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Sena Coskun and Husnu Dalgic

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Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

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Fertility in the US exhibits an increasingly more procyclical pattern. We argue that women's breadwinner status is behind procyclical fertility: (i) women's relative income in the family has increased over time; and (ii) women are more likely to work in relatively stable and countercyclical industries whereas men tend to work in volatile and procyclical industries. This creates a countercyclical gender income gap as women become breadwinners in recessions, producing an insurance effect of women's income. Our quantitative framework features a general equilibrium OLG model with endogenous fertility and human capital choice. We show that the change in gender employment cyclicality can explain 38 to 44% of the emergence of procyclical fertility. Our counterfactual analysis shows that in a world in which men become nurses and women become construction workers, we would observe "countercyclical fertility" but at the expense of lower human capital accumulation as families lean in more towards quantity in the quality-quantity trade-off.

JEL Classification: E24, E32, J11, J13, J16, J21, J24

Keywords: Fertility, fertility cyclicality, industry cyclicality, gender asymmetric employment, gender income gap, quality-quantity trade-off

Sena Coskun - sena.coskun@fau.de
FAU Erlangen-Nuremberg, Institute for Employment Research and CEPR

Husnu Dalgic - dalgic@uni-mannheim.de
University of Mannheim

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The Emergence of Procyclical Fertility: The Role of Gender Differences in Employment Risk*

Sena Coskun[†] and Husnu Dalgic[‡]

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Fertility in the US exhibits an increasingly more procyclical pattern. We argue that women's breadwinner status is behind procyclical fertility: (i) women's relative income in the family has increased over time; and (ii) women are more likely to work in relatively stable and countercyclical industries whereas men tend to work in volatile and procyclical industries. This creates a countercyclical gender income gap as women become breadwinners in recessions, producing an insurance effect of women's income. Our quantitative framework features a general equilibrium OLG model with endogenous fertility and human capital choice. We show that the change in gender employment cyclicality can explain 38 to 44% of the emergence of procyclical fertility. Our counterfactual analysis shows that in a world in which men become nurses and women become construction workers, we would observe "countercyclical fertility" but at the expense of lower human capital accumulation as families lean in more towards quantity in the quality-quantity trade-off.

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[†]FAU Erlangen-Nuremberg, Institute for Employment Research (IAB), CEPR. Email: sena.coskun@fau.de

[‡]University of Mannheim. Email: dalgic@uni-mannheim.de

1 Introduction

Fertility in the United States has been procyclical since the mid 1970s while it was countercyclical during the 1960s (Figure 1)[1]. In this paper, we provide a novel mechanism to explain the cyclical behavior of fertility based on women's breadwinner status in the family during the second half of the 20th century. Women's breadwinner status in the family has improved over time and we argue that women especially become bad times breadwinners; i.e., women's relative income increases in recessions. We show that improvement in the breadwinner status of women i) over time, and ii) especially during recessions caused a higher degree of fertility cyclicality. Figure 2 shows that the relative employment (f/m) is countercyclical; men tend to suffer more in economic downturns. In a recession, a typical man loses his job while a typical woman becomes the breadwinner of the family. Women who are breadwinners cannot afford to take time off to have children since they bear the time cost. One reason behind the countercyclical relative employment is that men and women tend to work in different types of industries, with men predominantly employed in procyclical industries while women are mostly employed in stable industries. From the lenses of our model, we argue that in a world in which men become nurses and women become construction workers, we would observe "countercyclical fertility", but it comes at the expense of lower human capital accumulation as families lean in more towards quantity in the quality-quantity trade-off because time costs become less expensive. Moreover, our model generates countercyclical fertility when women's contribution to the family budget is low in which case a recession is the perfect time to have a child as the opportunity cost is low but women do not bear the responsibility to support their family.

[1]The decline in fertility rate begins before the reported start date of the recession, which might imply that people are forward looking and sensitive to the changes in expectations (Buckles et al. (2021)). Throughout our paper, we use the time of conception (3 quarters of lag to births) to analyze the behavior of fertility around business cycles (correlation between conception and GDP). See the footnote under Figure 1. However, in line with Buckles et al. (2021)'s argument, we also look at the correlations between the observed birth rates and aggregate outcomes. See Appendix A.2, for robustness with different aggregate measures and timing and extracted trend components.

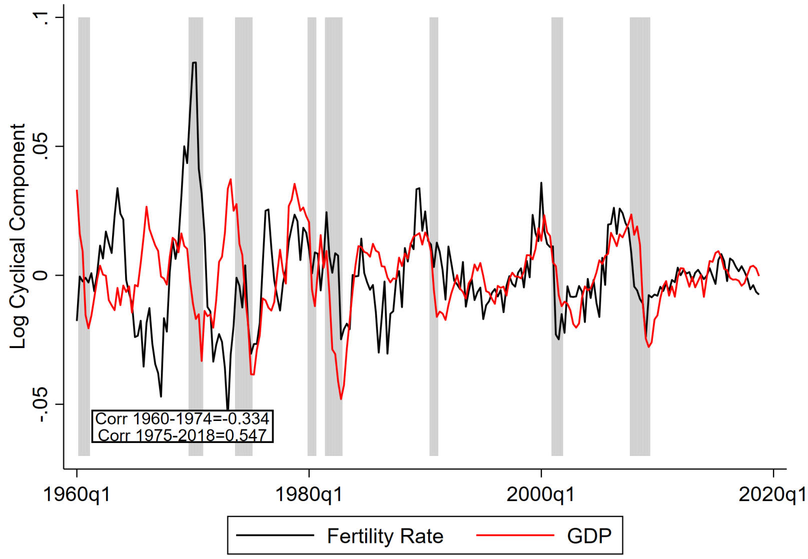


Figure 1: Fertility and Recessions

Note: Shaded areas indicate recessions. Recession dates are taken from NBER business cycles (from peak to trough). The data sources are the birth records from the National Health Statistics and real GDP from FRED. The fertility figure used is the seasonally adjusted quarterly fertility rate (number of total births/population of women aged 15-44) with 3 quarters of lag to account for the time of conception. To obtain the cyclical component, an HP filter with smoothing parameter $\lambda = 1600$ is used. See Appendix A.1 for more details on data sources.

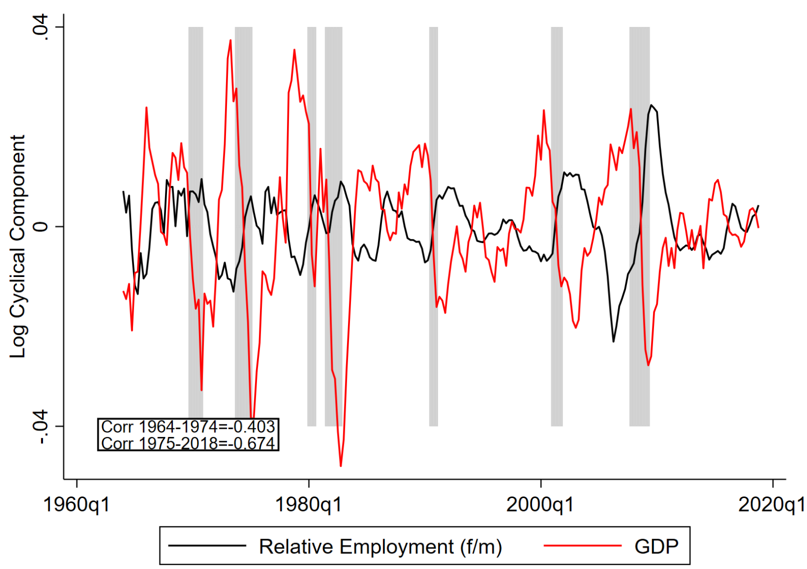


Figure 2: Relative Employment and Recessions

Note: Shaded areas indicate recessions. Recession dates are taken from NBER business cycles (from peak to trough). The seasonally adjusted total monthly employment series from BLS Current Employment Statistics is used with the HP filter with smoothing parameter $\lambda = 1600$ to obtain the cyclical component of aggregate employment at quarterly level. See Appendix A.1 for more details on data sources.

There is no intrinsic reason for fertility to be procyclical. Following Becker (1960), it is more straightforward to think about the income effect. However, as seen in Butz and Ward (1979), fertility may also be countercyclical due to the substitution effect brought about by a rapid increase in the female participation rate, as seen in the 1960s. In a recession, families observe their income falling and cannot afford more children. But at the same time, the time cost of children falls and families thus can have more children. In order to understand the cyclicality of fertility, we argue that it is essential to incorporate gender differences in the labor market, which is the main contribution of our paper. The gender differences we include in our model of fertility are relative income levels, relative income cyclicality, and child penalties. Our model is flexible enough to generate both procyclical and countercyclical fertility based on observed gender outcomes in the labor market.

In order to explore fertility dynamics under different gender income and cyclicality scenarios, we build a general equilibrium overlapping generations model in which families make fertility decisions and invest in their children's human capital. Our model captures several distinct features of fertility decisions by linking them in a unified framework. The model is calibrated to match levels (by age), the volatility and the cyclicality of fertility and women's relative income in the US over the period 1975-2018[2]. Key mechanisms of this framework include the quality-quantity trade-off, child penalties, and the differential impact of men's and women's income. To the best of our knowledge, our effort marks the first exploration of how all these channels interact with business cycles. In the model, parents care about their children's well-being (Becker and Barro (1988); Barro and Becker (1989)) through investing in their human capital (De La Croix and Doepke (2003)). Our analysis treats men's and women's income separately and introduces "child penalties" for women. The opportunity cost of having children is higher for women with high income due to child penalties, meaning that these women prefer to have fewer children but invest more in their human capital. We introduce both short-term and long-term child penalties following Kleven et al. (2019a,b). Short-term child penalties reflect the fact that women must take time off when they have children. Long-term penalties reflect related effects over longer time horizons that can result in permanent income losses for mothers, such as career breaks, depreciation of human capital and lower returns to experience. The observed volatility in men's and women's employment is fed into the model, which generates a countercyclical gender income gap, i.e., women's

[2]In this paper, we mainly focus on the period 70s onward in which the fertility rate reaches a plateau after large swings during the Great Depression and then the post-war baby boom (Doepke et al. (2015), Greenwood et al. (2000)). Moreover, women's labor market participation starts experiencing a secular increasing trend around that time with the start of the pill revolution (Goldin and Katz (2000)).

relative income tends to be higher when the output is low. In our model, gender asymmetries in income levels, income volatility and child penalties determine the cyclicality of fertility. Flexibility in our model allows us to generate countercyclical fertility under different gender asymmetry scenarios.

Not only does fertility become procyclical after the 70s, but also the degree of procyclicality increases substantially. In Figure 3, we show the 10-year rolling correlation between fertility and GDP cycles. While the correlation was strongly negative in the 60s as pointed out by Butz and Ward (1979), it became strongly positive after the 90s (also noted by Stetsenko (2010)). In this paper, we explore the role of "breadwinner women" in changing cyclicality of fertility. Women's breadwinner status improved over time as they participated more in the labor market. Moreover, the countercyclical gender income gap suggests they are more likely to be breadwinners in bad times. These two mechanisms contribute to the increasing procyclical feature of fertility. During the 60s, female participation rate was low and average women's income was only around 20% of that of men (Figure 4). Low share of women's income in the family budget causes only a modest income effect in response to negative shocks, but a significant substitution effect because the time cost of children is borne by women. During a recession, families lean towards higher fertility and lower quality in the quality-quantity trade-off because time cost as a share of family income is lower as opposed to significantly higher quality costs. In contrast, higher women's income over time creates a stronger income effect in response to negative shocks, as mentioned in Ahn and Mira (2002). Combined with the countercyclical gender income gap, time cost as a share of family income increases in a recession, which pushes families to decrease fertility more to keep quality more stable[3]. In our model, lower relative income alone explains 56 to 62% of the difference in fertility cyclicality between the 60s and the 70s-onward; where the differences in employment cyclicality (higher female employment volatility and lower male employment volatility during the 60s) can explain 38 to 44%.

We show that the relative employment (income) gap between men and women is countercyclical around business cycles. The seminal work on the "added worker effect" by Lundberg (1985) argues that women whose husbands become unemployed in a recession are likely to enter the labor market, temporarily increasing female participation. Mankart and Oikonomou (2017) also argue that added worker effect is the mechanism behind acyclical labor force participation. Bardóczy (2020) argues that secondary earners increase their labor supply in

[3]This finding is in line with Aparicio et al. (2020) who find that recessions are associated with lower number of births but increased child health outcomes in Spain.

response to job loss of the primary earner, a shift that acts as an automatic stabilizer in the economy. A more recent study by Guner et al. (2020b) argues that the added worker effect makes female employment relatively more stable as those who lose their jobs in a recession are offset by additional women entering the labor market. Thus, the added-worker effect can explain why gender employment and income are countercyclical. However, since the 90s female labor force participation has already been high[4]. A complementary channel "precautionary labor supply" is offered by Ellieroth (2019): women tend to hold on to their jobs when their husbands face high risk of unemployment, thus providing insurance to the family income. Ellieroth (2019, 2017) show that married women have much lower cyclical volatility of employment than married men, and argue that women's precautionary labor supply behavior accounts for 30% of married women's low cyclicality of employment, which provides intra-household insurance. In this paper, we focus on another channel, gender industry composition. We document that about 70% of men work in highly procyclical industries such as construction, manufacturing, professional services and retail, while 40% of women work in countercyclical industries (education and health services and government)[5] [6]. Accordingly, we show that female employment is much less volatile than male employment around business cycles (similar to Hoynes et al. (2012), Doepke and Tertilt (2016), Alon et al. (2020), Olsson (2018)). Similarly, Albanesi and Sahin (2018) show that gender asymmetry in industries is the main driver of cyclicality in the gender unemployment gap. Using PSID data, Boar (2021) also reports that service sector jobs exhibit lower income uncertainty compared to construction and finance. Whether due to the added worker effect, precautionary labor supply as suggested by Ellieroth (2019) or industry cyclicality, we observe more stable female employment over business cycles. As a result, the importance of female income increases during recessions as more women become the family breadwinner.

During economic downturns, men tend to lose their jobs at higher rates because they are employed in heavily procyclical industries, resulting in a negative impact on fertility because families cannot afford more children. On the other hand, female employment is either unaffected or affected positively due to the countercyclical properties of female-dominated

[4]Since most women are already in the labor market, increase in female labor participation slowed down. According to Albanesi (2019) and Fukui et al. (2019), this slowdown made the recoveries from recessions much slower.

[5]Saks and Shore (2005) document that teaching and healthcare occupations (which are female dominated) exhibit a lower degree of income riskiness than occupations like sales and management (which are male dominated).

[6]We use industries where the correlation between industry-level employment and aggregate employment is above 90%. See Table 7

industries. In turn, these better economic prospects for women reinforce the negative impact on fertility, since women who are breadwinners cannot afford to take time off and have children because their income serves as an insurance. We estimate employment volatilities of US industries from the data and run a counterfactual experiment. We show that if men work in countercyclical and women work in procyclical industries (men become nurses, women become construction workers), fertility is higher by 0.12% and it is countercyclical. However, the quality investment in children is 0.20% lower. On the other hand, in an economy where women work exclusively in countercyclical industries and men work in procyclical ones (the "women-nurse economy") we find that fertility is 0.15% lower than the benchmark and human capital is 0.25% higher. In other words, we argue that in a world in which men are nurses and women are construction workers, we would observe countercyclical fertility at the expense of lower human capital accumulation.

Our mechanism works through the relative magnitude of income and substitution effects both within and between genders. Despite changing time-use trends, such as a more balanced division of labor in child rearing, women continue to disproportionately bear the time cost of a child. Kleven et al. (2019a) find that women with children earn, on average, 20% less than women without children[7], whereas the effect on men is negligible. Thus, much of the opportunity cost of having a child is composed of women's foregone earnings. As a result, a negative income shock to women creates both income and substitution effects, whereas a negative shock to men's income creates only an income effect. Indeed, Autor et al. (2019) find that trade shocks to male-intensive employment diminish fertility while shocks to female-intensive employment raise it. Heckman and Walker (1990) identify the effect of increased women's wages on fertility by analyzing Swedish panel data and find that higher female wages lead to delayed childbirth and, as a result, lower fertility. In order to identify the effect of male income on fertility, unexpected job displacement has been used as an exogenous shock. Both Lindo (2010) and Amialchuk (2013) find that an unexpected shock to male income (job displacement) decreases fertility. Schaller (2016) attempts to track both effects by using exogenous labor demand shocks and gender employment indices in different industries. Consistent with the literature, she finds that male wages positively affect fertility,

[7] This is the combined effect of mothers who work less, who stop working, who face discrimination, or who change occupations. Gallen (2018) argues that part of the pay gap can be explained by the fact that women have lower productivity, especially when they become mothers. Women who give birth early in their careers suffer from child penalties that lead higher-earning women to postpone having children, while lower earners give birth earlier (Caucutt et al. (2002); Da Rocha and Fuster (2006)). Adda et al. (2017) argue that career choices are made alongside fertility choices; hence, there is sorting in occupations according to lifetime fertility choices which result in career costs.

while female wages negatively affect fertility. Similarly, Schmitt (2011) and Özcan et al. (2010) find that male unemployment affects fertility negatively whereas female unemployment affects it positively. Moreover, we show that the income effect arising from a shock to women's income becomes larger when the women's income share in the family is higher, which contributes to procyclical fertility. A high income effect can suppress the substitution effect emanating from women's income.

