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

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The Emergence of Procyclical Fertility:  
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Abstract  
Fertility in the US exhibits a procyclical pattern since 80s. We argue that gender differences in employment risk leads to procyclical fertility; men mostly work in volatile and procyclical industries whereas women are likely to work in relatively stable and countercyclical industries. Our quantitative framework features a general equilibrium OLG model with endogeneous fertility and human capital choice and it shows that current gender industry composition in the US data accounts for all of this procyclicaliy. Moreover, we argue that gender income ratio (female to male) is higher in bad times which tilts the quality-quantity trade-off towards quality.  

Key words: fertility, industry cyclicality, industry gender segregation, gender income gap, quality-quantity trade-off  
JEL Codes: E24, E32, J11, J13, J16, J21, J24  

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1 Introduction

Men and women tend to work in different types of industries, i.e. men are predominantly employed in procyclical industries whereas women are mostly employed in countercyclical industries. In this paper, we argue that gender asymmetric industry employment contributes to the procyclical feature of fertility. In a recession, a typical man loses his job, whereas a typical woman becomes the breadwinner; hence income effect through men’s employment and substitution effect through women’s employment decreases fertility in bad times. We argue that in a world where men become nurses and women become construction workers, we would observe “countercyclical fertility” at the expense of lower human capital accumulation.

![Figure 1: Fertility and Recessions](image)

Figure 1: Fertility and Recessions

Note: Shaded areas indicate recessions. Recession dates are taken from NBER business cycles (from peak to through). Data source is National Health Statistics birth records and Bureau of Labor Statistics. Seasonally adjusted monthly fertility rate (number of births to women aged 15-44/population of women aged 15-44) has been used. To obtain cyclical component, HP filter with smoothing parameter $\lambda = 129600$ has been used. Seasonally adjusted total monthly employment series from BLS has been used with the same HP filter to obtain cyclical component of the aggregate employment.

From a theoretical point of view, it is not obvious that fertility should be procyclical. It is more straightforward to think about income effect when considering the behavior of fertility around business cycles; in a recession, families observe their income falling and they cannot afford more children. However, as seen in Butz and Ward [1979], fertility could also be countercyclical due to the existence of substitution effect which became strong during 60s
where female participation rate increased very rapidly; in a recession, time cost of children falls and families have more children. In Figure 1, fertility moves countercyclically during 60s as pointed out by Butz and Ward [1979] (correlation between two cycles is -0.47 for the period 1964-1974)\(^1\). However in all the recession periods since 1975, we find that the fertility rate moves positively with the employment rate (correlation between two cycles is 0.43 for the period 1975-2018). With female participation exceeding 50% after 80s, the importance of female income in the family increased. Hence, in order to understand fertility dynamics, male and female income patterns need to be explored separately which is the contribution of this paper.

We document that around 70% of men work in highly procyclical industries such as construction, manufacturing, professional services and retail, where 40% of women work in countercyclical (education and health services and government) \(^2\). As a result, we show that women employment is much less volatile than men’s employment around business cycles (Hoynes et al. [2012]). In times of economic downturns, since males are employed in heavily procyclical industries, they lose their jobs which decreases household income and it has a negative impact on fertility because families cannot afford more children. On the other hand, female employment is either not affected or affected positively due to countercyclical properties of female dominant industries, better economic prospects of women also have a negative impact on fertility, because breadwinner women cannot afford to take time off and have children. Hence, procyclical feature of fertility is amplified due to 1-) differential impact of men and women income, 2-) different cyclicalities of industries and 3-) gender asymmetry in industries. In other words, in a world where men become nurses and women become construction workers, fertility would be countercyclical.

We document facts about characteristics of the labor market from a gender perspective. In addition to documenting national gender-industry cyclicalities, we also provide evidences at the state level. In our state level analysis, we show that in majority of states, men and women employment cycles are negatively correlated. The negative correlation is driven by the gender segregation in industries and lead to smaller business cycle size. Finally, in states where the gender segregation in industries is higher, men-women employment correlation is lower. Furthermore, in most of the states, women and men employment are negatively correlated which makes state level aggregate employment volatility lower. According to Albanesi [2019], in previous recessions women’s increased employment made recoveries much faster. She argues that jobless recoveries started at the time when female labor force participation rate reached to a plateau.

\(^1\)The decline in fertility rate starts before the reported start date of recession, which might imply that people experience job losses and update their expectations Buckles et al. [2018]

\(^2\)We take industries where the correlation between industry level employment and aggregate employment is above 90%. See Table 1
We argue that asymmetric industry employment makes fertility procyclical and lower. In order to explore fertility dynamics under different gender employment and cyclicality scenarios, we build a general equilibrium overlapping generations model, where families make fertility decisions as well as investment in their children’s human capital. Our model captures several distinct features of fertility decision by linking them in a unified framework. Quality-quantity trade-off, differential impact of male and female income, child penalties and interaction of these with the business cycles are the key mechanisms in our framework. To our best knowledge, we are the first to explore interaction of all these channels. In the model, parents care about their children’s well-being (Becker and Barro [1988], Becker et al. [1990]), through their human capital (De la Croix and Doepke [2003]). We contribute to the literature by treating male and female income separately and by introducing “child penalties” for the female. In the model, male and female income follow different income processes which are calibrated from the data. The model features quality-quantity trade-off à la Becker. For women with high income, opportunity cost of having children is higher due to child penalties, these women prefer having less children but invest more in their human capital. We introduce both short term and long term child penalties to be consistent with the findings of Kleven et al. [2019a,b]. Short term child penalties reflect the fact that women have to take time off when they have kids. Long term penalties on the other hand reflect the permanency of these penalties due to career breaks, depreciation of human capital, lower returns to experience etc...; i.e. mothers suffer from permanent income losses.

