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Essays on Female Labor Supply

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ESSAYS ON FEMALE LABOR SUPPLY

by

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Abstract

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The first chapter examines how women's local labor supply decisions affect the national gender wage gap. The national wage is the sum of weighted local wages, which combines local wages and local employment weights. Here, I emphasize the role of local employment weights, especially for women, which can reflect worker's labor supply decisions across locations. I show that, only for highly-educated women, there is a significant negative relationship between employment-to-population ratio and average log wage across locations. This relationship is stronger for married women with children. Since fewer highly-educated women are working in high-wage cities while more highly-educated women are working in low-wage cities (i.e. different employment weights), I argue that the national-level gender wage gap would be overstated. To test this hypothesis, I use two empirical strategies. First, I conduct a counterfactual gender wage gap analysis by replacing women's local employment weights with men's and show that the log wage difference between men and women with an advanced degree can be reduced by 2 percent. Second, I estimate the college-educated gender wage gap *with* location controls, which is 5 percent less than the gap *without* location controls.

In the second chapter, I study how occupational characteristics can affect women's timing of fertility and how women's labor supply after childbirth changes depending on the timing of fertility and their occupations. By considering occupational characteristics of time constraints and human capital depreciation among skilled occupations in the US, I find that college-educated women who work in high-hours occupations tend to delay their fertility. Moreover, I observe that a similar pattern of delaying fertility arises in occupations with interpersonal relationships, autonomy, and competitiveness. Finally, I show that women in high-hours occupations who delay fertility tend to decrease their labor supply after childbirth, mainly by reducing working hours or dropping out of the labor force rather than switching occupations.

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Table of Contents

List of Tables

List of Figures

Chapter 1

The Gender Wage Gap: The Importance of Locational Labor Supply Decisions of Women

1.1 Introduction

Despite women's rising share of the national labor force and greater educational attainment (Blau and Kahn 2017), the gender wage gap remains persistent, especially for highly-educated women. An extensive literature examines the factors that may cause the gender wage gap. Traditional explanations for the gender wage gap contain labor force participation (Juhn and Murphy 1997; Goldin 2006; Blau and Kahn 2007), education (Goldin et al. 2006; Black et al. 2008), job structure (Goldin 2014), motherhood (Anderson et al. 2003; Correll et al. 2007; Kuziemko et al. 2018), the family division of labor (Cortés and Pan 2019), discrimination (Goldin and Rouse 2000), and gender norms (Bertrand et al. 2015). However, there are only a few papers that consider that local labor market decisions may influence the estimated national gender wage gap.

In this paper, I examine how women's local labor supply decisions affect the national gender wage gap, focusing on high education level (college graduates or individuals with an advanced degree). The national log wage is essentially the sum of weighted local log wages which includes local log wages and local employment weights.[1] Given that local log wages substantially vary by locations, if there are distinct patterns of local employment weights, such as if women's local employment weights are quite different from men's weights, then this would affect the national log wage. When calculating the gender wage gap, we only include the wages of workers who are in the labor force and do not observe workers who choose to opt out of the labor force. However, if the decisions to opt out vary by locations, they influence the estimated gender wage gap thus the labor supply decisions by locations should be considered. I argue that the local employment weights play a role in understanding worker's labor supply decisions across locations, especially for highly-educated married women with children.

Given that women's labor supply decisions combined with motherhood can be more complicated than men's (Bertrand et al. 2010; Goldin 2014; Kuziemko et al. 2018; Schank and Wallace 2019), examining labor supply decisions of married women with children is important. However, we cannot observe married women with children in terms of the gender wage gap when they already dropped out of the labor force. This is why local employment weights can be a proxy for observing people who are out of the labor force, as similar that occupational distribution is used for a proxy for observing individuals who either switch occupations or drop out of the labor force (Cunningham and Zalokar 1992; Gabriel and Schmitz 2007; Cortés and Pan 2017; Kosteas 2019) Suppose highly-educated women, particularly married women with children, have different working patterns across locations, such as more women work in locations with lower wages, while fewer women work in locations with higher wages. Then the local employment weights would be different from that of men or not married women, thus the labor supply decisions across locations can affect the national gender wage gap.

I begin by documenting the relationship between the employment-to-population ra-

[1] Each location's employment weight is the working people in that location divided by the total number of working people in the overall sample.

tio (emp/pop) and log wage in each Metropolitan Statistical Area (MSA). Using the 2016 American Community Survey (ACS) 5-year aggregate (2012-2016), I find that there is a significant negative relationship between emp/pop and average log wage across MSAs, only for highly-educated women. Furthermore, this negative relationship is mostly driven by married women with children. These findings are robust when including MSA unemployment rates, which suggests that the observed pattern is not likely to be due to the differences in local labor demand. I argue that the national-level gender wage gap would be overstated even when the local gender wage gaps are the same due to the different employment patterns across locations.

To test this hypothesis, I use two empirical approaches. First, I conduct a counterfactual gender wage gap analysis by re-adjusting local employment weights. Since women's local employment weights reflect women's labor supply decisions across MSAs, I analyze how the women's labor supply decisions by locations can affect the national gender wage gap. As a counterfactual, I examine what the gender wage gap would have been if women's local labor supply decisions were the same as the men's labor supply decisions. The results show that the log wage difference between men and women is reduced by about 2 percent for people with an advanced degree but only 0.4 percent for high school graduates. This result supports the descriptive facts that the negative relationship between emp/pop and log wage only holds for highly-educated women. Moreover, since the negative association between emp/pop and log wage is mostly driven by married women, I also examine what the gender wage gap would have been if the local labor supply of married women was same as the local labor supply of not married women. The resulting log wage difference between men and women is reduced by 3.5 percent for college graduates.

For the second empirical approach, I estimate the gender wage gap *with* location fixed effects to test the significance of the negative relationship between emp/pop and log wage across MSAs for highly-educated women, following Black et al. (2009, 2014). Black et al. (2009, 2014) demonstrate that the college wage premium, the wage gap between college graduates and high school graduates, is independent of location if and only if preferences are homothetic. Even if homothetic preferences are met, one needs to add location-specific fixed effect to measure the inequality, otherwise the estimator could be biased. The results here show that, for those with higher education levels, the log wage difference between men and women is reduced by 5 percent with location controls. This supports the hypothesis that the gender wage gap would be overstated, since highly-educated women tend to work less in high-wage cities.

This paper is closely related to the literature on local labor markets. Costa and Kahn (2000) find that college-educated couples are more likely to be located in large metropolitan area because of more job offers for couples. Bacolod (2017) finds that gender wage gaps are narrower in larger cities and explains that skill formation is different between men and women.[2] Similarly, Hirsch et al. (2013) show that the unexplained gender wage gaps are narrower in large cities in Western Germany. My results show that despite more job opportunities and/or less employers' discrimination in large/high-wage MSAs, highly-educated women are less likely to work in high-wage cities. This finding is closed to the Black et al.'(2014) paper which shows that women's labor force participation rate (LFPR) is lower in MSAs with longer commuting time. While my results are also robust on LFPR in addition to emp/pop, I focus on the different patterns of emp/pop across locations, which directly affects the wage analysis. Also, while Black et al.'s (2014) finding is more pronounced to women with high school education, my analysis shows that only highly-educated women have a tendency to work less in high-wage cities.[3]

The rest of the paper is organized as follows. Section 2 introduces the data and descriptive statistics. Section 3 presents descriptive facts related to emp/pop and log wages across MSAs, specifically documenting the negative relationship between emp/pop and log wage across MSAs only for highly-educated women, mainly those women who are married with children. Section 4 constructs the counterfactual gender wage gap anal-

[2]Since women tend to work in jobs requiring more social or cognitive skills that can be more productive in large cities, we should observe the smaller gender wage gap in large cities.

[3]This paper is also related to recent literature that emphasizes the role of local characteristics on the national labor market. Black et al. (2013) find that failure to take into location account causes significantly overstate the decline in the black-white wage gap in U.S. over the past 60 years. Moretti (2013) stresses that the distribution of skilled and unskilled workers are not uniform across cities when it comes to college wage premium. Garrett and Kolesnikova (2015) state the importance of locational cost-of-living differences, and Albouy (2009) points out that the federal income tax does not take wage variation across cities into account. Pope and Sydnor (2010) find that test scores at the national level do not consider statistically significant variation in gender gaps across states.

ysis by re-adjusting local employment weights and emphasizes the importance of local employment weights in constructing the national wage gap. Section 5 reports the gender wage gap with location fixed effects and confirms the previous descriptive facts in Section 3. Section 6 concludes.

1.2 Data description

I use the 2016 American Community Survey (ACS) 5-year aggregate (2012-2016) in Integrated Public Use Microdata Series (IPUMS). The sample consists of non-Hispanic white men and women aged 25-55, who were either working for wages at least 27 weeks on previous year or non-working.[4] To ensure a reasonable sub-sample size, the sample is restricted to the 84 largest Metropolitan Statistical Areas (MSAs) among 260 MSAs. The sample size of the ACS is much larger than the Panel Study of Income Dynamics (PSID) or the Current Population Survey (CPS), so I can control the location at the level of MSA.[5]

The ACS data provides information on employment status which has three main categories: employed, unemployed, and not in the labor force. The labor force participation rate (LFPR) is calculated as the number of people who are employed or unemployed divided by the number of people in the sample. Similarly, the employment-to-population ratio (emp/pop) is calculated as the number of people who are employed divided by the number of people in the sample. Hourly wage is calculated as the sum of wage and salary income divided by total working hours, which is defined as weeks worked last year multiplied by usual hours worked per week. LFPR, emp/pop, and log hourly wage for each MSAs for the later analysis in this study are age-adjusted to control different age distributions across MSAs.

The schooling by gender and the gender wage ratio by education level are summarized in Table 1. As described in Blau and Kahn (2017), women's educational attainment is even greater than men in Panel A. For example, 16.96 percent of men attain advanced

[4] I use only workers for wage analysis, but additionally include non-working men and women for labor force participation rate and emp/pop.

[5] The sample size using the 2016 5-year aggregate in 84 MSAs is 1,252,497. In Blau and Kahn (2017), the sample sizes of the PSID and the CPS are shown as 4,824 and 44,947 in 2010, respectively.

degrees, while 21.35 percent of women attain advanced degrees. Despite women's greater educational attainment, the gender wage gap is wider at the higher education levels (college graduates and individuals with an advanced degree) in Panel B. College graduate women earn only 75.75 percent of college graduate men's hourly wage, whereas the ratios are 78.24 and 79.86 for high school and some college, respectively.[6]

Table A1 describes the summary statistics of men and women regarding the labor supply, the marital status, and the presence of children by education levels. The first summary statistics explains about the labor supply. LFPR and emp/pop increase as the attainment of education is higher, but the women's LFPR and emp/pop are still lower than those of men for each education level, respectively. For example, LFPR for men with college education in Panel A is 95.75 percent, which is higher than LFPR for women with college education in Panel B, which is 82.31 percent.

The second summary statistics of Table A1 describes the marital statues. I define three marital status categories: 1) married – married with a spouse, 2) been married – married but spouse absent or separated or divorced or widowed, and 3) single – single or never married. For instance, in Panel B of Table A1, the sample size of college graduates women is 244,947. Among them, 64 percent are married with a spouse, 12 percent are separated, widowed, or divorced and 25 percent are single/never married. The martial statues differ by education levels. The proportion of "married" status increases as education attainment is higher - the percentage of "married" status for women with an advanced degree is 67 percent, which is 10 percentage points higher than women with high school education. The proportion of "been married" status decreases as education attainment is higher - the percentage of "been married" for women with an advanced degree is 11 percent, which is 13 percentage points lower than women with high school education.

Finally, the summary statistics on children is also reported in Table A1. The ACS provides information on children – the number of own children (of any age or marital status) residing with each individual. In addition to that, ACS reports information on children under 5 – the number of own children age 4 and under, residing with each in-

[6]The wage ratio for high-school dropouts is noisy due to the relatively small sample shares of high-school dropouts — 2.20 percent of men and 1.23 percent of women.

dividual. Among college graduate women who are married with a spouse, 71 percent have children and 27 percent have children younger than 5, respectively. Additionally, notice that the non-marital childbearing rate is higher for less-educated women. Among single women with high school education, the percentage of having children is 33 percent, which is much higher than the percentage for single women with higher education having children.[7]

1.3 Descriptive facts

1.3.1 Log wage variation across MSAs

Since the unconditional log wage at the national level is essentially the sum of weighted local log wages, which includes local log wages and local employment weights in each MSA j, we have

$$ln(w_e^g) = \sum_j \left[ln(w_{j,e}^g) \times \left(\frac{emp_{j,e}^g}{\sum_j emp_{j,e}^g} \right) \right] \tag{1.1}$$

where g indexes gender, j MSAs, and e education level. I define $\frac{emp_{j,e}^g}{\sum_j emp_{j,e}^g}$ as the employment weight of each MSA j. Thus, for example, national college graduate men's log wage can be decomposed into two terms: college graduate men's log wage in each MSAj and college graduate men's employment weight in each MSAj.

Since there are two components of the national log wage, I first examine the log wage variation across 84 MSAs by education level.[8] Table 2 shows that cross-MSA variation in log wage is similar for all education levels. Standard deviations of log wage by each

[7] Lundberg et al. (2016) also address increasing marriage rates, decreasing divorce rates and decreasing non-marital childbearing rates as education attainment is higher.

[8] Among 260 MSAs, I contain 84 MSAs with at least 30 observations for each subgroup. Since the smallest subgroup for later analysis in this study is not married women with advanced degree and children, I include only those MSAs that have at least 30 observations for that subgroup. Due to the relatively small sample shares of high-school dropouts—only 4.98 percent of men and 3.62 percent of women—some MSAs do not have enough observations of high-school dropouts. Four out of 84 MSAs and 22 out of 84 MSAs have less than 30 observations for men and women high-school dropouts, respectively. My main analysis for further discussion would focus on high-school graduates, those with some college education, college graduates, and those with an advanced degree.

education level vary from 0.10 to 0.13 and 0.10 to 0.12 for men and women, respectively.[9] In Figure 1, the upper line for log wage variation of college graduates is similar to that of the lower line for high school graduates in Panels A and B. Thus, the variation in local log wage—the first component of the national log wage in equation (1) is similar by education level or by gender.

1.3.2 The Relation between MSA employment-to-population ratios and wages

Given that cross-MSA variation in log wages have similar patterns by education level or gender, I next examine the variation in the distribution of workers' labor supply—the employment weights in the second component of equation (1)—across MSAs by education level or gender. Since log wages vary across MSAs, if cross-MSA working patterns are distinct either by education level or gender, this would affect the national log wage. As Figure 2 illustrates, suppose there are two cities—high-wage city and low-wage city and the local log wage differences between men and women are 0.3, which is the same for both cities. Given a similar men's labor supply in the two cities, what if women's labor supply differs in both cities—more women work in the low-wage city and fewer women work in the high-wage city? Since men's labor supply is similar in both cities, the national weighted log wage for men would be 3.4, while the national weighted log wage for women would be 3.0. Despite local log wage differences being 0.3 in both cities, due to the difference in the labor supply of women in the two cities, the national log wage difference would be wider as 0.4. To put it differently, the national gender wage gap is overstated than the gender gap in each location.

The primary point is that if one wants to examine the gender wage gap, it would be problematic to simply look at the national average. Since the national average reflects both local wages and local employment weights, even when the local wage gaps are the same across locations as described in Figure 2, the national average wage depends on the

[9] Due to the small sample size of high-school dropouts, standard deviations for men and women high-school dropouts are relatively high. After including all races in 84 MSAs to increase sample size, standard deviations for men and women high-school dropouts fall to 0.10 and 0.09, respectively.

labor supply patterns across locations. This is why it is important to separate the local gender wage gap and aggregation across different local markets.

To analyze cross-MSA variation in labor supply, I estimate the following regression. Using the log wage of college graduates as a basic measure, I examine the relationship between emp/pop and log wage in each MSA j. Since the employment weights in equation (1) do not include non-working men and women, I measure the emp/pop for each location instead of the employment weights to examine the *relative* labor supply patterns across location. I first examine the relationship between men's emp/pop and women's log wage in each MSAj and, conversely, the relationship between women's emp/pop and men's wage in each MSAj.[10] To control local demand shocks, I include local unemployment rate in 2016 (X) as a control variable.

$$men's(women's)\ emp/pop_{\,j} = \beta_0 + \beta_1\ MSA\ women's(men's)\ log\ wage_j + X_j + \epsilon_j \quad (1.2)$$

The relationship between *men's* emp/pop and women's log wage is summarized in Panel A of Table 3. There is no significant association between emp/pop and log wage for men of all education levels. On the contrary, *women's* emp/pop has a negative relationship with men's log wage, only at higher education levels in Panel B. A 1 percent increase in the wage of men with college education is negatively associated with a 0.11 percentage points reduction in emp/pop of women with an advanced degree or 0.12 of women with college education. The estimate becomes quantitatively and statistically weaker for women with some college education and is not significant for women with high school education.

Figure 3 provides graphical evidence of a systematic correlation between emp/pop and log wage for each MSA. The negative association holds only for Panel C of Figure 3—women with college education. Thus, only highly-educated women have a tendency to work less in high-wage cities.[11] The rest of the panels show that there is no significant relationship between emp/pop and log wage for less-educated women or men at all

[10]Since men's employment is endogenously determined by men's log wage, I use MSA women's log wage instead, to exclude possible endogeneity. Similarly, I estimate women's emp/pop using men's log wage.

[11]See Figure A1 for college-educated women with detailed names of MSAs.

education levels.

Given that college or above-educated women can compete with men for college-level jobs, one might concern that this relationship rather shows the discrimination against women in high male college wage locations. To address this concern, I estimate women's emp/pop using women's college wages instead of men's. The negative relationship between women's emp/pop and wage is still robust as shown in Panel A of Table A2. Moreover, Panel B of Table A2 shows that the negative relationship between women's emp/pop and wage across locations is robust with wages of different education levels (e.g., emp/pop for each education level and corresponding log wages).

One might think that women's relative labor supply can be affected by different price levels. Even though data of consumer price index at the MSA level is not available, Black et al. (2014) shows that married women's local labor supply is negatively associated with housing price index and the association is insignificant. This suggests that the women's *low* emp/pop in high wage cities is rather an opposite direction of concern if one might expect that women are more likely to work in relatively expensive cities.

Finally, this negative association for women to work less in high-wage cities might be due to the different job matching opportunities or employer discrimination/attitudes across locations. Costa and Kahn (2000) find that college-educated couples are more likely to concentrate in larger metropolitan areas because of more potential job offers for couples.[12] Also, Bacolod (2017) and Hirsch et al. (2013) show that the unexplained gender wage gaps are narrower in large cities in the US and Western Germany, respectively. Given that high-wage cities are likely to be large cities, my finding suggests that women are less likely to work in high-wage cities despite more job opportunities or less discrimination.

[12]See Compton and Pollak (2007) for the opposite argument that the education of the husband primarily affects the couple's migration to a large metropolitan area.

1.3.3 Women's labor supply decisions by marital statuses/presence of children

The previous section shows that only highly-educated women are less likely to work in high-wage cities, while this tendency is not shown for less-educated women and/or men at all education levels. In this section, I hypothesis that women's local employment patterns can be differ by marital status and/or presence of children and provide a consumption-leisure model for this analysis presented in Appendix 2. The theory predicts that the presence of a spouse leads a woman to work relatively less in high-wage cities compared to a woman without a spouse. In the model where the presence of children affects women's labor supply, depending on the size of the substitution effect and the income effect, the results are different. When the substitution effect dominates the income effect (i.e., where the average wage is higher, a woman reduces leisure and increases working), women with children work relatively less than women without children. In the case when the income effect dominates the substitution effect (i.e., in higher-wage cities, a woman increases leisure and decreases working), the theory predicts that the effect of children on women's labor supply in higher-wage cities is ambiguous. With this theoretical predictions, empirical findings show that a negative relationship between emp/pop and wage across locations are mostly driven by married women with children for high education level. Then, I provide one possible explanation that the spouses' income could play a role in women's labor supply decisions across locations.[13]

The relationship between women's emp/pop and wage by marital status/presence of children

To study women's employment patterns across locations by marital status and/or presence of children, I first consider married women and not married women, respectively. "Married" is defined as married with spouse present out of the 6 marital statuses— married with spouse present, married with spouse absent, separated, divorced, widowed, and single. "Not married women" is defined as the rest of the marital statuses. Then

[13]See the Appendix 2 for a model of labor supply with a spouse and children for details.

holding the marital status constant, I examine women's emp/pop by "children" status using the equation (2).

Results for college-graduate women are presented in Panel A of Table 4. For the married women in columns (1)–(2), the negative correlation between emp/pop and wage is significant and stronger with a coefficient of –0.246 when they have children. A 1 percent increase in the men's college wage is associated with a 0.246 percentage point reduction in the emp/pop of college-educated married women with children. For the not married women in columns (3)–(4), the association is not significant (without children) or the magnitude of the coefficient is small (with children). In sum, the tendency to work less in high-wage cities are shown except for single women with no children, and mostly driven by married women with children.[14]

Next, I estimate the equation (2) for women with high school education. It might be possible that less-educated women also have a similar labor supply pattern by marital status/presence of children. If this is the case, the different selection into the marital status and/or presence of children across education levels affect the distinct pattern for highly-educated women. In the case of women with high school education in Panel B of Table 4, the estimated coefficients for subsamples are rather positive except for married women with children. Even though there is a negative relationship between emp/pop and wage for married women with children, the magnitude of the coefficient is much smaller than their highly-educated counterparts (–0.117).[15]

In sum, the employment pattern for highly-educated women to work less in high-wage cities is pronounced for married women with children. Moreover, the result shows that the employment pattern for less-educated married women with children is much weaker. This suggests that the distinct pattern to work less in high-wage cities for highly-educated women is not likely to be driven by different selection into several marital statuses/presence of children.