It is a major challenge in the literature on the one hand to generate a negative fertility-income relationship arising from quality-quantity trade-off and on the other hand to explain the positive relationship between fertility and income cycles (procyclical fertility). Several studies (Macunovich (1995, 1996); Mocan (1990); Silver (1965); Schaller (2016); Ahn and Mira (2002); Sobotka et al. (2011); Jones and Schoonbroodt (2016); Buckles et al. (2021)) examine the cyclicality of fertility and conclude that fertility is procyclical. Stetsenko (2010) considers both countercyclical and procyclical periods of fertility, but his model cannot generate procyclical fertility. Our framework is very similar to Jones and Schoonbroodt (2016), who find a pattern of procyclical fertility. Note that in Jones and Schoonbroodt (2016), the model can generate only one type of cyclicality (either procyclical or countercyclical) with a given set of parameterization. The only way to generate countercyclical fertility is to include only time cost and assume the inverse elasticity of intertemporal substitution is less than 1 (γ in our case). The main contribution of our paper is to show that incorporating gender differences in the labor market is essential to explain the cyclical behavior of fertility in a world with quality-quantity trade-off and time costs born mostly by women (which is empirically shown by Kleven et al. (2019a,b)). Our framework can generate both countercyclical (1960s), and procyclical periods (1970s onward) based on relative income (estimated separately for the periods 1964-1974 and 1975-2018) and changing gender employment volatility over time. The importance of high female wages in producing procyclical fertility is acknowledged by Ahn and Mira (2002) as they show how the income effect can become more dominant at high female wages. Our framework is heavily built on this argument and we show that relative income accounts for 56 to 62 % of the increasing fertility cyclicality over time. In our framework, a negative relationship between income and fertility can arise through female income but procyclicality arises mainly through male income[8]. In our benchmark calibration (1975-2018), the income effect slightly dominates the substitution effect for women such that an increase in women's income leads to a slight increase in fertility. Then, according to our

[8]Dettling and Kearney (2014) show that higher house prices increase fertility of home owners through the income effect and decreases fertility of non-owners which suggests a strong income effect

framework, the negative fertility-income relationship should flatten out with an increase in women's relative income by amplifying the income effect. Indeed, it has been shown that this negative relationship has been flattened out in recent years (Bar et al. (2018) and Doepke et al. (2022)). We contribute to the literature by showing that we can generate both procyclical and countercyclical fertility at the same time with reasonable assumptions and parameters through observed facts in the labor market: 1) child penalties fall mostly on women (Kleven et al. (2019a,b)); 2) women become breadwinners over time (high relative income in Figure 4); and 3) women are bad times breadwinners (lower employment cyclicality in Figure 1).

Several studies look at the effect of uncertainty on fertility decisions. Sommer (2016) studies the effect of unexpected earnings risk on fertility and finds that a higher earnings risk is associated with delayed and lower fertility. Guner et al. (2020a) show that labor market frictions (uncertainty about employment, inflexibility of work schedules) lowers fertility. On the other hand, a recent paper by Chabe-Ferret and Gobbi (2018) argues that economic uncertainty is the main driver behind baby booms and busts in the US. In our model, the effect of uncertainty on fertility depends on whether the uncertainty comes from men or women. In the model, women's income has an insurance property due to a countercyclical income gap. High uncertainty in women's income diminishes the insurance value by amplifying the substitution effect, hence making it more countercyclical, while high uncertainty in men's income makes fertility more procyclical.

To the best of our knowledge, our study is the first to highlight a link between the cyclicality of relative income and fertility dynamics, and the findings have implications for population growth and human capital accumulation. The current structure of the labor market, with women and men sorting into different types of industries, creates an insurance mechanism that helps smooth income fluctuations, makes fertility procyclical and tilts the quality-quantity trade-off towards quality. In a world where women's earnings are lower than men's earnings (e.g., the 1960s) or in a world in which male and female industry allocations are reversed (e.g., men are nurses and women are construction workers), fertility would be countercyclical at the expense of lower human capital accumulation.

2 Facts

In this section, we document several facts that are crucial to our mechanism, some of which have been previously documented in the literature. We show the data facts together with the details on sample selection and robustness and note how these are used when calibrating the model. First, we document the cyclicality of fertility and how it is related to different aggregate outcomes such as GDP and employment, as well as how it depends on timing (time of conception vs. birth). Second, we document the evolution of the gender gap in labor market outcomes (employment, hours and income). Third, we show the gender gap is countercyclical and this fact holds within families as well. Finally, we show that industry employment is gender asymmetric.

2.1 Cyclicality of Fertility is increasing

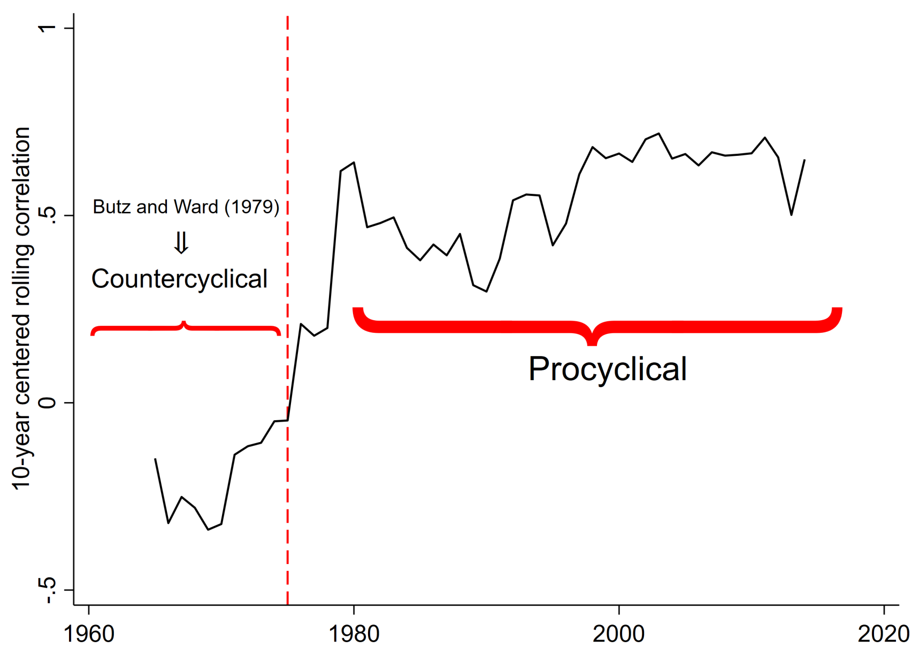


Figure 3: Fertility and GDP Correlation

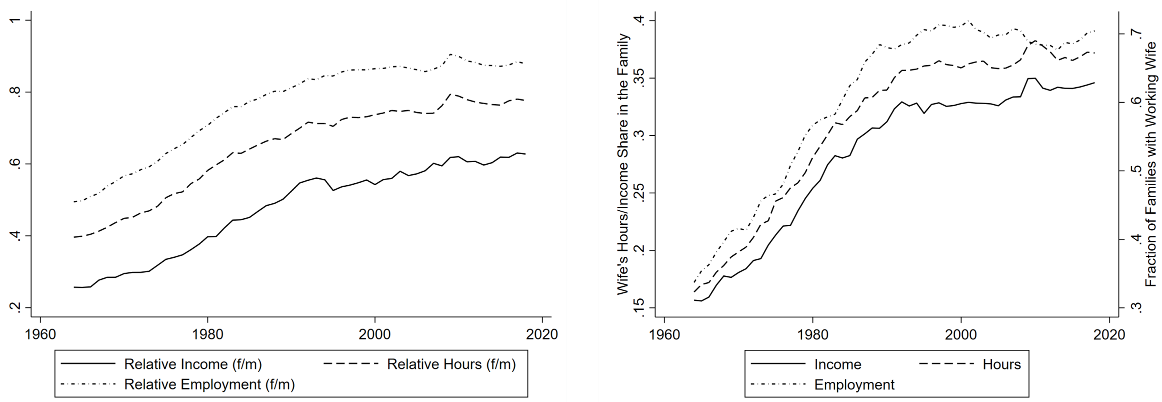
Note: Seasonally adjusted quarterly fertility rate is calculated from the same series in Figure 1, seasonally adjusted quarterly GDP is obtained from FRED for the years 1964-2018. HP filter with smoothing parameter $\lambda = 1600$ is applied to both series and 10-year centered rolling correlation between cyclical component of two series is reported. The vertical line is located in 1975 where the correlation turns from being negative to positive. See Appendix A.1 for more details on data sources.

In Figure 1 and Figure 3, we show that fertility is countercyclical during the 60s and it becomes more and more procyclical over time. This fact is in line with what Ahn and Mira (2002) argue about the impact of higher female wages over time causing more procyclical fertility. It is also important to note that the decline in fertility (adjusted to determine the conception date) starts slightly earlier than the decline in GDP, as also pointed out by Buckles et al. (2021). They argue that fertility behavior is forward looking and sensitive to changes in short run expectations. They also note that the fact that fertility is leading the GDP cycles does not exist for recessions earlier than 80s; the contemporaneous correlation between conception and GDP growth falls significantly for the earlier period and cyclicality of fertility was different in the earlier period as we also show in our paper and Butz and Ward (1979) documented earlier. In Appendix Figure 17, we show that our results are robust to using the period fertility measure (as used by Butz and Ward (1979); Chabe-Ferret and Gobbi (2018); Jones and Schoonbroodt (2016)); fertility evolves from a countercyclical period to a more and more procyclical period, consistent with our main fact whether we use lagged fertility (to coincide with conception) or period fertility[9] as the measure. We also confirm that the main facts are robust when we use the aggregate employment instead of GDP as the aggregate economic activity indicator (Appendix Figure 16).

2.2 The gender employment/income gap is decreasing

As also discussed by Goldin (2014), we show gender convergence in employment, hours and income in Figure 4. This fact holds true regardless of the sample restrictions or if we restrict ourselves to couples where the women is in a fertile age range (15-45). A decreasing gender gap means women contribute more to the family budget; hence their breadwinner status improves significantly over time. In our model, high women's income leads to large income effects, which in turn contribute to the procyclical fertility.

[9] According to Buckles et al. (2021), fertility is a leading indicator so that the decline in actual births coincides roughly with the GDP trough.



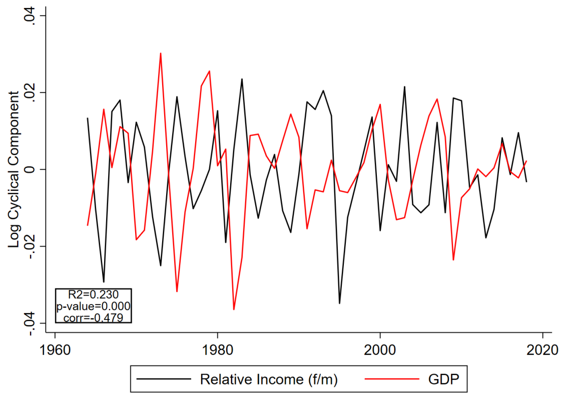
A. Aggregate B. Couples

Figure 4: Gender Gap

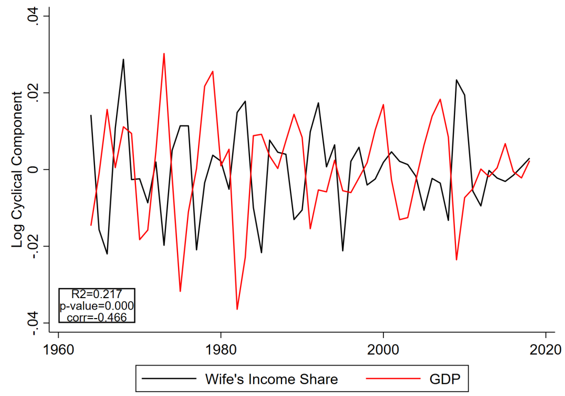
Note: IPUMS-CPS ASEC supplement for years 1964-2018 is used. On the left panel, average income, hours, and employment rate by gender are calculated from the sample of individuals aged 15-60 and the ratio of female-to-male is reported. On the right panel, couples are matched and a sample of couples where the wife is between 15-45 (fertile age range) is obtained. Wife's income and hours share are calculated at the family level and annual averages are reported. See Appendix A.1 for more details.

2.3 The gender income gap is countercyclical

In Figure 2, we show that relative employment is countercyclical in the US throughout the period we analyze. We further investigate the robustness of this fact by considering different measures. Figure 5 shows that the gender income gap (women/men) is countercyclical. In other words, women's income relative to men's income increases in recession times and decreases in boom times. The left panel shows the cyclical component of the difference of log annual women's vs. men's income and the cyclical component of GDP between the years 1964 and 2018. The right panel shows the same fact exclusively for couples and calculates the wife's income share in total family income as the outcome variable. Both figures indicate that the correlation between the gender income gap and GDP is highly negative. In Appendix Figure 24, we also show that relative hours are countercyclical as well.



A. Aggregate



B. Couples

Figure 5: Cyclicality of gender gap

Note: IPUMS-CPS ASEC supplement for years 1964-2018 is used. Relative income and wife's income share within family from Figure 4 and annual GDP from FRED is used to HP filter with smoothing parameter $\lambda = 6.25$ for the years 1964-2018. We report cyclical component of HP filtered series. See Appendix A.1 for more details.

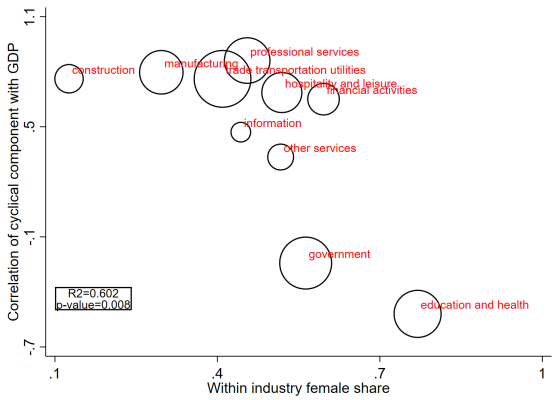
2.4 Industry employment by gender is asymmetric

We argue that the cyclical properties of industries and their gender makeup contribute to the countercyclical gender employment gap. We document that different industries have different cyclical properties and gender employment compositions. On the left panel of Figure 6, we show that industries with the highest female share exhibit the lowest business cycle risk (i.e. negative correlation with GDP) and vice versa. The industries with a high degree of cyclicality (high correlation with GDP) are also those with high employment volatility[10]. Industries with a countercyclical tendency are education, health services, and government, which together account for 40% of women's employment[11]. Meanwhile, the most procyclical industries are trade, transportation, utilities, professional services, construction, manufacturing, and leisure, which together employ 68% of men. In addition to male-dominated industries being more pro-cyclical, their employment volatility is also very high. On the right panel of Figure 6, we analyze if the gender industry sorting holds within families as well. We use the sample of matched couples where both spouses are working and the wife is at fertile age. We assign husband and wife to categories according to industry cyclicality risk which

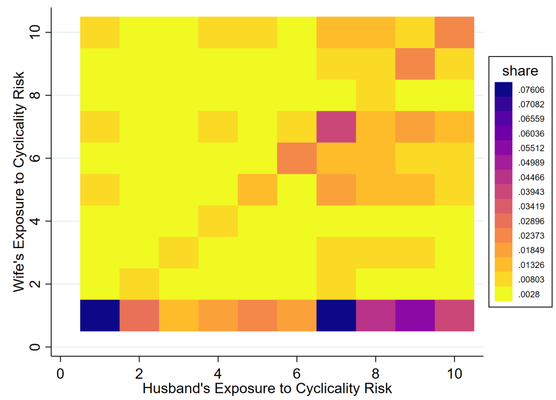
[10]In Appendix Table 7, we report industry cyclicality properties in a more detailed way for a longer period, i.e., 1975-2018. Note that female dominant industries exhibit a higher degree of countercyclicality in recent decades than before.

[11]Charles et al. (2018) find that college attendance decreases during boom times and increases during recessions. This finding can also be seen as a reason that education and health services are acyclical and even sometimes countercyclical.

is determined on the left panel. Exposure to cyclicality risk is 1 if the individual is working in the least cyclical industry (i.e. education and health services), and is 10 if the individual is working in the most cyclical industry (i.e. professional services). We plot the fraction of couples within each industry pair. First, among more than half of the couples in 2018, the wife is working in countercyclical industries (education and health services, and government). Second, among those couples, there is a high fraction in which the husband is working in the most cyclical ones (darkest colors appear on the bottom right)[12]. Finally, medium colors on the diagonals also suggest the existence of some assortativeness with respect to industries.



A. Aggregate



B. Couples

Figure 6: Exposure to Business Cycle Risk

Note: BLS Current Employment Statistics industry employment by gender is used in the left panel. Seasonally adjusted quarterly industry employment and GDP is HP-filtered with smoothing parameter $\lambda = 1600$ between 1990-2018. On the y-axis correlation of cyclical component of GDP and cyclical component of industry employment is reported. On the x-axis, average female share within industry is reported. The right panel uses 2018 IPUMS-CPS March Supplement, matched couples where the wife is in fertile age range (15-44). Both wife and husband are ranked according to their exposure to cyclicality risk which is a number between 1-10 where 1 corresponds to the least cyclical industry (education and health services) on the left panel and 10 corresponds to the most cyclical industry (professional services). The frequency of families at each industry pair is reported. See Appendix A.1 for more details.

3 Simple Model

In this section, we layout a simple model of fertility that captures several distinct features of fertility decisions by linking them in a unified framework. The quality-quantity trade-off, differential impact of men's and women's income, and child penalties, as well as their

[12]In Appendix Figure 23, we show the distribution of families according to industry riskiness and labor force status in 1968 and 2018.

interactions with business cycles are the key mechanisms in our framework. To the best of our knowledge, we are the first to explore the interaction of all these channels.