The model is calibrated to match levels (by age) and volatility of fertility in the US. Observed male and female employment volatility and cyclicality is fed into the model and we find that male and female employment cyclicalities alone can explain procyclical fertility. Current employment structure in the US contributes not only to procyclical fertility but also changes the level of fertility. As a result of the observed different cyclical behavior of male vs female employment, female income relative to male is higher in bad times and lower in good times. Due to long term child penalties faced by women, this creates a dynamic trade-off where families decrease fertility because they are afraid it will badly affect women’s future income, which will be valuable if there is a recession in the future. Instead families spend more on their children’s human capital, which tilts families toward quality in quality-quantity trade-off. In other words, in the absence of long term penalties, fertility might be procyclical or countercyclical depending on how male vs. female income changes around the business cycles. However, long term penalties affect families’ choice ex-ante; higher female income when families most need it makes them to respond by decreasing the level of fertility.

We show that if men work in countercyclical and women work in procyclical industries (men become nurses, women become construction workers), fertility is higher and countercyclical. However, quality investment on children would be lower and more volatile. In particular,
when we compare an economy where women work in countercyclical industries and men work in procyclical industries ("women nurses economy"), to an economy where men work in countercyclical and women work in procyclical industries ("men nurses economy"), we find that fertility is 0.17% lower and human capital is 0.24% higher in "women nurses economy". In other words, we argue that in a world where men become nurses and women become construction workers, we would observe "countercyclical fertility" at the expense of lower human capital accumulation.

In the past century, the US fertility rate experienced large boom and bust periods (Figure 11). Great depression (30s), post-war baby boom (40s, 50s) (Jones and Schoonbroodt [2016], Doepke et al. [2015]), women influx into the labor market (60s), technological progress in household sector (Greenwood et al. [2000]) and the pill revolution (70s) (Goldin and Katz [2000]) are major events which caused the total fertility rate to fluctuate between 2 and 3.6 children per women. Fertility reached a more stable level 1975 onwards, where there are still fluctuations (between 1.74 and 2.12 children per women). This paper studies cyclical properties of fertility during the period of "stable fertility", 1975-2017.

There are several studies (Macunovich [1995, 1996];Schaller [2016];Ahn and Mira [2002];Sobotka et al. [2011];Jones and Schoonbroodt [2016]; Buckles et al. [2018]) studying cyclicality of fertility and conclude that fertility is procyclical. We provide a novel explanation for procyclical feature of fertility; gender differences in employment risk. We link several pillars in the fertility literature and introduce an additional mechanism; 1- macroeconomic properties of female vs. male income 2- differential effect of female vs. male income on fertility, 3- interaction of cyclicality with quality-quantity trade-off. We barrow from the existing literature to complement our argument by using child penalties (Kleven et al. [2019a]) and differential impact of male vs. female income shocks on fertility (Heckman and Walker [1990];Lindo [2010]; Amialchuk [2013];Schaller [2016]).

Despite the changing trends on time use such as more balanced division of labor in child rearing, it is still the women who mostly bear the time cost of a child. Kleven et al. [2019a] find that women with children on average earn 20% less than women without children\(^3\). Hence the opportunity cost of having a child is foregone earnings of females. Heckman and Walker [1990] identify the effect of an increase in female’s wage on fertility by analyzing Swedish panel data and find that higher female wage leads to delaying childbirth and lower fertility as a result.

Women who give birth early in their careers, suffer from child penalties which leads fertility postponement for high wage women, whereas low wage women give birth earlier (Caucutt et al. [2002]). In order to identify the effect of male income on fertility, unexpected job displacement

\(^3\)This is the combined effect of mothers who work less, who stop working, who face discrimination, or who change occupations. Gallen [2018] argues that the part of the pay gap can be explained by the fact that mothers are less productive.
has been used as an exogeneous shock. Both Lindo [2010] and Amialchuk [2013] find that an unexpected shock to male income (job displacement) decreases fertility. Schaller [2016] attempts to find both effects by using exogenous labor demand shocks and gender employment indices in industries. Consistent with the literature, she finds positive effect for male wage and negative effect of female wage. Dettling and Kearney [2014] also shows that house prices (hence business cycles) have a positive impact on fertility. Similarly, Schmitt [2011] and Özcan et al. [2010] find that male unemployment affects fertility negatively whereas female unemployment affects positively. Following the papers which study the occupation riskiness by looking at the wage and unemployment volatility (Saks and Shore [2005]), Sommer [2016] studies the effect of unexpected earnings risk on fertility and finds that higher earnings risk is associated with delay in fertility and lower fertility. A comprehensive study by Adda et al. [2017] endogenize all life time choices and argue that career choices are made along with fertility choices, hence there is sorting in occupations according to fertility choices during life time.

To our best knowledge, we are the first to highlight a link between male vs. female industry cyclicality and fertility dynamics which have implications on population growth and human capital accumulation. Current labor market structure where women and men sort into different types of industries create an insurance mechanism which help smooth income fluctuations, makes fertility procyclical and tilts quality-quantity trade-off towards quality.

