rate



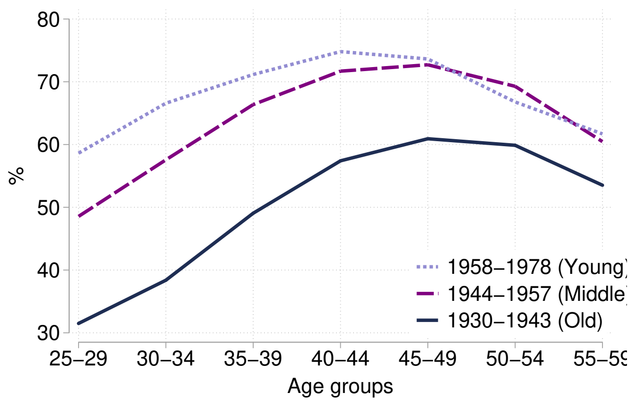
(b) Yearly working hours

Figure A.2: Married college-educated female labor market outcomes by husband's education.

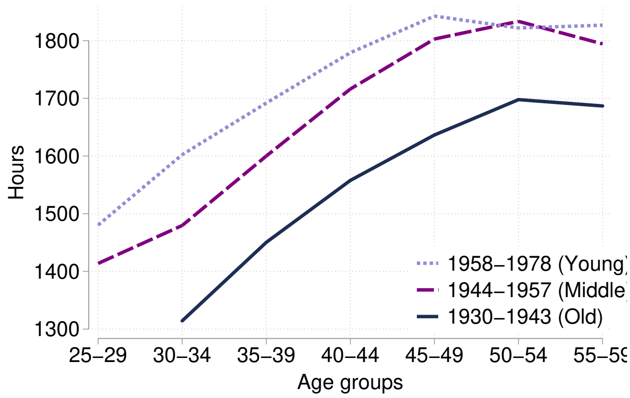
Source: CPS-ASEC microdata, March, 1963 to 2019.
Notes: The sample includes ever-married women aged 25-55 with at least a college education.



(a) Labor force participation



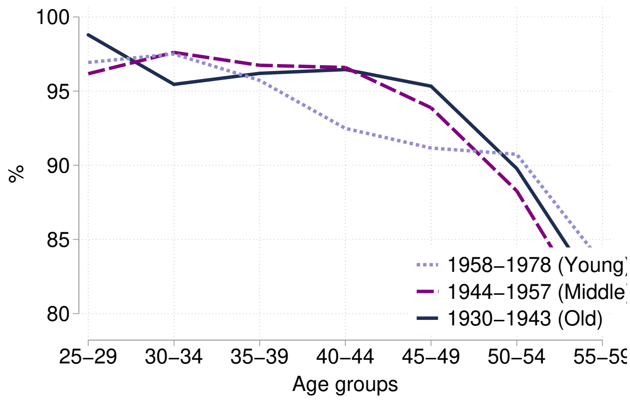
(b) Employment rate



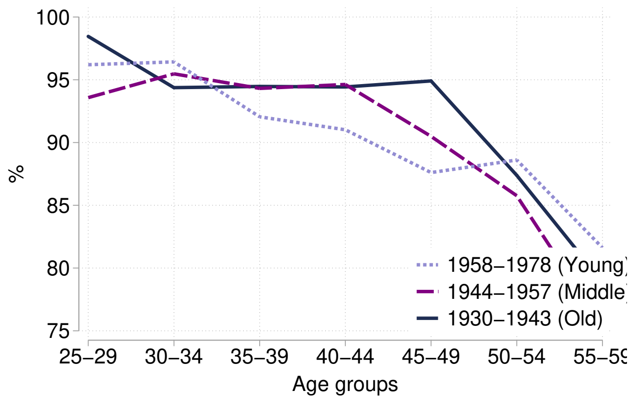
(c) Yearly working hours

Figure A.3: Ever-married non-college-educated female labor market outcomes.

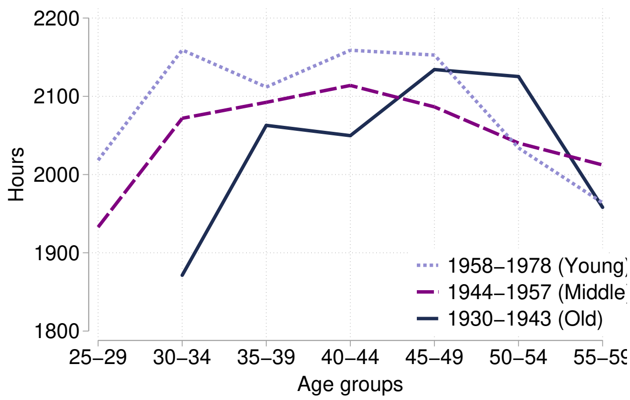
Source: CPS-ASEC microdata, March, 1963 to 2019.
Notes: The sample includes ever-married women aged 25-55 with less than a college education. The variable yearly working hours is computed as the product of the weeks worked last year times the usual hours worked per week last year.