We build an overlapping generations model with fertility and human capital expenditure decision. The model is similar to De La Croix and Doepke (2003) except each household is composed of two members. Each member is endowed with one unit of labor from which they can earn a wage (w_t^m and w_t^f, for men and women respectively) and they choose consumption (c_t) and saving (s_t) as well as the number of kids (we assume fertility, n_t, is a continuous variable). Families also care about the human capital of their kids (q_t) for which they need to make an expenditure (e_t per kid). Having kids mean that the family needs to take time off from work to care for their kids, which reduces their work time and makes a material expenditure (e_t). We denote τ^m and τ^f as the child penalties men and women face respectively. When old, families consume the returns to their savings.

$$\max_{c_t^t, c_{t+1}^t, s_t, n_t, e_t, q_t} \quad \log c_t^t + \beta \log c_{t+1}^t + \xi \log (q_t n_t)$$

$$\begin{aligned} c_t^t + s_t + e_t n_t &= w_t^m (1 - \tau^m n_t) + w_t^f (1 - \tau^f n_t) \\ c_{t+1}^t &= s_t (1 + r_{t+1}) \\ q_t &= e_t^{\eta} \end{aligned}$$

First order conditions lead to the following choice by families; for simplicity we assume $\beta(1+r_{t+1}) = 1$;

$$\begin{aligned} c_t^t = c_{t+1}^t &= \frac{w_t^f + w_t^m}{(1+\beta+\xi)} \\ e_t &= \frac{\eta}{1-\eta} \left(w_t^m \tau^m + w_t^f \tau^f \right) \\ n_t &= \underbrace{\frac{\xi(1-\eta)}{(1+\beta+\xi)}}_{\kappa} \frac{w_t^f + w_t^m}{\left(w_t^m \tau^m + w_t^f \tau^f \right)} \end{aligned}$$

Note that the changes in wages have different outcomes on fertility depending on which parent faces the larger child penalties. Empirical evidence (Kleven et al. (2019b) among many) is clear that child penalties (the effect of having a child on labor market outcomes) fall almost fully on women so that $\tau^f \gg \tau^m$;

$$\frac{\partial n_t}{\partial w_t^m} = \kappa \frac{w_t^f(\tau^f - \tau^m)}{\left(w_t^m \tau^m + w_t^f \tau^f\right)^2} > 0$$
$$\frac{\partial n_t}{\partial w_t^f} = \kappa \frac{w_t^m(\tau^m - \tau^f)}{\left(w_t^m \tau^m + w_t^f \tau^f\right)^2} < 0$$

An increase in men's wage leads to an increase in fertility due to the income effect whereas the effect of women's wage is a decline in fertility due to the substitution effect. To see how fertility moves with family income, we get Taylor expansion of n_t around (n_0, w_0^m, w_0^f);

$$\Delta n_t = \frac{w_0^m}{n_0} \overbrace{\frac{\partial n}{\partial w_m}(w_0^m, w_0^f)}^{+} \Delta w_t^m + \frac{w_0^f}{n_0} \overbrace{\frac{\partial n / n_0}{\partial w_f}(w_0^m, w_0^f)}^{-} \Delta w_t^f$$

where $\Delta x_t = \frac{x_t - x_0}{x_0}$ denotes percentage change from x_0. Further we assume wage processes follow;

$$w_t^m = w_0^m + w_0^m \sigma_m \varepsilon_t^m$$
$$w_f = w_0^f + w_0^f \sigma_f \varepsilon_t^f$$

where ε_t^m and ε_t^f are independent standard Gaussian random variables, and σ_m, σ_f are the standard deviations of men's and women's incomes respectively. Replacing the wage processes yields;

$$\Delta n_t = \frac{w_0^m}{(w_0^m + w_0^f)} \frac{w_0^f(\tau^f - \tau^m)}{\left(w_0^m \tau^m + w_0^f \tau^f\right)} \sigma_m \varepsilon_t^m + \frac{w_0^f}{(w_0^m + w_0^f)} \frac{w_0^m(\tau^m - \tau^f)}{\left(w_0^f \tau^m + w_0^m \tau^f\right)} \sigma_f \varepsilon_t^f$$

Note also the process for total household income;

$$\Delta(w_m + w_f) = \sigma_m \varepsilon_t^m \frac{w_0^m}{w_0^m + w_0^f} + \sigma_f \varepsilon_t^f \frac{w_0^f}{w_0^m + w_0^f}$$

Hence we can write cyclicality of fertility which is defined as the correlation between fertility and total income changes as;

$$cov\left(\Delta n, \Delta(w_m + w_f)\right) = \Xi_m \sigma_m^2 - \Xi_f \sigma_f^2$$

where, $\Xi_m = \left(\frac{w_0^m}{(w_0^m + w_0^f)}\right)^2 \frac{w_0^f(\tau^f - \tau^m)}{\left(w_0^m \tau^m + w_0^f \tau^f\right)} > 0$ and $\Xi_f = \left(\frac{w_0^f}{(w_0^m + w_0^f)}\right)^2 \frac{w_0^m(\tau^f - \tau^m)}{\left(w_0^f \tau^m + w_0^m \tau^f\right)} > 0$. In this simple model, in addition to the parameters, cyclicality of fertility depends on which income has higher volatility. In particular, the combination of relatively stable women's income and highly volatile men's income leads to procyclical fertility. Going beyond the first order approximation, we see how an increase in women's income affects how fertility changes. For simplicity, assume $\tau^m = 0$, and we write second derivatives as;

$$\begin{aligned}
\frac{\partial^2 n_t}{\partial \left(w_t^m\right)^2} &= 0 \\
\frac{\partial^2 n_t}{\partial \left(w_t^f\right)^2} &= 2\kappa \frac{w_t^m}{\left(w_t^f\right)^3 \tau^f} > 0 \\
\frac{\partial^2 n_t}{\partial w_t^f \partial w_t^m} &= -\kappa \frac{1}{w_f} < 0
\end{aligned}$$

$\frac{\partial^2 n_t}{\partial \left(w_t^f\right)^2} > 0$ means that as women's income goes up, fertility becomes less sensitive to women's income as her income effect increases (the gap between substitution and income effect shrinks). Similarly, fertility becomes less sensitive to men's income since high women income dampen the income effect of men (less important men's income in the family causes lower degree of income effect).

4 Quantitative Model

In our simple model, we show several key features of our mechanism: i) as long as child penalties are larger for women, women's income has a strong substitution effect, whereas the income effect is dominant with men's income; ii) the income effect of women goes up when women's income increases, which in turn increases procyclicality of fertility; and iii) cyclicality of fertility is determined by the relative magnitude of men's and women's income shocks.

In our extended general equilibrium model, we aim at quantifying on the one hand the role of differential cyclicality of men's and women's income and on the other hand the role of increasing female income over time in order to account for the changing cyclicality of fertility from the 60s until today. We extend the model by increasing the number of periods in which each generation lives as well as using a general equilibrium framework.

Our quantitative model extends our simple model by adding the possibility of postponing fertility; families can decide to have children later in their lives. Young families can delay having children when they face negative income shocks, and that delay can help them sustain desired fertility. Families can also insure themselves against income fluctuations through asset accumulation. Middle age families can also use accumulated assets to sustain desired fertility. These two features allow us to account for different behavior of younger and older households through their different capacities to buffer against shocks.

In the model, women are the main caregivers of children. They therefore face both short and long-term child penalties. People in the model live for 5 periods (child, young, middle, old and retired). Children live and consume with their parents. Young and middle households make fertility and quality decisions as well as choices related to consumption and saving. Old households continue working but cannot have children. When retired, households consume the returns to their accumulated assets. Consumption goods in the model are produced using inputs from male and female-dominated industries. In each industry, productivity follows an exogenous process that we estimate from the data. Investment in human capital leads to higher productivity once the children enter the labor market.

In our framework, the cyclicality of fertility depends on the breadwinner status of women, who primarily bear child penalties. Everything else being equal, higher and more stable women's income makes fertility more procyclical whereas high child penalties make it less procyclical by amplifying the substitution effect.

4.1 Household Problem

Households (HHs) of young and middle generations are able to make decisions about fertility, labor supply, and consumption. Old households do not make fertility decisions, but they still supply labor, earn wages, and save for retirement. Each member of the household is endowed with 1 unit of labor. Since households do not enjoy leisure, male members supply 1 unit of labor (later, we also introduce child penalties on men). However, as female members are the caregivers of children in the model, they supply child penalty adjusted labor (due to the time cost of children).

Young HHs

Young families make consumption, saving, and fertility-quality decisions. Male members supply 1 unit of labor ($l_t^{m,y} = 1$), whereas female members need to spend time caring for children ($l_t^{f,y} = (1 - \tau n_t^y)$).

$$
\begin{aligned}
V_t^y = \max_{c_t^y, a_t^y, n_t^y, e_t^y, q_t^y} & U^y(c_t^y, q_t^y, n_t^y) + \beta \mathbb{E} V_{t+1}^m(a_t^y, q_t^y, n_t^y) \\
s.t.\ & c_t^y + a_t^y + \bar{w} e_t^y n_t^y = w_t^{m,y} + w_t^{f,y}(1 - \tau_1 n_t^y)
\end{aligned}
$$

where c_t^y is the joint consumption of the family, a_t^y is the assets they accumulate, n_t^y is the number of children they have, and q_t^y is the human capital of their children. Similar to De La Croix and Doepke (2003), human capital is formed by investing $e_t^y \bar{w}$ per child, where $\bar{w}$ is the relative price of human capital investment,

$$
q_t^y = (\theta + e_t^y)^\eta
$$

Males and females earn w_t^m and w_t^f, respectively. Men spend one unit of labor, whereas women need to spend time raising their children (τn_t^y).

Middle HHs

Similar to young families, middle families make fertility-quality decisions. They have access to the returns on their assets accumulated when they were young. Male members supply 1 unit of labor ($l_t^{m,m} = 1$), whereas female members need to spend time caring for children ($l_t^{f,m} = (1 - \tau n_t^m) f(n_{t-1}^y, 0)$). In addition to the time cost, women who gave birth when they were young are subject to long-term child penalties (motivated by Kleven et al. (2019a)) through the function $f(n^y, n^m)$, where n^m is the number of children that a middle-age household has.

$$
\begin{aligned}
V_t^m(a_{t-1}^y, q_{t-1}^y, n_{t-1}^y) = & \max_{c_t^m, a_t^m, n_t^m, e_t^m, q_t^m} U^m(c_t^m, q_{t-1}^y, n_{t-1}^y, q_t^m, n_t^m) \\
& + \beta \mathbb{E} V_{t+1}^o(a_t^m, q_{t-1}^y, n_{t-1}^y, q_t^m, n_t^m) \\
s.t.\ c_t^m + a_t^m + \bar{w} e_t^m n_t^m = & w_t^{m,m} + w_t^{f,m} f(n_{t-1}^y, 0)(1 - \tau_1 n_t^m) + a_{t-1}^y R_t
\end{aligned}
$$

Old HHs

Old people continue working and make only consumption-saving decisions, although they do continue to derive utility from their children. Similarly, male members supply 1 unit of labor ($l_t^{m,o} = 1$), whereas female members still incur long-term child penalties ($l_t^{f,m} = f(n_{t-2}^y, n_{t-1}^m)$).

$$
\begin{aligned}
V_t^o(a_{t-1}^m, q_{t-2}^y, n_{t-2}^y, q_{t-1}^m, n_{t-1}^m) = & \max_{c_t^o, a_t^o} U^o(c_t^o, q_{t-2}^y, n_{t-2}^y, q_{t-1}^m, n_{t-1}^m) \\
& + \beta \mathbb{E} V_{t+1}^r(a_t^o, q_{t-2}^y, n_{t-2}^y, q_{t-1}^m, n_{t-1}^m) \\
s.t.\ c_t^o + a_t^o = & w_t^{m,o} + w_t^{f,o} f(n_{t-2}^y, n_{t-1}^m) + a_{t-1}^m R_t
\end{aligned}
$$

Retired HHs

Retired people consume the returns of their accumulated assets.

$$
\begin{aligned}
V_t^r &= \max_{c_t^r} U^r(c_t^r) \\
c_t^r &= a_{t-1}^o R_t
\end{aligned}
$$

4.2 Firm Problem

Consumption goods are produced using capital and labor,

$$Y_t = K_t^{\alpha} L_t^{1-\alpha}$$

Labor is composed of male and female labor

$$L_t = \left(z_t^m \left(L_t^m\right)^{1-\sigma} + z_t^f \left(L_t^f\right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

where z_t^m and z_t^f are the productivity of male- and female-dominated industries, respectively. In the benchmark, we calibrate the process of z_t^m, z_t^f to match the current men and women employment process. As counterfactual analysis, we explore different levels of industry segregation and calculate gender employment processes accordingly.

4.3 Demographics

Population Growth

We define the number of families in each generation i by N_t^i where $i \in \{y, m, o, r\}$. Young families at time t are born to young and middle parents at time $t-1$.

$$N_t^y = \frac{N_t^m}{2} n_{t-1}^y + \frac{N_t^o}{2} n_{t-1}^m$$

Each generation has an equal number of men and women so that $N_t^m n_{t-1}^y$ children are born to $\frac{N_t^m}{2}$ families . Population growth across generations is defined as

$$(1+n_t) = \frac{N_t^y}{N_t^m}$$

Fertility Rate

Define fertility rate as the total number of children born to young and middle-aged families divided by the total number of families.

$$Fertility\ Rate_t = \frac{n_t^y N_t^y + n_t^m N_t^m}{N_t^y + N_t^m}$$

If both the numerator and denominator are divided by N_t^m, by using the definition of population growth $(1+n_t) = \frac{N_t^y}{N_t^m}$, we get

$$Fertility\ Rate_t = \frac{n_t^y(1+n_t)+n_t^m}{2+n_t} \tag{1}$$

4.4 Equilibrium Conditions

Total Consumption

Total consumption is the sum of consumption by all generations;

$$C_t^y + C_t^m + C_t^o + C_t^r = C_t$$

Per-family consumption is therefore

$$N_t^y c_t^y + N_t^m c_t^m + N_t^o c_t^o + N_t^r c_t^r = C_t$$

Scaling by the number of retired families N_t^r, per-family consumption is c_t: $c_t = \frac{C_t}{N_t^r}$.

$$c_t^y(1+n_t)(1+n_{t-1})(1+n_{t-2}) + c_t^m(1+n_{t-1})(1+n_{t-2}) + c_t^o(1+n_{t-2}) + c_t^r = c_t$$

Capital accumulation

Total capital in the economy is the sum of accumulated assets;

$$A_{t-1}^y + A_{t-1}^m + A_{t-1}^o = K_t$$

Similarly, per-family capital is;

$$a_{t-1}^y(1+n_t)(1+n_{t-1})(1+n_{t-2}) + a_{t-1}^m(1+n_{t-1})(1+n_{t-2}) + a_{t-1}^o(1+n_{t-2}) = k_t$$

Labor force

We assume that the effective labor force is determined by the human capital expenditure made for that generation;

$$q_t L_t^{m,y} + q_{t-1} L_t^{m,m} + q_{t-2} L_t^{m,o} = L_t^m$$

$$q_t L_t^{f,y} + q_{t-1} L_t^{f,m} + q_{t-2} L_t^{f,o} = L_t^f$$

where q_t is the human capital of the generation. We define generational human capital [13];

$$q_t = \frac{q_{t-1}^y n_{t-1}^y / 2}{(1+n_t)} + \frac{q_{t-1}^m n_{t-1}^m / 2}{(1+n_t)(1+n_{t-1})} \tag{2}$$

Similarly, we scale the labor force by the number of retired families;

$$l_t^m = q_t l_t^{m,y}(1+n_t)(1+n_{t-1})(1+n_{t-2}) + q_{t-1} l_t^{m,m}(1+n_{t-1})(1+n_{t-2}) + q_{t-2} l_t^{m,o}(1+n_{t-2}) \tag{3}$$

$$l_t^f = q_t l_t^{f,y}(1+n_t)(1+n_{t-1})(1+n_{t-2}) + q_{t-1} l_t^{f,m}(1+n_{t-1})(1+n_{t-2}) + q_{t-2} l_t^{f,o}(1+n_{t-2}) \tag{4}$$

Factor prices

Competitive firms set marginal returns to respective factor prices;

$$r_t = \alpha K_t^{\alpha-1} L_t^{1-\alpha}$$

Return on capital is defined as;

$$R_t = 1 + r_t - \delta$$

[13] See Appendix A.4for the details.

where δ is the capital depreciation rate.

w_t^m and w_t^f are the wages per effective unit of labor earned by male and female workers;

$$w_t^m = z_t^m (1-\alpha) K_t^\alpha L_t^{\sigma-\alpha} (L_t^m)^{-\sigma} \tag{5}$$

$$w_t^f = z_t^f (1-\alpha) K_t^\alpha L_t^{\sigma-\alpha} (L_t^f)^{-\sigma} \tag{6}$$

However, each agent earns a wage rate that depends on the quality investment that has been made for their generation. For example, young men and women at time t earn $w_t^m q_t l_t^{m,y}$ and $w_t^f q_t l_t^{f,y}$,where q_t is the human capital of the current young generation (that depends on past investment in human capital) defined in Equation 2.