2 Data

In the empirical section, we have two goals to achieve. First, we would like to see how gender asymmetric industry employment changes the relationship between male and female income around the business cycles. Second, we would like to estimate our moments to be used in the model. We use national level targets in the calibration. But we show state level evidences to understand how industry segregation affects employment patterns for male and female as motivating facts. Due to the availability of state-industry level data from 1990 onward, we focus on 1990-2018 to be consistent throughout the paper. However, cyclical and gender properties of industries do not change during the period of 1975-2018.

We make use of publicly available data on fertility rates, and employment numbers. Fertility data; births to women at age 15-44 is taken from National Health Statistics micro-data and merged with female population data from Survey of Epidemiology and End Results (SEER) to calculate fertility rates for different age groups. Monthly fertility rates are also obtained from National Health Statistics database and digitized from monthly vital statistics reports. We take industry employment numbers at state level as well as monthly female and male employment at industry level from Bureau of Labor Statistics database. Monthly data has
been used to calculate the correlation between total employment changes and industry level employment changes. Finally, IPUMS-CPS has been used to estimate fraction of female workforce at state level and gender income ratio at national level.

3 Facts

3.1 Industry Employment is Gender Asymmetric

We document that different industries have different cyclical properties and gender employment composition. We document cyclical properties in two ways. First we document volatility of employment by documenting standard deviation of cyclical component of industry employment. Second, we document the correlation between industry level employment cyclical and total employment cyclicality to assess the degree of procyclicality. Table 1 shows that the correlation between industry employment changes to the total employment changes ranges from -0.24 to 0.98. Countercyclical industries are education, health services and government at which an important fraction (40%) of women are working. On the other hand, the most procyclical industries are trade, transportation, utilities, professional services, construction, manufacturing and leisure at which 68% of men are working. Moreover, not only male dominant industries are more pro-cyclical but also their employment volatility is very high.

<table>
<thead>
<tr>
<th>Industry</th>
<th>Std. Dev</th>
<th>Corr</th>
<th>Women Share</th>
<th>Men Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Education and Health Services</td>
<td>0.004</td>
<td>-0.24</td>
<td>21%</td>
<td>6%</td>
</tr>
<tr>
<td>Government</td>
<td>0.006</td>
<td>-0.07</td>
<td>19%</td>
<td>14%</td>
</tr>
<tr>
<td>Mining, Logging</td>
<td>0.05</td>
<td>0.48</td>
<td>0%</td>
<td>1%</td>
</tr>
<tr>
<td>Other Services</td>
<td>0.007</td>
<td>0.65</td>
<td>4%</td>
<td>4%</td>
</tr>
<tr>
<td>Information</td>
<td>0.02</td>
<td>0.73</td>
<td>2%</td>
<td>2%</td>
</tr>
<tr>
<td>Financial Activities</td>
<td>0.011</td>
<td>0.75</td>
<td>7%</td>
<td>5%</td>
</tr>
<tr>
<td>Leisure</td>
<td>0.011</td>
<td>0.92</td>
<td>10%</td>
<td>9%</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>0.022</td>
<td>0.95</td>
<td>7%</td>
<td>16%</td>
</tr>
<tr>
<td>Construction</td>
<td>0.038</td>
<td>0.96</td>
<td>1%</td>
<td>8%</td>
</tr>
<tr>
<td>Professional Services</td>
<td>0.02</td>
<td>0.96</td>
<td>12%</td>
<td>13%</td>
</tr>
<tr>
<td>Trade, Transportation, Utilities</td>
<td>0.014</td>
<td>0.98</td>
<td>16%</td>
<td>22%</td>
</tr>
<tr>
<td>Total</td>
<td>0.011</td>
<td>1</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 1: Correlation of Industry Employment Changes and Total Employment Changes

Note: Monthly employment data (1990-2018) is taken from Bureau of Labor Statistics. The cyclical component of industry level employment has been calculated by using HP filter with smoothing parameter $\lambda = 129600$. The first column represents the standard deviation of cyclical component, the second column represents the correlation of cyclical component of each industry with the aggregate employment changes. Third and fourth column represents the share of total women and men employment working in corresponding industry.

Charles et al. [2018] find that college attendance decreased during boom times and increased in recession times. This finding can be also thought as a reason why education, health services are acyclical, and even countercyclical sometimes.
3.2 Men employment is more procyclical/volatile

Men and women work in separate industries, as a result, men employment is much more volatile than female employment. In Figure 2, we plot total male and female employment cycles as well as two example male and female dominant industries.

![Figure 2: Male vs. Female Dominant Industries](image)

Note: Bureau of Labor Statistics. Shaded areas indicate NBER recessions.

3.3 Men and women employment cycles are negatively correlated at state level

Even though in Figure 2, aggregate women and men cycles are positively correlated, there is a lot of heterogeneity across states. When we look at the states separately, we find that in most of the states male and female employment cycles are negatively correlated.

3.4 The more negative the correlation, smaller the size of aggregate cycle

Figure 4 shows that in states where men and women employment are more negatively correlated, the aggregate employment does not exhibit large changes. This is due to the fact that the negative correlation between cycles smooths the overall movement in employment.
Figure 3: Correlation between men-women employment cycles by state
Note: Bureau of Labor Statistics state level annual employment numbers and estimated gender fraction of the labor force at state level from CPS have been used to document state level women-men employment in numbers. HP filter with smoothing parameter $\lambda = 6.25$ is used to get cyclical components and state level correlation between men and women employment cycles are calculated for years 1990-2018.