[14] I also divide the children into older children and young children. The negative association is clearer for married women with older children (not reported).

[15] I estimate the same regression for married *men* with children by each education level (not reported). For college-educated married men with children, there is a negative association between emp/pop and wage at the 5 percent significance level, but the magnitude of the coefficient is about a tenth of that of their female counterparts (–0.026). For HS educated married *men* with children, the coefficient is positive at the 10 percent significance level (0.042).

Discussion on spouse's characteristics

Why would the magnitude of a negative relationship between emp/pop and log wage vary by women's education level? Here, I provide one suggestive explanation that spouses' characteristics such as spouse's income could play a role in women's labor supply decisions. Since the income in the data is not permanent but transitory, it is limiting to analyze the spouse's income effect using the income variable. Thus, I use spouses' education level as a proxy for lifetime income for further analysis on spouses' characteristics.

As women's education levels rise, they are more likely to get married to highly-educated men (college graduates or those with an advanced degree). For college-graduate women and women with advanced degree, the percentage of matching with a highly-educated spouse is 67.77 percent and 77.95 percent, respectively. On the contrary, for women with high school education, the percentage of matching with a highly-educated spouse is only 17.17 percent.[16]

Using the descriptive facts that highly-educated women are more likely to get married to highly-educated, high-wage spouses, I next compare women's labor supply by different groups of spouses holding women's own education level constant. Would less-educated married women with highly-educated spouses behave similarly to the total sample of less-educated women? Or would highly-educated married women with less-educated spouses have similar working patterns to the total sample of highly-educated women? To answer this, I restrict the sample to high-school graduate women who are married to highly-educated men and highly-educated women who are married to less-educated men, respectively.[17]

Table A3 summarizes the descriptive statistics for married women with children and their sub-sample. In the case of high-school graduate married women with children in Panel A, for those who are married to a highly-educated spouse, LFPR and emp/pop are much lower than for the total sample of HS graduate married women with children. The

[16]When using log wage variable, spouses' log wage of high-school graduate women is 3.22, while spouses' log wage of college-graduate women is 3.62, which implies that the spouses of less-educated women earn only 66.8 percent of the spouses of highly-educated women.

[17]I define highly-educated spouses as those who are either college graduates or have an advanced degree. The less-educated spouses are high-school graduates.

LFPR for the total sample of high-school graduates is 63.55 percent, whereas for those who are married with highly-educated spouses is 55.57. Similarly, in the case of highly-educated married women with children in Panel B, the LFPR for highly-educated married women with less-educated spouses is 86.67 percent, which is much higher than for the total sample of highly-educated married women, 76.21 percent.[18] Therefore, although women have the same education level, women's labor supply patterns significantly differs by spousal income/education level as shown by Bertrand et al. (2010) and Goldin (2014).[19]

Since the LFPR and emp/pop for the overall U.S. suggests distinct differences in women's labor supply depending on spouses' education level, I compare labor supply decisions across MSAs by considering spouses' education using the equation (2). In the case of highly-educated women in columns (1)–(2) in Table 5, the employment pattern to work less in high-wage cities is much weaker for women with less-educated spouses (–0.100), compared to the total highly-educated women (-0.222). On the contrary, in the case of women with high school education, the negative association between emp/pop and wage becomes stronger for women with highly-educated spouses (–0.235), compared to the total women with Hs education (–0.117). Interestingly, when there is a strong employment pattern to work less in high-wage cities, the coefficient of the unemployment rate is rather weaker in magnitude and less significant. This suggests that women's labor supply patterns to work less are not likely to be affected by local market conditions, rather it implies women's voluntarily labor supply decisions.

To summarize, even though women's own education level is equivalent, women's labor supply decisions across MSAs are different depending on their spousal education level. The women's lower labor supply with high-income spouses holds not only at the national level (Bertrand et al. 2010; Goldin 2014) but also holds across locations.

[18] Instead of considering women with college education and an advanced degree, respectively, I combine the two education categories as highly-educated for further discussion on MSA analysis, for a reasonable sample size.

[19] Bertrand et al. (2010) find that the effect of motherhood on MBA women's employment is different by spousal earnings. When a woman has a high-earnings spouse, the probability that a woman is not working is more than twice as large compared to a woman with a lower-earnings spouse. Goldin (2014) also shows that the presence of children on women's labor supply significantly differs by spousal income.

Individual level analysis with linear probability model

Here, I examine the negative relationship between emp/pop and log wage at the individual level. Using individual-level outcome— labor force participation— allows us to show some suggestive evidence that the negative relationship between emp/pop and log wages for highly-educated women is at least in part from their decision whether to participate in the labor force or not. I estimate the following regression with a linear probability model:

$$y_{ij} = \alpha + \beta MSA\ men's\ wage_j + \eta(spouse's\ education \times marriage)_i + \gamma X + \epsilon_i \tag{1.3}$$

where the dependent variable is 1 if a woman is in the labor force and 0 otherwise. X includes individual level characteristics, such as age, age^2, marital status, and presence of children dummy variables as well as MSA level unemployment rate. The interactions of spouse's education and marital status have a vector of 4 dummies: married to high-school graduates (the excluded category), married to a spouse with some college education, married to college graduates, married to a spouse with an advanced degree. Standard errors are clustered at the MSA level to allow for the possibility of serial correlation within MSAs.

The negative relationship between highly-educated women's emp/pop and wage at the MSA level holds at the individual level as presented in Table 6. The estimated coefficient of β is negative and statistically significant in columns (1)–(2). This significant negative correlation becomes weaker and insignificant as women's education level is lower in columns (3)–(4). In addition to that, as her spousal education level rises, a woman is more likely to drop out of the labor force. The probability of being in the labor force for a woman with an advanced degree is negatively impacted when she is married to a man with an advanced degree, by 11.4 percentage points, than a woman who is married to a man with high school education. The lower probability of being in the labor force when spousal education level is higher is also found for a woman with other education levels. For example, for women with high school education in column (4), the probability of being in the labor force is lower by 15.0 percentage points when a woman is married to a man with an advanced degree, compared to a base group, while the negative coefficient of MSA wage is not significant.

In sum, individual-level analysis confirms the previous descriptive facts at the MSA-level analysis. Given that: 1) highly-educated women are less likely to work in high-wage cities and 2) this relationship is stronger for married women with children, the national gender wage gap would be overstated at the higher education levels due to the differences in women's labor supply decisions across locations.

1.4 Constructing the counterfactual gender wage gap

In this section, I conduct a counterfactual gender wage gap analysis to test the hypothesis that the national gender wage gap would be overstated since fewer highly-educated women work in high-wage cities while more highly-educated women work in low-wage cities. As described in Section 3, the unconditional log wage at the national level for each education level e can be decomposed into two parts: log wages in each MSA (A) and employment weights in each MSA (B):

$$ln(w_e^g) = \sum_j \left[\underbrace{ln(w_{j,e}^g)}_{A} \times \underbrace{\left(\frac{emp_{j,e}^g}{\sum_j emp_{j,e}^g} \right)}_{B} \right] \tag{1.4}$$

where $g = \{M, W, Mar, NMar\}$ indexes men, women, married women, and not married women, respectively, j MSAs , e is education level, and $\frac{emp_{j,k}^i}{\sum_j emp_{j,k}^i}$ is the employment weight of each MSA j. Not married women is defined all other marital statuses except married with spouse present— married with spouse absent, separated, divorced, widowed, and single.

Here, I examine the national gender wage gap by focusing on the second component of the national log wage, the employment weights in each MSA. I construct a counterfactual wage gap analysis by re-adjusting local employment weights. Based on the descriptive facts in previous section, I verify the effect of cross-MSA variation in women's labor supply on the national log wage by constructing a counterfactual wage gap analysis. In order words, given the log wages in each MSA, how do labor supply decisions affect the calculated national log wage and thereby the gender wage gap?[20] The intuition behind this strategy is the following: when calculating the gender wage gap, we only include the wages of women who are in the labor force and do not observe women who choose to opt out of the labor force. However, if the decisions to opt out varies by locations, they influence the estimated gender wage gap; thus, the labor supply decisions by locations should be considered.

To analyze the effect of cross-MSA variation in labor supply on the gender wage gap, I first calculate the predicted national women's log wage at each education level by replacing women's employment weights (B in eq. (4)) with men's employment weights (B' in eq. (5)) in each MSA, holding local wages constant. To put it differently, what would be the national log wage of women and gender wage gap if women's local labor supply decisions were the same as the men's labor supply decisions?

$$ln(w_e^W)^P = \sum_{j=1}^{84} \left[ln(w_{j,e}^W) \times \underbrace{\left(\frac{emp_{j,e}^M}{\sum_j emp_{j,e}^M} \right)}_{B'} \right] \tag{1.5}$$

Panel A of Table 7 presents the result. The actual unconditional log wage differences in column (1) are calculated as the actual men's log wage minus the actual women's log wage by each education level. Then, the predicted log wage differences in column (2) are the actual men's log wage minus the predicted women's log wage. For example, for workers with advanced degrees, the actual log wage difference is 0.290 and the predicted log wage difference after re-adjusting the local labor supply is reduced to 0.284. Next, the percentage change in log wage differences for advanced degrees in column (3) is –1.93, which means that the log wage difference reduces by about 2 percent. Notice that for lower education levels, the percentage change in log wage differences in column (3) are relatively lesser than for higher education levels. It supports the descriptive facts in Section 3—the labor supply of highly-educated women is less where the average wage

[20]Since the local wage is determined by labor supply and labor demand, if labor supply changes, the local log wage could also change. My analysis focuses on a partial equilibrium analysis.

is high and this is not the case for less-educated women. Therefore, for lower education levels, replacing women's employment weights with men's employment weights does not affect the predicted women's log wage sufficiently, so the percentage change in log wage differences for lower education levels is lesser than for higher education levels.

Recall that the negative relationship between women's emp/pop and MSA men's log wages is mostly driven by married women with children. With this in mind, I replicate the analysis of Panel A by replacing married women's employment weights with not married women's employment weights. What would be the national log wage and the gender wage gap if the labor supply decisions of married women across location were the same as not married women's? I replace term B in equation (4) by applying not married women's employment weights instead of married women's employment weights.[21] Due to the two subgroups of women—married women and not married women—C and D terms are added in equation (6), which are the weight of married women and the weight of not married women, respectively. Then term A in equation (4) becomes the weighted sum as

$$A = ln(w_{j,e}^{Mar}) \times \underbrace{\left(\frac{\sum_j emp_{j,e}^{Mar}}{\sum_j emp_{j,e}^{Mar} + \sum_j emp_{j,e}^{NMar}} \right)}_{C} + ln(w_{j,e}^{NMar}) \times \underbrace{\left(\frac{\sum_j emp_{j,e}^{NMar}}{\sum_j emp_{j,e}^{Mar} + \sum_j emp_{j,e}^{NMar}} \right)}_{D}. \tag{1.6}$$

And equation (4) becomes

$$ln(w_e^W)^P = \sum_{j=1}^{84} \underbrace{\left[ln(w_{j,e}^{Mar}) \times \underbrace{\left(\frac{\sum_j emp_{j,e}^{Mar}}{\sum_j emp_{j,e}^{Mar} + \sum_j emp_{j,e}^{NMar}} \right)}_{C} + ln(w_{j,e}^{NMar}) \times \underbrace{\left(\frac{\sum_j emp_{j,e}^{NMar}}{\sum_j emp_{j,e}^{Mar} + \sum_j emp_{j,e}^{NMar}} \right)}_{D} \right]}_{A} \times \underbrace{\left(\frac{emp_{j,e}^{NMar}}{\sum_j emp_{j,e}^{NMar}} \right)}_{B''}. \tag{1.7}$$

Panel B of Table 7 shows the counterfactual analysis results replacing married women's employment weights with not married women's employment weights. Using the predicted national women's log wages from equation (7), I compare them with the national men's log wages. Now, the percentage changes in log wage differences in column (3) are

[21]Since the local wages for men and women are different by occupation, industry, etc., the analysis of adopting men's employment weights might be limited. However, once occupation is chosen, it is less likely to change depending on the marital status. Hence, comparing local labor supply patterns between married women and not married women could be more reasonable.

even greater. For example, for college graduates, the log wage difference reduces by 3.46 percent.[22] Contrary to higher education levels, there is only a small percentage change in log wage differences for lower education levels, which again supports the descriptive facts that only highly-educated women tend to work less in high-wage cities.

In summary, the national wage consists of two terms: local wages and local employment weights. The literature on gender wage gap mainly focuses on the first component of equation (4), the wage part. In particular, these studies look at how labor force participation, education, work experience, family division of labor, social norms, and so on affect wages and, therefore, the gender wage gap. However, it is also important to understand the role of the second component, local employment weights. I provide one possible explanation that employment weights can reflect the differences in the labor supply decisions by locations. Given that women often drop out of the labor force after their first child (Kuziemko et al. 2018; Schank and Wallace 2019), examining labor supply decisions for married women with children is important, but we cannot observe them in terms of wage analysis. Employment weight can be a proxy for observing people who have dropped out of the labor market as similar that occupational distribution is used for a proxy for observing individuals who either switch occupations or drop out of the labor force (Cunningham and Zalokar 1992; Gabriel and Schmitz 2007; Cortés and Pan 2017; Kosteas 2019). In this respect, the national gender wage gap includes information on both local wages and local labor supply decisions.

1.5 Estimating the gender wage gap with location fixed effects

For the second empirical approach to test the hypothesis that the national gender wage gap is overstated due to different employment weights between women and men, I estimate the gender wage gap *with* location fixed effects, following Black *et al.* (2009, 2014).

[22]There might be age differences between married women and not married women that affect different employment weights. When I calculate predicted women's log wage with age-adjusted, the results are robust to those in Panel B of Table 10, suggesting age difference does not drive different employment weights between married women and not married women.

According to Black *et al*. (2014), in an equilibrium model of local labor markets, the inequality measure should be the same across locations, if and only if, preferences are homothetic.[23] Moreover, even if preferences are homothetic, we have to include location fixed effects unless the employment distribution of gender is the same across locations. I begin with the following equation to measure the gender wage inequality:

$$ln(w_i) = \beta_0 + \beta_1 I_{M,i} + X + \epsilon_i \tag{1.9}$$

where $ln(w_i)$ is log hourly wage, and $I_{M,i}$ is an indicator variable equal to one, if individual i is a man. X is a set of control variables, including age and schooling.

Firstly, I examine the assumption of people having homothetic preferences. Under homothetic preferences, the gender wage ratio should be the same across locations since the inequality ratio does not depend on local prices. Therefore, β_1 will be a meaningful single estimator under homothetic preferences. If preferences are not homothetic, then instead of a single β_1, we would have different $\beta_{1,j}$, for each location j.

To examine whether the gender wage gaps are same across locations, I estimate the gaps separately for each of the 84 MSAs. Instead of listing all MSAs, I summarize them in Panel A of Table 8. For instance, the average of the 84 MSA gender-wage ratios for college graduates is 77.05 percent, which means that, in an average MSA, women's wages are 77.05 percent of men's wages. When we consider the wage ratio distribution across MSAs, the 5^{th} percentile of the 84 MSA gender wage ratios is 69.55, while the 95^{th} percentile is 83.81. Figure 5 provides graphical evidence that local gender wage ratios vary across location. Since gender wage ratios vary by locations, the preferences are likely not homothetic. Therefore, interpreting the gender wage gap with a single estimator β_1

[23] They define the inequality index in location j is the ratio of the wage for the minority group 1 relative to the wage of the majority group 0. Applying this to the gender wage ratio, the inequality index for location j is the women's wage in j divided by men's wage in j. In equilibrium condition, workers must be indifferent about their city of residence and their utility of living in different cities should be the same. With this in mind, inequality index I in location j can be written as,

$$I_j = \frac{w_j^{women}}{w_j^{men}} = \frac{e(p_j, u^{women})}{e(p_j, u^{men})}, \tag{1.8}$$

where $e(\ )$ is the expenditure function. When preferences are homothetic, expenditure functions take a separable form, so that the index does not depend on local prices. See Black *et al*.(2014) for details.

would be limiting. Instead of β_1, the gender wage inequality should be measured with $\beta_{1,j}$, where j represents each MSA.

Black *et al.* (2014) emphasize that even if we are willing to assume homothetic preferences, we have to include location fixed effects to measure gender wage inequality properly. Only when the employment distribution of genders is the same across cities, equation (9) without location fixed effects still gives an unbiased estimator β_1. Panel B of Table 8 summarizes the employment distributions of genders across MSAs by education level. As we can see, there are large differences in employment distribution of genders across MSAs. For example, the average of 84 MSAs in the employment distribution of genders for college graduates is 0.91, which means, on average, there are 0.91 men college graduates for every woman college graduate in the sample. The gender distribution for college graduates differs from 0.78 at the 5th percentile of the 84 MSAs (Providence-Warwic, RI-MA) to 1.05 at the 95th percentile (San Diego-Carlsbad, CA). Therefore, location fixed effects should be included to measure the gender wage inequality for an unbiased estimator even under homothetic preferences.

I next test how much does the failure to include location fixed effects, when estimating the national gender ratio matters. I first estimate the gender wage gaps *without* location fixed effects as shown in equation (9). Second, as Blau and Kahn (2017) include regions and metropolitan dummy variables in their regressions to estimate the gender wage gap, I simply control for three of the four census regions and include a dummy variable for residence in a metropolitan area:

$$ln(w_i) = \beta_0 + \beta_1 I_{M,i} + X + region_i + metro_i + \epsilon_i. \tag{1.10}$$

Next, I include location fixed effects (θ_j) for each MSA. Namely, for an individual i in MSA j, we can estimate the following equation:[24]

[24]Typical wage decomposition includes occupation and industry dummies. One concern is that occupation$\times$ gender distribution is not the same across cities (e.g., female-dominated elementary school teachers or nurses, male-dominated physicians), so there could be a possible selection bias. What I want to examine is not the decomposition of the gender wage gap holding all covariates constant, but given women's labor supply decisions across locations, what is the total gender wage gap including location controls. Therefore, including all occupation dummies may give an incorrect estimate for measuring the gender wage gap by locational effect. Following Black et al.(2013, 2014), I include most exogenous variables, age

$$ln(w_{ij}) = \beta_0 + \beta_1 I_{M,ij} + X + \theta_j + \epsilon_{ij}. \tag{1.11}$$

Table 9 summarizes the estimated gender wage gaps. I construct three different samples: 84 MSAs, 260 MSAs, and both 260 MSAs and non-MSA for estimations reported in Panels A, B, and C, respectively. I also report the results for three different categories in columns (1)–(3): all education levels, from high-school education to advanced degrees; HS education; and college education or above. In Panel B of 260 MSAs, the national gender wage gap *without* the location factor in column (1) is 0.2597.[25] Including regions and metropolitan area dummy variables reduces the gender wage gap to 0.2591. Finally, with location fixed effects, the estimated coefficient decreases further to 0.2549, by 0.0042.

To examine whether the estimated coefficient for higher education levels decreases more than for lower education level, I separately consider HS education and college education or above in columns (2)–(3). For high school education, the magnitude of decrease in the coefficient when including location fixed effects is small. On the contrary, the decrease in the coefficients when including location fixed effects are more pronounced for college education or above. When including 260 MSAs in Panel B, the coefficient for college education or above is reduced from 0.2538 to 0.2461, which is a decrease about 4 percent. Similarly, in case of Panel C, the coefficient for college education or above is reduced from 0.2540 to 0.2416, which is a decrease about 5 percent. These results suggest that controlling for locations reduces the gender wage gap significantly at higher education levels but not for lower education level.[26] Therefore, including location controls

and schooling. Nevertheless,I also estimate the regression for each skilled occupation group to check for robustness (not shown here) for college education or above. To ensure a sufficient number of observations, I construct 16 broad occupation groups following Cortés and Pan (2019) and estimate the regression for each group. The estimated results including location controls shows qualitatively similar results for 4 occupation groups, which comprises about 60 percent of the sample observations among the 16 groups. (executive, administrative, and managerial occupations; business and financial operations occupations; computer and mathematical occupations; and teaching and library occupations.)

[25]These estimates are in the form of log points that approximate percent when close to zero. To convert them into percent form, we need to use $e^{\beta} - 1$ formula. For example, 0.2695 log points is 29.65 percent. That is, men earn 29.65 percent more than women.

[26]For example, in Panel B of high school education, the confidence interval *without* location factor is $[0.2767, 0.2853]$ and the confidence interval *with* location factor is $[0.2754, 0.2838]$. There is no statistically significant difference between the gender wage gaps estimated with and without fixed effect. This supports the previous descriptive findings that there is no negative relationship between emp/pop and log wages across MSAs for less education level. On the other hand, the confidence interval for college education or

can reflect the different local employment patterns between men and women for high education level.

In summary, since highly-educated women in high-wage MSAs are under-represented and highly-educated women in low-wage MSAs are over-represented, the national average wage for women with higher education is under-estimated. As a result, the national gender wage gap with higher education is overstated without controlling the location factor. To confirm this hypothesis, I show that the gender wage gap *with* location controls reduces by 5 percent, compared to *without* location controls. Therefore, a failure to control for location factor can give us a misleading measure of the gender wage gap, given that highly-educated women work relatively less in high-wage cities.[27]

1.6 Conclusion

Using the 2016 ACS 5-year aggregate data, I find that there is a significant negative relationship between emp/pop and average log wages across MSAs, only for highly-educated women. Moreover, this negative relationship is mostly driven by married women with children. With these descriptive facts in mind, I conduct the counterfactual gender wage gap analysis by replacing the local women's employment weights with the men's employment weights, to examine what the gender wage gap would have been if women's local labor supply decisions were the same as the men's. I show that the log wage difference between men and women can be reduced by about 2 percent for people with an advanced-degree. Additionally, to test the significance for the negative relationship between emp/pop and log wages across MSAs for highly-educated women, I estimate the gender wage gap *with* location controls. Results show that the wage gap is indeed reduced, confirming the hypothesis that the national gender wage gap for high education level would overestimated due to the differences in women's labor supply decisions

above *without* location factor is [0.2506, 0.2569] and the confidence interval *with* location factor is [0.2431, 0.2492]. Confidence intervals do not overlap each other, so there is a statistically significant difference between the gender wage gap estimated with and without fixed effect. It confirms that there is a negative relationship between emp/pop and log wages across MSAs for higher education levels.