(a) Labor force participation



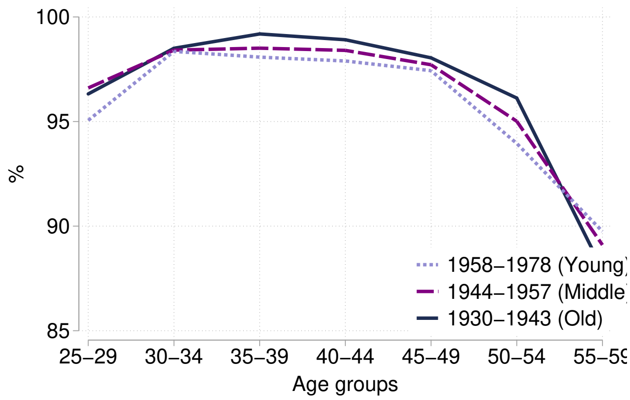
(b) Employment rate



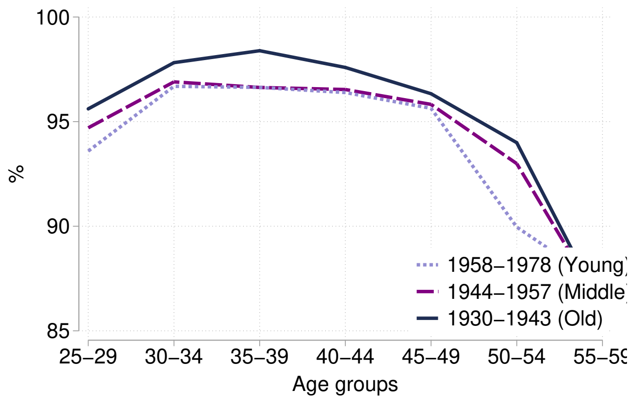
(c) Yearly working hours

Figure A.4: Never married college-educated female labor market outcomes.

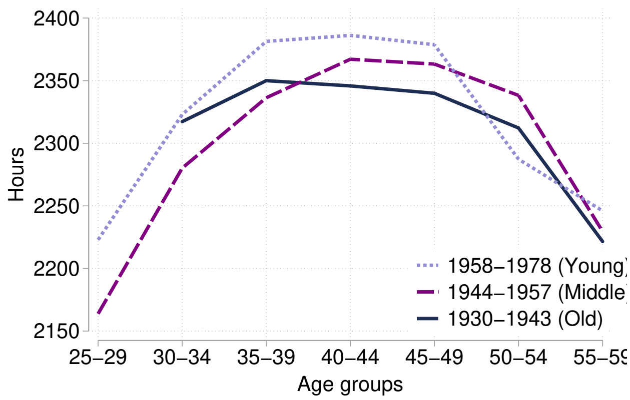
Source: CPS-ASEC microdata, March, 1963 to 2019.
Notes: The sample includes never-married women aged 25-55 with a college education. The variable yearly working hours is computed as the product of the weeks worked last year times the usual hours worked per week last year.



(a) Labor force participation



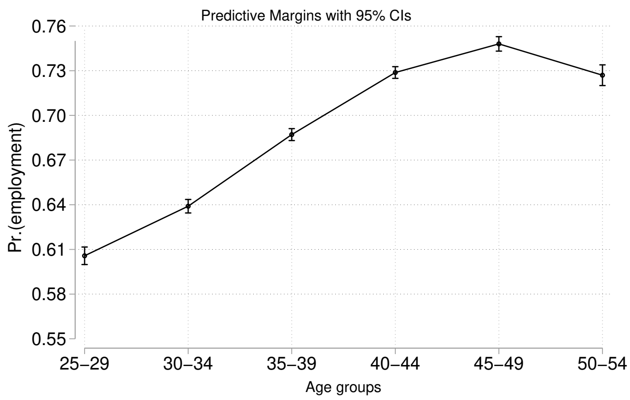
(b) Employment rate



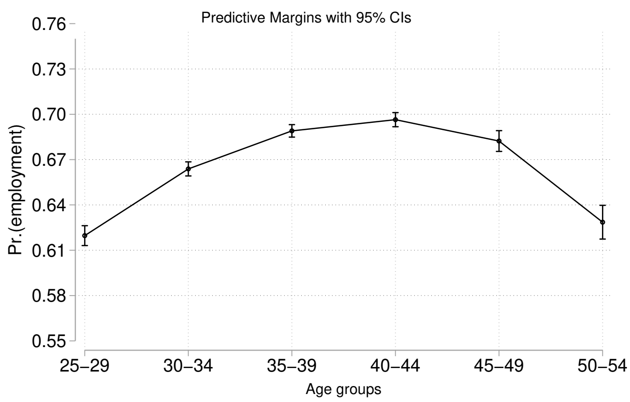
(c) Yearly working hours

Figure A.5: Ever-married college-educated male labor market outcomes.