Figure 4: Employment cycle size
Note: Bureau of Labor Statistics

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3.5 The more gender asymmetric industry employment is, the more negative the correlation is

In Figure 5, we observe that in states where a larger fraction of men are working in manufacturing-construction and women are working education, health and government, men and women employment is more negatively correlated. Hence, the fact that men and women are working in industries with negatively correlated cycles provide a better insurance as it lowers the aggregate volatility of employment in that state.

![Figure 5: Industry segregation](image)

Note: Industry segregation is defined as the fraction of women who are working in education, health and government services and men working in construction and manufacturing to the total employment

4 Model

Our model captures several distinct features of fertility decision by linking them in a unified framework. Quality-quantity trade-off, differential impact of male and female income, child penalties and interaction of these with the business cycles are the key mechanisms in our framework. To our best knowledge, we are the first to explore interaction of all these channels.

We build an overlapping generations model where families make fertility choice as well as investment in their children’s human capital, motivated by the quality-quantity trade off (De la Croix and Doepke [2003]). Investment in human capital leads to higher productivity
once the children enter the labor market. In the model, women are the main care givers of children. Hence, they face short-term 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 decision as well as consumption and saving choices. Old households continue working but cannot have children. When retired, households consume the returns to their accumulated assets. Consumption good in the model is produced using inputs from men and women dominant industries. Each industry productivity follows an exogenous process, which we estimate from the data. We run several counterfactual experiments to see how different gender income risk affect fertility and human capital.

4.1 Household Problem

Young and middle generations are able to make fertility decisions as well as labor supply and consumption decisions. Old households do not have fertility decision but they still supply labor and earn wages and save for the 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. However, female members are the caregiver of the children in the model, so they supply child penalty adjusted labor (due to time cost of children).

Young HHs

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

$$V_{t}^{y} = \max_{c_{t}, a_{t}, n_{t}, q_{t}} U^{y} (c_{t}^{y}, q_{t}^{y}, n_{t}^{y}) + \beta E V_{t+1}^{m} (a_{t}^{y}, q_{t}^{y}, n_{t}^{y})$$

$$c_{t}^{y} + a_{t}^{y} + \bar{w} e_{t}^{y} n_{t}^{y} = w_{t}^{m,y} + w_{t}^{f,y} (1 - \tau n_{t}^{y})$$

where $c_{t}^{y}$ is the joint consumption of the family, $a_{t}^{y}$ is the assets they accumulate, $n_{t}^{y}$ 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 children, where $\bar{w}$ is the relative price of human capital investment,

$$q_{t}^{y} = (\theta + e_{t}^{y})^{n}$$
Males and females earn $w^m_t$ and $w^f_t$ respectively. Males spend one unit of labor whereas women need to spend time rearing their children ($\tau n^y_t$).

**Middle HHs**

Similar to young families, middle families make fertility-quality decision. They have access to the returns on their assets accumulated when they were young. Male members supply 1 unit of labor ($l^{m,m}_t = 1$), whereas female members need to spend time caring for children ($l^{f,m}_t = (1 - \tau n^m_t) f(n^y_{t-1}, 0)$). In addition to 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.

\[
V^m_t(a^y_{t-1}, q^y_{t-1}, n^y_{t-1}) = \max_{c^m_t, a^m_t, n^m_t, c^m_t, a^m_t} U^m(c^m_t, q^y_{t-1}, n^y_{t-1}, q^m_t, n^m_t) + \beta EV^o_{t+1}(a^m_t, q^y_{t-1}, n^y_{t-1}, q^m_t, n^m_t) \\
\quad c^m_t + a^m_t + \bar{w} c^m_t n^m_t = w^m_t + w^f_t f(n^y_{t-1}, 0) (1 - \tau n^m_t) + a^m_{t-1} R_t
\]

**Old HHs**

Old people continue working and only make consumption-saving decision but continue to derive utility from their children. Similarly, male members supply 1 unit of labor ($l^{m,o}_t = 1$), whereas female members still incur long term child penalties ($l^{f,m}_t = f(n^y_{t-1}, n^m_{t-1})$).

\[
V^o_t(a^m_{t-1}, q^y_{t-2}, n^y_{t-2}, q^m_{t-1}, n^m_{t-1}) = \max_{c^o_t, a^o_t} U^o(c^o_t, q^y_{t-2}, n^y_{t-2}, q^m_{t-1}, n^m_{t-1}) + \beta EV^o_{t+1}(a^o_t, q^y_{t-2}, n^y_{t-2}, q^m_{t-1}, n^m_{t-1}) \\
\quad c^o_t + a^o_t = w^m_{t-1} + w^f_{t-1} f(n^y_{t-2}, n^m_{t-1}) + a^m_{t-1} R_t
\]

**Retired HHs**

Retired people consume the returns of their accumulated assets.

\[
V^r_t = \max_{c^r_t} U^r(c^r_t) \\
\quad c^r_t = a^o_{t-1} R_t
\]
4.2 Firm Problem

Consumption good is produced using capital and labor,

\[ Y_t = K_t^\alpha L_t^{1-\alpha} \]

Labor is composed of male and female labors

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

where \( z_t^m \) and \( z_t^f \) are productivities of male and female dominated industries respectively. For simplicity we assume complete segregation of genders; all males work in \( m \) industry and all females work in \( f \) industry.\(^5\)

4.3 Demographics

Population Growth

We define the number of families at 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 equal number of men-women so that \( N_t^m n_{t-1}^y \) number of children form \( \frac{N_t^m n_{t-1}^y}{2} \) families. Define the population growth across generations

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

Fertility Rate

Define fertility rate as the total number children born to young and middle age families over the total number of families.