[27] We need to be careful in interpreting the national gender wage gap in Table 9 though, because it holds under the homothetic preferences assumption, which is not likely to happen in the real world.

across locations.

In addition, I emphasize the role of spouse's characteristics, such as the spouse's education, in labor supply decisions of women with children. Even holding women's education constant, I show that depending on spouse's education level, women's labor supply decisions by locations become different. In particular, there is a stronger negative relationship between emp/pop and log wages for women with highly-educated spouses, but a weak relationship for women with less-educated spouses. In this respect, this paper also can be linked to the literature on marriage matching, the family labor supply, and the family division of labor.

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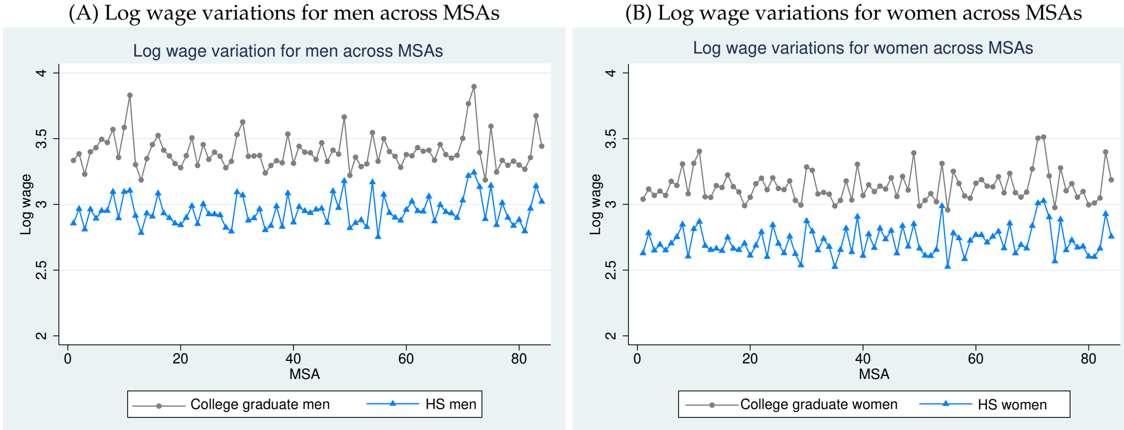
List of Appendices

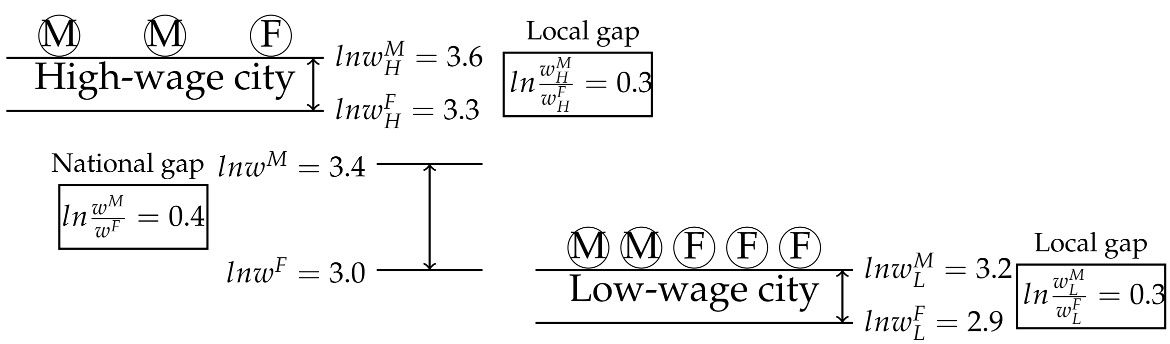
Figure 1.1: Log Wage Variations across MSAs by Education Level

(A) Log wage variations for men across MSAs (B) Log wage variations for women across MSAs



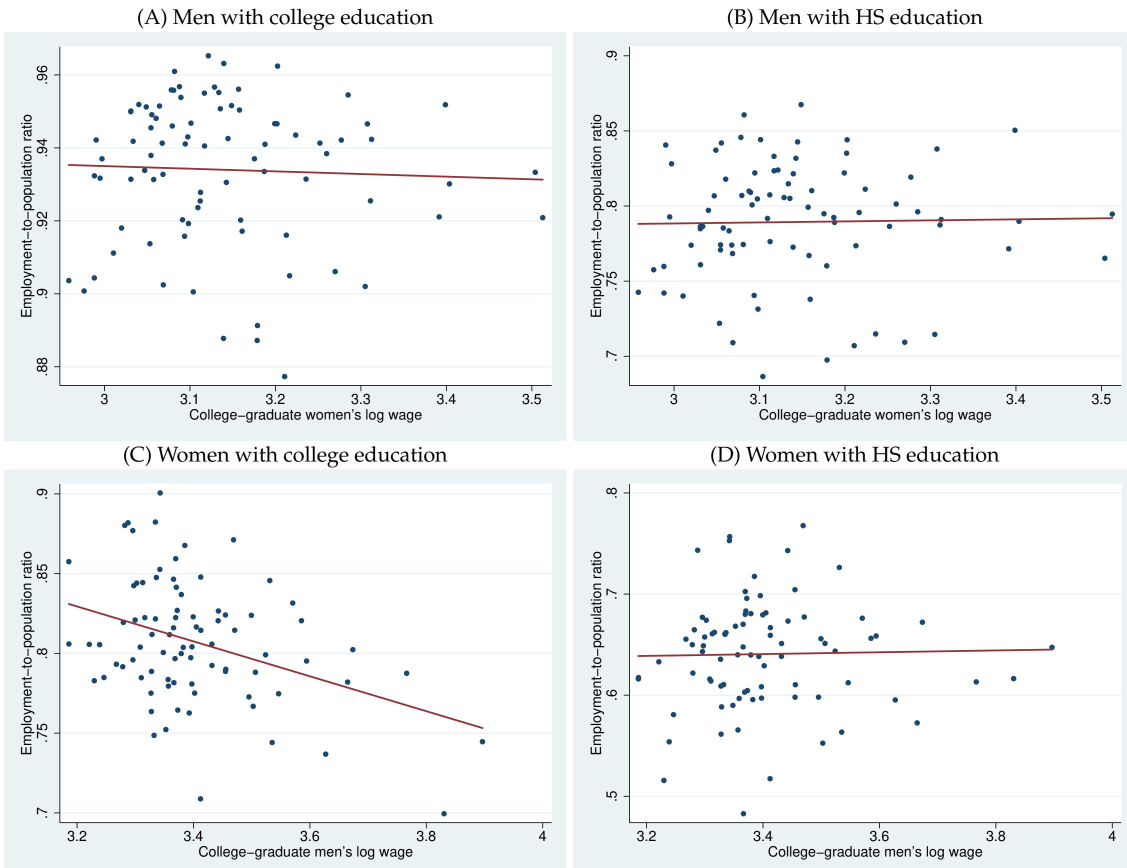
Notes: Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs. The unit of observation is an MSA.

Figure 1.2: The relation between national gender wage gap and local gender wage gaps



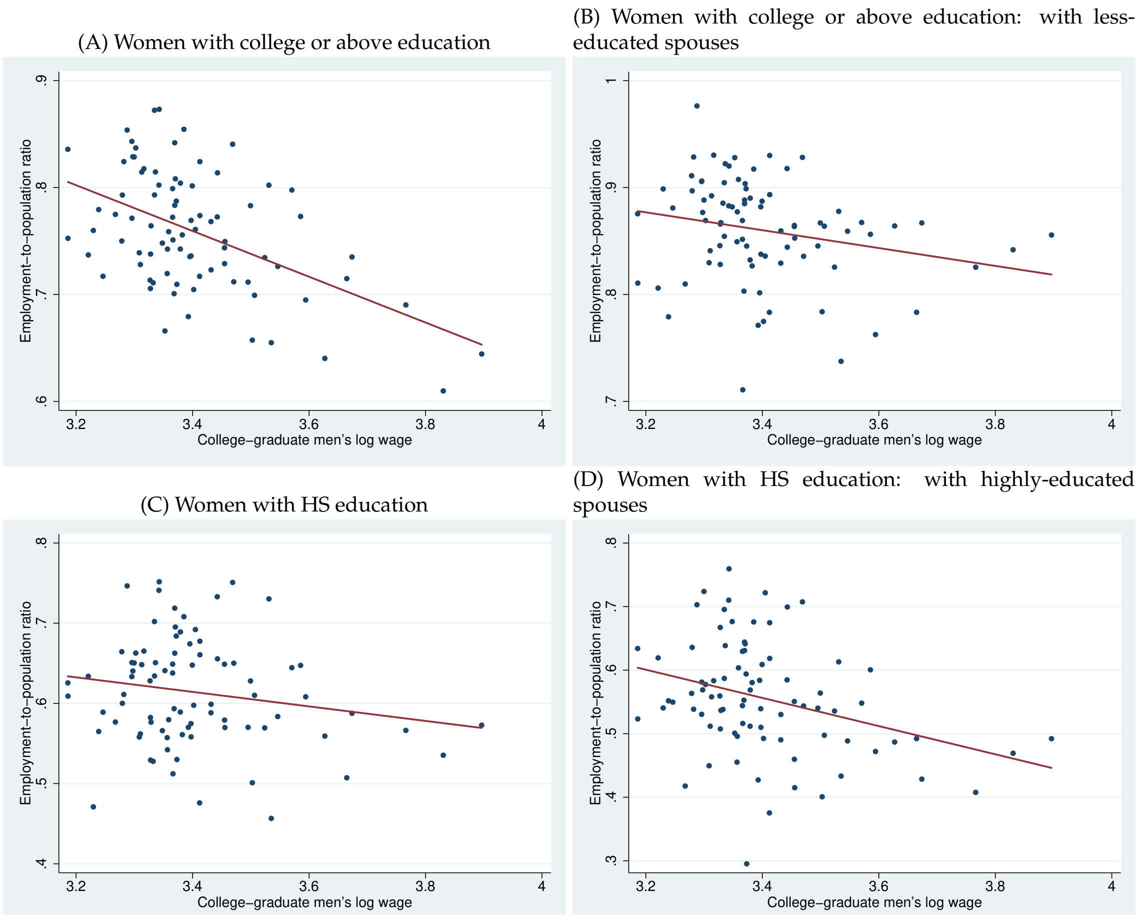
Notes: M refers a male worker and F refers a female worker. Suppose there are two cities—high-wage city and low-wage city and the local log wage differences between men and women are 0.3, which is the same for both cities. National weighted log wage for men would be 3.4, because two male workers work in each city. On the contrary, national weighted log wage for women would be 3.0, since more women work in low-wage city. Despite local log wage differences being 0.3 in both cities, due to the difference in the labor supply of women in the two cities, the national log wage difference would be wider as 0.4.

Figure 1.3: The Relationship between emp/pop and log wage across MSAs



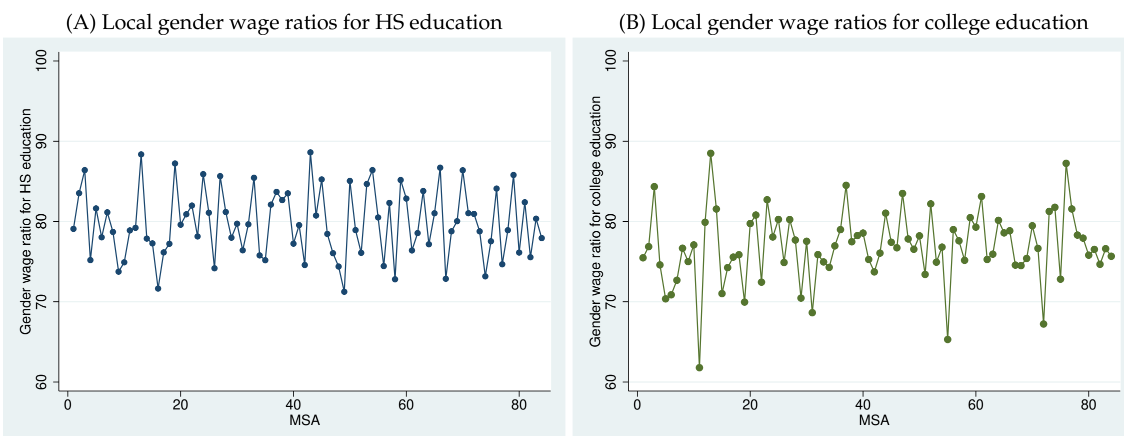
Notes: Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs. The unit of observation is an MSA.

Figure 1.4: The Relationship between Emp/Pop and Log Wage across MSAs: Married women with children



Notes: Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs. The unit of observation is an MSA. Highly-educated spouses refers those with college education or above. The less-educated spouses are those with HS education.

Figure 1.5: Gender wage ratios across MSAs by education levels



Notes: Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs. The unit of observation is an MSA.

Table 1.1: Schooling by gender and gender wage ratio by education level

Panel A: Schooling by gender			
	Men	Women	Difference (Men-Women)
Less than high school	2.20%	1.23%	0.97
High school	26.06%	20.52%	5.54
Some college	23.68%	24.23%	-0.55
College	31.10%	32.67%	-1.57
Advanced degree	16.96%	21.35%	-4.39
Panel B: Gender wage ratio by education level			
	Men's log wage	Women's log wage	Wage ratio
Less than high school	2.71	2.41	74.11
High school	2.98	2.74	78.24
Some college	3.13	2.91	79.86
College	3.48	3.20	75.75
Advanced degrees	3.73	3.44	74.85

Notes: Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs. Wage ratio is calculated as exp(log hourly wage for women of each education level minus corresponding log hourly wage of men)$\times$ 100. Numbers are weighted by individual weights given by the ACS.

Table 1.2: Log wage variations across MSAs by education levels

Panel A. Men				
	Mean	St.dev	Min	Max
High school education	2.95	0.11	2.75	3.24
Some college	3.10	0.10	2.92	3.38
College education	3.40	0.13	3.19	3.90
Advanced degrees	3.64	0.13	3.40	4.10
Panel B. Women				
	Mean	St.dev	Min	Max
High school education	2.72	0.11	2.52	3.03
Some college	2.88	0.10	2.71	3.19
College education	3.14	0.12	2.96	3.51
Advanced degrees	3.37	0.10	3.20	3.69

Notes: Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs.

Table 1.3: The relationship between emp/pop and log wage for each MSA

	(1) Advanced degree	(2) College	(3) Some college	(4) High school
Panel A. Dependent variable: men's emp/pop in each MSAs				
Log wage of men with college education	-0.010	-0.008	-0.019	0.005
	(0.013)	(0.015)	(0.026)	(0.033)
Unemployment rate	-0.003	-0.010***	-0.021***	-0.024***
	(0.002)	(0.002)	(0.003)	(0.004)
Observations	84	84	84	84
R^2	0.014	0.204	0.307	0.293
Panel B. Dependent variable: women's emp/pop in each MSAs				
	(1) Advanced degree	(2) College	(3) Some college	(4) High school
Log wage of men with college education	-0.111***	-0.121***	-0.057**	-0.019
	(0.028)	(0.027)	(0.029)	(0.032)
Unemployment rate	-0.004	-0.014***	-0.022***	-0.034***
	(0.004)	(0.005)	(0.005)	(0.004)
Observations	84	84	84	84
R^2	0.195	0.231	0.167	0.334

Notes: Robust standard errors in parentheses,* $p<0.10$, ** $p<0.05$, *** $p<0.01$. Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs. The unit of observation is an MSA.

Table 1.4: The relationship between women's emp/pop and wage across locations by marital status/presence of children

Panel A. Women with college education
Dependent variable: women's emp/pop in each MSAs

	Married		Not married	
	(1)	(2)	(3)	(4)
	Without children	With children	Without children	With children
Log wage of men with college education	-0.081**	-0.246***	0.003	-0.107***
	(0.038)	(0.038)	(0.023)	(0.037)
Unemployment rate	-0.004	-0.015**	-0.013***	-0.019***
	(0.005)	(0.006)	(0.004)	(0.004)
Observations	84	84	84	84
R^2	0.072	0.270	0.116	0.171

Panel B. Women with HS education
Dependent variable: women's emp/pop in each MSAs

	Married		Not married	
	(1)	(2)	(3)	(4)
	Without children	With children	Without children	With children
Log wage of men with college education	0.002	-0.117***	0.040	0.099*
	(0.048)	(0.039)	(0.037)	(0.055)
Unemployment rate	-0.026***	-0.032***	-0.033***	-0.036***
	(0.009)	(0.007)	(0.006)	(0.007)
Observations	84	84	84	84
R^2	0.115	0.217	0.310	0.291

Notes: Robust standard errors in parentheses,* $p<0.10$, ** $p<0.05$, *** $p<0.01$. Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs. The unit of observation is an MSA. Married is defined as married with spouse present, while not married is defined as the rest of the marital statuses—married with spouse absent, separated, divorced, widowed, or single/never married.

Table 1.5: Women's labor supply decisions across MSAs

Married women with children only Dependent variable: women's emp/pop in each MSAs				
	(1) Highly-educated	(2) Highly-educated with less-educ sp	(3) HS graduates	(4) HS graduates with high-educ sp
Log wage of men with college education	-0.222*** (0.036)	-0.100*** (0.036)	-0.117*** (0.039)	-0.235*** (0.051)
Unemployment rate	-0.009* (0.005)	-0.020*** (0.005)	-0.032*** (0.007)	-0.016* (0.008)
Observations	84	84	84	84
R^2	0.254	0.185	0.217	0.112

Notes: Robust standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01. Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs. The unit of observation is an MSA. Highly-educated women refers women with college education or above. Highly-educated spouses refers those with college education or above. The less-educated spouses are those with HS education.

Table 1.6: Individual-level regression, 84 MSAs

Dependent variable: y=1 if she is in the labor force				
	(1) Advanced degree	(2) College graduates	(3) Some college	(4) HS graduates
MSA college graduate men's log wage	-0.079*** (0.019)	-0.086*** (0.020)	-0.063** (0.030)	-0.038 (0.049)
Some college$_{sp}$ ×marriage	-0.012*** (0.004)	-0.009* (0.005)	-0.043*** (0.005)	-0.005 (0.005)
College graduates$_{sp}$ ×marriage	-0.065*** (0.004)	-0.108*** (0.006)	-0.106*** (0.006)	-0.063*** (0.007)
Advanced degree$_{sp}$ ×marriage	-0.114*** (0.006)	-0.198*** (0.009)	-0.203*** (0.009)	-0.150*** (0.013)
Controls				
Age FE	O	O	O	O
Marital status	O	O	O	O
Children dummies	O	O	O	O
MSA unemployment rate	O	O	O	O
N	154,731	241,462	177,860	175,761

Notes: Cluster standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01. Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs. High school dropouts are excluded due to the small sample size. The regressions are weighted using ACS individual weights.

Table 1.7: The counterfactual wage gap analysis

Panel A. Replacing women's employment weights with men's	(1) actual ln wage diff.	(2) predict ln wage diff.	(3) % change in ln wage diff.
HS education	0.245	0.244	-0.40
Some college	0.225	0.223	-1.01
College education	0.278	0.274	-1.47
Advanced degree	0.290	0.284	-1.93

Panel B. Replacing married women's employment weights with not married women's	(1) actual ln wage diff.	(2) predict ln wage diff.	(3) % change in ln wage diff.
HS education	0.245	0.243	-0.87
Some college	0.225	0.223	-0.68
College education	0.278	0.268	-3.46
Advanced degree	0.290	0.282	-2.65

Notes: Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs. Actual log wage difference is men's log wage minus women's log wage. Predicted log wage difference is men's log wage minus predicted women's log wage. Actual wage ratio is exp(women's log wage minus men's log wage)$\times$ 100. Predicted wage ratio is exp(predicted women's log wage minus men's log wage)$\times$100.