Source: CPS-ASEC microdata, March, 1963 to 2019.
Notes: the sample includes ever-married men aged 25-59 with at least a college education.



(a) Not fertility controls



(b) Fertility controls

Figure A.6: Marginal effects for non-college-educated women in Young cohorts

Source: CPS-ASEC microdata, March, 1963 to 2019.
Notes: The sample includes ever-married women with less than college education.

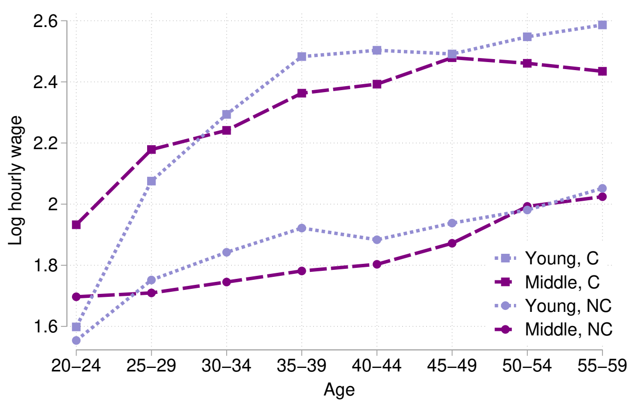
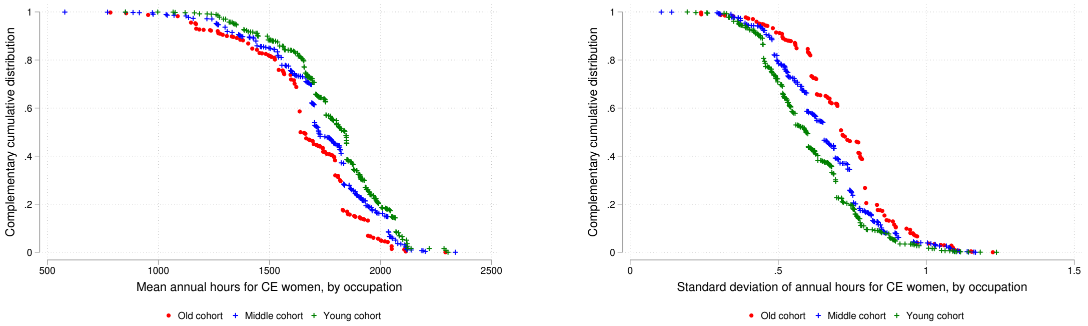


Figure A.7: Life-cycle profile of earnings by education

Source: PSID 1968-2015

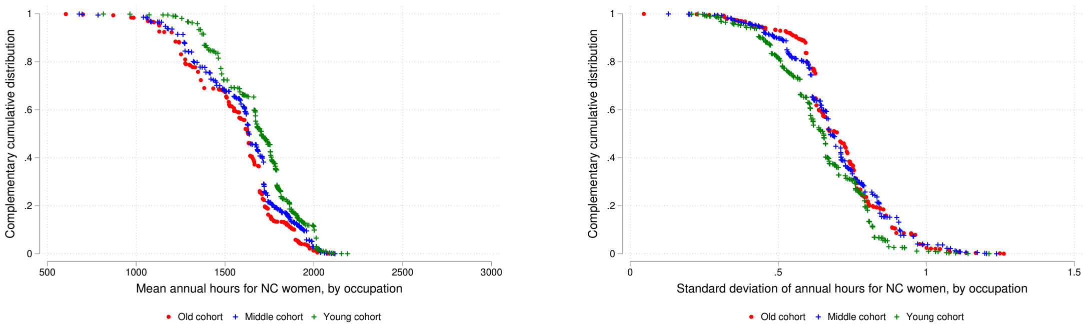


(a) Mean annual hours worked

(b) Standard deviation hours worked

Figure A.8: Complementary Cumulative Distribution, College-educated Women: by 3-Digit Occupations

Source: CPS (1976-2015). Sample: college-educated married women.
The scatter plots show the complementary cumulative distribution of women over occupations in terms of the log of female mean annual hours in an occupation (left panel) or the standard deviation of female log annual hours in an occupation (right panel) in the corresponding time period.



(a) Mean annual hours worked

(b) Standard deviation hours worked

Figure A.9: Complementary Cumulative Distribution, Non-College-educated Women: by 3-Digit Occupations

Source: CPS (1976-2015). Sample: non-college-educated married women.
The scatter plots show the complementary cumulative distribution of women over occupations in terms of the log of female mean annual hours in an occupation (left panel) or the standard deviation of female log annual hours in an occupation (right panel) in the corresponding time period.