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

\(^5\) In our quantitative analysis, we are going to explore different levels of segregation when calibrating parameters.
Divide both numerator and denominator by $N_t^m$ and by using the definition of population growth $(1 + n_t) = \frac{N_t^y}{N_t}$, get

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

4.4 Equilibrium Conditions

Total Consumption

Total consumption is the sum of the consumption of all generations

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

In terms of per family consumption,

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

We scale the by the number of retired families $N_t^r$ to get per family $c_t$: $c_t = \frac{C_t}{N_t}$.

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

Capital accumulation

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

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

Similarly, in terms of per family

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

Labor Force

We assume that effective labor force is determined by human capital expenditure that has been 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 the generation human capital \(^6\),

\[ q_t = \frac{q_{t-1} n_{t-1}^y}{(1 + n_t)} + \frac{q_{t-1} n_{t-1}^m}{(1 + n_t)(1 + n_{t-1})} \]

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

\[ q_t L_t^{m,y}(1 + n_t)(1 + n_{t-1})(1 + n_{t-2}) + q_{t-1} L_t^{m,m}(1 + n_{t-1})(1 + n_{t-2}) + q_{t-2} L_t^{m,o}(1 + n_{t-2}) = L_t^m \]

\[ q_t L_t^{f,y}(1 + n_t)(1 + n_{t-1})(1 + n_{t-2}) + q_{t-1} L_t^{f,m}(1 + n_{t-1})(1 + n_{t-2}) + q_{t-2} L_t^{f,o}(1 + n_{t-2}) = L_t^f \]

**Factor Prices**

Competitive firms set marginal returns to respective factor prices.

\[ r_t = \alpha K_t^{\alpha - 1} L_t^{1-\alpha} \]

\( w_t^m \) and \( w_t^f \) are wages per effective unit of labor that male and female workers earn.

\[ w_t^m = z_t^m (1 - \alpha) K_t^\alpha L_t^{\sigma - \alpha} (L_t^m)^{-\sigma} \]

\[ w_t^f = z_t^f (1 - \alpha) K_t^\alpha L_t^{\sigma - \alpha} (L_t^f)^{-\sigma} \]

But each agent earns a wage rate which depends on the quality investment that has been made for their generation.

\[ w_t^{m,y} = w_t^m q_t , \quad w_t^{m,m} = w_t^m q_{t-1} , \quad w_t^{m,o} = w_t^m q_{t-2} \]

\[ w_t^{f,y} = w_t^f q_t , \quad w_t^{f,m} = w_t^f q_{t-1} , \quad w_t^{f,o} = w_t^f q_{t-2} \]

\(^6\)See Appendix for the details.
5 Calibration

We calibrate parameters to match US fertility rate for young (15-30) and middle age (30-45) women as well as the volatility of fertility estimated from the data between 1990-2018. We estimate male and female dominant industry productivities from the data using industry employment as proxy. Then, we feed in these productivities into the model, to see how well it is able to generate procyclical fertility.

Utility Function

Young families derive utility from consumption and the children that they make

\[ U^y(c^y_t, q^y_t, n^y_t) = \left( \frac{c^y_t}{1-\gamma} \right) + \xi \left( \frac{n^y_t q^y_t + \lambda}{1-\sigma_n} \right) \]

where \( \lambda \) is the childlessness utility. For middle and old families, the utility function takes the form,

\[ U^m(c^m_t, q^y_{t-1}, n^y_{t-1}, q^m_t, n^m_t) = \left( \frac{c^m_t}{1-\gamma} \right) + \xi \left( \frac{n^y_{t-1} q^y_{t-1} + n^m_t q^m_t}{1-\sigma_n} \right) \]

\[ U^o(c^o_t, q^y_{t-2}, n^y_{t-2}, q^m_{t-1}, n^m_{t-1}) = \left( \frac{c^o_t}{1-\gamma} \right) + \xi \left( \frac{n^y_{t-2} q^y_{t-2} + n^m_{t-1} q^m_{t-1}}{1-\sigma_n} \right) \]

For retired families,

\[ U^r(c^r_t) = \left( \frac{c^r_t}{1-\gamma} \right) \]

Parameters

The model is calibrated such that one period is 15 years. Discount rate is taken \( \beta = 0.74 \), which corresponds to 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 parameters of quality function, we use De la Croix and Doepke [2003]. We estimated utility weight of children and childlessness utility (\( \xi, \lambda \)) from the data to match observed fertility rates in the US. Similarly, we estimate the elasticity of children utility to match the standard deviation of total fertility rate. 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]. In Kleven et al. [2019a], they show that child penalty increases linearly with the number of children. In the long run, Danish mothers suffer from around 10% earning loss per child. In Kleven et al. [2019b], they show that US mothers, regardless of the number of children they have, suffer from around 30% earning loss. We extrapolate linear child penalty feature together with the average fertility rate being 2 children per woman for the US and assign \(\tau_1 = \tau_2 = 0.15\) in our calibration.