Table 1.8: Gender Wage Ratio and Employment Distribution of Gender by MSAs

Panel A.Local Gender Wage Ratio by Education Level	Mean	St.dev	5%	25%	50%	75%	95%
HS education	79.63	3.98	72.99	76.52	79.49	82.55	85.79
Some college	81.03	3.33	75.69	78.62	81.31	83.22	86.85
College education	77.05	4.17	69.55	74.51	76.67	79.43	83.81
Advanced degree	76.88	4.81	69.94	73.65	76.69	80.13	85.87

Panel B. Employment Distribution of Gender by Education Level	Mean	St.dev	5%	25%	50%	75%	95%
Total	0.98	0.06	0.88	0.94	0.98	1.01	1.09
HS education	1.32	0.13	1.14	1.24	1.32	1.41	1.54
Some college	0.98	0.12	0.81	0.87	0.96	1.06	1.22
College education	0.91	0.09	0.78	0.84	0.90	0.96	1.05
Advanced degree	0.68	0.11	0.52	0.60	0.68	0.74	0.88

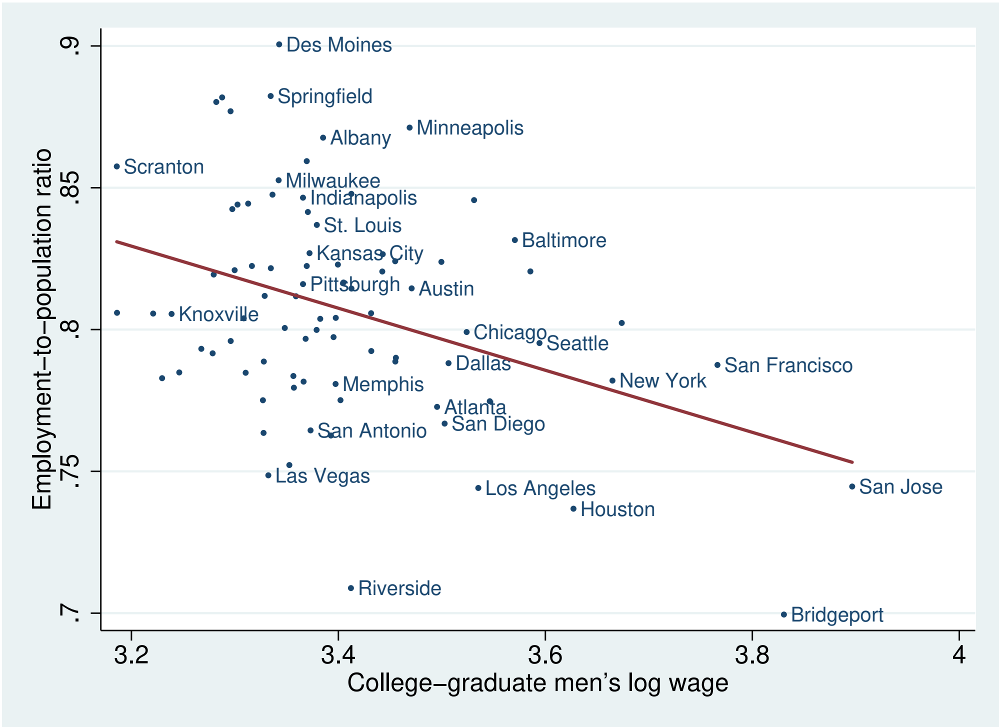
Notes: Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs. Wage ratio is calculated as exp(log hourly wage for women of each education level minus corresponding log hourly wage of men)$\times$100. Numbers are weighted by individual weights given by the ACS, then age-adjusted to control different age distributions across MSAs.

Table 1.9: Gender Wage Gaps in Log Hourly Wage

Panel A. 84 MSAs	(1) Total	(2) HS education	(3) College or above
Without location factor	0.2575	0.2722	0.2560
	(0.0013)	(0.0025)	(0.0018)
With region, metro dummy	0.2569	0.2719	0.2554
	(0.0012)	(0.0025)	(0.0017)
With location fixed effects	0.2535	0.2703	0.2503
	(0.0012)	(0.0025)	(0.0017)
Panel B. 260 MSAs	Total	HS education	College or above
Without location factor	0.2597	0.2810	0.2538
	(0.0011)	(0.0022)	(0.0016)
With region, metro dummy	0.2591	0.2807	0.2529
	(0.0011)	(0.0022)	(0.0016)
With location fixed effects	0.2549	0.2796	0.2461
	(0.0011)	(0.0021)	(0.0016)
Panel C. 260 MSAs + non-MSA region	Total	HS education	College or above
Without location factor	0.2695	0.2986	0.2540
	(0.0010)	(0.0018)	(0.0015)
With region, metro dummy	0.2665	0.3003	0.2474
	(0.0010)	(0.0017)	(0.0014)
With location fixed effects	0.2628	0.2992	0.2416
	(0.0009)	(0.0017)	(0.0014)

Notes: Robust standard errors are reported in parenthesis. Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs. Total refers workers from high-school education to advanced degrees. College or above refers workers with college education or advanced degree.

Figure A1.1: Emp/Pop of college-educated women with names of MSAs



Notes: Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs. The unit of observation is an MSA.

Table A1.1: Descriptive statistics by education level

Panel A: Men	Less than high school	High school	Some college	College	Advanced degrees
Sample size	25,950	203,890	163,291	217,087	126,151
Labor force participation	57.81	84.11	90.53	95.75	97.10
Employment-to-population ratio	49.87	79.13	86.92	93.60	95.54
Married with a spouse	0.37	0.50	0.55	0.63	0.72
With children	0.71	0.70	0.71	0.72	0.75
With children, under 5	0.18	0.20	0.25	0.28	0.30
Separated/widowed/divorced	0.23	0.18	0.14	0.08	0.08
With children	0.26	0.29	0.30	0.29	0.29
With children, under 5	0.04	0.04	0.04	0.04	0.03
Single/never married	0.41	0.32	0.30	0.29	0.20
With children	0.15	0.11	0.08	0.03	0.02
With children, under 5	0.06	0.05	0.04	0.01	0.01

Panel B: Women	Less than high school	High school	Some college	College	Advanced degrees
Sample size	20,752	185,656	183,309	244,947	156,730
Labor force participation	37.14	68.13	76.86	82.31	88.86
Employment-to-population ratio	30.94	63.82	73.47	80.24	87.25
Married with a spouse	0.42	0.57	0.58	0.64	0.67
With children	0.70	0.69	0.73	0.71	0.72
With children, under 5	0.17	0.14	0.20	0.27	0.30
Separated/widowed/divorced	0.31	0.24	0.22	0.12	0.11
With children	0.48	0.52	0.56	0.53	0.52
With children, under 5	0.07	0.07	0.08	0.07	0.06
Single/never married	0.27	0.20	0.20	0.25	0.22
With children	0.42	0.33	0.27	0.08	0.07
With children, under 5	0.16	0.13	0.11	0.03	0.02

Notes: The data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white men and women (including non-working) aged 25-55 in 84 MSAs. Summary statistics are weighted by individual weights given by the ACS.

Table A1.2: Robustness tests on the relationship between emp/pop and log wage for each MSA

Panel A. Dependent variable: women's emp/pop in each MSAs				
	(1) Advanced degree	(2) College	(3) Some college	(4) High school
Log wage of *women* with college education	-0.092**	-0.099***	-0.049	-0.002
	(0.036)	(0.034)	(0.038)	(0.042)
Unemployment rate	-0.003	-0.012**	-0.021***	-0.034***
	(0.004)	(0.005)	(0.005)	(0.004)
Observations	84	84	84	84
R^2	0.095	0.148	0.156	0.332

Panel B. Dependent variable: women's emp/pop in each MSAs				
	(1) Advanced degree	(2) College	(3) Some college	(4) High school
Log wage of men with advanced degree	-0.131***			
	(0.022)			
Log wage of men with college		-0.121***		
		(0.027)		
Log wage of men with some college			-0.030	
			(0.043)	
Log wage of men with high school				0.045
				(0.047)
Unemployment rate	-0.004	-0.014***	-0.021***	-0.034***
	(0.003)	(0.005)	(0.005)	(0.004)
Observations	84	84	84	84
R^2	0.282	0.231	0.147	0.341

Notes: Robust standard errors in parentheses,* $p<0.10$, ** $p<0.05$, *** $p<0.01$. Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs. The unit of observation is an MSA.

Table A1.3: Descriptive Statistics on Married Women with Children

Panel A. HS graduate married women with children			
	(1) Sample size	(2) Labor force participation	(3) Employment-to-population ratio
Total	75,364	63.55	60.41
With highly-educated sp	13,342	55.57	52.99
Panel B. Highly-educated married women with children			
	(1)	(2)	(3)
Total	192,878	76.21	74.64
With less-educated spouses	21,685	86.67	84.84

Notes: Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs.

A Model of Labor Supply with a Spouse and with Children

Consider here a standard consumption-leisure model. From the descriptive facts in Section 3, the negative relationship between the emp/pop and log wages across MSAs is mostly driven by married women with children. Hence, two conditions matter: 1) the effect of having a spouse on women's labor supply and 2) the effect of having children on women's labor supply. Woman's utility function is given by $u(c, \alpha\ell)$, where c is consumption, ℓ is leisure, α is equal to one if a woman doesn't have children and $\alpha > 1$ if a woman has children. By allowing the value of α is greater for women with children, the marginal utility of leisure for women with children is higher than that for women without children and thereby the marginal rates of substitution for women with children are steeper than that for women without children. Moreover, by allowing α is continuous for women with children, women have difference characteristics have different preferences of leisure. For example, women with more children or women with younger children have stronger preference of leisure than women with fewer children or women with older children.

There is one period and one representative consumer having the above utility function is strictly increasing, strictly concave and twice differentiable. Here the usual budget constraint, $c \leq w(1-\ell)$ where w is real wage and price of consumption is normalized as one, is modified by including spousal income, $I(w)$.

The budget constraint satisfies,

$$c \leq w(1-\ell) + I(w)$$

where $I(w)$ is equal to zero for a woman without a spouse and $I(w) > 0$ for a woman with a spouse. Assume that where the wage level is higher, the spouse income is also higher. i.e. $\frac{dI(w)}{dw} > 0$ and $I(w)$ is once differentiable. i.e $I'(w)$ is a constant positive number. Thus, a married woman has an additional endowment, which depends on different wage levels across locations.

Then, the consumer solves the following problem.

$$\max_{c,\ell} u(c, \alpha\ell)$$

subject to

$$c = w(1-\ell) + I(w).$$

Substituting the constraint into the objective function and differentiating with respect to ℓ gives the first-order condition

$$-wu_1(w(1-\ell) + I(w), \alpha\ell) + \alpha u_2(w(1-\ell) + I(w), \alpha\ell) = 0.^{28} \tag{1.12}$$

Now we examine the effect of wages across locations on leisure. Since we can't explicitly solve for ℓ as a function of w, apply the implicit function theorem and totally differentiate (11) with respect to w and ℓ to get

$$[-u_1 - w\{1-\ell+I'(w)\}u_{11} + \alpha\{1-\ell+I'(w)\}u_{21}]dw + [w^2u_{11} - 2\alpha w u_{12} + \alpha^2 u_{22}]d\ell = 0.$$

Then, we have

$$\frac{d\ell}{dw} = \frac{u_1 + \{1-\ell+I'(w)\}(wu_{11} - \alpha u_{12})}{w^2u_{11} - 2\alpha w u_{12} + \alpha^2 u_{22}}. \tag{1.13}$$

where $I'(w)$ is a positive constant number when she has a spouse and zero otherwise. Due to the strict concavity of utility function, the denominator is negative, but we cannot sign the numerator. We will consider two cases respectively, where the substitution effect dominates the income effect and the income effect dominates the substitution effect.

[28] Note that u_1 represents the derivative of the first term of the utility function and u_2 presents the derivative of the second term of the utility function.

The effect of having a spouse on women's labor supply

[29] **Case 1:** The substitution effect dominates the income effect. i.e. $\frac{d\ell}{dw} < 0$. In the case when the substitution effect dominates the income effect, a woman reduces leisure and increases working where the average wage is higher. The presence of a spouse's income causes the numerator in equation (12) to become less positive, so the $\frac{d\ell}{dw}$ is less negative. Therefore, where the average wage is higher, a woman with a spouse reduces leisure but the magnitude of reducing leisure is smaller, thus the magnitude of increase in working is also smaller.[30] It is worth emphasizing that a woman with a spouse *does* increase working where the average wage is higher, but not as much as a woman without a spouse when the substitution effect dominates the income effect.

Case 2: The income effect dominates the substitution effect. i.e. $\frac{d\ell}{dw} > 0$. In the case when the income effect dominates the substitution effect, a woman increases leisure and decreases working where the average wage is higher. The presence of a spouse's income causes the numerator in equation (12) to become more negative, so the $\frac{d\ell}{dw}$ is more positive. Therefore, where the average wage is higher, a woman with a spouse increases leisure and the magnitude of increase in leisure is bigger and the magnitude of decrease in working is also bigger.

The effect of having children on women's labor supply

Case 1: The substitution effect dominates the income effect. i.e. $\frac{d\ell}{dw} < 0$. In the case when the substitution effect dominates the income effect, a woman reduces leisure and increases working where the average wage is higher. Due to the increase in marginal

[29] I assume that the presence of children is constant, either having children or being without children, respectively, and examine the presence of a spouse on women's labor supply only. Thus, the utility function is the same but only the budget constraint is different by the presence of a spouse.

[30] Separating the total effect into the substitution effect and the income effect, we can notice that the presence of a spouse only affects the income effect and the size of the income effect gets bigger when she has a spouse. i.e. when the wage level goes up, she is more likely to consume leisure and reduce working.

utility of leisure in the presence of children, now the slope of leisure demand changes as α changes. By the assumption, the numerator in equation (12) is positive, so the effect of the presence of children on women's labor supply is the following:

$$\frac{\partial \frac{d\ell}{dw}}{\partial \alpha} = \frac{\{-(1-\ell+I'(w))u_{12} \overbrace{[den]}^{negative} \} - \{ \overbrace{[num]}^{positive}(-2wu_{12}+2\alpha u_{22})\}}{den^2} > 0. \tag{1.14}$$

Therefore, where the average wage is higher, a woman with children reduces leisure and the magnitude of reducing leisure is smaller, thus the magnitude of increase in working is also smaller.

Case 2: The income effect dominates the substitution effect. i.e. $\frac{d\ell}{dw} > 0$. In the case when the income effect dominates the substitution effect, a woman increases leisure and decreases working where the average wage is higher. By the assumption, the numerator in equation (12) is negative, so the effect of the presence of children on women's labor supply is the following:

$$\frac{\partial \frac{d\ell}{dw}}{\partial \alpha} = \frac{\{-(1-\ell+I'(w))u_{12} \overbrace{[den]}^{negative} \} - \{ \overbrace{[num]}^{negative}(-2wu_{12}+2\alpha u_{22})\}}{den^2}. \tag{1.15}$$

In this case, the sign is ambiguous. However, to correspond with the data which shows that a woman with children increases leisure and the magnitude of increasing in leisure is larger, we can conjecture the direction in equation (14).

To summarize, the theory predicts that a woman with a spouse work relatively less in high-wage cities compared to a woman without a spouse regardless of whether the income or the substitution effect dominates. In the model where the presence of children affects women's labor supply, depending on the size of the substitution and the income effect, the results are different. When the substitution dominates the income effect, the effect of children on women's labor supply in high-wage city is clear: women with children are work relatively less than women without children. When the income effect dominates the substitution effect, the theory predicts that the effect of children on women's labor supply in high-wage city is ambiguous. However, using the data which shows that women with children are likely to work less in high-wage city, we can conjecture the direction of the effect of presence of children on women's labor supply.

Chapter 2

High-Hours Occupations, Timing of Fertility, and Labor Supply of Skilled Women

2.1 Introduction

After childbirth, women often reduce their labor supply such as dropping out of the labor force or working fewer hours (Bertrand et al. 2010; Goldin 2014; Kuziemko et al. 2018). Since the change in female employment due to childbirth is associated with life-cycle perspective earnings (Bertrand et al. 2010; Goldin 2014; Kleven et al. 2019), *when* to have a child—the timing of fertility can have a strong impact on future employment and earnings (Miller 2011; Wilde et al. 2010). For example, Rindfuss et al. (1996) show that, compared to less-educated women, college-educated women dramatically shifted their fertility toward older ages due to the higher opportunity cost of taking care of children. In the other direction, Miller (2011) shows that delaying fertility leads to a substantial increase in earnings, as women can accumulate more human capital the longer they work, especially if they are college educated.

Given that different occupational characteristics such as working long hours, flexibility, or competitive pressure play an important role in explaining women's career or labor supply decisions (Cha 2013; Cha and Weeden 2014; Cortés and Pan 2017 ; Goldin and Katz 2016; Yu and Kuo 2017), the type of occupation a woman has can be a key to understanding the timing of fertility. For example, prevalence of working long hours can affect the timing of fertility. In respect to time constraints for married mothers who balance both career and household work (Jacobs and Gerson 2004; Stone 2007), it is worth exploring how working long hours affects women's timing of fertility and labor supply after childbirth. Moreover, once a woman's career is interrupted by childbirth, it takes a while for her to adapt to work upon returning.[1] Because occupations differ in the extent to human capital depreciation, the costs of career interruptions after childbirth would vary substantially across occupations. Therefore, it is also important to consider how occupational characteristics, especially related to human capital depreciation, can affect the timing of fertility.

In this paper, I study how occupational characteristics can delay fertility and how women's labor supply after childbirth depends on the timing of fertility and occupations. As a main and starting point of occupational characteristics, I use working long hours, measured by the share of men working 50 or more hours per week. Then additional occupational characteristics related to human capital depreciation are considered. Thus, my empirical analysis focuses on three parts: 1) the relationship between high-hours occupations and women's age at first birth to examine whether job structures requiring working long hours cause women to delay their fertility; 2) the relationship between occupational features requiring larger human capital depreciation and women's delaying fertility; 3) employment after childbirth by considering the timing of fertility and their occupations.

Before the empirical analysis, I present a simple theoretical framework to understand how the human capital depreciation affects the timing of fertility and labor supply after childbirth. Based on a model from Fernández, Fogli, and Olivetti (2002) where utility

[1] Previous literature shows that human capital depreciates during a woman's career interruption (Mincer and Polachek 1974; Mincer and Ofek 1982), and other literature emphasizes the importance of continuous work experience in earnings and wages (Light and Ureta 1995; Miller 2011).

consists of only consumption and childcare, I extend the model into three periods. In the model, a married woman decides the timing of fertility in either period 1 or period 2 as well as labor supply in every period. The married woman with a child splits her time endowment into market production and childcare, while a married woman before giving birth spends her entire time endowment only for market production. I assume that her wage rate after childbirth decreases to reflect the human capital depreciation, where the magnitude of depreciation rate varies across occupations. I show that a woman is more likely to delay fertility when her occupation has a higher depreciation rate in human capital. In addition, I show that a woman, who delays fertility in larger depreciation rate in human capital, is more likely to reduce her labor supply after childbirth.

To provide suggestive empirical evidence of the theoretical prediction, I use several US data: the 1980–2000 Census, the 2011 American Community Survey (ACS) three-year aggregate (2009–2011), the 2017 ACS five-year aggregate (2013–2017), the Occupational Information Network (O*NET), and the National Longitudinal Survey of Youth 1997 (NLSY97).

First, using 95 skilled occupations over four decades from the Census and ACS, I find that women working in high-hours occupations are likely to delay their fertility, focused on those who are aged 25–40, married, and have a bachelor's or advanced degree(s). Interestingly, this result is robust when excluding graduates, suggesting women do not simply delay their fertility due to additional schooling. One concern is reverse causality; i.e., more women who delay fertility in an occupation drive the prevalence of working long hours. By including a lead variable of the share of men working high-hours at time t+1, following Cortés and Pan (2016), I provide evidence that the relationship between high-hours occupations and delaying fertility is not entirely driven by reverse causality. I also address the concern of selection bias; i.e., women who are more work-oriented or prefer to remain childless voluntarily choose high-hours occupations. In my analysis, women in high-hours occupations have a rather higher probability of having one or more children, which is the opposite direction of the self-selection concern.

Next, I provide one suggestive explanation of delaying fertility with respect to human capital depreciation, in addition to time constraint. By merging various occupational characteristics in O*NET and the recent 2017 ACS five-year aggregate, I also observe a tendency of delaying fertility in occupations that require active interpersonal relationships, high levels of autonomy, and high competitiveness. Human capital depreciation may explain this connection as theoretical results predict. Since human capital is assumed to depreciate more in these occupations when careers are interrupted, I suggest that delaying fertility can be understood in the context of job continuity and lifetime earnings.[2]

Given that it seems to be rational for women in high-hours occupations to delay fertility, would women who delay fertility return to their occupations after childbirth? If not, would they drop out of the labor force or reduce their working hours? To answer these questions, I examine whether labor supply changes after childbirth are affected by the timing of fertility and their occupations using two different data: 1) a panel construction using the Census and ACS and 2) the NLSY97.

With the Census and ACS, I use the occupational distribution as a proxy for observing individuals who either switch occupations or drop out of the labor force in light of existing literature (Cunningham and Zalokar 1992; Gabriel and Schmitz 2007; Cortés and Pan 2017; Kosteas 2019). This distribution is measured as the share of a given group working in a particular occupation. Then to consider the employment change after the first birth, I examine the *change* in occupational distribution as women get older. The results show that women who delay fertility are more likely to exit high-hours occupations, while women who give birth early do not have any distinct tendency to exit their occupations. One potential explanation of this result is that motherhood could be more of a burden than expected due to time constraints from balancing both career and family (Bertrand 2013; Kuziemko et al. 2018). Especially, the difficulty of balancing could be the case for women who delay fertility in high-hours occupations.

Finally, using the NLSY97, I track women's employment changes at the individual level. I confirm that there is a positive and significant interaction between high-hours occupations and delaying fertility on employment changes, such as dropping out of the labor force and reducing working hours.[3] By analyzing each employment status, I find

[2] I define human capital as the job expertise obtained by continuing a career, within similar education level.

[3] Due to the small sample size, high-hours occupations and delaying fertility are defined as dummy

that women tend to not only drop out of the labor force but also reduce working hours after their first childbirth. In respect to human capital accumulation, this decrease in working hours seems to be rational, since women can continue their careers. Thus, both analyses using the Census/ACS and the NLSY97 consistently show that women who delay fertility while working in high-hours occupations are more likely to reduce their labor supply after their first childbirth.

This paper is closely related to the literature on fertility decisions. Many prior studies examine fertility in respect to education (Amin and Behrman 2014; Baudin et al. 2015; Brewster and Rindfuss 2000; Rindfuss et al. 1996). Most of these papers show that compared to less-educated women, highly educated women have less fertility and bear children at later ages. While the aforementioned studies show the link between education and fertility, Miller (2011) and Wilde et al. (2010) show that delaying fertility increases wages and earnings of mothers in the US as women can accumulate more human capital. Although widely developed models analyze total fertility/fertility timing with education levels and/or earnings, the literature on the relationship between delaying fertility and occupational characteristics is limited. Adda et al. (2017) view that expectation about future desired fertility affects the women's choice of occupations, because skill depreciation varies across occupations. On the contrary, I assume that women consider the timing of fertility after developing their human capital first (education and occupations) as the similar view with Kuziemko et al. (2018).[4] Kuziemko et al. (2018) point out that dynamic labor supply model simply assumes that women fully anticipate human capital and fertility decisions, which is not likely in their empirical evidence.