B Tables

Table B.1: Estimates of the probability of employment for the Young cohorts

	Model (I)	Model (II)	Model (III)	Model (IV)
	dy/dx	dy/dx	dy/dx	dy/dx
Age groups=30-34	-0.0356***	-0.00238	0.0115*	0.0246***
	(-7.62)	(-0.49)	(2.25)	(4.12)
Age groups=35-39	-0.0289***	0.0144**	0.0429***	0.0370***
	(-5.93)	(2.78)	(7.97)	(5.86)
Age groups=40-44	0.00575	0.0465***	0.0782***	0.0370***
	(1.15)	(8.82)	(14.21)	(5.36)
Age groups=45-49	0.0247***	0.0537***	0.0831***	0.00924
	(4.63)	(9.54)	(14.26)	(1.15)
Age groups=50-54	0.0235***	0.0210**	0.0495***	-0.0384***
	(3.84)	(3.16)	(7.29)	(-3.81)
College educated wife=1	-0.0653***	-0.0641***	-0.0632***	-0.0659***
	(-26.17)	(-25.78)	(-25.51)	(-22.76)
Husband's income	-0.0878***	-0.0836***	-0.0809***	-0.0917***
	(-47.06)	(-45.20)	(-44.13)	(-43.30)
Husband's full-time-full-year indicator=1	0.0188***	0.0216***	0.0225***	0.0120*
	(4.35)	(4.99)	(5.21)	(2.42)
Mother=1		-0.115***	-0.0451***	0.0966***
		(-47.41)	(-13.07)	(10.62)
Number of children			-0.0481***	-0.0466***
			(-39.60)	(-34.53)
Age youngest child				0.0127***
				(33.70)
Observations	142702	142702	142702	115538
Year	Yes	Yes	Yes	Yes
Husband's work type	Yes	Yes	Yes	Yes
Native indicator	Yes	Yes	Yes	Yes

t statistics in parentheses

Source: March CPS

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This Table computes the marginal probability for the college-educated women belonging to the Young cohorts.

Table B.2: Estimates of the probability of employment for all the cohorts, Model (I)

	Old	Middle	Young
	dydx	dydx	dydx
Age groups=30-34	-0.0462***	-0.0452***	-0.0356***
	(-3.37)	(-7.14)	(-7.62)
Age groups=35-39	0.00773	-0.0248**	-0.0289***
	(0.49)	(-3.26)	(-5.93)
Age groups=40-44	0.0593**	0.0323***	0.00575
	(3.27)	(3.67)	(1.15)
Age groups=45-49	0.0726***	0.0502***	0.0247***
	(3.57)	(5.03)	(4.63)
Age groups=50-54	0.0487*	0.0465***	0.0235***
	(2.09)	(4.14)	(3.84)
College educated husband=1	-0.101***	-0.0593***	-0.0653***
	(-12.66)	(-16.23)	(-26.17)
Husband's income	-0.102***	-0.0924***	-0.0878***
	(-10.93)	(-28.05)	(-47.06)
Husband's full-time-full-year indicator=1	0.0730***	0.0343***	0.0188***
	(4.86)	(5.93)	(4.35)
Observations	21347	70674	142702
Year	YES	YES	YES
Husband's work type	YES	YES	YES
Native indicator	YES	YES	YES

t statistics in parentheses

Source: March CPS

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This Table computes the marginal probability for the college-educated women belonging to the Old, Middle and Young cohorts.

Table B.3: Estimates of the probability of employment for all the cohorts, Model (IV)

	Old	Middle	Young
	dydx	dydx	dydx
Age groups=30-34	0.0301	0.0215**	0.0246***
	(1.73)	(2.93)	(4.12)
Age groups=35-39	0.0442*	0.0307***	0.0370***
	(2.32)	(3.43)	(5.86)
Age groups=40-44	0.0280	0.0307**	0.0370***
	(1.26)	(2.77)	(5.36)
Age groups=45-49	-0.0116	-0.00964	0.00924
	(-0.47)	(-0.70)	(1.15)
Age groups=50-54	-0.101***	-0.0617***	-0.0384***
	(-3.57)	(-3.77)	(-3.81)
Mother=1	0.118***	0.0798***	0.0966***
	(7.97)	(8.05)	(10.62)
Number of children	-0.0174***	-0.0361***	-0.0466***
	(-5.15)	(-17.72)	(-34.53)
Age youngest child	0.0242***	0.0168***	0.0127***
	(24.13)	(30.97)	(33.70)
College educated husband=1	-0.0845***	-0.0633***	-0.0659***
	(-9.33)	(-14.42)	(-22.76)
Husband's income	-0.134***	-0.0991***	-0.0917***
	(-14.26)	(-25.34)	(-43.30)
Husband's full-time-full-year indicator=1	0.0783***	0.0347***	0.0120*
	(4.72)	(5.07)	(2.42)
Observations	16026	52596	115538
Year	YES	YES	YES
Husband's work type	YES	YES	YES
Native indicator	YES	YES	YES

t statistics in parentheses

Source: March CPS

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.4: Fertility decisions of college-educated married women by cohort