In the model, income earned by women and men are defined by;

$$Inc_t^f = w_t^f l_t^f$$
$$Inc_t^m = w_t^m l_t^m$$

where the labor force is defined in equations 3 and 4, and wages are defined by equations 5 and 6. Note that women's and men's income incorporate respective productivity shocks as well as child penalties for women. Finally we define the relative income as;

$$Rel_t = \frac{Inc_t^f}{Inc_t^m} \tag{7}$$

5 Calibration

The model is calibrated such that one period is 15 years. The discount rate is set as $\beta = 0.74$, which corresponds to a yearly steady-state interest rate of 2%. We assume standard parameters for capital share ($\alpha = 0.35$), risk aversion ($\gamma = 2$), and depreciation rate (annual depreciation rate of 10%). For the curvature of quality function, we use $\eta = 0.63$ from De La Croix and Doepke (2003). We set a linear child penalty function

$$f(n^y, n^m) = (1 - \tau_2 n^y - \tau_2 n^m)$$

We set $\tau_1 = \tau_2 = 0.15$ to be consistent with Kleven et al. (2019a). Kleven et al. (2019a) show that the child penalty increases linearly with the number of children. In the long run, Danish mothers suffer earning losses of about 10% per child. Kleven et al. (2019b) demonstrate that US mothers, regardless of their number of children, suffer from an earning loss of about 30%. We extrapolate a linear child penalty feature along with an average fertility rate of 2 children per women for the US and assign $\tau_1 = \tau_2 = 0.15$ in our calibration. We set the elasticity of substitution between men vs women labor $\sigma = 0.44$ from Ngai and Petrongolo (2017). Young families derive utility from consumption and the children born to them;

$$U^y(c_t^y, q_t^y, n_t^y) = \frac{(c_t^y)^{1-\gamma}}{1-\gamma} + \xi \frac{(n_t^y q_t^y + \lambda)^{1-\sigma_n}}{1-\sigma_n}$$

where λ is the childlessness utility. For middle-aged and old families, the utility function takes the form;

$$U^m(c_t^m, q_{t-1}^y, n_{t-1}^y, q_t^m, n_t^m) = \frac{(c_t^m)^{1-\gamma}}{1-\gamma} + \xi \frac{(n_{t-1}^y q_{t-1}^y + n_t^m q_t^m)^{1-\sigma_n}}{1-\sigma_n}$$

$$U^o(c_t^o, q_{t-2}^y, n_{t-2}^y, q_{t-1}^m, n_{t-1}^m) = \frac{(c_t^o)^{1-\gamma}}{1-\gamma} + \xi \frac{(n_{t-2}^y q_{t-2}^y + n_{t-1}^m q_{t-1}^m)^{1-\sigma_n}}{1-\sigma_n}$$

And, for retired families;

$$U^r(c_t^r) = \frac{(c_t^r)^{1-\gamma}}{1-\gamma}$$

We assume that industry productivities (z_t^m,z_t^f) follow 15-year AR(1) processes with means μ_m and μ_f respectively. Error terms are jointly normally distributed[14];

$$\log(z_t^m) = (1-\rho_m)\mu_m + \rho_m \log(z_{t-1}^m) + \varepsilon_t^m \tag{8}$$

$$\log(z_t^f) = (1-\rho_f)\mu_f + \rho_f \log(z_{t-1}^f) + \varepsilon_t^f \tag{9}$$

[14] In the benchmark, we assume that error terms are not correlated. The results are qualitatively similar if the correlation is positive.

$$\begin{bmatrix} \varepsilon_t^m \\ \varepsilon_t^f \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \varepsilon_t^m \\ \varepsilon_t^f \end{bmatrix}, \begin{bmatrix} \sigma_m^2 & 0 \\ 0 & \sigma_f^2 \end{bmatrix} \right)$$

We use the cyclical components of male and female employment as proxies for productivities. We then estimate ρ_m,ρ_f, σ_m, σ_f from the annual data (see Appendix Table 9). By following the approach of Jones and Schoonbroodt (2016), we estimate 15-year frequency adjusted parameters for use in the model[15]. We normalize $\mu_m = 1$ and we estimate μ_f in the model such that average female-to-male income in the model as defined in Equation 7 is equal to the data counterpart estimated from IPUMS-CPS.

For the rest of the parameters (see Table 8) we calibrate the model[16] to match the US data. In Table 1, we show that our model matches targeted moments well: number of children per young and old agents, volatility and cyclicality of fertility, and relative income. In the US data, cyclicality of fertility ranges from -0.15 to 0.59 between the earlier period 1964-1974 and the benchmark period 1975-2018. Our model is qualitatively able to generate the cyclicality ranging from countercyclical to procyclical fertility; however, quantitatively it is not able to produce such a wide range. The model's estimated fertility cyclicality ranges between -0.10 and 0.24. Unlike previous research, the model is able to generate both countercyclical and procyclical fertility without changing model parameterization, which is an important contribution of our paper.

In the data, young women's fertility is more procyclical (less countercyclical in the 60s) compared to that of older women. Our model is able to generate this observation as well. The difference is due to the possibility of postponing fertility. Young families' fertility is more sensitive to income fluctuations because they can delay having children to reduce expenses during a recession.

[15] We also estimate 15-year frequency standard deviations for productivity and fertility with the same method. See Appendix A.4 for the details.

[16] We use a third order perturbation to solve our model, we calibrate the stochastic steady state to the data. See Aruoba et al. (2006) for accuracy of higher order perturbation methods. We also tried 4th order, which did not make a meaningful change in the results.

Targeted Moments	Description	Data	Model
$n_{y,1975-2018}$	Number of children per woman aged 15-29	1.287	1.291
$n_{m,1975-2018}$	Number of children per woman aged 30-44	0.652	0.657
$\sigma_{fertrate,1975-2018}$	Standard deviation of fertility rate	0.011	0.010
$\rho(fertrate,Y)_{1975-2018}$	Cyclicality of fertility rate in 1975-2018	0.592	0.240
$\rho(fertrate,Y)_{1964-1974}$	Cyclicality of fertility rate in 1964-1974	-0.153	-0.096
$(Inc_f/Inc_m)_{1975-2018}$	Relative Income (f/m) in 1975-2018	0.523	0.555
$(Inc_f/Inc_m)_{1964-1974}$	Relative Income (f/m) in 1964-1974	0.284	0.259
Untargeted Moments			
$\rho(Inc_f/Inc_m,Y)_{1975-2018}$	Cyclicality of relative income in 1975-2018	-0.420	-0.217
$\rho(Inc_f/Inc_m,Y)_{1964-1974}$	Cyclicality of relative income in 1964-1974	-0.655	-0.114
$\sigma_{fertrate,1964-1974}$	Standard deviation of fertility rate	0.028	0.016
$\sigma(n_{y,1975-2018})$	Standard deviation of fertility rate of women aged 15-29	0.013	0.012
$\sigma(n_{m,1975-2018})$	Standard deviation of fertility rate of women aged 30-44	0.010	0.013
$\rho(n_y,Y)_{1975-2018}$	Cyclicality of fertility rate of women aged 15-29 in 1975-2018	0.595	0.340
$\rho(n_m,Y)_{1975-2018}$	Cyclicality of fertility rate of women aged 30-44 in 1975-2018	0.495	-0.028
$\rho(n_y,Y)_{1964-1974}$	Cyclicality of fertility rate of women aged 15-29 in 1964-1974	-0.093	0.106
$\rho(n_m,Y)_{1964-1974}$	Cyclicality of fertility rate of women aged 30-44 in 1964-1974	-0.330	-0.268

Table 1: Targeted vs. Untargeted Moments

Note: Age specific fertility rate (number of children born to women aged x/ number of women aged x) is multiplied by 15 to find number of children born to young and middle age women (15-29 and 30-44 respectively) and average across years is calculated. HP filter with smoothing parameter $\lambda = 6.25$ is used for the fertility series 1964-2018 as well as real GDP and standard deviation of the cyclical component is reported for the corresponding years. Cyclicality of fertility is defined as the correlation between cyclical components of fertility rate and GDP after HP-filtering. Unless otherwise specified, fertility rates are for the age group 15-44. Relative income measures are calculated using IPUMS-CPS ASEC supplement for the years 1964-2018. Our sample consists of individuals between 15-60 (to be model consistent) and we use labor earnings as the measure (including people who do not have any earnings). See Appendix A.1 for data sources.

6 Results

In Section 5, we show that our model can generate empirical regularities in the data. We can generate both countercyclical and procyclical fertility only through changes in observed labor market characteristics (relative income and volatility). Our model also does well in matching untargeted moments such as differences in fertility volatility and cyclicality across age groups. In this section, we explore the channels through which our model can account for empirical facts and we quantify the role of each channel in explaining the emergence of procyclical fertility.

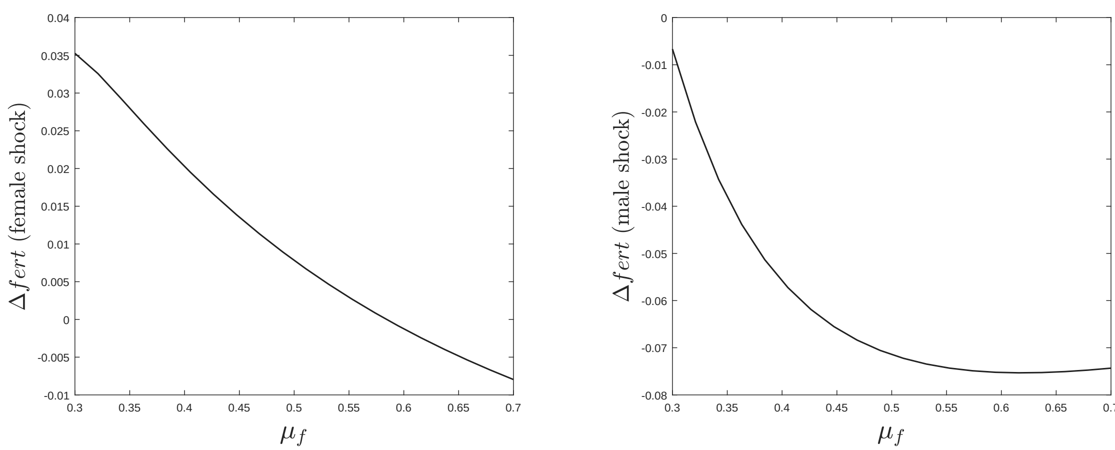
First, we explain the mechanism in the model through demonstrating how income and substitution effects change with respect to relative spousal income, income cyclicality and child penalties. Second, we do a decomposition exercise to assess what fraction of the change in fertility cyclicality can be explained by change in relative income and/or change in gender differences in employment risk. Third, we run counterfactuals which are aimed at altering "women's breadwinner status" to answer the questions "how would fertility be if gender difference in employment risk were different and/or female income share in the family were different?". Finally, we assume a gender-symmetric scenario and quantify the effect of gender symmetry in the labor market on fertility outcomes and on the aggregate economy.

6.1 Fertility Response to Shocks

In the simple model (Section 3), as long as women bear most of the child penalties, they display a strong substitution effect such that high women's income is associated with high fertility, whereas men have a dominant income effect[17]. In the quantitative model, the mean of women productivity process (μ_f) controls the relative income (see the discussion in Section 5). A higher μ_f that raises relative income of women in the family means women have a higher breadwinner status in the family. In Figure 7, we plot the response of fertility to a 10% negative shock to women (left panel) and men (right panel) productivities as a function of the parameter μ_f. The left panel of Figure 7 shows that fertility increases significantly when female income decreases by 10%, especially when female-to-male income is low (low μ_f); however the increase in fertility in response to a negative female income shock is less pronounced at high relative income levels. This difference occurs because the income effect is stronger when female income is substantial in the family. In other words, the substitution effect tends to dominate the income effect for women at low relative income levels. The right panel of Figure 7 demonstrates the fertility changes in response to 10% negative shock to male income. Because men do not exhibit a substitution effect as they do not incur any time cost, a negative income shock always decreases fertility. However, fertility decline is more pronounced at high relative income levels. This difference occurs because when women's income is a higher share of the family income, the time cost of children (which is borne by women) is high. Conversely, when women earn a smaller share of income in the family, the time cost of having children is low, but expenditure costs in particular become very expensive

[17] We show in the simple model case that results do not change qualitatively as long as male time costs are smaller than female time costs. Following Kleven et al. (2019b)'s findings, we assign zero-time cost for men which reflects the impact of having a child on labor market outcomes (not necessarily if fathers spend time or not).

when the majority of family income depends on male income. As a result, families choose to respond more heavily via quality rather than quantity when relative income is low. We show how quality expenditure responds with respect to income shocks in Figure 8. At low relative income levels, families decrease the quality expenditure more substantially in response to negative income shocks because quality becomes particularly more expensive relative to the time cost in recession times. Hence, in the quality-quantity trade-off, families lean towards quantity in recessions when relative income is low. In other words, low income families choose to have more children and invest less in quality because the relative cost of quality is high for them (Becker and Lewis (1973); De La Croix and Doepke (2003)). In Section 7.1, we discuss further how time vs. expenditure costs move when family income is low.



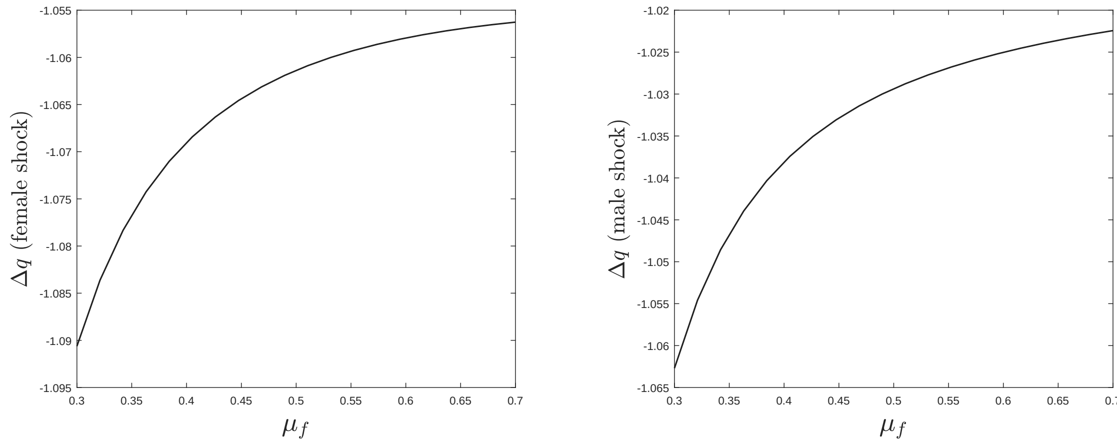
A. Negative Female Income Shock

B. Negative Male Income Shock

Figure 7: Change in Fertility with respect to female-to-male income

Note: y-axis plots the fertility response following a shock to -10% shock to female or male income as a function of μ_f. Fertility response is averaged over two periods to capture the postponing effect of young families. Note that $\mu_{f,1975-2018} = 0.65$ in the benchmark and $\mu_{f,1964-1974} = 0.3$ in the 60s (which corresponds to 0.55 and 0.26 respectively in relative income).

In Figure 9, we show similarly how fertility changes with 10% female (left panel) and male (right panel) income shocks as a function of the volatility of women productivity. Volatility of women productivity (σ_f) also governs women's breadwinner status in bad times.



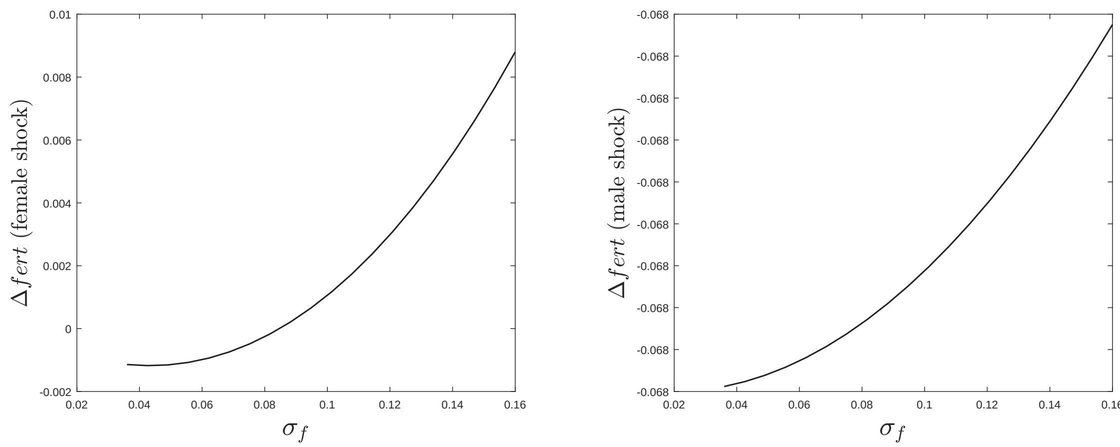
A. Negative Female Income Shock B. Negative Male Income Shock

Figure 8: Change in Quality with respect to female-to-male income

Note: y-axis plots the response of quality following a shock to -10% shock to female or male income as a function of μ_f. Note that $\mu_{f,1975-2018} = 0.65$ in the benchmark and $\mu_{f,1964-1974} = 0.3$ in the 60s (which corresponds to 0.55 and 0.26 respectively in relative income).