This paper also contributes to the recent literature on employment of married mothers. Cha (2013) and Cortés and Pan (2016, 2017) find that mothers working in overwork or male-dominated occupations are more likely to exit the occupation or drop out of the labor force, but these studies do not address the timing of fertility or employment after childbirth. Fitzenberger et al. (2013) estimate the average treatment effect on the treated

variables.

[4]Using German data, Adda et al. (2017) show that a woman who knows she will remain childless is more likely to work in occupations with abstract tasks rather than routine and manual occupations. However, their sample is limited to women who attend lower/intermediate-track schools (ending after grades 9 and 10 and without high-track schools), and the analysis also focuses on total fertility, not the timing of fertility.

on employment, where treatment is first childbirth now against waiting using German data. They find that the causal effect of childbirth on female labor supply is large and persistent over time. Kuziemko et al. (2018) show that women in the US and UK experience a substantial drop in employment after their first childbirth. While Fitzenberger et al. (2013) or Kuziemko et al. (2018) consider the employment effect after the first birth, their analysis more focus on by different education level, not across occupations. Bertrand et al. (2010) or Goldin (2014) show that MBA female graduates experience job interruptions and reduction in working hours due to the presence of children, and those factors can account for future lower earnings path.

The rest of the paper is organized as follows. Section 2 presents a simple model of human capital depreciation, timing of fertility, and labor supply after childbirth. Section 3 introduces the data and descriptive statistics. Section 4 examines the relationship between high-hours occupations and women's average age at first birth. Section 5 explores the occupational characteristics related to human capital depreciation. Section 6 discusses employment changes after the first childbirth, depending on the timing of fertility and their occupations. Section 7 concludes.

2.2 Theoretical Framework

2.2.1 Model

In this section, I discuss the theoretical background to understand how the depreciation rate in human capital affects the timing of fertility and labor supply after childbirth. I construct a model based on Fernández, Fogli, and Olivetti (2002) and extend it into three periods. In the model, a married woman decides the timing of fertility between the period 1 and 2 as well as labor supply in every period.[5] The married woman can provide both market production and childcare, while the spouse can only provide market production. They consume the whole earnings from the market production in every period.

I introduce a woman's utility in each period t which consists of consumption plus

[5]Since my empirical work examines the timing of fertility, not the total fertility, I assume that a woman will have a child in either period 1 or 2.

childcare as below:

$$\max_{c_t,h_t} u_t = c_t + (1-h_t)^{\frac{1}{2}},$$

the budget constraint satisfies $c_t = w_t h_t$, where w_t is the wage rate for a woman in period t, h_t denotes the time spent on the market production, and $1-h_t$ represents the time spent on the childcare.[6] Substituting the budget constraint into the utility function gives,

$$\max_{h_t} u_t = w_t h_t + (1-h_t)^{\frac{1}{2}}.$$

The utility is linear in market production (and thus market earnings) and strictly concave in childcare, because childcare can only be provided by a woman, while consumption is still available with spouse's income. Therefore, the marginal utility for initial time spending in childcare (as h $\rightarrow$ 1) is greater than the marginal utility in market production.[7]

The lifetime utility is the sum of utilities in each period. I assume that the wage rate w does not change over time before she gives birth. After giving birth, her wage rate in the following period is lowered by the proportion ρ to reflect the less accumulated human capital by spending time on childcare. In the model, the married woman with a child splits her time endowment into market production and childcare, while a married woman before giving birth spends her entire time endowment only for market production.

$$U^i = u_1^i + u_2^i + u_3^i,$$

for $i = \{e, \ell\}$, e denotes early fertility and ℓ represents late fertility.

Suppose that a woman has early fertility in period 1. Since she gives birth in period 1, the utility in period 1 includes childcare and the wage rate in period 2 is lowered into ρw.

[6] The budget constraint for a married woman should be $c_t = w_t h_t + N$, where N is a non-labor income, i.e., a husband's earnings. Since the husband is independent with the timing of fertility, his income is assumed to be fixed as N over time. In this analysis, N does not affect a woman's timing of fertility and labor supply, I will drop N.

[7] The main results do not change even though the utility is assumed to be strictly concave in consumption, as long as the marginal utility in childcare is greater than the marginal utility in market production.

The maximization problem is as follows:

$$\begin{aligned}\max_{h_1^e,h_2^e,h_3^e} U^e &= u_1^e + u_2^e + u_3^e \\ &= \{wh_1^e + (1-h_1^e)^{\frac{1}{2}}\} + \{\rho w h_2^e + (1-h_2^e)^{\frac{1}{2}}\} + \{\rho w h_3^e + (1-h_3^e)^{\frac{1}{2}}\}.\end{aligned} \tag{2.1}$$

The first order conditions with respect to h_1^e, h_2^e, and h_3^e are

$$\begin{aligned} w - \frac{1}{2}(1-h_1^e)^{-\frac{1}{2}} &= 0, \\ \rho w - \frac{1}{2}(1-h_2^e)^{-\frac{1}{2}} &= 0, \\ \rho w - \frac{1}{2}(1-h_3^e)^{-\frac{1}{2}} &= 0. \end{aligned}$$

Therefore we have the solutions, $h_1^e = 1 - (\frac{1}{2w})^2$, $h_2^e = h_3^e = 1 - (\frac{1}{2\rho w})^2$.[8] Note that compared to h_1^e, she reduces her labor supply in period 2, due to the depreciated wage, ρw.

On the other hand, now suppose that a woman has late fertility in period 2. Since she does not give birth in period 1, the utility in period 1 only comes from the market production, and the wage rate remains at w in period 2 and then decreases to ρw in period 3. The maximization problem is as follows:

$$\begin{aligned}\max_{h_2^\ell,h_3^\ell} U^\ell &= u_1^\ell + u_2^\ell + u_3^\ell \\ &= w + \{wh_2^\ell + (1-h_2^\ell)^{\frac{1}{2}}\} + \{\rho w h_3^\ell + (1-h_3^\ell)^{\frac{1}{2}}\}.\end{aligned} \tag{2.2}$$

Since she spends her time only for market production in period 1, $h_1^\ell = 1$ in this case. Then, we have solutions, $h_2^\ell = 1 - (\frac{1}{2w})^2$ and $h_3^\ell = 1 - (\frac{1}{2\rho w})^2$. Notice that $h_2^\ell > h_2^e$, because the wage for a woman who delays fertility remains the same as w. After the childbirth, the wage decreases to ρw in period 3, so $h_3^\ell = h_3^e$.

[8]To satisfy the interior solution, $h_t^e \in (0,1)$, for $t = 1,2,3$, $w > \frac{1}{2}$ in period 1, $w > \frac{1}{2\rho}$ in period 2 and 3 are required.

2.2.2 Timing of Fertility

The lifetime utilities for women who has early fertility and who has late fertility can be calculated as U^{ℓ}, U^{e}:

$$U^{\ell} = w + \left[w\Big\{1 - \Big(\frac{1}{2w}\Big)^2\Big\} + \frac{1}{2w}\right] + \left[\rho w\Big\{1 - \Big(\frac{1}{2\rho w}\Big)^2\Big\} + \frac{1}{2\rho w}\right] \tag{2.3}$$

$$U^{e} = \left[w\Big\{1 - \Big(\frac{1}{2w}\Big)^2\Big\} + \frac{1}{2w}\right] + \left[\rho w\Big\{1 - \Big(\frac{1}{2\rho w}\Big)^2\Big\} + \frac{1}{2\rho w}\right] + \left[\rho w\Big\{1 - \Big(\frac{1}{2\rho w}\Big)^2\Big\} + \frac{1}{2\rho w}\right] \tag{2.4}$$

Therefore, an individual woman decides to have late fertility if and only if $U^{\ell} > U^{e}$. By subtracting eq.(4) from eq.(3), we have

$$\begin{aligned} U^{\ell} - U^{e} &= \underbrace{-\frac{1}{4w}}_{A<0} + \underbrace{\left[w\Big\{1 - \Big(\frac{1}{2w}\Big)^2\Big\} + \frac{1}{2w} - \rho w\Big\{1 - \Big(\frac{1}{2\rho w}\Big)^2\Big\} - \frac{1}{2\rho w}\right]}_{B>0} \\ &= -\frac{1}{4w} + \left[(1-\rho)w + \frac{1}{4w}(1 - \frac{1}{\rho})\right]. \end{aligned} \tag{2.5}$$

Term A in equation (5) is the utility loss from not having a child in period 1. Since the marginal utility for the childcare is greater than that for the market production, the woman who has late fertility has the lower utility in period 1 than the woman who has early fertility. On the contrary, term B in equation (5) is the utility gain from receiving the same wage, w, without depreciation of wage in period 2. Note that term B is always strictly positive because the utility in period 2, $u_2 = w\Big\{1 - \Big(\frac{1}{2w}\Big)^2\Big\} + \frac{1}{2w}$, increases with w and the wage rate falls into ρw when she gives birth early.[9]

Now I can consider how the timing of fertility is affected by the depreciation rate of human capital. Taking a derivative with respect to ρ gives,

[9] Given the utility function in period 2,

$$u_2 = w\Big\{1 - \Big(\frac{1}{2w}\Big)^2\Big\} + \frac{1}{2w} = w + \frac{1}{4w},$$

by taking a derivative with respect to w, we have

$$\frac{\partial u_2}{\partial w} = 1 - \frac{1}{4w^2} = 1 - \Big(\frac{1}{2w}\Big)^2 > 0.$$

$$\frac{\partial(U^\ell - U^e)}{\partial \rho} = -w + \frac{1}{4\rho^2 w} = -w\Big\{1 - (\frac{1}{2\rho w})^2\Big\} = -wh_2^e < 0.$$

Therefore, when ρ decreases, the utility gain from delaying fertility is relatively larger. Hence, a woman is more likely to delay fertility when her occupation has a higher depreciation rate in human capital.

2.2.3 Labor Supply after Childbirth

Previously, I show that when ρ is relatively low, a woman is more likely to have late fertility. Let's consider two different cases with ρ_l and ρ_h, where $\rho_l < \rho_h$. If the depreciation rate is low as ρ_l, the woman will choose to delay fertility, whereas if it is high as ρ_h, she will choose to give birth early. Therefore, we can check how the labor supply after childbirth depends on both the human capital depreciation and the timing of fertility by comparing these two cases.

In the case that a woman has late fertility with ρ_l in period 2, labor supply after childbirth is $h_3^\ell = 1 - (\frac{1}{2\rho_l w})^2$, whereas if a woman has early fertility with ρ_h in period 1, labor supply after childbirth is $h_2^e = 1 - (\frac{1}{2\rho_h w})^2$. Notice that a woman who delays fertility with ρ_l is more likely to reduce labor supply because of $\rho_l < \rho_h$.

In summary, my theoretical results predict that a woman is more likely to delay fertility as her human capital depreciates more upon returning to work after childbirth. Moreover, a woman who delays fertility in larger depreciation rate in human capital is more likely to reduce her labor supply after childbirth.

2.3 Data and descriptive statistics

2.3.1 US Census and American Community Survey

For the main analysis, I use data from the 1980, 1990, and 2000 US Census; the 2011 ACS three-year aggregate; and the 2017 ACS five-year aggregate.[10] The sample consists of

[10] I refer to the 2011 ACS data as corresponding to the 2010 time period.

native-born individuals with at least a bachelor's degree who are working full time (35 hours or more) and for wages.[11] To construct a consistent set of occupations over the survey time periods, I use Dorn's (2009) occupation classification.[12] Following Cortés and Pan (2019), I then limit the sample to those who work in 95 skilled occupations.[13] I define working high-hours as working 50 or more hours per week, and construct the share of men working high-hours in an occupation among college-educated men aged 25–55 (Kuhn and Lozano 2008; Cha and Weeden 2014; Cortés and Pan 2016). Age at first birth is calculated as a woman's current age minus the oldest child's age among married women with children.[14]

Table 1 summarizes the descriptive statistics for the Census and ACS data. Panel A shows that for married women with children, there are modest increases in average age, having an advanced degree (master's/doctoral and professional degree), and age at first birth from 1980 to 2017.[15] Panel B shows that at the occupation level, age at first birth increases over time, from 26.61 in 1980 to 29.04 in 2017. The share of men working 50 or more hours also significantly increases, especially until 2000. For example, in 1980 this ratio was 0.29; it increased to 0.43 in 2000 and then decreased to 0.35 in 2017.[16]

The share of men working high-hours varies across occupations, as shown in Table A2. In 2010, for example, physicians, chief executives, lawyers, financial specialists, and marketing specialists have relatively high shares of men working high-hours. The change in this share from 1980 to 2010 also varies by occupations. Over the time period, chief executives (32.7 percent) have the largest increase in share of men working high-hours, and other occupations such as engineers, financial specialists, lawyers, and human resources

[11] Flags for occupation and women's age are dropped from the sample.

[12] In addition to Dorn's occupation classification, occupation codes are modified using the crosswalk between 2009 ACS and 2010–2011 ACS from Integrated Public Use Microdata Series (IPUMS).

[13] Cortés and Pan (2019) define skilled occupations as satisfying at least two of the following three conditions: 1) managerial and professional specialty occupations (codes 3-200), 2) share of college-educated workers in 2010 is higher than the share of college-educated workers in the working population, and 3) men's median income in 2010 is greater than that across occupations. Table A2 provides a list of the 95 skilled occupations.

[14] Age at first birth below 21 is excluded from the sample, since the paper focuses on the timing of fertility for working women.

[15] See Table A1 for summary statistics of individual-level married men with children.

[16] This trend on the share of working high-hours is consistent with Kuhn and Lozano (2008). Using the Current Population Survey (CPS) from 1979 to 2006, they find that the increase in working long hours was the strongest before 1990 and reversed somewhat after 2000.

managers show a relatively large increase in prevalence of working long hours. On the contrary, librarians, social workers, registered nurses, teachers, and pharmacists have relatively low share of men working high-hours. Over time, pharmacists see a large decline in prevalence of working long hours (–14.7 percent). Similarly, funeral directors, religious workers, veterinarians, and respiratory therapists also see a decrease in prevalence of working long hours over time.

Figure 1 illustrates the trend in women's average age at first birth by year/education level, which is the main interest variable in this paper. The figure shows an increase in women's age at first birth for all education levels over the past few decades. Within the same education level, women's average age at first birth increases over time, especially for highly educated women (college graduates and advanced degree graduates). For example, the increase in women's age at first birth for high school graduates from 1980 to 2017 is 0.9 years, whereas the increases in women's age at first birth for college graduates and advanced degree graduates are 2.3 and 3.0 years, respectively. Moreover, the gap in ages at first birth between less-educated and highly educated women increases over time. For instance, there was a 3.3-year gap between high school graduates and college graduates in 1980, whereas the gap increased to 4.7 years in 2017. These results show that mostly highly educated women appear to delay fertility over time.

2.3.2 Occupational Information Network

I use the O*NET to understand the occupational characteristics of high-hours occupations (version 23.0, released in 2018). The O*NET is a database containing hundreds of occupation-specific descriptions. From two classifications of "work context" and "work activities," I choose eight occupational characteristics related to human capital depreciation. Then I divide into three categories: interpersonal relationships, autonomy, and competitiveness. The O*NET creates indexes for occupational characteristics by averaging responses—on a 1–5 scale in most cases (e.g., time pressure 1: never; 5: everyday). Since the O*NET occupation codes are different from those in the ACS, I first match them using the crosswalk from the IPUMS and the O*NET. If one occupation code in the ACS corresponds to several O*NET codes, O*NET characteristics are weighted by the number of sample in each O*NET category.[17] Each of the O*NET characteristics are normalized to have a mean of zero and a standard deviation of one.

2.3.3 National Longitudinal Survey of Youth 1997

To examine labor supply changes after childbirth, I use the NLSY97, a panel data set that covers 8,984 individuals. Respondents were born between 1980 and 1984 and were 32–38 at the time of last survey year in 2017. They were interviewed annually from 1997 to 2010 and then biannually from 2011. I focus on married college-educated women who gave birth after age 22, were working full time, and were not self-employed at the year of their first birth.[18] Women who divorced, separated, or were widowed after their first childbirth are excluded from the sample. Women who gave birth in 2012, 2014, or 2016 are dropped due to the biannual survey construction, and women who gave birth in 2017 are also dropped because changes in employment status after childbirth are not observable.

Table 2 provides summary statistics for the NLSY97. The total number of observations is 750 with 199 individuals, so the average of employment status is 3.8 times per person. Among changes in employment status, the percentage of those dropping out of the labor force is 9 percent and the percentage of those switching an occupation and workplace is 11 percent.[19] Reducing working hours are the most common changes in employment status after childbirth: the percentage of those switching to part time (less than 35 hours per week) is 13 percent, and the percentages of those reducing their working hours by more than 5 hours or 10 percent are 25 percent, respectively.

[17]For example, the post-secondary teacher in the ACS corresponds to several codes in the O*NET, such as business teachers, computer science teachers, and math science teachers.

[18]Survey years from 2003 are included in the sample when oldest respondents became age 22.

[19]I consider both changes in occupation and workplace together because the change in occupation can also occur due to a promotion in the same workplace. Note that the information on workplace comes from the weekly employment number provided in the NLSY97.

2.4 High-hours occupations and women's average age at first birth

In this section, I discuss how occupational characteristics affect women's timing of fertility. As a main measure of occupational characteristics, I use working long hours, as measured by the share of men working 50 or more hours per week.[20] Kuhn and Lozano (2008) find that in the US, working long hours is increasing over time, especially for college-educated, salaried men. Though the increase in working high-hours reversed somewhat after 2000 in the US, its prevalence still remains still higher than in other countries (Cortés and Pan 2016). Cortés and Pan (2017) use the prevalence of working 50 or more hours as a proxy for workplace inflexibility and Cha (2013) mentions that occupations with working long hours are mostly male-dominated.[21] Prevalence of working long hours is also discussed as the reason for persistent earnings gap (Bertrand et al. 2010; Cha and Weeden 2014; Goldin and Katz 2011).

Since high-hours occupations are more likely to cause time constraints for married mothers who, unlike men, need to balance career and household work (Jacobs and Gerson 2004; Stone 2007), it is meaningful to study the relationship between high-hours occupations and women's age at first birth. Using the Census and the ACS from 1980–2010, I study this relationship with panel construction at the occupation level and address possible concerns such as additional schooling, reverse causality, or self-selection. Then, using the recent ACS, I check whether the previous panel construction is consistent at the individual level and, more importantly, how spouses' high-hours occupations affect women's timing of having a child and vice versa.

[20] Note that I use the share of *men* working high-hours in an occupation to exclude any possible endogeneity between the share of *women* working high-hours and women's timing of fertility in an occupation.

[21] Using the American Time Use Survey (ATUS), Cortés and Pan (2016) find that working long hours is highly correlated with workplace flexibility, such as working on weekends or non-standard hours. Cha (2013) argues that working long hours is strongly associated with a higher proportion of men in the workplace, including nonprofessional occupations such as production, operative, and protective service occupations.

2.4.1 Share of men working high-hours and women's average age at first birth at the occupation level

To study the relationship between the share of men working high-hours and married women's timing of fertility while working in an occupation, I begin by showing a descriptive illustration using cross-occupation data from 1980 to 2010. As Figure 2 shows, in each decade there is a clear, positive cross-occupation relationship between the share of men working 50 or more hours per week and women's average age at first birth. Women tend to delay their fertility while working in occupations with a higher share of men working high-hours. This tendency is somewhat weaker in 1980 but becomes stronger in other periods.[22]

To examine the effect of the share men working high-hours on women's average timing of fertility by occupation, the following regression is estimated:

$$Age\ at\ first\ birth_{ot} = \alpha + \beta \cdot Share\ of\ high\_hours_{ot} + \eta \cdot X_{ot} + \phi_o + \phi_t + \epsilon_{ot}, \qquad (2.6)$$

where o and t refer to an occupation and each decade, respectively. Age at first birth in the main regression implies the average women's age at their first birth among married women aged 25–40 in each occupation level. Share of high hours is defined as the ratio of men working 50 or more hours per week among college-educated male workers aged 25–55. X_{ot} is a vector of control variables such as average log wages of men and women, married women's average number of children, and share of master's or doctoral degree by dependent variables.[23] ϕ_o and ϕ_t are occupation and time fixed effects, respectively. Standard errors are clustered at the occupation level, and the regression is weighted by the number of individuals of the dependent variable.[24]

[22]Note that this correlation in Figure 2 is robust when excluding graduates.

[23]Note that the average number of children is fixed for those aged 25–40, but the share of those with a master's or doctoral degree depends on the group of dependent variables. For example, when the dependent variable is married women aged 25–55 with children, the share of those with a master's or doctoral degree is calculated by that of married women aged 25–55 with children.

[24]Note that if the proportions of miscarriage, abortion, or infertility are positively related to high-hours occupations, the β in equation (1) can be over-estimated. On the other hand, if there are 1) women who still defer the childbirth after age 40, or 2) women who delay the childbirth but eventually end up with no child, then the β can be under-estimated.

Table 3 presents the result of the regression in equation (6). Column (1) of Table 3 considers only occupation and year fixed effects, while column (2) also includes control variables such as log wages of men and women, number of children, and the share of those with a master's or doctoral degree. The estimated coefficients on the share of men working high-hours in an occupation in columns (1)–(2) are both positive and significant at the 1 percent level. The coefficient in column (2) indicates that the 10 percent increase in the prevalence of working long hours in an occupation is associated with the increase in age at first birth by 0.23.