We set \(\bar{w}\) (relative price of human capital investment) equal to average wage rate in the steady state \(((w_m + w_f)q/2)\). We assume that industry productivities \((z^m_t, z^f_t)\) follow 15-year AR(1) processes. Errors terms are jointly normally distributed.

\[
\begin{align*}
\log(z^m_t) &= \rho_m \log(z^m_{t-1}) + \epsilon^m_t \\
\log(z^f_t) &= \rho_f \log(z^f_{t-1}) + \epsilon^f_t \\
\begin{bmatrix}
\epsilon^m_t \\
\epsilon^f_t
\end{bmatrix} &\sim N(0, \begin{bmatrix}
\sigma^2_m & \sigma_{mf} \\
\sigma_{mf} & \sigma^2_f
\end{bmatrix})
\end{align*}
\]

We use cyclical components of male and female employment as proxies for productivities. We then estimate \(\rho_m, \rho_f, \sigma_m, \sigma_f\) from the annual data. By following approach in Jones and Schoonbroodt [2016], we estimate 15 year frequency adjusted parameters to be used in the model.\(^7\)

\(^7\)See Appendix for the details.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>$n^y$</td>
<td>Number of children per women of age 15-29</td>
<td>0.7</td>
<td>National Health Statistics</td>
</tr>
<tr>
<td>$n^m$</td>
<td>Number of children per women of age 30-44</td>
<td>1.275</td>
<td>National Health Statistics</td>
</tr>
<tr>
<td>$\sigma(fertility rate)$</td>
<td>Annual standard deviation of fertility cycle</td>
<td>0.009</td>
<td>National Health Statistics</td>
</tr>
<tr>
<td>$\beta$</td>
<td>Discount Rate</td>
<td>0.74</td>
<td>interest rate 2% per annum</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>Capital Share</td>
<td>0.35</td>
<td></td>
</tr>
<tr>
<td>$\delta$</td>
<td>Depreciation</td>
<td>0.79</td>
<td>10% annual depreciation rate</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>Risk aversion</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>$\eta$</td>
<td>Curvature of quality function</td>
<td>0.63</td>
<td>De la Croix and Doepke [2003]</td>
</tr>
<tr>
<td>$\theta$</td>
<td>Minimum quality expenditure</td>
<td>0.01</td>
<td>De la Croix and Doepke [2003]</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>Elasticity of substitution (men vs women)</td>
<td>0.44</td>
<td>Ngai and Petrongolo [2017]</td>
</tr>
<tr>
<td>$\tau_1$</td>
<td>Time cost of children</td>
<td>0.15</td>
<td>Kleven et al. [2019a,b]</td>
</tr>
<tr>
<td>$\tau_2$</td>
<td>Child penalty</td>
<td>0.15</td>
<td>Kleven et al. [2019a,b]</td>
</tr>
<tr>
<td>$\sigma_m$</td>
<td>Standard deviation of male employment shock</td>
<td>0.08</td>
<td>BLS, Authors’ calculation</td>
</tr>
<tr>
<td>$\sigma_f$</td>
<td>Standard deviation of female employment shock</td>
<td>0.05</td>
<td>BLS, Authors’ calculation</td>
</tr>
<tr>
<td>$\sigma_{mf}$</td>
<td>Correlation between male and female employment shock</td>
<td>0.88</td>
<td>BLS, Authors’ calculation</td>
</tr>
<tr>
<td>$\sigma_n$</td>
<td>Utility of children elasticity</td>
<td>1.48</td>
<td>Standard deviation of fertility rate</td>
</tr>
<tr>
<td>$\xi$</td>
<td>Utility of children weight</td>
<td>1.58</td>
<td>Number of children per young, middle $(n^y, n^m)$</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Childlessness utility</td>
<td>0.61</td>
<td>Number of children per young, middle $(n^y, n^m)$</td>
</tr>
</tbody>
</table>

Table 2: Parameters
6 Results

We calibrate the model to match the level and the volatility of the fertility rate observed in the data\textsuperscript{8}. Then we assess, how well we are able to capture procyclicality of fertility. In our sample, annual correlation between fertility and employment cycles between years 1990-2016 is found to be 0.69. Our model predicts 0.79 correlation in our simulations. In Figure 6, we plot employment-fertility cycles from the annual US data as well as an example simulation from the model.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{fig6.png}
\caption{Procyclicality of Fertility}
\end{figure}

In order to see the effect of cyclicalities on fertility and human capital decisions, we consider three counterfactual economies as well as the benchmark economy. The differences in these economies stem from two features of the labor market; 1-volatility of men vs. women industries, 2-correlation between men and women industries. In our benchmark economy, the standard deviation of male and female industries are calibrated to match standard deviations of male and female employment. In complete segregation with current gender bias, or “women nurses” economy, standard deviations are estimated to match standard deviations of male and female dominated industries; i.e. education, health, government for female, construction and manufacturing for male. In women nurses economy, not only male employment becomes very volatile as opposed to stable female employment, but also the correlation becomes negative, due to countercyclicality of female industries. In complete segregation with opposite gender bias, or “men nurses” economy, we assign the same calibrated parameters as in “women nurses” economy to the opposite gender. Note that “women nurses” economy is a subset and extreme version of current labor market, however “men nurses” economy is a counterfac-

\textsuperscript{8}We use third order polynomial approximation around the deterministic steady state.
tual economy. Finally, we assume “no gender asymmetry” by calibrating standard deviations to match standard deviation of national employment by also imposing perfect correlation between genders.