Low female income volatility means women's breadwinner status improves in bad times as income fluctuations come mostly from men's income and women's income stays stable even when men's income is low. When women's income is stable (low σ_f), the women's substitution effect is dampened. This effect occurs because women would like to reduce fertility as a precaution in case the family income is low in the future[18]. Conversely, fertility responds more positively to female income shocks when female income volatility is high (left panel). High female income volatility means women's breadwinner status deteriorates in bad times of the economy; as a result, a negative income shock to female income is the perfect time to have a child as the opportunity cost is minimized. Similarly, the right panel in Figure 9 shows that fertility decreases less in response to a 10% male income decline, especially when female income volatility is high (the change is quantitatively small). In this case, quality becomes more expensive relative to quantity, and families slide towards quantity in the quality-quantity trade off.

[18]We discuss this mechanism in Section 7.3



A. Negative Female Income Shock B. Negative Male Income Shock

Figure 9: Change in Fertility with respect to female income volatility

Note: y-axis plots the fertility response following a shock to -10% shock to female or male income as a function of σ_f. Fertility response is averaged over two periods to capture the effect on the lifetime choice of the young families. Note that $\sigma_f = 6.6\%$ in the benchmark, $\sigma_f = 3.8\%$ in the women dominant industries and $\sigma_f = 16\%$ in men dominant industries.

In Figure 10, we summarize the joint effect of relative income on the one hand and relative income volatility on the other hand in affecting cyclicality of fertility. Cyclicality of fertility is maximized (most procyclical) when relative income is high and female income volatility is low. In this scenario, women's breadwinner status is the highest because their income is a substantial part of the family budget, creating a significant income effect in response to negative shocks. Moreover, because their income is less volatile compared to their spouses, making them bad times breadwinners, they decrease their fertility in a recession as a precaution. Fertility is most countercyclical when female income share is the lowest, and women have more volatile income. A low female income can generate only a modest income effect in response to negative shocks. And having more volatile income means that women have a lower opportunity cost of having a child in recession times because their income share is even lower during recessions. As a result, when women have low and/or volatile income, they perceive recessions, when the opportunity cost is minimized, as the perfect time to have a child.

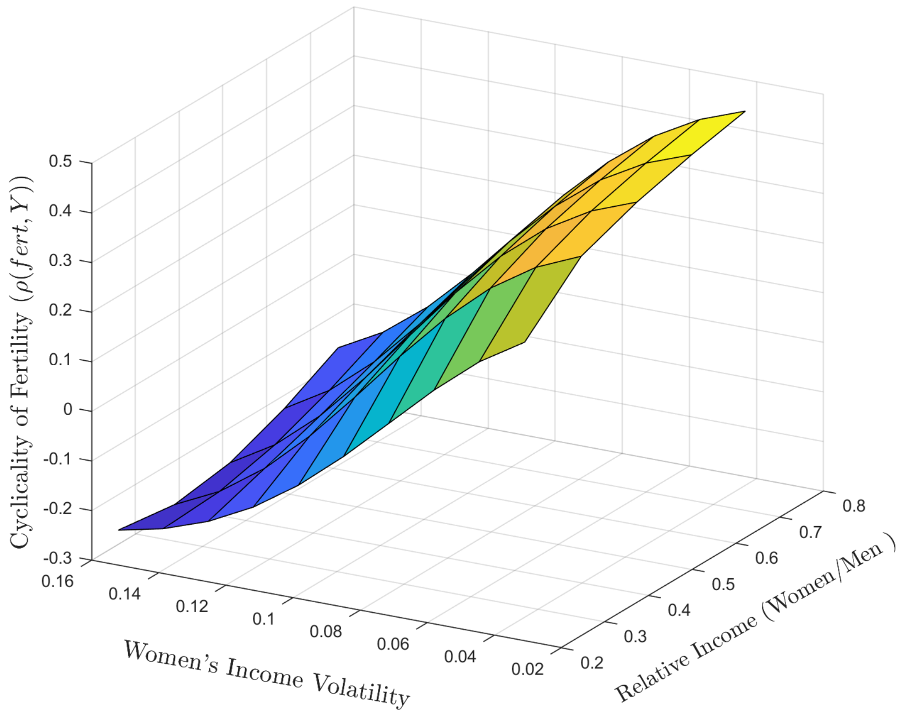


Figure 10: Cyclicality of Fertility, Relative Income, Employment Volatility
Note: Cyclicality of fertility is estimated as the correlation between HP-Filtered output and fertility. Women's income volatility is σ_f, in order to isolate the effects coming from total volatility, we fix $\sigma_f + \sigma_m = \bar{\sigma}$ where $\bar{\sigma}$ corresponds to the sum of standard deviations in the benchmark so that high σ_f is associated with low σ_m. Relative income is defined as in Equation 7. The movement in relative income is achieved by moving $\mu_f \in [0.2 - 0.7]$. As we move μ_f, we scale $\bar{w}^* = \frac{1+\mu_f}{1+\mu_{f,1975-2018}}\bar{w}$ so that the cost of quality investment is adjusted by the total family income.

6.2 The Role of Gender Differences in Employment Risk

In order to see the effect of cyclicality of the gender income gap on fertility and human capital decisions, we consider two counterfactual economies as well as the benchmark economy. The differences in these economies stem from the volatility of male- and female-dominated industries. In our benchmark economy, the standard deviations of these industries are calibrated to match the standard deviations of male and female employment as observed in the data. In complete segregation (i.e., only women work in female-dominated industries and vice versa), or the "women-nurse economy"; the standard deviations are estimated to match those of male- and female-dominated industries; i.e. education, health and government for women and construction and manufacturing for men. In the "women-nurse economy"; male employment becomes much more volatile than female employment. For the "men-nurse economy"; which features complete segregation with the opposite gender bias, we assign the same calibrated parameters as in the "women-nurse economy" to the opposite gender. Thus, the "women-nurse economy" is a subset and extreme version of the current labor market, while the "men-nurse economy" is a counterfactual economy. The details of this estimation are explained in Appendix A.4.

In Figure 11, we show that in our benchmark economy, relative income cycles are countercyclical, making female income more precious in downturns. During bad times, women's income share in the family goes up such that the time cost of having children is higher. Therefore, when relative income is countercyclical, women become the breadwinner during bad times and cannot afford to stay home to have more children. In the more extreme scenario of the "women-nurse economy", the gender income gap is even more countercyclical than the benchmark; and in the "men-nurse economy", we find a procyclical gender income gap which means female income is less precious in recessions, and hence the opportunity cost of having a child is lower.

We find more procyclical fertility in the "women-nurse economy" and countercyclical fertility in the "men-nurse economy". In Table 2, we document steady states of these economies. Making gender asymmetry more extreme, i.e., moving from the benchmark to the "women-nurse economy" makes fertility 0.15% lower and more procyclical; the correlation coefficient between output and fertility cycles goes up from 0.24 to 0.41, a 71% increase in procyclicality. The investment in human capital increases by 0.25% in the steady state. When male income is more volatile, women's income relative to men's becomes countercyclical (i.e., women are the breadwinners in a recession). This makes women's income more precious and, through the substitution effect, families have fewer children but invest more in their human capital. Conversely, fertility is countercyclical (correlation between fertility and output is -0.25) and 0.12% higher in the "men-nurse economy" but at the expense of 0.20% lower human capital in the steady state. Here, women's income relative to men's is procyclical, making women's income less valuable. As a result, women prefer to have more children instead of investing in their children's human capital.

We show that both the level and cyclicality of fertility and the level of quality investment are jointly determined based on child penalties and differential gender income risks. In the hypothetical "women-nurse" economy, where women are complete insurance providers of their families, fertility is 0.15% lower but the quality investment is 0.25% higher than the benchmark. As a result, output is 0.09% and consumption 0.05% higher than in the benchmark economy. In a way, as long as the gender asymmetry in child penalties persists, gender segregation in the labor market might benefit the aggregate economy through the human capital accumulation channel even though depressing the overall fertility level. This effect occurs because women become breadwinners when the family income is low. From the perspective of risk-averse agents, women earn more in relative terms when marginal utility is high, making their income more precious. In the quality-quantity trade-off, the economy is pushed towards quality because the relative weight of women's income is higher as women bear the time cost of children. In the counterfactual "men-nurse economy", we observe high relative income when the output is high. Women's income is therefore less precious, because it is high when the marginal utility of income is low. Hence, families in this economy are pushed towards quantity because the relative weight of women's income is low. We discuss this mechanism in more detail in Section 7.3.

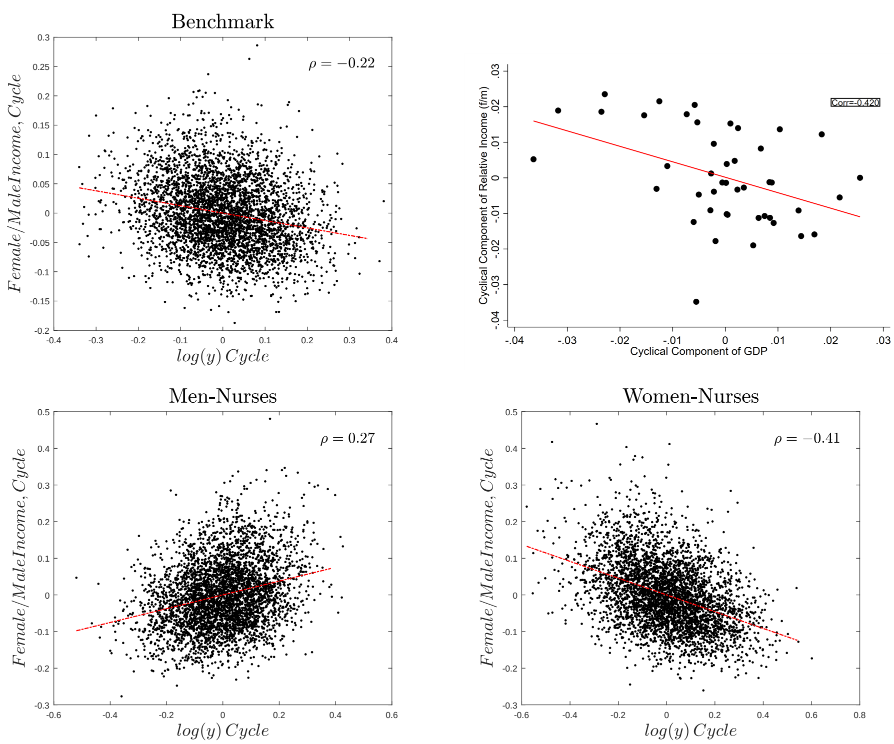


Figure 11: Cyclicality of gender income gap under counterfactuals
Note: Female/Male income cycle is calculated as HP filtering the relative income (Equation 7). Income cycle is calculated as HP-Filtering log output. Data counterpart is calculated using IPUM-CPS ASEC supplement for individuals aged 15-60 for the years 1975-2018, by HP filtering relative income (labor earnings) and annual real GDP with smoothing parameter $\lambda = 6.25$ and reporting cyclical components.

	$\rho(GDP, fertility)$	$\sigma(fertility)$	%Δ from benchmark			
	Cyclicality	Volatility	Fertility	Quality	Consumption	Output
Benchmark	0.24	0.08				
Women-nurse	0.41	0.12	-0.15%	0.25%	0.05%	0.09%
Men-nurse	-0.25	0.11	0.12%	-0.20%	-0.02%	-0.07%

Table 2: Counterfactuals-Employment Risk

Note: Benchmark economy corresponds to the benchmark calibration 1975-2018. Women-nurse economy corresponds to having stable women's productivity (estimated from health-education-government employments) and volatile men's productivity (estimated from construction-manufacturing employment). Men-nurse economy is the opposite of women-nurse economy. Cyclicality of fertility is defined as the correlation of HP-Filtered fertility and HP-Filtered output. $\sigma(fertility)$ is the standard deviation of HP-Filtered fertility. We estimate the standard deviation of employment cycles of these industries in the same way we estimate male and female employment (see Section A.4).

We then simulate a recession shock which is 1-standard deviation shock to both male and female income, and we report impulse responses of fertility and quality under 3 different scenarios in Figure 12. We find that in the "women-nurse economy", fertility is more responsive to a recession shock, while quality is less responsive. In the "women-nurse economy", families have a better income insurance mechanism, as women's income is more stable. On the other hand, stable female income during a recession period makes it possible to sustain high and smooth human capital. In the "men-nurse economy", female income falls substantially in a recession; hence a preference emerges for taking time off to have more children due to the substitution effect that makes fertility countercyclical. It is not, however, possible to maintain high quality given that they have more children combined with a low income. Note also that as anticipated, young families who decrease their fertility when a recession hits, recover when they are middle aged by increasing fertility; however, the recovery does not replace the decline in fertility during their youth.

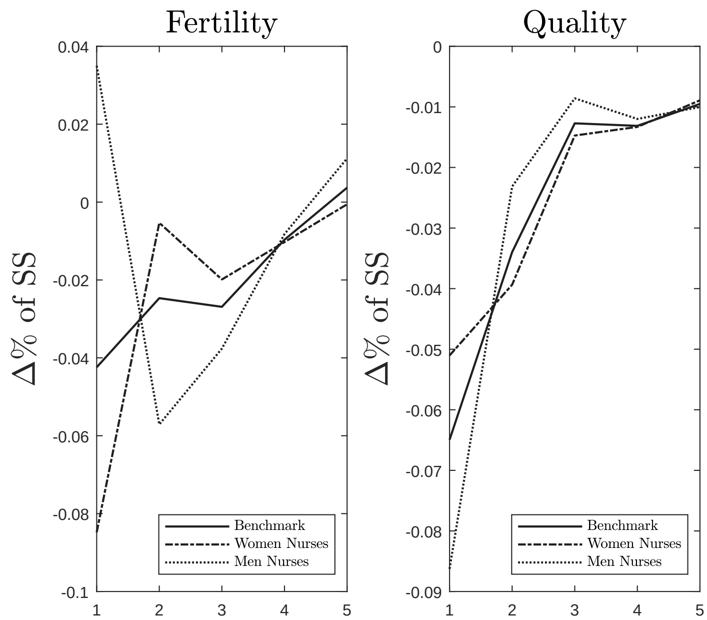


Figure 12: Impulse response to a recession shock

Note: Impulse responses of fertility (Equation 1) and human capital (quality, Equation 2) are displayed as percent changes from the steady state. The shock employed is a 1 standard deviation shock to both men and women productivities.

6.3 The Role of Relative Income: The Emergence of "Countercyclical" Fertility

We show that although fertility is countercyclical in the 60s, it becomes more and more procyclical starting from the mid-70s (Figure 3). There are two major differences in the labor market between the 60s and the 70s onward (Table 3). One is that women's to men's relative income is substantially higher in the latter period. The other is that women's employment volatility becomes significantly lower than men's while it was slightly higher during the 60s. We show in Figure 10 how female-to-male income and relative employment volatility affect cyclicality of fertility. We now quantify the role of these two mechanisms by changing one at a time in explaining the emergence of procyclical fertility, seen in Table 4. We show that starting from the 70s and changing only the female-to-male income (as in the 60s) leads to a decrease in cyclicality of fertility form 0.24 to 0.03. Changing only female and male employment volatility leads to a decline from 0.24 to 0.09. We conclude that 38 to 44 % of the change in cyclicality of fertility can be explained by changing gender employment volatility, and 56 to 62 % of it can be explained by increasing relative income [19]. The details of this exercise are in Appendix A.4. In sum, the emergence of procyclical fertility arises due to two different aspects of breadwinner women: higher income over time and lower income volatility.

	Female-to-Male Income	Female Employment Volatility	Male Employment Volatility
1964-1974	0.28	1%	0.9%
1975-2018	0.52	0.8%	1.2%

Table 3: Benchmark vs. 60s
Note: IPUMS-CPS ASEC supplement is used to calculate female-to-male income gap for the sample 15-60. BLS Current Employment Statistics is used to calculate male and female employment volatility of HP-filtered cyclical component of annual employment series by gender. Reported female-to-male income is the data counterpart.

	Data 1975-2018			Data 1964-1974
ρ (Fertility, GDP)	0.59			-0.15
	Benchmark	Female-to-Male Income (only)	Employment Volatility (only)	Female Income Share +Employment Volatility
$\rho(Fertility, Y)$	0.24	0.03	0.09	-0.10

Table 4: Decomposition of relative income and gender specific employment volatility
Note: Fertility cyclicality for different time periods are the ones shown in Figure 20. The model counterpart of $\rho(Fertility, Y)$ is calculated as the HP-filtered correlation between fertility and output. (i) 'Income only' scenario lowers $\mu_f = \mu_{f,1964-1974}$ and at the same time adjusts $\bar{w}_{1964-1974} = \frac{1+\mu_{f,1964-1974}}{1+\mu_{f,1975-2018}} \bar{w}_{1975-2018}$. (ii) 'Volatility only' scenario sets σ_f, σ_m to estimated 1964-1974 values. Last column combines (i) and (ii) so that the model matches 1964-1974 period.