Women may delay their fertility due to additional schooling rather than working long hours. It is worth emphasizing that the coefficient in column (2) is significant after controlling for the share of women with master's or doctoral degrees. To further address this concern, when I exclude women with advanced degrees, the regression coefficient of college graduates in column (3) is similar in magnitude to column (2) and is still significant. These two points provide evidence that women do not simply delay their fertility because of additional schooling.

On the other hand, one might think that men working in high-hours occupations also tend to delay having a child. To check this possibility, I estimate a regression for married men aged 25–40 instead of married women. The coefficient in this regression, shown in column (4), is not only smaller in magnitude than the ones in columns (2)–(3) but is also statistically insignificant. This result can be interpreted that the timing of having a child depends on women's occupations rather than men's due to time out of the labor force during pregnancy and after birth.

To check the robustness of the main regression, I first expand the age composition by including older groups in Table 4. In column (1) of Panel A, the baseline coefficient on the share of men working high-hours is 2.303. When I expand the age composition of married women into ages 25–45, 25–50, or 25–55, the estimated coefficients become somewhat smaller in magnitude but are still significant at the 5 percent level. Therefore, the relationship between high-hours occupations and delaying fertility is robust to different age compositions of married women. Second, I apply the alternative measure of working long hours such as more than 41, 45, or 55 hours. The coefficients in Panel B of Table 4 become larger as the measure of working long hours changes from 41 hours (2.015) to 55 hours (3.559), suggesting the positive association between high-hours occupations and women's age at first birth is robust to different measures of working long hours.

Before turning to the analysis at the individual level, two possible concerns should be addressed. First, there could be a possibility of reverse causality that more women who delay fertility drive the prevalence of working long hours. If the occupation has more women who delay fertility, then it is more likely to have fewer women in the occupation with children, that drives the prevalence of working long hours in that occupation. To address this possibility, following Cortés and Pan (2016), I also include the lead variable of the share of men working high-hours at time t+1.[25] If women who delay fertility cause the prevalence of working long hours, one might have expected to see that the share at t+1 should be significantly correlated with women's age at first birth. Panel C of Table 4 shows that the lead variable of the share of men working high-hours is not significant and has a negative sign for any alternative measures of high hours. Moreover, the coefficients on this share at time t are similar in magnitude than that of Panel B and are statistically significant. Therefore, there is an evidence that the relationship between prevalence of working long hours and delaying fertility is not entirely driven by reverse causality.

The other concern is selection bias: it is possible that women who are more likely to remain childless or are more work-oriented choose high-hours occupations. If this is the case, high-hours occupations do not cause women to delay fertility, but rather work-oriented women self-select into high-hours occupations. To address this concern, instead of women's age at first birth, I replace the dependent variable with the women's average number of children or the ratio of having children. If women self-select their occupations, one might have expected to that the share of men working high-hours should be negatively associated with the women's average number of children or the ratio of having children. Table A3 presents the regression results with various dependent variables. When including only occupation and year fixed effects, none of the alternative dependent variables is significant in Panel A. When I add other control variables, the coefficients in

[25] For the share of men working high-hours at t+1 year in 2010, I use the 2017 ACS five-year aggregate. Thus, the number of observations remains the same.

columns (1)–(3) in Panel B are significant at the 5 percent level, but the signs are positive, which is the opposite direction of the selection bias concern. Hence, there is an evidence that the tendency to delay fertility while working in high-hours occupations is not entirely driven by self-selection.[26]

2.4.2 Evidence from individual-level analysis: Role of spouse's occupation

The previous section shows that women working in high-hours occupations tend to delay their fertility, with panel construction at the occupation level. In this section, I explore whether this relationship is consistent at the individual level using the recent 2017 ACS five-year aggregate. More importantly, by adding spouses' characteristics, we can understand how they affect the timing of having a child, especially when the spouses work in high-hours occupations.

The sample consists of native-born married individuals aged 25–55 with at least a bachelor's degree, are working full time (35 hours or more), and have a spouse with at least a bachelor's degree.[27] The sample is restricted to individuals working in 95 skilled occupations, as shown in Table A2.

To study the effect of a spouse's high-hours occupation on a woman's age at first birth at the individual level, the following regression is estimated:

$$Age\ at\ first\ birth_{io} = \alpha + \beta \cdot Share\ of\ high\_hours_o + \eta \cdot X_i' + \gamma \cdot Share\ of\ high\_hours_o^{sp} + \epsilon_{io}, \tag{2.7}$$

where i and o refer to an individual and occupation, respectively. Age at first birth is a woman's individual age at first birth and the share men of working high-hours follows the same definition in equation (6). The vector X_i includes not only individual-level characteristics, such as number of children, age, age^2, a vector of race dummies, a dummy variable of having a graduate degree, and log hourly wage; it also includes spouses' char-

[26] This test of addressing the concern of selection bias cannot fully rule out the possibility of self-selection, because the sample is already selected from those who only remain in the labor market.

[27] Out of the total sample with spouse information (533,992), 73 percent of respondents have spouses with at least a bachelor's degree (389,395).

acteristics such as age, race, education, and log hourly wage. The share of men working high-hours in a given *spouse's* occupation is included in some specifications, and then the sample is further restricted to spouses working in 95 skilled occupations in this case.[28] Standard errors are clustered at the occupation level and regression is weighted by personal weight.

The regression results on the main interest group of married women aged 25–40 are presented in columns (1)–(4) of Table 5. The estimated coefficient after controlling for individual-level characteristics of respondents and spouses is 1.343 in column (2), while the coefficient is 3.796 in column (1) without all controls. Next, to understand how a spouse's occupation affects a woman's timing of fertility, I include the share of men working high-hours in a given *spouse's* occupation in column (3). The magnitude of the coefficient on the share of men working high-hours in one's own occupation is 1.202, which is similar to column (2). The share of men working high-hours in a spouse's occupation is also significantly associated with a woman's age at first birth, but the magnitude of the coefficient is smaller, 0.792. Therefore, delaying fertility of a married woman is more affected by her own occupation rather than her spouse's occupation.

Since the marriage year is available from the 2008 ACS, we can check the robustness of the coefficient on the share of men working high-hours in a given occupation by controlling a woman's age at marriage. The estimated coefficients on share of men working high-hours in one's own occupation or a spouse's occupation in column (4) become somewhat smaller than column (3), but they are still significant. The coefficient on a woman's age at marriage is also positively and significantly associated with a woman's age at first birth. This suggests that, even holding a woman's age at marriage constant, a woman tends to delay her fertility when she works in a high-hours occupation rather than when her spouse works in high-hours occupation.

To check whether the estimation is consistent by age group, I expand the women's age composition in columns (5)–(7) using a preferred estimate in column (3).[29] As ex-

[28]Out of the sample with spouses who have at least a bachelor's degree (389,395), 73 percent of spouses work in 95 skilled occupations (284,565).

[29]Since the control variable of the age at marriage is highly correlated with the age at first birth, the estimation in column (3), which excludes the age at marriage, is preferred.

pected, the coefficients on the share of men working high-hours in one's own occupation are similar in magnitude and are significant. On the other hand, the size of coefficients on the share of men working high-hours in a given *spouse's* occupation become smaller and less significant when including older groups. This implies that when a spouse's occupation has a higher share of working high-hours, younger women are more likely to delay having a child than older women.

Finally, we can examine whether a married *man* delays having a child when both he and his wife work in a high-hours occupation. I estimate the regression for married men by age groups using the preferred estimate in column (3). The coefficients on the share of men working high-hours in one's own occupation in columns (8)–(11) of Table 5 are positive but not statistically significant except for married men aged 25–40. On the contrary, the coefficients on the share of men working high-hours in a *spouse's* occupation are significant at the 1 percent level and larger in magnitude for all age groups of married men. This result implies that a man's age at first birth increases when his wife works in a high-hours occupation rather than he works in a high-hours occupation. Even though having a child is a joint decision between spouses, the wife's occupation plays an important role in the timing of having a child compared to husband's, as the wife is the one who experiences a career interruption due to fertility.

2.5 Occupational characteristics of high-hours occupations in terms of human capital depreciation

The previous section highlights that women working in high-hours occupations tend to delay fertility. Given that married mothers need to balance both career and household work (Jcobs and Gerson 2004; Stone 2007), high-hours occupations can be an additional time constraint for them. Then would the time constraint be the only reason of delaying fertility? In this section, I explore other possible reason of delaying fertility other than time constraint. More specifically, I provide one suggestive explanation of delaying fertility with respect to human capital depreciation. When women's careers are interrupted by childbirth, their skills could become obsolete and personal relationships could drift apart. Moreover, upon returning to work, women might need a longer time or more effort to adapt. I hypothesize that these types of human capital depreciation can arise more frequently in high-hours occupations. For example, high-hours occupations are likely to require more personal relationships, autonomy, and competitiveness. As a result, human capital depreciation can be greater in high-hours occupations when work experience is discontinued due to childbirth.

It is worth emphasizing that human capital in this section is not the standard definition of human capital that can be explained by education level. Here I define human capital as job expertise from career continuity within similar education level. Earlier literature shows that human capital depreciates during a woman's career interruption (Mincer and Polachek 1974; Mincer and Ofek 1982).[30] Light and Ureta (1995) and Miller (2011) emphasize the importance of continuous work experience in earnings and wages.[31] In this respect, I understand women delaying fertility in the context of work continuity and lifetime earnings.

To study various occupational characteristics related to human capital depreciation, I use the O*NET which is a database containing hundreds of occupation-specific characteristics (version 23.0, released in 2018). Out of two classifications of "work context" and "work activities" in the O*NET, I choose eight occupational characteristics that would be closely related to human capital depreciation. Then I group them into three categories—interpersonal relationships, autonomy, and competitiveness. Interpersonal relationships consist of having contact with others, establishing and maintaining interpersonal relationships, coordinating or leading others, and having impact of decisions on co-workers or company results. Autonomy is measured by unstructured work, the freedom to make decisions, or decision-making frequency. Last, competitiveness is measured by the level of competition.

[30] Using the NLSY68, these studies show that the depreciation rate increases in the level of education and becomes greater for women with more years of experience at the time of the interruption.

[31] Light and Ureta (1995) show that 12 percent of the gender wage gap can be explained by the different timing of work experience. Their estimation shows that the return to continuous work experience is higher than the standard work experience models. Miller (2011) finds that delaying motherhood can influence women's career path, such as increases in earnings and wages.

To consider the relationship between prevalence of working long hours and human capital depreciation, I merge several occupation-based indexes from the O*NET with a similar time-frame 2017 ACS five-year aggregate.[32] Given the distribution of share of men working high-hours by occupation level from the ACS, I extract two groups—one from below the 25 percentile (low-hours occupations) and the other from above the 75 percentile (high-hours occupations). For each group of occupations, I compute the mean and standard deviation of each O*NET characteristics in Table A4. All mean values for the three categories with eight characteristics are larger for the group of high-hours occupations than the group of low-hours occupations. This descriptive statistics suggest that the group of high-hours occupations is more likely to have active interpersonal relationships, high degrees of autonomy, and higher competitiveness. Figure 3 illustrates the strong positive cross-occupation relationship between the share of men working high-hours and the three occupational categories, respectively.

Because high-hours occupations are closely associated with occupational features with larger human capital depreciation, I also estimate the relationship between women's average age at first birth and average indexes representing human capital depreciation. From the equation (6), I replace the share of men working high-hours with the averaged indexes of occupational characteristics in human capital depreciation. Thus, I estimate the following regression:

$$Age\ at\ first\ birth_o = \alpha + \beta \cdot Human\ capital\ depreciation_o + \eta \cdot X_o + \epsilon_o, \tag{2.8}$$

where o refers to occupation. The averaged indexes of occupational characteristics are normalized to have a mean of zero and a standard deviation of one.[33]

In Table 6, when including characteristics of interpersonal relationships, autonomy, competitiveness, respectively in columns (1)–(3), the estimated coefficients are statistically significant except for autonomy in column (2) (p-value =0.114). I then estimate the

[32] I use the recent 2017 ACS five-year aggregate to match O*NET's occupational characteristics because the O*NET database began in the 2000s and is constantly updated with current occupational features.

[33] There are possible limitations of averaging several characteristics: 1) occupational characteristics are not independent, 2) even though that each distribution is independent, I assume that weights are the same across occupational characteristics following other papers (Goldin 2014; Yu and Kuo 2017).

association between indexes of human capital depreciation and women's age at first birth by averaging all eight characteristics in column (4).[34] The result shows that a one standard deviation increase in the normalized average index is associated with women's average age at first birth by 0.177, suggesting women who work in occupations that require active interpersonal relationships, high autonomy, and high competitiveness are more likely to delay fertility. One possible explanation is that women delay fertility in occupations that have a higher depreciation of human capital when careers are interrupted.[35] Moreover, when including both occupational characteristics of working high-hours (i.e., duration of the typical work week) and high-human capital in column (6), the magnitude of coefficients become larger and more statistically significant. This result can be interpreted that not only the time constraint by working long hours but also occupational features of larger skill depreciation lead to delayed fertility.

To better understand the timing of fertility and human capital depreciation, Figure 4 provides a theoretical background using two earnings profiles for occupations with lower and higher depreciation rates, respectively. For simplicity, suppose that the earnings profile for a woman without a child is the same across occupations with profile oc. Suppose that a woman can have different timings of fertility, at time t_e and t_l, respectively, and the time out of the labor force after childbirth is one year for both cases.

In Figure 4(a), a woman decides the timing of fertility between t_e and t_ℓ by comparing forgone earnings due to one year of work experience interruption (light gray areas) and the opportunity of raising her earnings profile by delaying fertility (dark gray area). In this case, the net gain of delaying fertility is not sizable, so her timing of fertility does not impact her lifetime earnings. On the other hand, when it comes to a higher depreciation rate of human capital in Figure 4(b), the loss in her lifetime earnings profile after childbirth (dark gray area) becomes greater when she gives birth at an earlier age, t_e. Additionally, if a new earnings profile after childbirth has a lower return on experience due to reduced opportunities for training/promotion or reluctance to invest in developing new skills at

[34] Due to the possible multicollinearity of three categories, those characteristics are averaged and then normalized instead of estimating with separate β's.

[35] Using the O*NET and the NLSY 97, Yu and Kuo (2017) find that mothers have a bigger wage penalty when their occupations impose more competitive pressure.

work (Miller 2011), the loss can be even larger. Therefore, when the depreciation rate of human capital is higher and the return to experience after childbirth is lower than that for a woman without a child, the timing of fertility can be delayed in the context of lifetime earnings and careers.[36]

To summarize, I show that high-hours occupations are closely related to occupations imposing interpersonal relationships, autonomy, and competitiveness. Since women in these occupations are more likely to delay fertility, I suggest the possibility that women tend to delay their fertility in occupations where human capital depreciation is more likely to be greater. Thus, delaying fertility can be a rational behavior in terms of work continuity and lifetime earnings.

2.6 Employment after childbirth

In this section, I explore how women's employment change after childbirth, depending on the timing of fertility and their occupations. For example, given that lawyers tend to delay fertility compared to elementary school teachers, would their labor supply decisions after childbirth be different from elementary school teachers' decisions? If women change their employment after childbirth, are they more likely to drop out of the labor force, reduce working hours, or change occupations?

To answer these questions, I conduct two different analyses using the Census/ACS and the NLSY97, respectively. First, I construct a panel using the Census and the ACS at the occupation level. This panel has a sufficient number of observations over time but cannot track labor supply changes at the individual level. To overcome this limitation, I also use the NLSY97 individual panel as supportive evidence, though the sample size is small.

[36] For details on earnings profiles, see Blau et al. (2013) and Miller (2011).

2.6.1 Evidence from the Census/ACS

Using the 1980–2000 Census and the 2011 ACS three-year aggregate, I construct a panel data at the an occupation-level. I use the occupational distribution as a proxy for observing individuals who either switch occupations or drop out of the labor force (Cunningham and Zalokar 1992; Gabriel and Schmitz 2007; Cortés and Pan 2017; Kosteas 2019). The occupational distribution for a given interest group is measured as the share of the given group working in a particular occupation. Then to consider the change in labor supply after the first childbirth, I examine the *change* in occupational distribution as women get older.

Specifically, the following regression is estimated:

$$\frac{women\_gr(i+1)_{ot}}{women\_gr(i+1)_{t}} - \frac{women\_gr(i)_{ot}}{women\_gr(i)_{t}} = \alpha + \beta \cdot Share\ of\ high\_hours_{ot} + \eta \cdot X_{ot} + \phi_o + \phi_t + \epsilon_{ot}, \quad (2.9)$$

where o and t refer to an occupation and each period, respectively. The estimation is the same as equation (6), except for the dependent variable. The dependent variable here is the *change* in occupational distribution of a given demographic group. To capture labor supply changes as women age following the first birth, I divide the sample into three intervals (i) by ages—young, intermediate, and older.[37] Based on three intervals, two demographic groups are defined by the timing of fertility: women who have their first birth in the young interval and women who delay fertility in the intermediate interval.[38] $women\_gr(i)$ represents the demographic group of women whose current ages are in the same interval as ages at first birth, whereas $women\_gr(i+1)$ refers to the group of women whose current ages are in the next age interval. For example, for women who delay fertility in the 2011 ACS, $\frac{women\_gr(i)_{ot}}{women\_gr(i)_{t}}$ indicates the occupational distribution of women whose current ages and ages at first birth are both in the ages 29–35 interval, while $\frac{women\_gr(i+1)_{ot}}{women\_gr(i+1)_{t}}$ indicates the occupational distribution of women whose ages at first birth are in the ages 29–35 interval but whose current ages are between ages 36–42. The difference in the occupational distribution over time implies how much a given demographic group in that

[37] For example, ages 23–28, ages 29–35, and ages 36–42.

[38] Based on women's median age at first birth in each period, I define two demographic groups; note that these groups mostly include women whose ages at first birth are between the 5th and the 95th percentile of the distribution.

occupation relatively enter or leave as they age. Therefore, if the coefficient β in equation (9) is negative, a given demographic group is more likely to exit high-hours occupations when they get older.

An analysis of the prevalence of working long hours on change in occupational distribution is given in Table 7. Main demographic group is women who delay fertility among intermediate ages cohort in columns (1)–(3). In column (1), the estimated coefficient on the share of men working high-hours when controlling only occupation and year fixed effects is –0.161, but it is not statistically significant. Interestingly, when including the average number of children, the coefficient becomes larger in magnitude (–0.255) and is statistically significant at the 5 percent level. The coefficient remains robust (–0.221) when including other control variables such as log wages of men/women and the share of graduates, meaning a 10 percent increase in the share of men working high-hours is associated with a 2.2 percentage point reduction in the employment share of women who delay fertility as they age.

It is worth emphasizing that the coefficient on the average number of children of married women is positive and statistically significant. In column (3) of Table 7, the 0.1 increase in the average number of children is associated with a 2.3 percentage point increase in the employment share of women who delay fertility as they age. One explanation of this result can be that women after the first birth tend to work continuously in occupations that have a higher share of female employees with children. Notice that the coefficient on the share of men working high-hours becomes significant only when including average number of children of married women—this suggests that women- or family-friendly work environments can play an important role for women's labor supply decisions after the first birth.[39]

For women who do not delay fertility in young ages cohort, the coefficients β in columns (6)–(8) of Table 7 become smaller and are not statistically significant. This result can be interpreted as women who give birth early do not have a distinct tendency

[39] As an additional exercise, I also estimate column (3) using the married *men*'s average number of children. In this case both coefficients on the share of men working high-hours and the number of children do not provide significant estimates (not reported). This result further supports that a family-friendly work environment is more closely related to women's average number of children rather than men's.

to exit high-hours occupations.[40] In this respect, it is somewhat puzzling that women who delay fertility to maximize their lifetime earnings and job expertise are more likely to exit high-hours occupations after childbirth. One potential explanation is that highly educated women underestimate the effect of motherhood on employment. Kuziemko et al.(2018) show that highly educated women underestimate the difficulty of balancing both a career and childcare, so this under-estimation causes them to become pessimistic on performing both market work and household work. Similarly, Bertrand (2013) finds that college-educated women who achieve the double goal of career and family do not have a greater life satisfaction—combination of career and family gives rather increase in sadness,stress, and tiredness. Even though they do not consider the employment beliefs or emotional well-being by occupations or timing of fertility, motherhood could be more of a burden in high-hours occupations due to time constraints from this balancing, especially for those who delay fertility.

Notice that the age intervals for the two demographic groups are different: For women who do not delay fertility, $women\_gr(i)$ and $women\_gr(i+1)$ represent young and intermediate age intervals, whereas for women who delay fertility, they represent intermediate and older age intervals. Therefore, there is a possibility that women naturally exit high-hours occupations as they become older for reasons such as competitiveness, intensity, or time pressure.[41] In that case, the tendency to exit high-hours occupations arises due to natural age effects rather than to labor supply changes after childbirth.

To address this concern, I conduct falsification tests by estimating equation (9) for women without children and men in the same age intervals as women who give birth.[42]

[40]Strictly speaking, the analysis presented here has some limitations. By constructing $women\_gr(i)$ as women whose current ages are in the same interval as age at first birth (for example, current ages and ages at first birth are both in the 23–28 interval), there are some women whose current age is 28 but their age at first birth is 23 (5-year gap). Similarly, by defining $women\_gr(i+1)$ as women whose current ages are in the next age interval to ages at first birth (for example, current ages are in the 29–35 interval and ages at first birth are in the 23–28 interval), some women may be 29 years old and give birth at 28 (1-year gap). In this case, the latter does not always reflect the larger gap between current ages and ages at first birth. I assume that, *on average*, the regression captures the difference in occupational distribution as they age. The regressions are not presented here; I only include samples, where $women\_gr(i+1)$ always have larger gaps in ages than $women\_gr(i)$. The estimated coefficients are quite robust, –0.202 with a 5 percent significance level for women who delay fertility and –0.083 with no significance for women who do not delay fertility.