Cohort	Number of children	Age 1st child	Not mothers at age 40
1930-43, Old	2.51	25.4	10.0%
1944-57, Middle	1.90	26.7	16.0%
1958-78, Young	1.98	28.9	12.0%

Source: CPS June Fertility Supplement (1976-2018).

Table B.5: Fertility decisions of college-educated married women by cohort and the husband's education

	Number of children		Age 1st child	
Cohort	**NC husband**	**C husband**	**NC husband**	**C husband**
1930-43, Old	2.46	2.46	24.8	25.7
1944-57, Middle	1.89	1.91	25.8	27.2
1958-78, Young	1.88	2.01	27.3	29.4

Source: CPS June Fertility Supplement (1976-2018).

Table B.6: Mincer regression for the Middle and the Young cohorts with more controls

	Middle cohort	Young cohort
Age dummy (< 30)	-0.227***	-0.329***
	(0.046)	(0.059)
Experience	0.0150***	0.00967**
	(0.003)	(0.003)
Age dummy (< 30) × Experience	0.000325	0.0283***
	(0.005)	(0.008)
Number of children	-0.0595***	0.0172
	(0.015)	(0.014)
Husband's education	0.00912	0.0569***
	(0.009)	(0.007)
Husband's hourly wage	0.152***	0.112***
	(0.032)	(0.024)
Husband's FT contract dummy	0.0704*	0.131***
	(0.029)	(0.036)
FT contract dummy	0.0140	-0.233**
	(0.041)	(0.074)
Husband's experience	-0.00767***	0.00301
	(0.002)	(0.003)
Constant	1.734***	1.152***
	(0.157)	(0.147)
Observations	4926	3376
R-squared	0.0859	0.126

Standard errors in parentheses

Source: PSID 1968-2015

Sample: College-educated married women

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.7: Mincer regression for the Middle and the Young cohorts in one regression

Age dummy (< 30)	-0.162***
	(0.042)
Experience	0.0140***
	(0.002)
Age dummy (< 30) × Experience	-0.00177
	(0.004)
Dummy Young cohort	0.139**
	(0.049)
Dummy Young cohort × Age dummy (< 30)	-0.303***
	(0.068)
Dummy Young cohort × Experience	-0.00347
	(0.003)
Dummy young cohort × Age dummy (< 30) × Experience	0.0378***
	(0.010)
Constant	2.121***
	(0.032)
Observations	9124
R-squared	0.0536

Standard errors in parentheses

Source: PSID 1968-2015

Sample: College-educated married women

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.8: Mincer regression for college-educated married women by cohort

	Middle cohort	Young cohort
Age dummy (< 30)	-0.162***	-0.466***
	(0.042)	(0.053)
Experience	0.0140***	0.0105***
	(0.002)	(0.003)
Age dummy (< 30) × Experience	-0.00177	0.0360***
	(0.004)	(0.009)
Constant	2.121***	2.261***
	(0.032)	(0.037)
Observations	5420	3704
R-squared	0.0412	0.0725

Standard errors in parentheses

Source: PSID 1968-2015

Sample: College-educated married women

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.9: Mincer regression for the Middle and the Young cohorts

	Middle	Young
Experience	0.0282***	0.0413***
	(0.003)	(0.006)
Experience^2	-0.000449***	-0.000949***
	(0.000)	(0.000)
Constant	2.087***	2.082***
	(0.023)	(0.035)
Observations	3894	2720
R-squared	0.0567	0.0447

Standard errors in parentheses
Source: PSID 1968-2015
Sample: college-educated married women
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.10: Mincer regression for all the Middle cohort (left) and the Young cohort (right)

	<30	>30
Experience	0.00554	0.0309***
	(0.009)	(0.004)
Experience^2	0.000183	-0.000554***
	(0.000)	(0.000)
Constant	2.135***	2.091***
	(0.033)	(0.032)
Observations	740	2972
R-squared	0.00881	0.0461

Standard errors in parentheses
Source: PSID 1968-2015
Sample: college-educated married women
Note: < 30 includes women below 30
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	<30	>30
Experience	0.0865***	0.0218**
	(0.026)	(0.008)
Experience^2	-0.00793***	-0.000488
	(0.002)	(0.000)
Constant	1.926***	2.267***
	(0.066)	(0.056)
Observations	822	2022
R-squared	0.0168	0.0104