6.4 The Role of Child Penalties

In this section, we analyze the impact of short-term child penalties on responsiveness of fertility. We calibrate the benchmark model with the child penalty parameters by using the estimated empirical child penalties by Kleven et al. (2019a) which fall only on women. As a result, men exhibit only the income effect in response to their own wage shocks and women

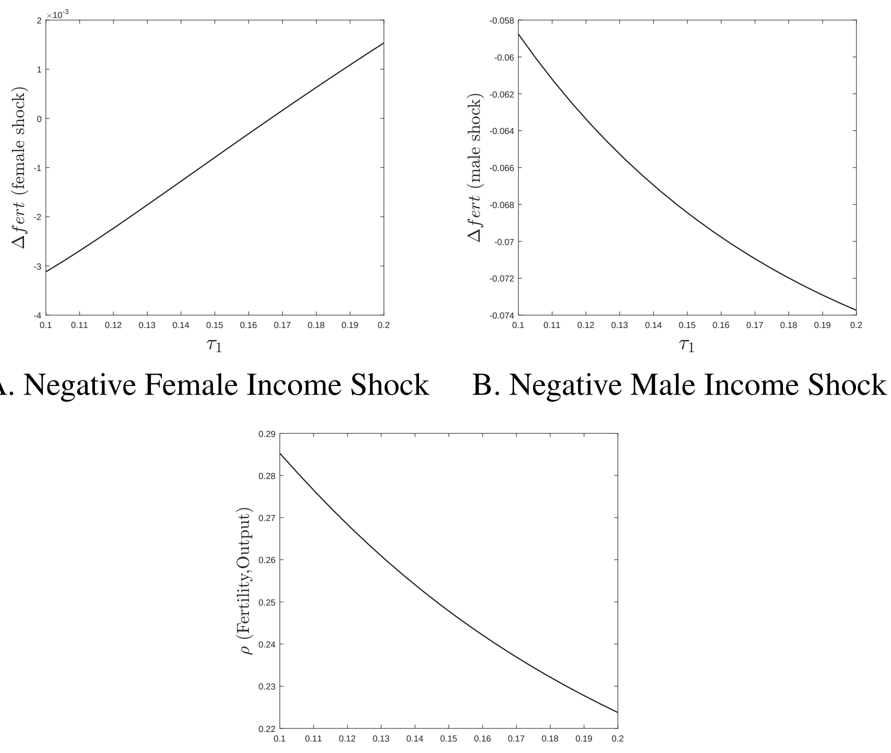
[19] The calculation is done based on the distance in cyclicality between the two periods. Assuming each period as a benchmark separately gives different numbers as the role of each factor also depends on other factors; i.e. gender volatility differences matter more when relative income is high.

exhibit both income and substitution effects in response to own wage shocks. We are answering two questions in this section. First, how would the responsiveness of fertility change in response to male and female income shocks if child penalties were different? Second, how would the fertility respond to male and female income shocks if men also incurred part of the child penalties.

In Figure 13, we show that higher child penalties for women induce the fertility response to be more positive (or less negative) when women face a negative income shock. The reason is that the opportunity cost of having a child is lower when time costs are large and women face a negative income shock. On the other hand, we show that higher child penalties for women lead fertility to respond more negatively to male income shocks. When child penalties are larger for women, having a child is costly for the family and increases the share of male income in the family. When men experience a negative income shock, it is even less likely for a family to have a child because doing so will incur double income losses (one coming from child penalties on women, the other from male income loss). Hence, higher child penalties on women induce fertility to be more negatively affected from male income shocks.

Figure 13 also plots cyclicality of fertility as a function of τ_1. As child penalties increase, fertility becomes less procyclical. This result occurs because high child penalties make women's substitution effect stronger. Although we do not have time series evidence on the evolution of child penalties, we might expect that these were larger in the 60s. Although that possibility might potentially contribute to the increasing degree of procyclical fertility, we are not quantifying it in our paper.

In Figure 14, we keep the overall level of child penalty as in the calibrated model ($\tau_1 = 0.15$) and we redistribute it between men and women. The left side of the x-axis correspond to the calibrated model where child penalties fall only on women and the right side correspond to the case where all child penalties are incurred by men. When male child penalties are higher (τ_m), men also exhibit the substitution effect in addition to the income effect in response to income shocks; hence such penalties suppress the negative fertility response with respect to their own (male) negative income shocks. This suppression stems from the fact that the opportunity cost of having a child is lower when men do incur child penalties and their income is lower because of the shock. In addition, higher child penalties on men (lower child penalties on women) make fertility respond more negatively in response to female income shocks. When part of the time costs is lifted from women, their substitution effect becomes smaller and their income effect gets larger. In other words, women's income becomes a more important part of the family income when they incur lower penalties and their spouse incurs more. As a result, female income shocks dampen fertility more when men also incur child penalties. In Figure 14, we also show how cyclicality of fertility changes depending on the share of child penalties between the two parents. Fertility is the most procyclical when child penalties are shared equally by parents. Without gender asymmetries, our model produces procyclical fertility as discussed in Section 6.5 in more detail. As one parent becomes the main caregiver (who sustains more of the child penalties), that parent becomes subject to the substitution effect which lowers the procyclicality of fertility. One possible extension of our model would be to make which parent faces child penalties a choice variable wherein families can shift child penalties onto the parent who faces a negative income shock. We suspect that this might make fertility less procyclical as well as higher, but the effect on quality might be ambiguous. On the one hand, high fertility decreases quality because of the quality-quantity trade-off. On the other hand, families will pay lower child penalties which might increase income available to invest in quality.

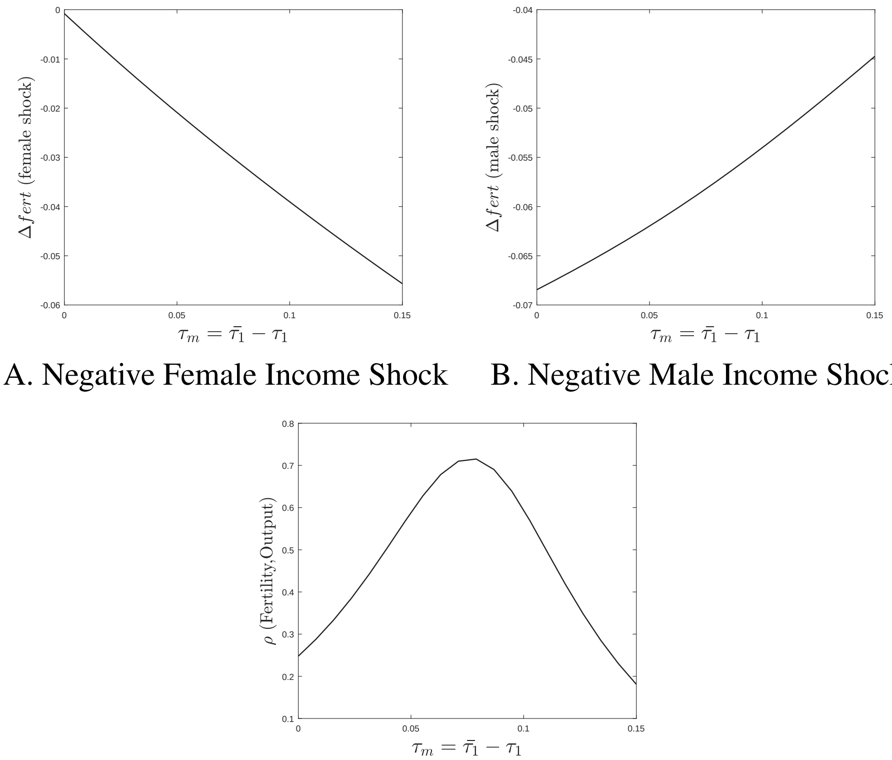


A. Negative Female Income Shock   B. Negative Male Income Shock

C. Cyclicality

Figure 13: Change in Fertility with respect to female time cost

Note: Top figures plot the fertility response to a -10% shock to women's (top left) and men's (top right) productivities as a function of τ_1. Fertility response is averaged over two periods to capture the effect on the lifetime choice of the young families. Bottom figure plots the steady state correlation between HP-filtered output and fertility as a function of τ_1. Note that $\tau_1 = 0.15$ in the benchmark.



A. Negative Female Income Shock B. Negative Male Income Shock

C. Cyclicality

Figure 14: Change in Fertility with respect to male time cost
Note: Top figure plots the fertility response to a -10% shock to women's (top left) and men's (top right) productivities as a function of child penalties on men, τ_m. Fertility response is averaged over two periods to capture the effect on the lifetime choice of the young families. Bottom figure plots the steady state correlation between HP-filtered output and fertility as a function of τ_m. In order to isolate the effects of increasing total child penalties, the increase in τ_m is matched by a decrease in τ_1. Thus, high child penalties on men are associated with low child penalties on women. Note that $\tau_1 = 0.15$ and $\tau_m = 0$ in the benchmark.

6.5 The Case of Gender Symmetry

In this paper, we argue that gender asymmetry in labor market outcomes has an impact on fertility in terms of both its level and its cyclicality. In this section, we show how having more gender similarity changes the fertility level on the quality-quantity trade-off margin and cyclicality of fertility. Gender convergence occurs in many dimensions such as employment, hours, pay and occupation choice as discussed by Goldin (2014). Hence, we ask what would our model predict in a world of complete gender symmetry in the labor market. In Table 5, we show deviations from the benchmark economy under different gender equality scenarios. Currently, our model exhibits three main sources of gender inequality. First is income (which we calibrate as the productivity difference); second is employment volatility;

and third is the time cost of children which has two components: current child penalties and long-term child penalties. Our benchmark calibration shows the correlation between fertility and GDP cycles as 0.24. In the second row of Table 5, we equalize female productivity to male productivity and observe that cyclicality of fertility increases from 0.24 to 0.32. It does so because women's income increases accordingly, creating a larger income effect against negative shocks that then make fertility more procyclical, as explained in Section 6.1 and mentioned by Ahn and Mira (2002). In the third row, when we equalize male and female employment volatility[20], cyclicality of fertility declines to 0.13. Lower male employment volatility and higher female employment volatility break down the "bad times breadwinner women" argument by decreasing the income effect for men and increasing the substitution effect for women; fertility becomes less procyclical as a result. Hence, equality in income and in volatility work in opposite directions in affecting cyclicality of fertility. Further, when we implement both income and volatility equality at the same time, shown in row 4, we observe that cyclicality of fertility decreases slightly compared to the benchmark. Next, we analyze the impact of equal child penalties. We distribute the observed long-term and short-term child penalties equally to men and women and show that cyclicality of fertility increases substantially to 0.69. Note that the complete gender equality case features the same income process and the same child penalties for men and women, such that the model collapses to traditional fertility models in which there is one household, single income process and all the costs are incurred by the unique household. As in Jones and Schoonbroodt (2016) among others, our model predicts procyclical fertility in the case of complete gender equality. However, by introducing observed gender asymmetries into the model we show that we can generate countercyclical fertility.

7 Mechanism

In this paper, we provide a novel mechanism in explaining the cyclicality of fertility and more specifically the emergence of procyclical fertility after a period of countercyclical fertility. We argue that countercyclical gender income gap is a crucial mechanism in explaining fertility behavior around business cycles during a time period when women participate in the labor market. We further argue that our model can generate both countercyclical and procyclical periods only with changes in the labor market, that are possible only in models with

[20]We take the average of observed male and female employment volatility and assign the average standard deviation of men and women in the benchmark.

separate men and women labor.

	$\rho(GDP, fertility)$ (Cyclicality)	$\sigma(fertility)$ (Volatility)
Benchmark	0.240	0.08
Income equality (productivity) only	0.315	0.06
Volatility equality only	0.129	0.08
Both income and volatility equality	0.222	0.06
Equal time cost	0.693	0.04
Income equality + volatility equality + equal time cost	0.685	0.03

Table 5: Counterfactuals: Gender Equality

Note: $\rho(GDP, fertility)$ is HP-Filtered correlation between output and fertility and $\sigma(fertility)$ is the standard deviation of fertility. (i) "Income equality']" scenario sets $\mu_f = 1$ and also raises $\bar{w}$ so that quality expenditure price is also higher. (ii) "volatility equality" scenario sets $\sigma_f = \sigma_m$, which is equal to the average standard deviation in the benchmark. (iii) "Both income and volatility equality" employs both (i) and (ii). (iv) Equal time cost sets $\tau_1 = \tau_2 = \tau_m = \tau_{2,m} = 0.075$ so that child penalties fall on men and women symmetrically. (v) the last scenario combines $(i), (ii), (iv)$ so that from the perspective of the model, men and women are perfectly symmetric.

We show that relative income changes both over time and around recessions are the key in shaping fertility patterns in a world where women bear the majority of the time cost and incur child penalties. When families are deciding what to do when it comes to fertility, they are jointly deciding how many kids to have and how much to spend on them. When they face income shocks, they reconsider this decision by analyzing the time cost of having another child vs. the expenditure cost of having another child. The changes in the time cost of children during a recession depend entirely on women's breadwinner status in the family (her relative income level and volatility). The changes in the expenditure cost depend on the cost of expenditure as share in the family budget (higher share when women earn less). When a recession hits on the quality-quantity trade-off margin, families decide whether or not to have a child by comparing the changes in the time costs relative to the changes in the quality costs.

7.1 Time Cost vs. Expenditure Cost

In order to show how time costs and expenditure costs change in recession times under different scenarios, we run a simple exercise. In this section, we look at how the change in time vs. expenditure costs influences fertility in our model. In Table 6, we show the numerical outputs from our benchmark and counterfactual economies, and report time and expenditure costs as a share of family income and how these change when the recession[21] hits. The third column shows the percentage change in the time cost of an extra child in a recession compared to normal times. We observe that time cost increases the most in the "women-nurse" economy, while relative income increases the most in a recession due to much less volatile female income. Time cost increases the least in the 60s economy as the relative income is the lowest and women have slightly more volatile income. Moreover, time cost decreases in the "men-nurse" economy; because women work in volatile industries but men work in safe ones, relative income decreases in downturns. The sixth column shows the change in expenditure cost of an extra child in a recession compared to normal times. We observe that expenditure cost increases the most in the "women-nurse" economy because men are working in the most volatile industries and still provide a large fraction of family income in such an economy. Hence, a recession significantly reduces the total family income making the expenditure cost share very high. An important margin in the family decision is to understand how time costs change relative to the change in expenditure costs through the quality-quantity trade-off.

In the seventh column of Table 6, we report the change in time cost relative to the change in quality cost. Time cost relative to expenditure cost increases the most in the "women-nurse" economy which is the economy with the highest procyclical fertility (8th column). Here our benchmark economy exhibits the second largest relative increase in time cost and exhibits the second largest procyclicality measure. In the 60s economy, time costs increases only modestly, but in relative terms quality costs are increasing more substantially. The reason is that in this economy, time costs are a relatively small portion of family income while quality costs are a more substantial portion because relative income is low. Hence, we observe countercyclical fertility as a result of leaning towards quantity rather than quality, as quality becomes more expensive in recessions. Finally, we observe a fall in time costs of a child in the "men-nurse" economy. In this case, families prefer quantity more and we observe the highest degree of countercyclical fertility. In other words, observed ordering of fertility cyclicality (column 8) is the same as the ordering of ratio of change in time vs. expenditure cost (column 7). The more time cost increases (relative to expenditure cost) in a recession, the more procycylical fertility occurs.

[21] The recession corresponds to the periods from the simulation where the output is below the 25th percentile

Cost of an extra child as a share of total family income								
	Time Cost $100\frac{\tau w_t^f l_t^f}{w_t^f l_t^f + w_m l_t^m}$			Expenditure Cost $100\frac{\bar{w}}{w_t^f l_t^f + w_m l_t^m}$				
	Mean	Recession	Δ(p.p)	Mean	Recession	$\Delta(p.p)$	Ratio	$\rho(GDP,\text{fertility})$
Benchmark	5.34	5.51	3.19	10.24	12.75	24.52	0.13	0.24
Women Nurse	5.34	5.82	8.89	10.30	14.54	41.27	0.22	0.41
Men Nurse	5.33	5.05	-5.24	10.18	13.10	28.74	-0.18	-0.26
60s	3.08	3.17	2.68	20.32	25.96	27.74	0.10	-0.10

Table 6: Time Costs vs. Quality Costs

Note: We simulate the model for 2000 periods. Mean is defined as the average of all periods whereas recessions correspond to the periods where the output is below more than 1 standard deviation from the mean.

7.2 Quality-Quantity Trade-off

Many studies confirm that women's role as the main caregiver leads them to take time off from the labor market and incur child penalties when they give birth. In our model, women incur short-term and long-term child penalties which lead them to experience lower earnings when they have children. As a result, women's wages have a substitution effect, with higher female wages making children more costly to the family. In families in which the female wage is higher, couples have fewer children but they invest more in the children's human capital (quality-quantity trade-off) (Jones et al. (2010); De La Croix and Doepke (2003); Becker and Lewis (1973)).

To show this channel in our model, we exogenously change the average productivity of z^f and z^m. We keep the average productivity constant while moving the ratio z^f/z^m when we simulate the model. In Figure 15, we plot average fertility and the quality and cyclicality of fertility with respect to the average relative wage (w_f/w_m) for every value of z^f/z^m.

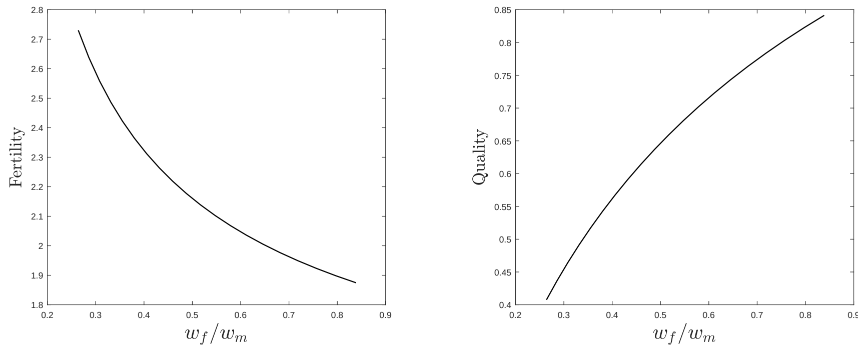


Figure 15: Quality-Quantity Trade-off

Note: X-axis moves relative income by changing $\mu_f \in [0.3, 0.7]$ at the same time lowering μ_m so that $\mu_f + \mu_m = 1 + \mu_{f,1975-2018}$. Y-axis plots stochastic steady state fertility and quality.