In Table 3, we document steady states of these economies. Making gender asymmetry more extreme, i.e. moving from benchmark to “women nurses” makes fertility lower and less procyclical. The investment in human capital increases in steady state. When male income is more volatile, women income relative to men income becomes countercyclical (women breadwinner in a recession). This makes women income more precious and through substitution effect, families have less children but invest more in their human capital. Conversely, we get countercyclical and higher fertility in “men nurses” economy but at the expense of lower human capital in the steady state. Here women income relative to men income procyclical which makes women income less valuable so women prefer having more children instead of investing in their human capital.
<table>
<thead>
<tr>
<th></th>
<th>$\rho(L, n)$ (Cyclicality)</th>
<th>$\sigma(fertility)$ (Volutility)</th>
<th>$\sigma(q)$</th>
<th>$%\Delta Fertility$ from benchmark</th>
<th>$%\Delta Quality$ from benchmark</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Benchmark</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_m = 0.08, \sigma_f = 0.05, \rho_{mf} = 0.88$</td>
<td>0.72</td>
<td>0.064</td>
<td>0.037</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td><strong>Complete Segregation with current gender bias</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_m = 0.15, \sigma_f = 0.02, \rho_{mf} = -0.16$</td>
<td>0.49</td>
<td>0.13</td>
<td>0.033</td>
<td>-0.06%</td>
<td>0.07%</td>
</tr>
<tr>
<td><strong>Complete Segregation with opposite gender bias</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_m = 0.02, \sigma_f = 0.15, \rho_{mf} = -0.16$</td>
<td>-0.28</td>
<td>0.067</td>
<td>0.064</td>
<td>0.1%</td>
<td>-0.2%</td>
</tr>
<tr>
<td><strong>No Gender Asymmetry</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_f = \sigma_m = 0.06, \rho_{mf} = 1$</td>
<td>0.82</td>
<td>0.047</td>
<td>0.037</td>
<td>0.02%</td>
<td>-0.02%</td>
</tr>
</tbody>
</table>

**Table 3: Counterfactuals**

Note: Standard deviations in complete segregation cases reflects the ones of most extreme gender bias industries, i.e. construction and manufacturing for male, education, health, services for female. We estimate standard deviation of employment cycles of these industries the same way we estimate male and female employment with AR processes.
Figure 7 shows fertility and human capital investment in response to a “recession shock”. We assume a recession shock is a 1-std shock to the more volatile industry and 1-std times the correlation to the other industry. In “women nurses” economy, families have better income insurance mechanism due to negative correlation between male and female income around business cycles. This feature makes fertility less procyclical. However, due to the fact that male income effect and women substitution effect kicks in at the same time, fertility becomes more volatile. However, income insurance channel in a recession time makes possible to sustain high and smooth human capital. In “men nurses” economy, female income falls a lot in a recession, hence they prefer taking time off to have more children due to substitution effect which makes fertility countercyclical. However, they cannot afford to keep quality high because they have more children and low income.

![Figure 7: Impulse Response to Recession Shock](image)

7 Mechanism

Many studies confirm that, due to being the main caregiver, women need to take time off from the labor market and incur child penalties when they give birth. In the model, women incur short term and long term child penalties which lead to decline in earnings when women have children. As a result, women’s wage has substitution effect; i.e. higher female wage makes

\[(-\sigma_m, -\rho \sigma_f), \text{ whereas in men nurses economy the shock is } \left[-\sigma_m \rho, -\sigma_f\right]\]
children more costly to the family. In families where female wage is higher, couples have less children but they invest more in their human capital (quality-quantity trade-off) (Doepke and Tertilt [2016]).

To show this channel in our model, we exogenously change, average productivity of $z^f$ and $z^m$. We keep the average productivity constant and move the ratio $z^f/z^m$,we simulate the model. In Figure 8, we plot average fertility, quality and cyclicality of fertility with respect to average relative wage ($w_f/w_m$) for every value of $z^f/z^m$. In addition to negative fertility-income and positive quality-income relationship, we also highlight procyclicality of fertility. When female wage is higher, the weight of female income in the family income becomes higher hence, fertility becomes even more related to business cycles, hence it exhibits higher correlation with aggregate employment changes.

![Figure 8: Quality-Quantity Trade-off and Procyclicality](image)

**Why does cyclicality matter for quality-quantity trade-off?**

In Figure 9, we simulate the model and plot income vs. relative wage for three different economies; benchmark, women nurses and men nurses. When male industries are more volatile (benchmark and women nurses economies), relative wage goes up in a recession; i.e. when the output is low. In these economies, women become the breadwinner of the family in a recession. From the perspective of risk averse agents, it is as if women earn more on average because women’s income becomes more precious due to the fact that women earn more in
relative terms when marginal utility is high. In the quality-quantity trade-off, the economy is pushed towards quality, because the relative weight of women’s income is higher.

In the counterfactual “men nurses” economy, we observe high relative wage when the output is high. Hence, women’s income is not as precious, because it is high when marginal utility is low. Hence, families in this economy is pushed towards quantity because relative weight of women’s income is low.