Standard errors in parentheses
Source: PSID 1968-2015
Sample: college-educated married women
Note: < 30 includes women below 30
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.11: Mincer regression for all sample working women (left) and below 30 years old (right)

	Young cohort	Experiment 1
Experience	0.0413***	0.0425 ***
	(0.006)	(0.000)
Experience^2	-0.000949***	-0.000713***
	(0.000)	(0.000)
Constant	2.082***	2.252***
	(0.035)	
Observations	2720	214976
R-squared	0.0567	0.157

Standard errors in parentheses
Source: PSID 1968-2015
Sample: college-educated married women

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

	Young cohort	Experiment 1
Experience	0.0865 ***	0.0962 ***
	(0.026)	(0.006)
Experience^2	-0.00793***	0.00139
	(0.002)	(0.001)
Constant	1.926***	2.147***
	(0.066)	(0.008)
Observations	822	33998
R-squared	0.0168	0.149

Standard errors in parentheses
Source: PSID 1968-2015
Sample: college-educated married women younger than 30 years old
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.12: Mincer regression for married women by cohort and education

	Middle	Middle, NC	Middle, C	Young	Young, NC	Young, C
Age dummy (< 30)	-0.00868	0.0170	-0.0843	-0.482***	-0.372***	-0.529***
	(0.033)	(0.039)	(0.059)	(0.047)	(0.061)	(0.070)
Experience	0.0339***	0.0328***	0.0279***	0.0282***	0.0222***	0.0281***
	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)	(0.008)
Age dummy (< 30) × Experience	-0.00997	0.0103	-0.0124	0.118***	0.0940***	0.135***
	(0.006)	(0.007)	(0.010)	(0.014)	(0.016)	(0.024)
Experience^2	-0.000456***	-0.000388***	-0.000391**	-0.000560***	-0.000174	-0.000644*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age dummy (< 30) × Experience^2	-0.000236	-0.00110**	0.000190	-0.00772***	-0.00467***	-0.0130***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)
Constant	1.662***	1.464***	2.035***	1.883***	1.692***	2.171***
	(0.026)	(0.031)	(0.048)	(0.038)	(0.049)	(0.057)
Observations	19491	12850	5420	13924	8561	3704
R-squared	0.0516	0.0539	0.0433	0.0682	0.0656	0.0800

Standard errors in parentheses
Source: PSID 1968-2015
Sample: Married women
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.13: Fertility decisions of college and non-college educated women by cohort

	College	**Non-college**	**College**	**Non-college**
Cohort	**Number of children**		**Age at first birth**	
Old	2.51	3.12	24.75	22.44
Middle	1.90	2.32	26.42	22.58
Young	1.98	2.23	29.00	23.87

Source: CPS June Fertility Supplement (1976-2018).

C Computational Appendix

C.1 Stochastic structure for children's ageing

In this Appendix, I show how to retrieve the stochastic structure that governs the transition probabilities for the vector state of the number of children at different ages takes, which I denote by $\mathbf{n}' = \Lambda_j(\mathbf{n}, b)$.

I denote by λ_1 and λ_2 the probabilities that an individual baby becomes a school-age child, and that an individual school-age child becomes a teen in a given period, respectively. Moreover, I assume that the aging event is independent across children. Notice that $bp^j(N)$ is the probability that there is a newborn in the next period. Denote by $P_i(x \mid n_i)$ the probability that x children in stage $i \in \{1, 2\}$ (babies, school-age) move on to the next stage the next period (school-age, teenager), conditional on there being n_i children in that stage in the current period. Table C.1 shows these, for babies and school-age children.

Table C.1: Probabilities of ageing by number of children, $P_i(x \mid n_i)$

n_i	Number of children ageing			
	0	1	2	3
0	1	0	0	0
1	$1-\lambda_i$	λ_i	0	0
2	$(1-\lambda_i)^2$	$\lambda_i(1-\lambda_i)$	λ_i^2	0
3	λ_i^3	$\lambda_i(1-\lambda_i)^2$	$\lambda_i^2(1-\lambda_i)$	λ_i^3

To compute the whole set of probabilities of transition from state $\mathbf{n} = [n_0, n_1, n_2, n_3]$, I follow the algorithm, where $\bar{P} = P_1(x_1 \mid n_1)P_2(x_2 \mid n_2)$:

for $x_1 \in \{0, 1, 2, 3\}$ **do**
  for $x_2 \in \{0, 1, 2, 3\}$ **do**
    if $n_0 = 1$ **then**
      $\mathbf{n}' = [0, n_1 - x + 1, n_2 + x - y, n_3 + y]$ w.p. $(1 - bp^j(N))\bar{P}$ or
      $\mathbf{n}' = [1, n_1 - x + 1, n_2 + x - y, n_3 + y]$ w.p. $bp^j(N)\bar{P}$;
    else
      $\mathbf{n}' = [0, n_1 - x, n_2 + x - y, n_3 + y]$ w.p. $(1 - bp^j(N))\bar{P}$ or
      $\mathbf{n}' = [1, n_1 - x, n_2 + x - y, n_3 + y]$ w.p. $bp^j(N)\bar{P}$;
    end
  end
end