7.3 Why does cyclicality of gender income gap matter for the quality-quantity trade-off?

To see this mechanism in our model, consider the fertility decision of a middle-aged household;

$$\overbrace{U_2^m(q_{t-1}^y, n_{t-1}^y, q_t^m, n_t^m) + \beta \mathbb{E}_t U_2^o(q_{t-1}^y, n_{t-1}^y, q_t^m, n_t^m)}^{\text{Marginal benefit of having children}} = \overbrace{U_1^m(c_t^m)\left(\bar{w}e_t^m + w_t^f \tau_1\right)}^{\text{Marginal current cost}} \\ + \overbrace{\beta \mathbb{E}_t\left(U_1^o(c_{t+1}^o) w_{t+1}^f \tau_2\right)}^{\text{Marginal future cost}} \quad (10)$$

where U_2 denotes the marginal utility of the household with respect to children while U_1 is the marginal utility of consumption. The left side of equation 10 is the current and expected future marginal utility of having a child. Similarly, the right-hand side is the current and expected future marginal cost of having a child. Marginal current cost is composed of marginal expenditure on a child's human capital ($\bar{w}e_t^m$) and the foregone earnings of the mother ($\tau_1 w_t^f$). The marginal current cost of having children determines the procyclicality of fertility. When the marginal utility and relative female income is high, having a child is more costly. The marginal future costs are the long-term child penalties ($w_{t+1}^f \tau_2$). Consider the marginal future cost of having children due to the long-term child penalty;

$$\mathbb{E}_t\left(U_1(c^o_{t+1})w^f_{t+1}\tau_2\right) = \tau_2\mathbb{E}_t\left(U_1(c^o_{t+1})\right)\mathbb{E}_t\left(w^f_{t+1}\right) + \tau_2 cov\left[U_1(c^o_{t+1}), w^f_{t+1}\right] \tag{11}$$

According to Equation11, covariance between marginal utility and female income matters for fertility decisions. When female/male income is countercyclical, covariance between the future marginal utility of consumption and female income is positive, which increases the expected cost of having a child.

To summarize, the cyclicality of women's relative income determines the procyclicality of fertility. At the same time, it interacts with long-term child costs and affects the cost of having children independent of the current cycle. When the female/male income ratio is countercyclical, as observed in the data, the average cost of having children is higher. Families thus have fewer children and are able spend more on the human capital of each child.

8 Conclusion

In this paper, we establish a link between fertility and the macroeconomic and gender dynamics of the labor market. We argue that the procyclical trend in fertility depends on the cyclical features of the industries in which men and women work as well as women's share of household income. Men are predominantly employed in procyclical industries such as construction and manufacturing, while women disproportionately work in countercyclical industries such as education, health, and government. In a recession, a typical man loses his job and a typical woman becomes the breadwinner of the family. The gender income gap is thus typically countercyclical, which makes female income more precious due to its insurance effect. Women therefore decrease fertility in order to keep working when a recession hits, which creates procyclical fertility. Combined with the long-term child penalties that women experience, countercyclical female income increases the cost of having children and leads to lower fertility on average. Instead, families opt to invest more in the children they do have.

In our empirical analysis, we show that fertility has moved procyclically since the mid-1970s. We document gender-asymmetric industry characteristics and conclude that 70% of men work in highly procyclical industries and 40% of women work in countercyclical industries. As a result, men have higher employment volatility than women, and it is more procyclical.

In order to quantify the effect of gender asymmetry on fertility and to incorporate the quality dimension of fertility choices, we build a general equilibrium overlapping generations model where families make decisions regarding fertility and the investment in their children's human capital. We find that the level of women's income as well as the cyclicality of male and female incomes can explain procyclical fertility. Gender asymmetry in industries and the countercyclicality of female-dominated fields makes women's income more valuable and pushes families towards quality in the quality-quantity trade-off via a substitution effect. If, however, men work in countercyclical industries and women in procyclical ones (e.g., more men become nurses and more women become construction workers), fertility is higher and countercyclical while the quality investment in children is lower and more volatile. Moreover, our framework explains the "countercyclical fertility" period set forth in Butz and Ward (1979) as influenced by lower women's income during that period.

We introduce gender asymmetries in standard macro models of fertility. A possible extension might be endogenizing some of these asymmetries. Endogenizing the industry choice and which parent to bear child penalties are natural extensions to further look into the heterogeneity. Moreover, analyzing the effects of gender asymmetries in the labor market on intra-household bargaining might be a possible avenue for further research.

We contribute to the literature by highlighting a link between the quality-quantity trade-off, the differential impact of male and female income, and child penalties, as well as the interaction of these factors with business cycles and fertility dynamics, with implications for population growth and human capital accumulation. The current labor market structure, in which women and men sort into different types of industries, creates an insurance mechanism that helps to smooth income fluctuations, making fertility procyclical and tilting the quality-quantity trade-off towards quality.

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A Appendix

A.1 Data

A.1.1 Fertility

We rely primarily on Birth Records from National Health Statistics to calculate total births and age-specific births. In order to calculate fertility rates, we use Survey of Epidemiology and End Results (SEER) provided by NBER. Using micro-data on birth records and SEER give us a time series of 1969-2018. To include earlier years in our analysis, we use the reports provided by Center of Disease Control, Vital Statistics of the United States, Volume-Natality and digitize the numbers provided in annual reports.

The measure we are using is the fertility rate which is defined as total births/ female population aged 15-44 in reported figures. However, when we are calibrating the model, to be in line with model assumptions, we stick on age limits and we calculate the fertility rate of women aged 15-29 and 30-44 separately, as well as standard deviation of fertility rate from the total births to women 15-44/female population 15-44 (which rules out any births occurring outside this range, which is a negligible number).

Micro-data birth records cover the universe of all births in the US. However, during the early period of data coverage, some states were only providing 50% of all births occurring within the state. All the states started to provide 100% of the data but it did not happen simultaneously. Thus, when calculating the total births, we are identifying the timing of a sudden jump in birth numbers and multiply the number of births for the years before the jump for each state. This procedure gives smooth birth series at the state level. However, the state of New York has a discontinuous series of births which we could not smooth out by identifying the sudden jump due to sample change. We identified the change in sample reporting year as 1972. After adjusting for this, the total births are 23% lower between 1973 and 1976 compared to 1972 and then back to normal levels. It is a large difference to be caused by any natural changes in births, and it is a small difference to be caused by change in the sample size from 50% to 100%. We also could not find any information regarding the procedure of reporting x% of total births. As a result, we adjust births in New York between 1973 and 1976 by multiplying the total births by 1.3 to obtain a smooth series. The measures we obtain through this procedure or by digitizing the Vital Statistics Reports give us similar results as described below.

In Figure 1, we use seasonally adjusted monthly fertility rates (total births/female population aged 15-44), obtained through digitizing Table 1-20 in Vital Statistics Reports in each age group. We also show in Figure 22, total births obtained through micro-data birth records for the years 1968-2018 and augmented by digitizing total births for the years 1964-1967 and applying seasonal adjustment procedure by ourselves. The two measures are in line with each other in terms of cyclical properties.

Model targets are calculated using average fertility rate of 15-29 year olds and 30-44 year olds separately for the period 1964-2018. Corresponding fertility rates are total number of births of 15-29 (30-44) year olds/ female population 15-29 (30-44) year olds. Number of children of young and older women is calculated by multiplying corresponding fertility rate by 15 (assuming same annual fertility rate within each age group). The annual fertility rate of 15-44 year olds is HP filtered with smoothing parameter $\lambda = 6.25$ for the period 1964-2018. Standard deviation of cyclical component and correlation with GDP is calculated for the periods 1964-1974 and 1975-2018 separately. Figure 20 reports the cyclical component of fertility rate calculated through the explained procedure and the data.

A.1.2 GDP

There are two GDP series taken from the FRED website and used throughout the analysis. One is the annual GDP, "Real Gross Domestic Product, Billions of Chained 2012 Dollars, Annual, Seasonally Adjusted Annual Rate". The other one is "Real Gross Domestic Product, Billions of Chained 2012 Dollars, Quarterly, Seasonally Adjusted Annual Rate".

A.1.3 Employment by Gender and Industry

We use Current Employment Statistics from Bureau of Labor Statistics to report aggregate employment, employment by gender and employment by industry. Figures 2, and 6 and Table 7 use seasonally adjusted monthly employment statistics (in the case of quarterly statistics, quarterly averages are taken) by CES. Although the CES employment measure deviates from the commonly used CPS employment measure (it counts number of payroll jobs), it is the best source of employment statistics with reliable industry information. Further, it is because our analysis relies on gender-industry information when running counterfactuals, that we use CES statistics throughout our analysis. Moreover, in order to be consistent in the analysis, we restrict ourselves to the period 1964-2018; although fertility information is available for earlier years as we report in Figure 1, industry-gender information is not available for the years before 1964.

A.1.4 Employment Rate, Income and Hours

We use IPUMS-CPS ASEC supplement to document gender specific labor market outcomes, by restricting the sample to the model appropriate age-groups as well as analyzing the behavior of couples. We match 1990 census industry codes to NAICS categories by using the cross-walk provided by the Census Bureau. In the right panel of Figure 6, BLS equivalent main industry categories are identified using this procedure. Our sample is individuals aged 15-60 (unless otherwise specified) whose employment, hours, and income are well-defined. After we calculate annual averages, we adjust the income by its lead to account for the fact that individuals report last year's income. We tried several different age selections (25-55, 20-64) and all the results are robust with respect to the sample selection and we used model consistent age selection (15-60).

A.2 Supplementary Figures

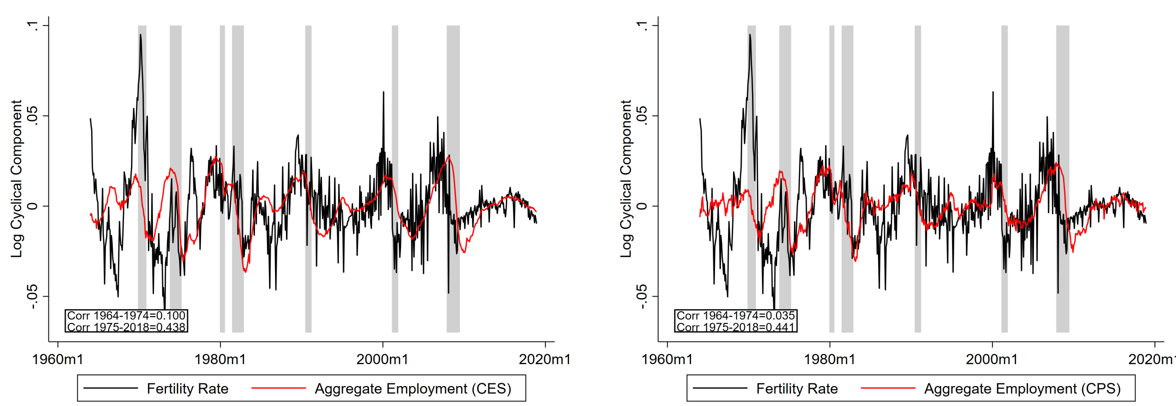


Figure 16: Fertility and Recessions (Employment as Aggregate Outcome)
Note: Figure 1 is replicated using monthly statistics and aggregate employment instead of GDP. The fertility figure used is the seasonally adjusted monthly fertility rate (number of total births/population of women aged 15-44) with 9 months of lag to account for the time of conception. We use HP-filtering with smoothing parameter $\lambda = 129600$ for the period 1964-2018 and report the cyclical components. The left panel uses BLS Current Employment Statistics as a measure of aggregate economic activity and the right panel uses monthly employment from CPS which is extracted from FRED website.

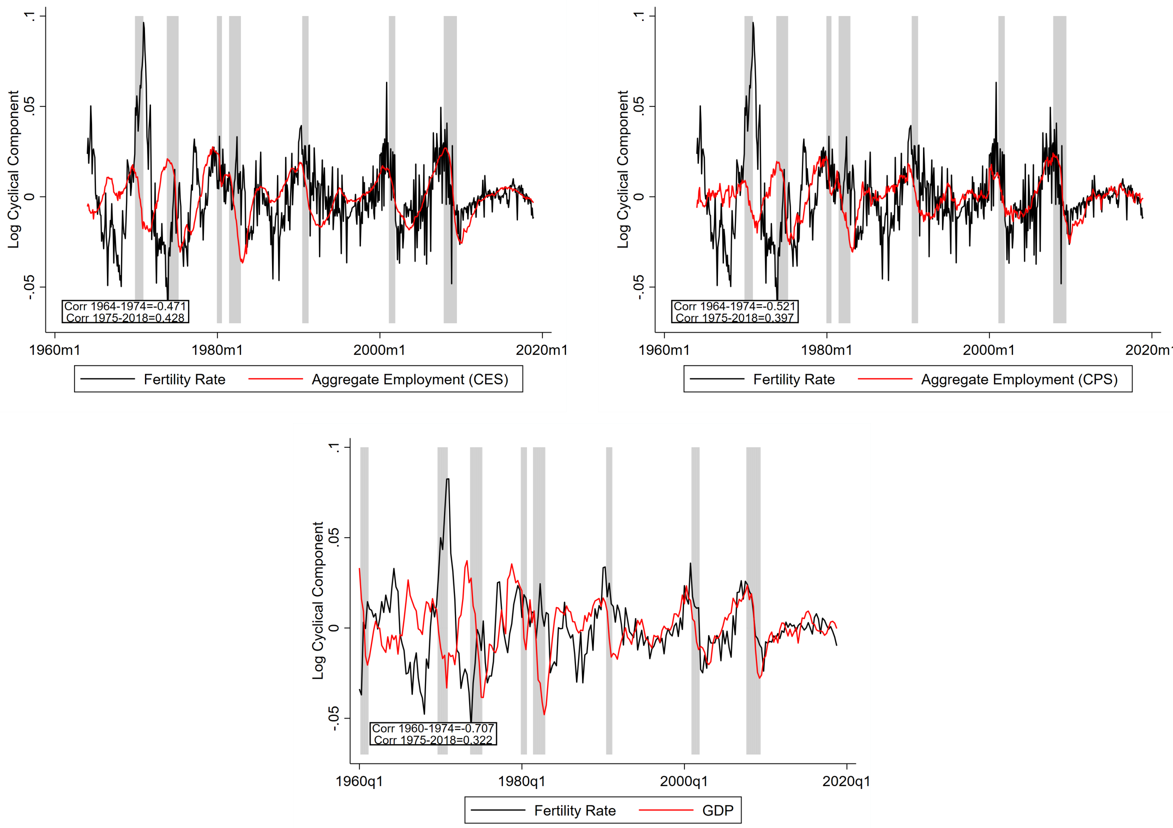


Figure 17: Fertility and Recessions (Contemporaneous Measure)

Note: Figure 1 and Figure 16 are replicated using the period fertility rate as the main measure (without using 3 quarters of lag to account for the time of the conception).

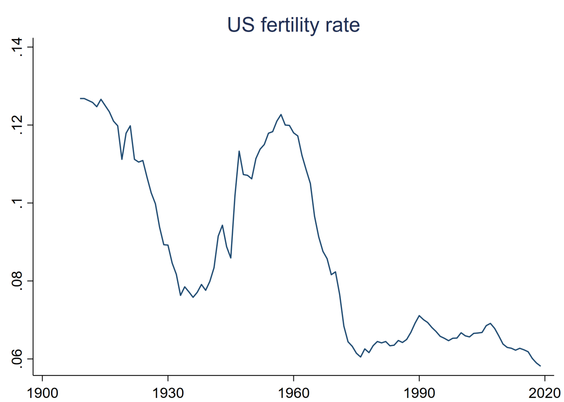


Figure 18: Fertility rate in the last century (1909-2019)

Note: Data source is Center of Disease Control, Vital Statistics of the United States, Volume-Natality. Fertility rate corresponds to total births/ female population aged 15-44.