[41]The tendency to naturally exit the occupation can arise in both labor supply and demand sides. Workers can voluntarily exit high-hours occupations or employees may not want to hire older workers any longer.

[42]Since these falsification groups have no age at first birth, the difference in occupational distributions

The results of these falsification tests are presented in Table 7. For women without children in the intermediate age cohort, the estimated coefficient on the share of working high-hours in column (4) is less significant, and the magnitude (–0.084) is much smaller than women who delay fertility. Moreover, for women without children in the young age cohort, the coefficient β is not significant. For men, the coefficients are not statistically significant and have mixed signs for all age cohorts in columns (5) and (10). These results suggest that the tendency for women who delay fertility to exit high-hours occupations is not entirely driven by natural age effects but instead arises due to labor supply decisions *after childbirth*.

Note that there could be some limitations of using the Census and the ACS, since those data are cross-sectional. For example, I implicitly assume that women in different age intervals follow the same lifetime path related to labor supply decisions given a demographic group. Thus, in the following section I use the NLSY97 as supportive and complementary evidence, because it enables us to track labor supply changes at the individual level.

2.6.2 Evidence from the NLSY97

The previous section shows that women who delay fertility tend to exit high-hours occupations, while women who give birth early do not. In this section, I study labor supply decisions after the first birth at the individual level. By using the NLSY97, I can check the consistency with the Census/ACS.

The sample consists of married women who have at least a bachelor's degree and had their first birth after at least age 22. To examine the changes in employment after the first birth, the sample is limited to women who were working full time at the year of first birth, except for those who are self-employed. To control the unobserved characteristics between employment and marital status, I exclude from the sample women who divorced, separated, or were widowed after the first birth. The total number of observa-

only depends on the current ages. For example, for women without children in the intermediate age cohort in the 2011 ACS, $women\_gr(i)$ indicates women whose current ages are in the 29–35 cohort, while $women\_gr(i+1)$ represents women whose current ages are in the 36–42 cohort.

tions is 750 with 199 individuals, so the average of employment status is 3.8 times per person.

To analyze whether labor supply changes differ by either occupations or the timing of fertility, I then estimate the following regression:

$$\begin{aligned} Employment\_change_{it} = \alpha + \beta_1\ High\_hours_{io} + \beta_2\ Delay\_fertility_i \\ + \beta_3\ (High\_hours_{io} \times Delay\_fertility_i) + \delta X_{it} + \phi_t + \epsilon_{it}, \end{aligned} \tag{2.10}$$

where i,t, and o refer to individual, each survey year, and occupation, respectively. I characterize the changes in employment status as six cases: drop out of the labor force, reduce working hours as (i) working less than 35 hours per week (part-time worker), ii) reducing working hours more than 5 hours, iii) reducing working hours more than 10 percent, change both occupation and workplace, or switch to self-employment. The dependent variable, *Employment_change*, is a dummy variable for a combination of the six employment changes.

Due to the small sample size, high-hours occupations are now defined as the share of employees working 45 or more hours per week being higher than the median share across occupations (16.54 percent). *High_hours* is a dummy variable equal to one if a woman worked in a high-hours occupation during the year of first birth. *Delay_fertility* is also a dummy variable equal to one if the first birth occurred after at least age 30.[43] X_{it} includes control variables such as age, age^2, vector of race dummies, number of children, and a dummy variable for having a graduate degree. ϕ_t refers to the year fixed effects, and the error term is clustered at the individual level. The individual weights given by the NLSY97 are applied in regressions. The main interest variable is the interaction term between *High_hours* and *Delay_fertility*. If the coefficient β_3 is positive, there is a positive effect of the interaction term on employment changes.

In Table 8, I report the regression results for each employment change in columns (1)–(6) and combinations of employment changes in columns (7)–(9). The coefficient β_3 on dropping out of the labor force is positive and marginally significant (0.113) in column

[43] Age 30 is based on the median (29) and mean age at first birth (28.72) among 199 individuals.

(1), implying that women in high-hours occupations who delay fertility are more likely to drop out of the labor force. Second, for three different definitions of reducing working hours, the coefficients of the interaction term in columns (3)–(4) are greater in magnitude (0.206 and 0.188, respectively) than in column (2) (0.132), since reducing working hours by more than 5 hours or by 10 percent are more relaxed definitions than switching to part time. On the contrary, the coefficients of the interaction term for switching occupations/workplaces and switch to self-employment are not significant in columns (5)–(6). However, these two results in columns (5)–(6) might not be reliable because regular rotations can be also counted in switching occupations/workplaces, and the cases of becoming self-employed is quite small, as shown in Table 2.[44] Using dropping out of the labor force and reducing working hours, which are significant in each case, three combinations of employment changes are estimated in columns (7)–(9). All three coefficients of the interaction term become more significant and greater in magnitude. As expected, when using the relaxed definitions of reducing working hours in columns (8)–(9), the coefficients of the interaction term are larger (0.319 and 0.302, respectively) than the coefficient in column (7) (0.246).[45]

In the previous section with the Census/ACS, occupational distribution is used as a proxy for observing individuals who exit the occupations, but either switching an occupation or dropping out of the labor force are not distinguishable from each other. On the other hand, the NLSY97 enables us to track each employment change. The results in Table 8 suggest that rather than switching an occupation, women are more likely to drop out of the labor force and reduce working hours after their first childbirth. Moreover, by considering individual working hours, the NLSY97 can capture the significance of reducing working hours by more than 5 hours or 10 percent *within full-time status*, which is not possible in the Census/ACS. In respect to human capital, women in high-hours occupations who delay fertility seem to be somewhat rational, as they can continue their career

[44]For example, a woman who worked as an elementary school teacher can become a middle school teacher due to educational demand.

[45]For the robustness check, I additionally include the control variable of spousal income because women's labor supply after childbirth may vary with spousal income (Bertrand et al. 2010; Goldin 2014). The estimated results shows qualitatively similar results even though the sample size reduces to 703 due to the missing observations.

by reducing working hours.

As an additional exercise, I estimate the same regression in equation (10) by creating a vector of four dummies using high-hours occupation and delaying fertility. By doing so, I can compare employment changes, especially for women who delayed fertility, in occupations with different working hours. More specifically, the following regression is estimated:

$$\begin{aligned} Employment\_change_{it} = \alpha + \beta_1\ High\_hours_{io} \cdot delay\_fertility_i + \beta_2\ High\_hours_{io} \cdot not\_delay\_fertility_i \\ + \beta_3\ Not\_high\_hours_{io} \cdot not\_delay\_fertility_i + \delta X_{it} + \phi_t + \epsilon_{it} \end{aligned} . \tag{2.11}$$

The base group is women who delayed fertility but were not working in high-hours occupations at the year of their first childbirth. Therefore, the coefficient β_1 implies the relative employment change for women who delayed fertility and were working in high-hours occupations, compared to the base group. In columns (7)–(9) of Table A5, the coefficients β_1 on combinations of dropping out of the labor force and reducing working hours are all positive and significant. This result confirms the previous analysis results using the Census and ACS—women who delay fertility are more likely to exit the occupations when working in high-hours occupations.

In summary, I find that there is a positive and significant interaction between high-hours occupations and delaying fertility on employment changes, such as dropping out of the labor force and reducing working hours. Thus, both analyses using the Census/ACS and the NLSY97 provide a consistent result that women who delay fertility and work in high-hours occupations are more likely to reduce their labor supply. This finding is also closely related to the previous literature showing that mothers are more likely to exit high-hours occupations (Cha 2013; Cortés and Pan 2016, 2017; Goldin 2014) or educated women exhibit statistically significant declines in employment after their first childbirth (Bertrand et al. 2010; Fitzenberger 2013; Kuziemko et al. 2018; Schank and Wallace 2019).

2.7 Conclusion

In this paper, I examine the relationship between high-hours occupations, women's age at first birth, and employment changes after childbirth. The results show that women working in high-hours occupations tend to delay fertility. This behavior can be understood with respect to human capital depreciation: since high-hours occupations require interpersonal relationships, autonomy, and competitiveness, human capital can depreciate more in those occupations when careers are interrupted. Therefore, one possible explanation is that women working in high-hours occupations tend to delay fertility to maximize their lifetime earnings. I also find that women who delay fertility in high-hours occupations tend to decrease their labor supply after the first birth, mainly by reducing working hours or dropping out of the labor force.

Due to the lack of hourly wages in each occupation for women who continue working after childbirth, directly measuring the magnitude of human capital depreciation is limited.[46] Moreover, it is difficult to determine if women plan to change their labor supply after childbirth at the beginning of their career or if they change it unexpectedly after giving birth in my analysis. When women change their labor supply decisions unexpectedly, motherhood would be more of a burden than expected (Kuziemko et al. 2018). Therefore, future studies on the reasoning behind this labor supply change should be pursued, such as examining social norms or unequal gender roles (Arpino et al. 2015; Bertrand et al. 2015; Bertrand et al. 2016; Fernández and Fogli 2009; Myoung et al. 2020; Raley et al. 2012). Finally, to reconcile both women's career and mother's role in the household, further research is needed on policy instruments such as extended parental leave and active job training after the interruption of careers.

[46] Yu and Kuo (2017) examine the motherhood wage penalty by occupational characteristics using the NLSY97. Respondents were in their mid-30s in last round of the NLSY97, so focusing on college-educated women, especially those who gave birth after age 30, would be still limited.

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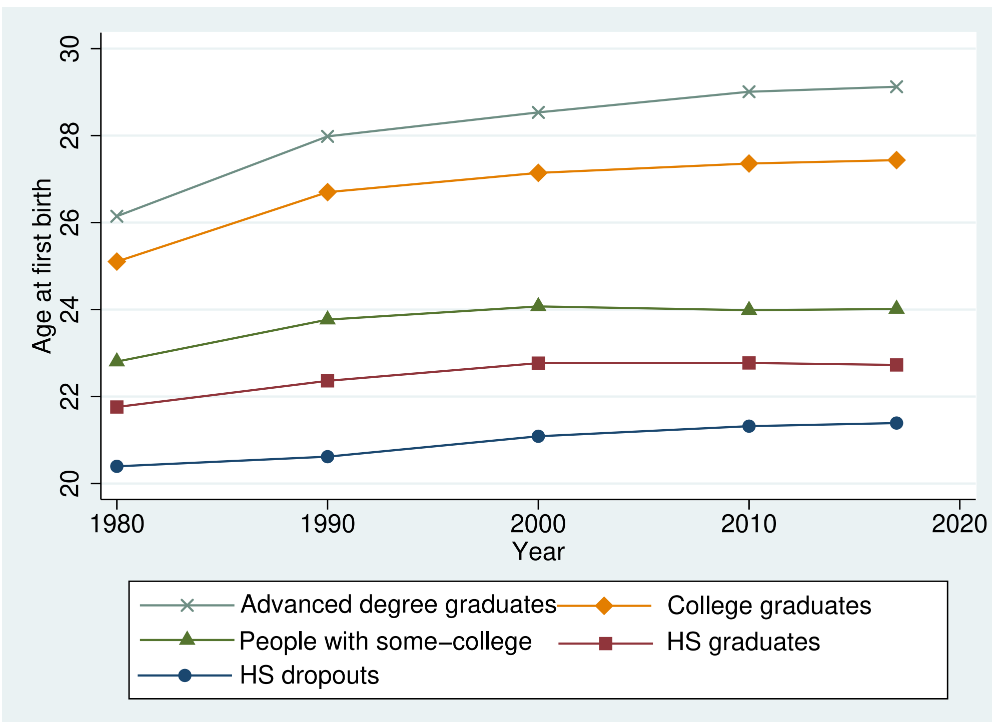
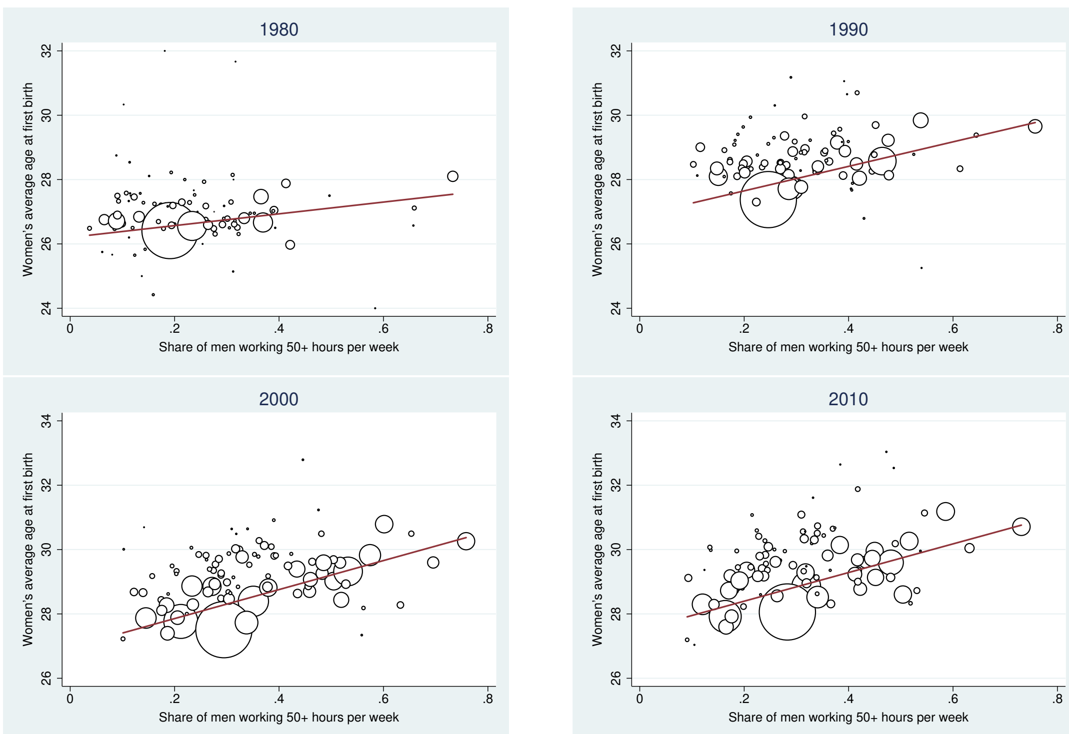
List of Appendices

Figure 2.1: Women's average age at first birth by year/education level



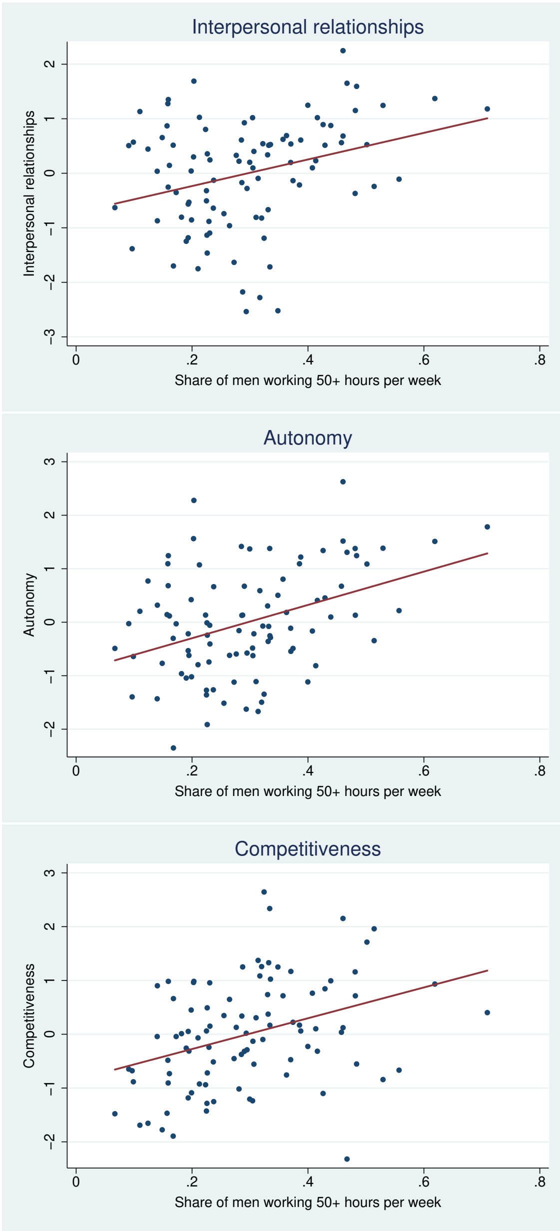
Notes: Data are from the 1980 to 2000 US Census, the 2011 ACS three-year aggregate (2009-2011), and the 2017 ACS five-year aggregate (2013-2017). The sample consists of native-born married women aged 25–40 with at least a bachelor's degree who are working full time (35 hours or more) and for wages in reported week.

Figure 2.2: Cross-occupation relationship between the share of men working high-hours and women's average age at first birth



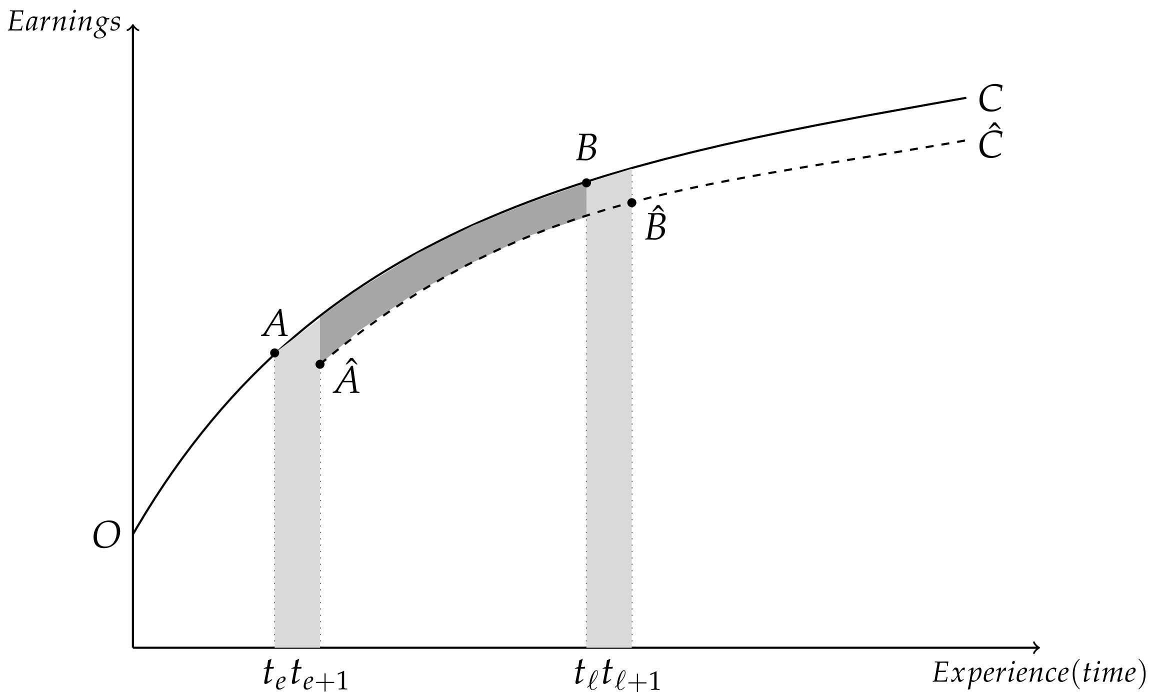
Notes: The unit of observation is an occupation. Data are from the 1980 to 2000 US Census and the 2011 ACS 3-year aggregate (2009-2011). Share of men working 50+ hours per week is constructed among college-educated male workers aged 25–55 in each occupation. Age at first birth is calculated among married women aged 25–40 who have children. The figures include 95 skilled-occupations and are weighted by the number of married women with children aged 25-40 in each occupation.

Figure 2.3: Cross-occupation relationship between the share of men working high-hours and other occupational characteristics

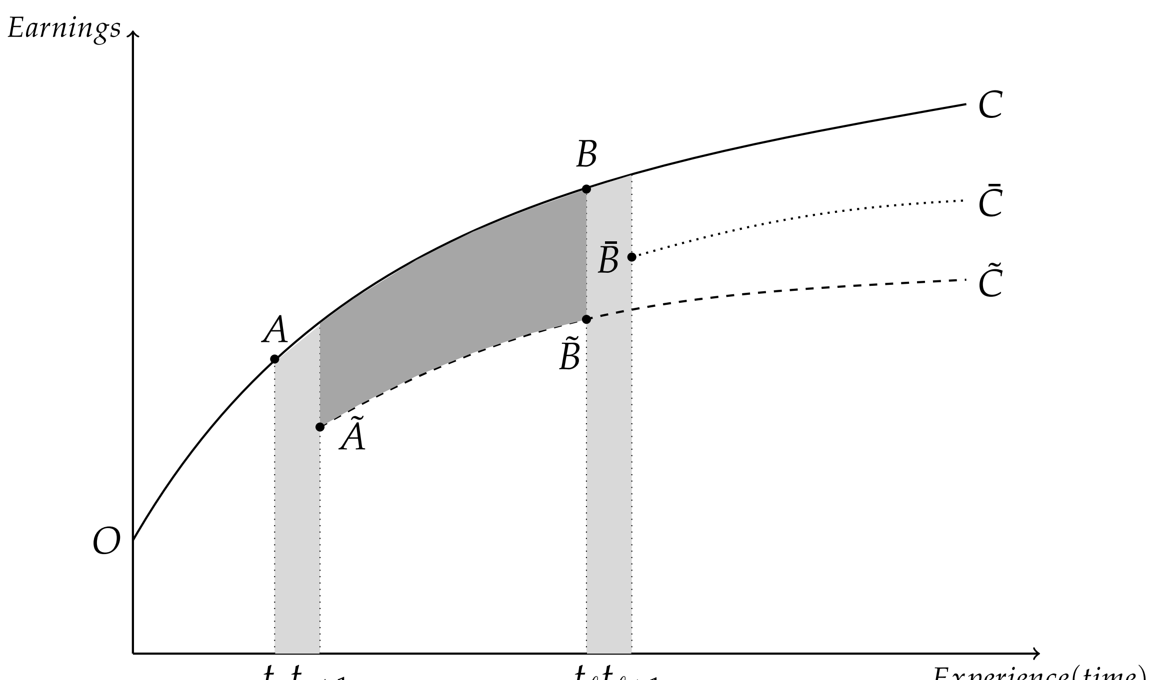


Notes: The unit of observation is an occupation. Data is from the 2017 ACS five-year aggregate and the O*NET. Interpersonal relationships consist of having contact with others, establishing and maintaining interpersonal relationships, coordinating or leading others, and having impact of decisions on co-workers or company results. Autonomy contains structured vs. unstructured work, freedom to make decisions, and frequency of decision making. Competitiveness refers to the level of competition. All three categories are normalized to have a mean of zero and a standard deviation of one, respectively.