C.2 Taste shocks

All of the decisions women make in the model are discrete. To facilitate the numerical solution of the model, I include a taste shock to women's utility in every period. This helps by smoothing out labor force participation and fertility decisions. The shocks can be interpreted as unobserved state variables that add noise to the women's decisions. Moreover, the calibration and results are robust to their inclusion. For an in-depth discussion of this computational method, see Iskhakov et al. (2017).

Thus, I assume that in every period, women receive a vector of additive-separable taste shocks μ. In periods when they can still have children and need to choose on pregnancy $b \in \{0,1\}$ in addition to labor force participation $h^f \in \{0, \frac{1}{4}, \frac{1}{2}\}$, they receive a vector of six shocks, one for every element in $\{0, \frac{1}{4}, \frac{1}{2}\} \times \{0,1\}$. In periods when they cannot have any more children and need only to choose labor force participation, they receive a vector of three shocks, one for every element in $\{0, \frac{1}{4}, \frac{1}{2}\}$:

$$\mu = \begin{cases} \left(\mu_{0,0}, \mu_{\frac{1}{4},0}, \mu_{\frac{1}{2},0}, \mu_{0,1}, \mu_{\frac{1}{4},1}, \mu_{\frac{1}{2},1}\right) & \text{if } j < \bar{J} \text{ and } N < 3 \\ \left(\mu_0, \mu_{\frac{1}{4}}, \mu_{\frac{1}{2}}\right) & \text{otherwise} \end{cases}$$

All of these shocks are i.i.d, drawn from an Extreme Value Type I distribution with scale parameter σ_μ. The modified value function in states $\left(x^f, \mathbf{n}, v^m, v^f\right)$ is:

$$W_j\left(x^f, \mathbf{n}, v^m, v^f, \mu\right) = \\ \begin{cases} \max\{W_j^{h^f,b}\left(x^f, \mathbf{n}, v^m, v^f\right) + \sigma_\mu \mu_{h^f,b}\}_{h^f \in \{0,\frac{1}{4},\frac{1}{2}\}, b \in \{0,1\}} & \text{if } j < \bar{J} \text{ and } N < 3 \\ \max\{W_j^{h}\left(x^f, \mathbf{n}, v^m, v^f\right) + \mu_h\}_{h^f \in \{0,\frac{1}{4},\frac{1}{2}\}} & \text{otherwise,} \end{cases}$$

where $W_j^{h^f,b}$ and $W_j^{h^f}$ represent the value, ex-taste shock, of choosing labor force participation h^f and pregnancy status b for a woman in period j, or just labor force participation h^f, in states $\left(x^f, \mathbf{n}, v^m, v^f\right)$:

$$\begin{aligned} W_j^{h^f,b}\left(x^f, \mathbf{n}, v^m, v^f\right) &= u^{h^f,b}\left(c, l, \mathbf{n}\right) + \beta \mathbb{E}^{\sigma_\mu}\left[W_{j+1}\left(x'^f, \mathbf{n}', v'^m, v'^f\right)\right] \\ W_j\left(x^f, \mathbf{n}, v^m, v^f\right) &= u^{h^f}\left(c, l, \mathbf{n}\right) + \beta \mathbb{E}^{\sigma_\mu}\left[W_{j+1}\left(x'^f, \mathbf{n}', v'^m, v'^f\right)\right], \end{aligned}$$

where $\mathbb{E}^{\sigma_\mu}$ denotes the expectations over future taste shocks, and in both cases, choice and state variables need to be retrieved from the constraints and laws of motion.

The main consequence of introducing the taste shocks is that the policy function becomes probabilistic. Given the distribution assumed for them, the probability that a woman chooses pregnancy decision b and labor force participation h^f in states $\left(x^f, \mathbf{n}, v^m, v^f\right)$ when $j < \bar{J}$ and $N < 3$ is the logit probability:

$$P_j\left(h^f, b \mid x^f, \mathbf{n}, v^m, v^f\right) = \frac{\exp\left(\frac{W_j^{h^f,b}\left(x^f,\mathbf{n},v^m,v^f\right)}{\sigma_\mu}\right)}{\sum_{i\in\{0,1,2,3\}}\sum_{k\in\{0,1\}}\exp\left(\frac{W_j^{i,k}\left(x^f,\mathbf{n},v^m,v^f\right)}{\sigma_\mu}\right)}.$$