![Benchmark](image1.png) ![Women Nurses](image2.png) ![Men Nurses](image3.png)

Figure 9: Cyclicality and Gender Income Ratio in the Model

In Figure 10, we plot cyclical components of aggregate employment and gender income ratio in the US. The figure shows that gender income gap is countercyclical; female income relative to male income goes up in recessions and the correlation between gender income ratio and aggregate cycles is -0.32. In our model, cyclicity of wage gap \( w_f/w_m \) depends on cyclicity of industries where women and men work.
To see this mechanism in our model, consider the fertility decision of a middle household.

\[
U_2(q_{t-1}^y, n_{t-1}^y, q_{t}^m, n_{t}^m) + \beta E_t U_2(q_{t-1}^y, n_{t-1}^y, q_{t}^m, n_{t}^m) = U_1(c_{t}^m)(\bar{w}e_t^m + w_t^f \tau_1)
\]

Marginal benefit of having children

Marginal current cost

Marginal future cost

\[
\text{Marginal current cost} = \bar{w}e_t^m + w_t^f \tau_1
\]

\[
\text{Marginal future cost} = \beta E_t U_1(c_{t+1}^o)w_{t+1}^f \tau_2
\]

\[
E_t(U_1(c_{t+1}^o)w_{t+1}^f \tau_2) = \tau_2 E_t(U_1(c_{t+1}^o)) E_t(w_{t+1}^f) + \tau_2 \text{cov} \left[ U_1(c_{t+1}^o), w_{t+1}^f \right]
\]

According to 2, covariance between marginal utility and female income matters for fertility decision. When female/male income is countercyclical, covariance between future marginal
utility of consumption and the female income is positive, which increases the expected cost of having a child.

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

8 Conclusion

In this paper, we establish a link between fertility and macroeconomic dynamics of the labor market from a gender perspective. We argue that procyclical feature of fertility depends on the cyclical features of industries where men and women work. Men are predominantly employed in procyclical industries such as construction and manufacturing whereas women mostly work in countercyclical industries such as education, health and government. In a recession, a typical men loses his job and a typical women becomes the breadwinner in the family. Hence, female/male income ratio is typically countercyclical; which makes female income more precious due to its insurance effect. Combined with the long-term child penalties on women, countercyclical women income increases the cost of having children and leads to lower fertility. Instead, families opt for investing more in their children.

In our empirical analysis, we show that fertility moves procyclically since mid 70s. We document gender asymmetric industry characteristics and we conclude that 70% of men work in highly procyclical industries and 40% of women work in countercyclical industries. As a result, men’s employment volatility is much higher than women’s employment volatility and it is more procyclical. In our state level analysis, we show that in majority of states, men and women employment cycles are negatively correlated. The negative correlation is driven by the gender segregation in industries and lead to smaller business cycle size.

In order to quantify the effect of gender asymmetry on fertility and also incorporate the quality dimension on fertility choice, we build a general equilibrium overlapping generations model where families make fertility decisions as well as investment on their children’s human capital. We find that male and female employment cyclicalities alone can explain procyclical fertility. Gender asymmetry in industries and procyclicality makes female income relative to male income is countercyclical which makes female income more valuable and pushes families through substitution effect towards quality in quality-quantity trade-off. On the other hand, if men work in countercyclical and women work in procyclical industries (men become nurses, women become construction workers), fertility is higher and countercyclical. However, quality investment on children would be lower and more volatile.
We contribute to the literature by highlighting a link between quality-quantity trade-off, differential impact of male and female income, child penalties and interaction of these with the business cycles and fertility dynamics which has implications on population growth and human capital accumulation. Current labor market structure where women and men sort into different types of industries create an insurance mechanism which help smooth income fluctuations, makes fertility procyclical and tilts quality-quantity trade-off towards quality.

References


A Appendix

Figure 11: Total Fertility Rate in the last Century (1917-2017)
Data source: National Health Statistics, Office of Population Research (Princeton University)

Figure 12: Fertility and Recessions
Note: National Health Statistics, US total fertility rate between 1975-2018. Shaded areas indicate recession periods
Estimating Shock Processes

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

$$\log(\nu^m_t) = \delta_m \log(\nu^m_{t-1}) + e^m_t$$
$$\log(\nu^f_t) = \delta_f \log(\nu^f_{t-1}) + e^f_t$$

We find that $\hat{\delta}_m = 0.47$, $\hat{\delta}_f = 0.5$, $\sigma(e_m) = 0.011$, $\sigma(e_f) = 0.007$, $\text{corr}(e_m, e_f) = 0.88$. We then simulate a long series of data and construct our productivity measure.

$$\log(z^m_t) = \sum_{j=0}^{14} \log(\nu^m_{t+j})$$
$$\log(z^f_t) = \sum_{j=0}^{14} \log(\nu^f_{t+j})$$

We then estimate

$$\log(z^m_t) = \rho_m \log(z^m_{t-1}) + e^m_t$$
$$\log(z^f_t) = \rho_f \log(z^f_{t-1}) + e^f_t$$

and find $\hat{\rho}_m = \hat{\rho}_f = 0.04$, $\sigma(e_m) = 0.096$, $\sigma(e_f) = 0.057$, $\text{corr}(e_m, e_f) = 0.88$.

Generation Quality

Define $N^y_t(y)$ as the number of young families born to young parents at $t - 1$. Similarly, $N^y_t(m)$ 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 $t$.

$$N^y_t(y)q^y_{t-1} + N^y_t(m)q^m_{t-1} = N^y_t q_t$$

$$N^y_{t-1}(n^y_{t-1}/2)q^y_{t-1} + N^m_{t-1}(n^m_{t-1}/2)q^m_{t-1} = N^y_t q_t$$
\[ N_t^m (n_{t-1}^y / 2) q_{t-1}^y + N_t^o (n_{t-1}^m / 2) q_{t-1}^m = N_t^y q_t \]

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

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