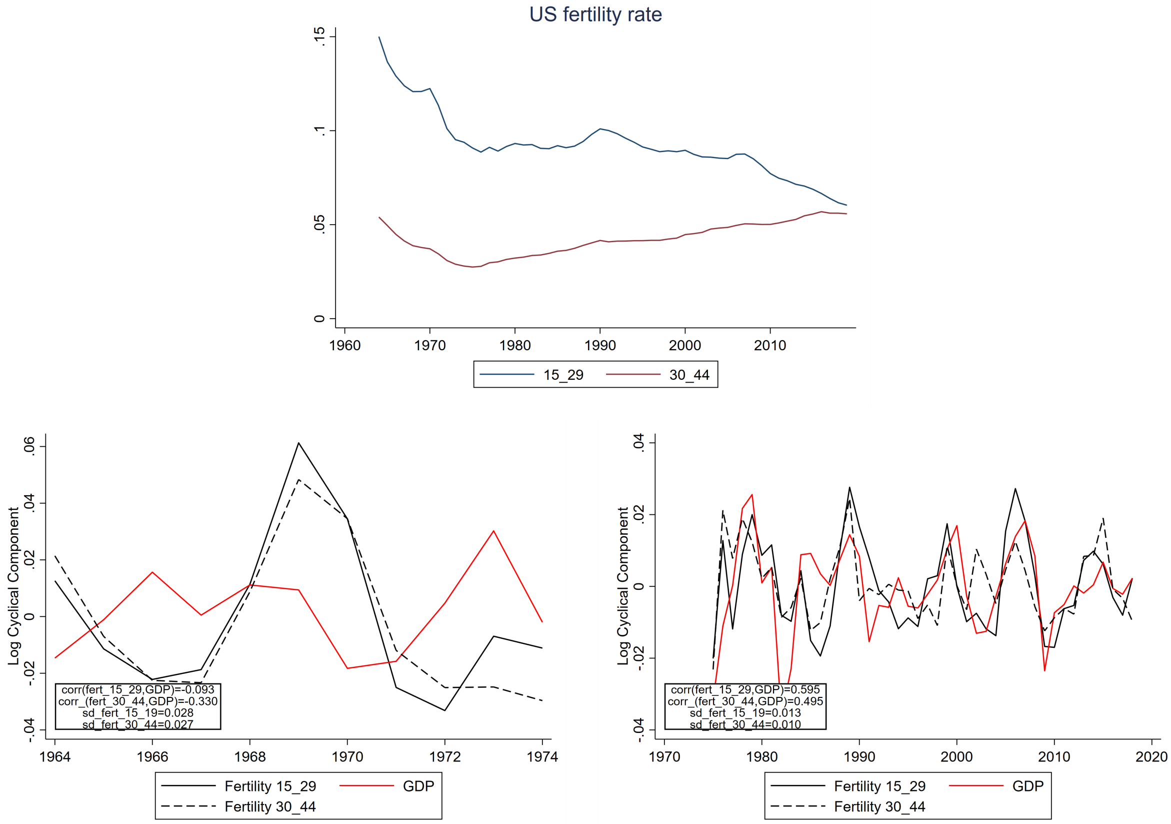


Figure 19: Fertility Rate and Cyclical Component by Age
Note: Fertility rate for the specific age groups are HP-filtered separately for the years 1964-2018 and standard deviations of cyclical components as well as the correlation with GDP deviations are calculated for the mentioned time periods. These measures are used as targeted and untargeted moments in Table 1.

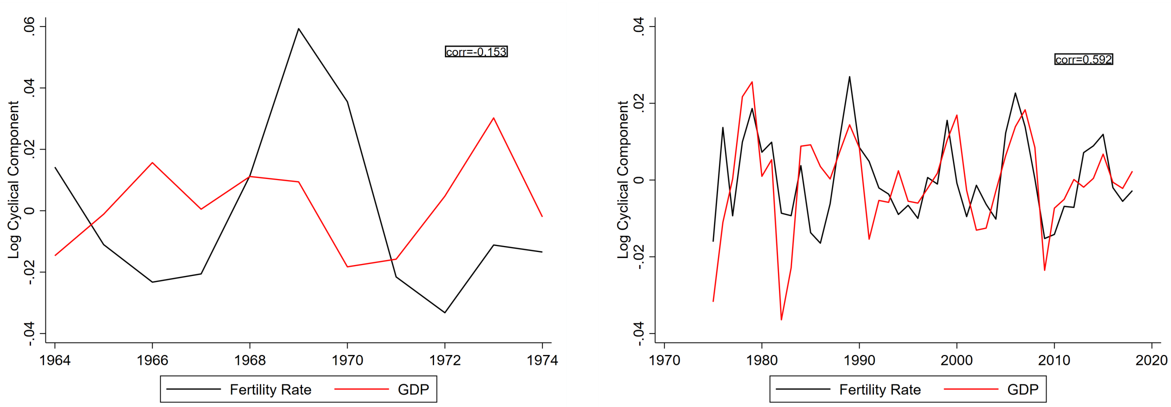
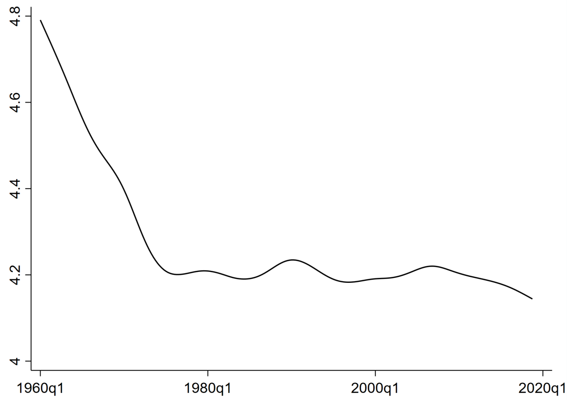
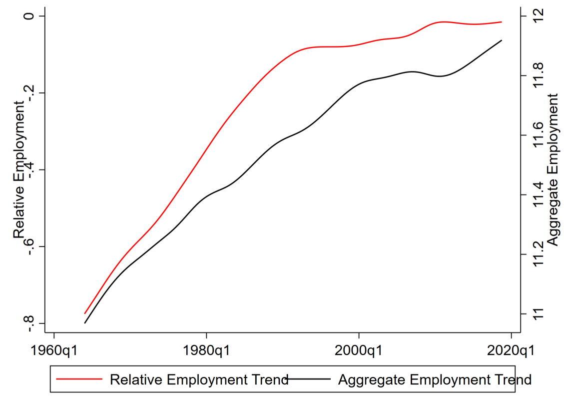


Figure 20: Cyclical Component of Annual Fertility Rate for Model Computation
Note: Fertility rate is HP-filtered for the years 1964-2018 and standard deviations of cyclical components as well as the correlation with GDP deviations are calculated for the mentioned time periods. These measures are used as targeted and untargeted moments in Table 1.

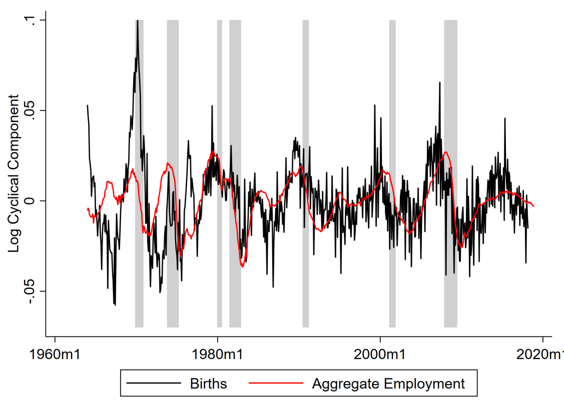


A. Fertility Rate

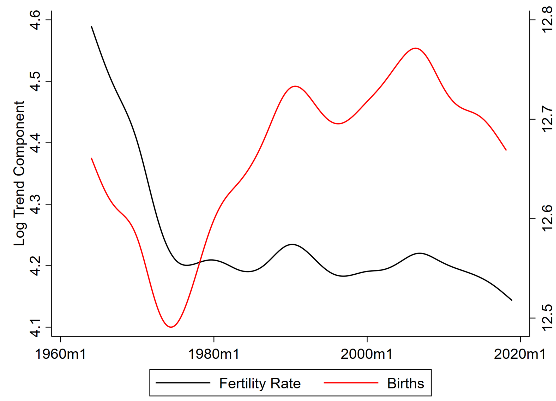


B. Employment

Figure 21: Trend Component of Fertility, Employment and Relative Employment
Note: The trend components of the series in Figure 1.



A. Cyclical Component



B. Trend Component

Figure 22: Births and Employment
Note: The left panel shows cyclical component of aggregate births calculated from micro-data birth records and seasonally adjusted. Aggregate employment is obtained through CES statistics. The right panel shows the trend component of births in the left panel and fertility rate in Figure 1.

Industry (i)	$\rho(i,GDP)$	$\rho(i,L)$	L_{fi}/L_i	L_{fi}/L_f	L_{mi}/L_m	Total Volatility	Cyclical Volatility
Government	0.17	0.36	0.54	0.19	0.14	0.73	0.12
Education and health	0.26	0.44	0.77	0.19	0.05	0.56	0.15
Other services	0.46	0.74	0.49	0.04	0.04	0.91	0.42
Information	0.52	0.76	0.46	0.02	0.02	2.04	1.06
Financial activities	0.55	0.74	0.59	0.07	0.05	1.17	0.64
Professional services	0.72	0.90	0.44	0.11	0.12	1.83	1.32
Hospitality and leisure	0.77	0.92	0.50	0.10	0.08	1.18	0.91
Trade transportation utilities	0.79	0.98	0.40	0.17	0.22	1.39	1.10
Construction	0.79	0.96	0.12	0.01	0.08	3.92	3.09
Manufacturing	0.83	0.94	0.30	0.10	0.18	2.26	1.87

Table 7: Industry Cyclicality and Gender Composition

Note: Monthly employment data (1975-2018) are taken from Bureau of Labor Statistics Current Employment Statistics and quarterly averages are calculated. The cyclical component of industry-level employment is calculated using an HP filter with smoothing parameter $\lambda = 1600$. The first column represents the correlation of the cyclical component of each industry with GDP and the second column with aggregate changes in employment. The third column represents female share of employment within each industry. The fourth and fifth columns represent women's and men's share of total employment in the corresponding industry. The sixth column represents the standard deviation of the cyclical component and the seventh column represents standard deviation of the predicted value of a regression of the HP-residual of industry employment on the HP-residual of GDP.

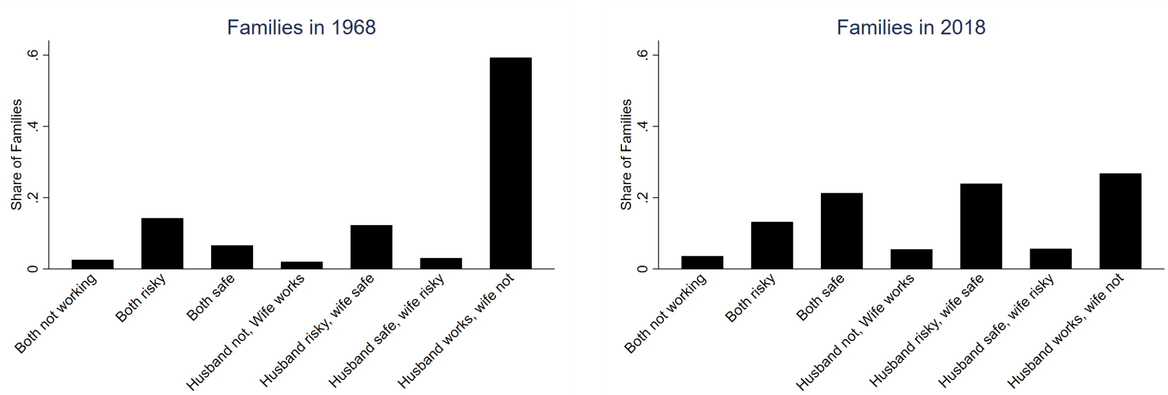
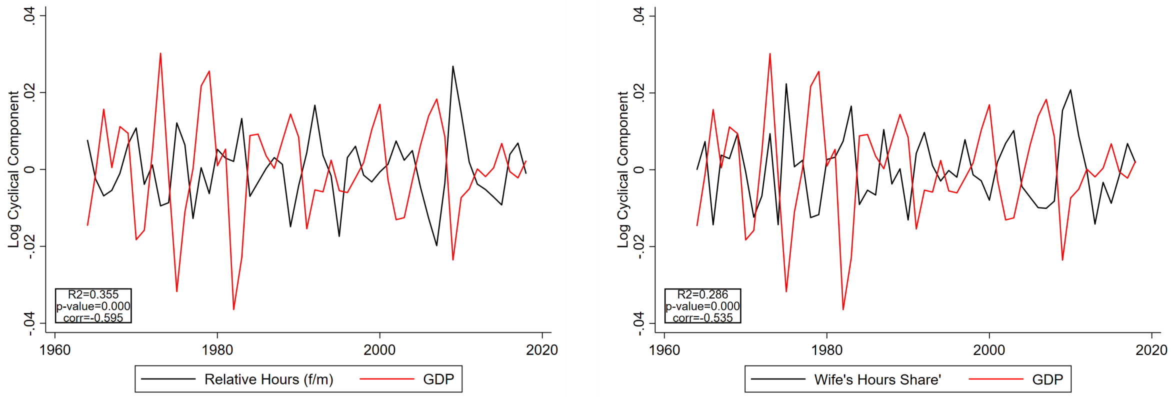


Figure 23: Family types

Note: 2018 IPUMS-CPS ASEC supplement, matched couples where the wife is between 15-45. Risky industries are construction, manufacturing, trade, transportation and utilities, and professional services which are the ones with highest cyclical volatility. Safe industries are financial activities, hospitality and leisure, information, education, health, government, other services. The definitions of safe vs risky industries are based on Figure 6 where the correlation with GDP exceeds 90%.



A. Aggregate B. Couples

Figure 24: Countercyclical gender hour gap

Note: IPUMS-CPS ASEC supplement is used. Relative hours and wife's hours share within family from Figure 4 and annual GDP from FRED is used to HP filter with smoothing parameter $\lambda = 6.25$ for the years 1964-2018. We report cyclical component of HP filtered series.

A.3 Model Tables

Parameter	Description	Value	Source
β	Discount rate	0.74	interest rate 2% per annum
α	Capital share	0.35	
δ	Depreciation	0.79	10% annual depreciation rate
γ	Risk aversion	2	
η	Curvature of quality function	0.63	De La Croix and Doepke (2003)
σ	Elasticity of substitution (men vs women)	0.44	Ngai and Petrongolo (2017)
τ_1	Time cost of children	0.15	Kleven et al. (2019a,b)
τ_2	Child penalty	0.15	Kleven et al. (2019a,b)
Calibrated Parameters			
σ_n	Utility of children elasticity	1.81	
ξ	Utility of children weight	1.48	
λ	Childlessness utility	0.29	
θ	Minimum quality	0.15	
$\bar{w}$	Cost of quality expenditure	0.14	
$\mu_{f,1975-2018}$	Mean female productivity	0.65	
$\mu_{f,1964-1974}$	Mean female productivity	0.3	

Table 8: Parameters

A.4 Model Estimation

A.5 Estimating Shock Processes

We use annual data on female and male employment from BLS Current Employment Statistics. We first apply an HP filter to the data with $\lambda = 6.25$ to obtain the cyclical component. Then, we run the regressions below to the obtained cyclical components.

$$\log(v_t^m) = \delta_m \log(v_{t-1}^m) + e_t^m \tag{12}$$

$$\log(v_t^f) = \delta_f \log(v_{t-1}^f) + e_t^f \tag{13}$$

We find that $\hat{\delta}_m = 0.5$, $\hat{\delta}_f = 0.5$, $\sigma(\hat{e}_m) = 0.012$, $\sigma(\hat{e}_f) = 0.008$. Following the methodology by Jones and Schoonbroodt (2016), we then simulate a long series of data and construct our productivity measure.

$$\log(z_t^m) = \sum_{j=0}^{14} \log(v_{t+j}^m)$$

$$\log(z_t^f) = \sum_{j=0}^{14} \log(v_{t+j}^f)$$

We then estimate

$$\log(z_t^m) = \mu_m(1-\rho_m) + \rho_m \log(z_{t-1}^m) + \varepsilon_t^m$$
$$\log(z_t^f) = \mu_f(1-\rho_f) + \rho_f \log(z_{t-1}^f) + \varepsilon_t^f$$

and find $\hat{\rho}_m = \hat{\rho}_f = 0.04$, $\sigma(\hat{\varepsilon}_m) = 0.09$, $\sigma(\hat{\varepsilon}_f) = 0.066$ for the benchmark 1975-2018. Table 9 shows the estimated data and simulated model counterparts for benchmark as well as counterfactual economies.

	Data (Annual)		Model	
	σ_m	σ_f	σ_m	σ_f
Benchmark (1975-2018)	1.2%	0.8%	9%	6.6%
60s (1964-1974)	0.9%	1%	6.7%	8.7%
Women Nurse	2.1%	0.5%	16%	3.9%
Men Nurse	0.5%	2.1%	3.9%	16%

Table 9: Gender-Industry Employment Volatilities

Note: BLS Current Employment Statistics are used to calculate the employment volatility. Annual employment data between 1964-2018 are HP-filtered with smoothing parameter $\lambda = 6.25$ for men and women. Standard deviations of error terms from Equations 12 and 13 for the corresponding years are reported in the first two columns. In women nurse economy, women's employment volatility corresponds to the employment volatility of education, health services, and government where men's employment volatility corresponds to the employment volatility of construction and manufacturing industries. Men nurse economy is the opposite of women's economy where the standard deviations are switched between genders. For the parameters used in the model, we employ the methodology in Jones and Schoonbroodt (2016) to find 15-year process estimated.

Generation Quality

Define $N_t^y(y)$ as the number of young families born to young parents at $t-1$. Similarly, $N_t^y(m)$ is defined as the number of young families born to middle parents at $t-1$.

Define q_t as the average human capital of young agents at time t;

$$N_t^y(y)q_{t-1}^y + N_t^y(m)q_{t-1}^m = N_t^y q_t$$

$$N_{t-1}^y(n_{t-1}^y/2)q_{t-1}^y + N_{t-1}^m(n_{t-1}^m/2)q_{t-1}^m = N_t^y q_t$$

$$N_t^m(n_{t-1}^y/2)q_{t-1}^y + N_t^o(n_{t-1}^m/2)q_{t-1}^m = N_t^y q_t$$

$$N_t^m/N_t^y(n_{t-1}^y/2)q_{t-1}^y + N_t^o/N_t^y(n_{t-1}^m/2)q_{t-1}^m = q_t$$

$$\frac{(n_{t-1}^y/2)q_{t-1}^y}{1+n_t} + \frac{(n_{t-1}^m/2)q_{t-1}^m}{(1+n_t)(1+n_{t-1})} = q_t$$