Otherwise, the probability that a woman chooses labor force participation h in states $\left(x^f, \mathbf{n}, v^m, v^f\right)$ is the logit probability:

$$P_j\left(h^f \mid x^f, \mathbf{n}, v^m, v^f\right) = \frac{\exp\left(\frac{W_j^{h^f}\left(x^f,\mathbf{n},v^m,v^f\right)}{\sigma_\mu}\right)}{\sum_{i\in\{0,1,2,3\}}\exp\left(\frac{W_j^{i}\left(x^f,\mathbf{n},v^m,v^f\right)}{\sigma_\mu}\right)}.$$

One additional benefit of using Extreme Value Type I shocks is that the expected value function is given by the tractable log-sum formula from (McFadden, 1973):

$$\mathbb{E}^{\sigma_\mu}\left[W_{j+1}\left(x'^f, \mathbf{n}', v'^m, v'^f\right)\right] =$$
$$\begin{cases} \sigma_\mu \log\left(\sum_{i\in\{0,1,2,3\}}\sum_{k\in\{0,1\}}\exp\left(\frac{W_j^{i,k}\left(x^f,\mathbf{n},v^m,v^f\right)}{\sigma_\mu}\right)\right) & \text{if } j < \bar{J} \text{ and } N < 3 \\ \sigma_\mu \log\left(\sum_{i\in\{0,1,2,3\}}\exp\left(\frac{W_j^{i}\left(x^f,\mathbf{n},v^m,v^f\right)}{\sigma_\mu}\right)\right) & \text{otherwise.} \end{cases}$$

Using backward induction starting in period J, one can easily retrieve the expected value functions and the probabilistic policy functions.

D Policy Implications

The new profile of labor supply for college-educated married women seems to have long-lasting effects over the life cycle. While the event of having a kid always discouraged women from work and decreased hours worked, Goldin and Mitchell (2017) show that they take more time out of the labor force after having their kid. Why do these women take more time to return to the labor market compared to previous cohorts? In this paper, I propose a supply-side explanation regarding income taxation. In the United States, the tax system is progressive, and married couples can choose between filing their tax return jointly or individually. Despite this, almost all couples file jointly. Filing separate returns as married couples results in a higher tax liability. The main reason relies on the rates applied to taxable income for single filers and married couples.[32] In particular, most tax brackets for married couples are twice the size of those for singles, implying a marriage bonus by filing jointly rather than each partner filing as a single person.

The combination of progressive and joint taxation, where individuals are taxed at the household level, distorts the labor supply decisions of the secondary earner, usually women. This mechanism has been well-studied in the literature.[33] In this paper, I explore the effect of a shift from a joint to an individual taxation system on the sagging middle effect. Figure D.1 illustrates the mechanism I have in mind. It shows the marginal tax rate women pay for different yearly income levels by marital status and the husband's age. Two conclusions can be derived from this simple exercise. First, the marginal tax on single women is lower than that levied on married women. This implies that the change from joint to individual taxation might induce women to participate in the labor market. Second, the distortion in the female labor supply increases with the husband's age because they tend to have, on average, higher earnings. Therefore the postponement of births combined with joint taxation might explain why women born in the Young cohort group take longer time out of the labor force during the childbearing ages. To understand the role of income taxation in generating long-lasting effects in the labor market, I run the following counterfactual analysis: introduce individual taxation.

[32] Taxable income is the adjusted gross income minus either the standard deduction or allowable itemized deductions.

[33] See for example: Guner et al. (2012), Bronson and Mazzocco (2018), Bick et al. (2019) and Borella et al. (2019).

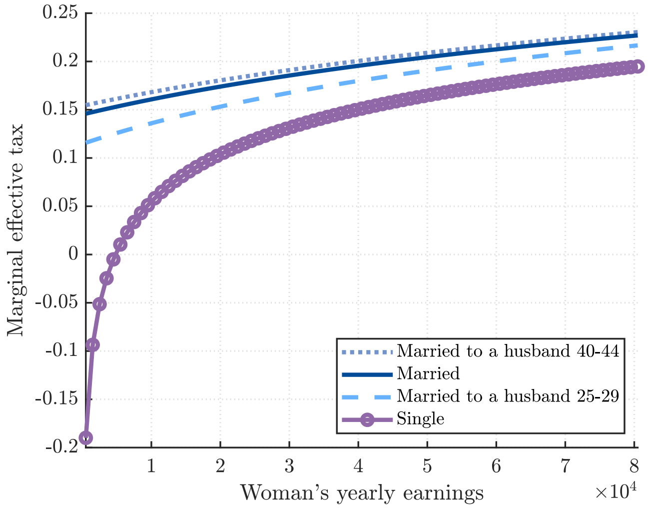


Figure D.1: Female marginal tax

Source: CPS for the mean of the husband's earnings and Borella et al. (2022).