Figure 2.4: Earnings profiles and the timings of fertility depending on the human capital depreciation



(a) Occupations with lower depreciation rate of human capital



(b) Occupations with larger depreciation rate of human capital

Notes: t_e refers to early fertility and t_ℓ indicates later fertility. Assume that the time out of the labor force

Table 2.1: Summary statistics for the Census/ACS

Panel A.Individual Level					
	1980	1990	2000	2010	2017
Married women with children					
Age	37.34	38.78	40.39	40.66	40.89
	(7.49)	(6.74)	(7.25)	(7.41)	(7.24)
Black	0.10	0.08	0.07	0.08	0.07
	(0.30)	(0.27)	(0.26)	(0.26)	(0.26)
Hispanic	0.02	0.02	0.03	0.05	0.06
	(0.15)	(0.15)	(0.18)	(0.22)	(0.24)
White non-Hispanic	0.83	0.83	0.79	0.74	0.72
	(0.38)	(0.38)	(0.41)	(0.44)	(0.45)
Others	0.05	0.07	0.10	0.14	0.14
	(0.22)	(0.25)	(0.30)	(0.34)	(0.35)
Masters	0.38	0.32	0.31	0.34	0.36
	(0.49)	(0.47)	(0.46)	(0.47)	(0.48)
Doctoral and Professional degree	0.12	0.08	0.10	0.11	0.12
	(0.33)	(0.28)	(0.30)	(0.31)	(0.33)
Hourly wage	12.84	15.87	18.26	20.01	20.45
	(6.17)	(8.89)	(12.92)	(13.64)	(14.87)
Working more than 50 hours	0.08	0.14	0.20	0.21	0.21
	(0.28)	(0.35)	(0.40)	(0.40)	(0.41)
Age at first birth	26.55	27.82	29.16	29.66	29.87
	(4.35)	(4.49)	(4.86)	(4.98)	(4.96)
N	55,602	113,184	155,806	136,915	247,413
Panel B.Occupation Level					
Females' age at first birth	26.61	28.04	28.54	28.93	29.04
	(0.39)	(0.71)	(0.92)	(0.91)	(0.91)
Share (men working$\geqslant$50 hrs)	0.29	0.37	0.43	0.38	0.35
	(0.15)	(0.14)	(0.15)	(0.14)	(0.14)
Log(Hourly wage for male)	2.79	2.93	3.00	3.05	3.04
	(0.18)	(0.20)	(0.24)	(0.24)	(0.25)
Log(Hourly wage for female)	2.45	2.64	2.72	2.78	2.77
	(0.08)	(0.11)	(0.15)	(0.20)	(0.22)
Females' number of children	0.96	1.03	1.05	1.18	1.19
	(0.21)	(0.28)	(0.19)	(0.19)	(0.19)
Females' share of graduates	0.48	0.35	0.34	0.45	0.49
	(0.15)	(0.19)	(0.21)	(0.23)	(0.23)
N	95	95	95	95	95

Notes: Data are from the 1980 to 2000 US Census, the 2011 ACS three-year aggregate (2009-2011), and the 2017 ACS five-year aggregate (2013-2017). The sample consists of native-born individuals aged 25–55 with at least a bachelor's degree who are working full time (35 hours or more) and for wages in reported week. Age at first birth, number of children, and share of graduates in Panel B are calculated among married women aged 25–40. Summary statistics are weighted by individual weight (Panel A) and by cell size (Panel B). Standard deviations are reported in parentheses. See Table A1 for summary statistics of individual level, married men with children.

Table 2.2: Summary statistics for the NLSY97

Variable	N	Mean	SD	Min	Max
Race and Ethnicity					
Black	199	0.04	0.20	0	1
Hispanic	199	0.04	0.20	0	1
White non-Hispanic	199	0.91	0.28	0	1
Others	199	0.01	0.07	0	1
Age at first birth	199	28.72	2.58	23	35
Year of birth	199	2010.51	2.71	2004	2015
Graduates	199	0.46	0.50	0	1
Changes on employment statuses					
Drop out of the labor force	750	0.09	0.28	0	1
Switch to the self-employed	750	0.06	0.23	0	1
Switch an occupation & workplace	750	0.11	0.31	0	1
Switch to a part-time worker	750	0.13	0.34	0	1
Reduce working hours more than 5 hours	750	0.25	0.43	0	1
Reduce working hours more than 10 percent	750	0.25	0.43	0	1

Notes: Data is from the NLSY97 (2003-20117). The sample consists of married women who have at least a bachelor's degree and had their first birth after at least age 22. The sample is limited to women who were working full time at the year of childbirth, except for those who are self-employed. Women who divorced, separated, or were widowed after the first childbirth are excluded from the sample. Also, women who have their first birth in 2012, 2014, or 2016 dropped due to the survey construction of the NLSY97. Summary statistics are weighted by individual weights given by the NLSY97.

Table 2.3: The relationship between the share of men working high-hours and women's average age at first birth: Occupation level

	(1) Married women	(2) Married women	(3) College graduates	(4) Married men
High-hours	3.057***	2.303***	2.462***	1.466
	(0.944)	(0.568)	(0.691)	(0.907)
Controls	No	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	379	379	365	380
R^2	0.936	0.957	0.927	0.968

Notes: Clustered standard errors in parentheses,* p<0.10, ** p<0.05, *** p<0.01. The unit of observation is an occupation by year. Data are from the 1980 to 2000 US Census and the 2011 ACS three-year aggregate (2009-2011). The sample consists of native-born individuals aged 25–55 with at least a bachelor's degree who are working full time (35 hours or more) and for wages in reported week. Control variables include log wages of men and women aged 25–55, average number of children of women aged 25–40, and share of master's or doctoral degrees in a given demographic group. Podiatrists in 1980 is no observation, so the number of observations is 379. Regression is weighted by the number of individuals of the dependent variable.

Table 2.4: Robustness tests on the relationship between the share of men working high-hours and women's average age at first birth: Occupation level

Panel A. Alternative age group				
	(1)	(2)	(3)	(4)
	ages 25-40	ages 25-45	ages 25-50	ages 25-55
High-hours	2.303***	2.014***	1.741**	1.778**
	(0.568)	(0.725)	(0.749)	(0.824)
Controls	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	379	379	379	379
R^2	0.957	0.961	0.967	0.966
Panel B. Alternative definition of working high-hours				
	(1)	(2)	(3)	(4)
	41+	45+	50+	55+
High-hours	2.015***	2.113***	2.303***	3.559***
	(0.564)	(0.565)	(0.568)	(0.865)
Controls	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	379	379	379	379
R^2	0.957	0.957	0.957	0.958
Panel C. Including t+1 of high hours				
	(1)	(2)	(3)	(4)
	41+	45+	50+	55+
High-hours	2.372***	2.536***	2.571***	3.665***
	(0.705)	(0.705)	(0.642)	(1.061)
High-hours (t+1)	-1.280	-1.436	-0.833	-0.330
	(1.080)	(1.034)	(0.896)	(1.386)
Controls	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	379	379	379	379
R^2	0.958	0.958	0.957	0.958

Notes: Clustered standard errors in parentheses,* p<0.10, ** p<0.05, *** p<0.01. The unit of observation is an occupation by year.Data is from the 1980 to 2000 US Census and the 2011 ACS 3-year aggregate (2009-2011). The sample consists of native-born individuals aged 25–55 with at least a bachelor's degree who are working full time (35 hours or more) and for wages in reported week. Control variables include log wages of men and women aged 25–55, average number of children of women aged 25–40, and share of master's or doctoral degrees in a given demographic group. Regression is weighted by the number of individuals of the dependent variable.

Table 2.5: The relationship between the share of men working high-hours in an occupation and a woman's age at first birth: Individual level cross-sectional analysis

	Married women							Married men			
	25-40				25-45	25-50	25-55	25-40	25-45	25-50	25-55
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Share of high-hours	3.796***	1.285***	1.156***	0.737***	1.572***	1.695***	1.812***	0.501**	0.389	0.282	0.246
	(0.600)	(0.305)	(0.317)	(0.212)	(0.414)	(0.444)	(0.470)	(0.228)	(0.309)	(0.314)	(0.324)
Share of high-hours$_{sp}$			0.718***	0.317***	0.419***	0.292**	0.286**	0.820***	1.199***	1.358***	1.507***
			(0.144)	(0.106)	(0.131)	(0.123)	(0.124)	(0.113)	(0.139)	(0.112)	(0.119)
Age at marriage				0.371***							
				(0.013)							
Controls											
Age, Race, Children	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Graduate degree, Log wage	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Share of high hours$_{sp}$	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of Marriage	No	No	No	Yes	No	No	No	No	No	No	No
Spouse Characteristics	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	71,571	63,441	51,663	51,663	75,272	94,491	106,619	54,099	83,925	110,053	128,424

Notes: Cluster standard errors in parentheses,* p<0.10, ** p<0.05, *** p<0.01. Data is from the 2017 ACS five-year aggregate (2013-2017). The sample consists of native-born married individuals aged 25–55 with at least a bachelor's degree, are working full time (35 hours or more), and have a spouse with at least a bachelor's degree. Control variable includes age, age^2, a vector of race dummies, a dummy variable of having a graduate degree, and log hourly wage; it also includes spouses' characteristics such as age, race, education, and log hourly wage. The share of men working high-hours in a give *spouse's* occupation is included in some specifications, and then the sample if further restricted to spouses working in 95 skilled occupations in this case. The Regression is weighted by personal weight.

Table 2.6: The relationship between high-human capital occupations and women's average age at first birth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Human capital depreciation	0.151*	0.126	0.172**	0.177**		0.182**	0.173**
	(0.083)	(0.079)	(0.083)	(0.073)		(0.070)	(0.069)
Duration of typical work week					0.146*	0.152**	0.123*
					(0.074)	(0.071)	(0.074)
Interaction term							0.106*
							(0.055)
Interpersonal relationships	Yes	No	No	Yes	No	Yes	Yes
Autonomy	No	Yes	No	Yes	No	Yes	Yes
Competitiveness	No	No	Yes	Yes	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	94	94	94	94	94	94	94

Notes: Robust standard errors in parentheses,* $p<0.10$, ** $p<0.05$, *** $p<0.01$. The unit of observation is an occupation. Data is from the 2017 ACS five-year aggregate and the O*NET (version 23.0, released in 2018). For easier interpretation, average of O*NET indexes are re-normalized to have a mean of zero and a standard deviation of one. Interpersonal relationships consist of having contact with others, establishing and maintaining interpersonal relationships, coordinating or leading others, and having impact of decisions on co-workers or company results. Autonomy contains structured vs. unstructured work, freedom to make decisions, and frequency of decision making. Competitiveness refers to the level of competition. Duration of typical work week is a direct measure of working high-hours from the O*NET. Control variables include log wages of men and women, average number of children of married women, the share of women having a graduate degree. Out of 95 skilled occupations, teachers, n.e.c (159) are excluded from the regression due to the missing O*NET characteristics corresponding to that.

Table 2.7: The relationship between the share of men working high-hours and change in occupational distribution, by ages cohort (Census/ACS)

	Intermediate ages cohort					Young ages cohort				
		Delaying fertility		Women without children	Men		Not delaying fertility		Women without children	Men
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Share of high-hours	-0.161	-0.255**	-0.221**	-0.084*	-0.006	-0.063	-0.082	-0.048	-0.010	0.023
	(0.154)	(0.123)	(0.104)	(0.043)	(0.015)	(0.096)	(0.058)	(0.046)	(0.030)	(0.020)
Average number of children		0.266**	0.230**	0.078**	0.019*		0.114***	0.065**	0.020	0.010
		(0.121)	(0.107)	(0.037)	(0.010)		(0.038)	(0.025)	(0.015)	(0.008)
Controls										
Number of children	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Log wages of men and women	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Share of graduates	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	361	361	361	360	361	336	336	336	336	336
R^2	0.188	0.542	0.559	0.473	0.860	0.241	0.445	0.572	0.446	0.848

Notes: Cluster standard errors in parentheses,* p<0.10, ** p<0.05, *** p<0.01. The unit of observation is an occupation by year. Data are from the 1980 to 2000 US Census and the 2011 ACS 3-year aggregate (2009-2011). The sample consists of native-born individuals aged 25–55 with at least a bachelor's degree who are working full time (35 hours or more) and for wages in reported week. Control variables include log wages of men and women aged 25–55, average number of children of women aged 25–40, and share of master's or doctoral degrees in a given demographic group. Regression is weighted by the number of individuals of the dependent variable.

Table 2.8: Employment changes after the first childbirth (NLSY97)

	O.L.F	Part-time	$Hours \geq 5hrs$	$Hours \geq 10\%$	$Change\_occ$	$Change\_selfemp$	O.L.F&part	O.L.F&5hrs	O.L.F&10%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High_hours· Delaying fertility	0.113*	0.132*	0.206**	0.188*	0.069	0.071	0.246***	0.319***	0.302***
	(0.060)	(0.073)	(0.099)	(0.103)	(0.061)	(0.046)	(0.089)	(0.108)	(0.113)
High_hours	-0.039	-0.090*	0.040	0.011	-0.012	-0.007	-0.129**	0.001	-0.029
	(0.049)	(0.051)	(0.065)	(0.061)	(0.050)	(0.039)	(0.062)	(0.072)	(0.068)
Delaying fertility	-0.056	-0.176**	-0.245***	-0.234***	-0.062	-0.046	-0.231***	-0.300***	-0.290***
	(0.045)	(0.069)	(0.078)	(0.087)	(0.047)	(0.030)	(0.077)	(0.082)	(0.092)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	750	750	750	750	750	750	750	750	750

Notes: Data is from the NLSY97 (2003-20117). The sample consists of married women who have at least a bachelor's degree and had their first birth after at least age 22. The sample is limited to women who were working full time at the year of childbirth, except for those who are self-employed. Women who divorced, separated, or were widowed after the first childbirth are excluded from the sample. Control variables include age, age^2, vector of race dummies, number of children, and a dummy variable for having a graduate degree. The error term is clustered at the individual level and individual weights given by the NLSY97 are applied in regressions. Dependent variables in each column are as below:

- Column (1) O.L.F: drop out of the labor force
- Column (2) Part-time: working less than 35 hours per week
- Column (3) $Hours \geq 5hrs$: reducing working hours more than 5 hours
- Column (4) $Hours \geq 10\%$: reducing working hours more than 10 percent
- Column (5) $Change\_occ$: change both occupation and workplace
- Column (6) $Change\_selfemp$: change to self-employment
- Column (7): column (1) + column (2)
- Column (8): column (1) + column (3)
- Column (9): column (1) + column (4)

Table A2.1: Summary statistics for the Census/ACS, married men with children

Panel A.Micro Data					
	1980	1990	2000	2010	2017
Married men with children					
Age	39.30	40.37	41.79	42.26	42.40
	(7.58)	(6.79)	(7.03)	(7.10)	(7.09)
Black	0.03	0.04	0.04	0.05	0.05
	(0.17)	(0.18)	(0.20)	(0.21)	(0.21)
Hispanic	0.02	0.02	0.03	0.04	0.05
	(0.14)	(0.14)	(0.16)	(0.20)	(0.22)
White non-Hispanic	0.91	0.89	0.84	0.77	0.74
	(0.28)	(0.32)	(0.37)	(0.42)	(0.44)
Others	0.04	0.06	0.09	0.14	0.16
	(0.19)	(0.23)	(0.29)	(0.34)	(0.37)
Masters	0.30	0.26	0.26	0.28	0.30
	(0.46)	(0.44)	(0.44)	(0.45)	(0.46)
Doctoral and Professional degree	0.28	0.19	0.19	0.16	0.16
	(0.45)	(0.40)	(0.39)	(0.37)	(0.36)
Hourly wage	19.81	24.01	27.55	28.89	29.61
	(9.98)	(15.84)	(21.98)	(20.94)	(22.44)
Working more than 50 hours	0.32	0.39	0.45	0.40	0.38
	(0.46)	(0.49)	(0.50)	(0.49)	(0.48)
Age at first birth	28.23	29.40	30.86	31.52	31.70
	(4.70)	(4.89)	(5.10)	(5.05)	(5.01)
N	197,890	239,105	260,567	190,497	306,646

Notes: Data are from the 1980 to 2000 US Census and the 2011 ACS three-year aggregate (2009-2011), and the 2017 five-year aggregate ACS. The sample consists of native-born individuals aged 25–55 with at least a bachelor's degree who are working full time (35 hours or more) and for wages in reported week.

Table A2.2: A list of 95 skilled-occupations in the Census/ACS

occ1990dd	Occupation	Share of men working high-hours in 2010 (%)	Changes in shares (2010-1980)
84	Physicians	73.1	-0.2
4	Chief executives, public administrators, and legislators	63.2	32.7
178	Lawyers and judges	58.6	17.3
86	Veterinarians	54.5	-11.2
34	Business and promotion agents	53.8	22.5
176	Clergy and religious workers	53.1	-12.8
199	Athletes, sports instructors, and officials	51.9	2.2
13	Managers and specialists in marketing, advertising, PR	51.6	12.6
14	Managers in education and related fields	50.4	17.1
255	Financial services sales occupations	48.9	17.4
258	Sales engineers	48.7	21.1
22	Managers and administrators, n.e.c.	48.1	11.2
254	Real estate sales occupations	48.0	5.9
88	Podiatrists	47.2	6.0
7	Financial managers	45.2	19.6
19	Funeral directors	45.0	-13.4
274	Salespersons, n.e.c	44.5	15.4
8	Human resources and labor relations managers	43.2	15.7
15	Managers of medicine and health occupations	42.2	12.1
18	Managers of properties and real state	41.8	9.6
47	Petroleum, mining, and geological engineers	41.8	10.5
106	Physician assistants	41.8	2.5
187	Actors, directors, and producers	41.8	7.3
26	Management analysts	41.7	10.9
25	Other financial specialists	41.2	21.3
226	Airplane pilots and navigators	38.4	6.7
154	Subject instructors, college	38.3	1.8
186	Musicians and composers	37.4	8.0
166	Economists, market and survey researchers	37.0	14.1
253	Insurance sales occupations	36.6	5.2
77	Agricultural and food scientists	36.5	19.0
37	Management support occupations	36.0	16.6
188	Painters, sculptors, craft-artists, and printmakers	35.2	7.5
157	Secondary school teachers	34.1	10.7
256	Advertising and related sales jobs	34.1	8.4
183	Writers and authors	34.0	2.9
189	Photographers	34.0	4.5
97	Dieticians and nutritionists	33.8	7.9
83	Medical scientists	33.4	-5.5
89	Other health and therapy occupations	33.2	7.9
45	Metallurgical and materials engineers	33.2	23.0
48	Chemical engineers	32.9	21.7
33	Purchasing managers, agents, and buyers, n.e.c	32.0	14.3
69	Physicists and astronomists	31.9	13.8
23	Accountants and auditors	31.9	14.5
27	Personnel, HR, training	31.7	14.1
198	Announcers	31.7	7.3
76	Physical scientists, n.e.c.	31.5	17.8

Table A2.2: A list of 95 skilled-occupations in the Census/ACS (Continued)

occ1990dd	Occupation	Share of men working high-hours in 2010 (%)	Changes in shares (2010-1980)
56	Industrial engineers	31.4	19.0
43	Architects	31.3	8.4
195	Editors and reporters	31.0	9.6
418	Police and detectives public service	29.3	5.5
156	Primary school teachers	28.3	9.2
194	Art/entertainment performers and related occupations	27.8	-7.5
57	Mechanical engineers	26.9	15.4
159	Teachers, n.e.c	26.3	-0.1
185	Designers	26.0	6.6
66	Actuaries	25.8	14.5
167	Psychologists	24.6	5.0
53	Civil engineers	24.4	11.0
55	Electrical engineers	24.2	14.8
59	Engineers and other professionals, n.e.c	24.0	10.0
169	Social scientists and sociologists, n.e.c.	24.0	4.0
103	Physical therapists	23.8	-2.2
36	Inspectors and compliance officers, outside	23.4	11.5
79	Foresters and conservations scientists	23.1	8.0
99	Occupational therapists	23.0	19.3
68	Mathematicians and statisticians	22.9	14.4
85	Dentists	22.8	0.8
234	Legal assistants and paralegals	22.6	4.7
87	Optometrists	22.4	-1.3
165	Archivists and curators	21.5	2.8
65	Operations and systems researchers and analysts	21.3	10.5
64	Computer systems analysts and computer scientists	20.5	8.2
73	Chemists	20.3	11.2
24	Insurance underwriters	19.9	11.0
44	Aerospace engineers	19.7	11.6
229	Computer software developers	19.1	10.1
78	Biological scientists	18.8	1.4
75	Geologists	18.6	0.3
104	Speech therapists	18.5	8.7
105	Therapists, n.e.c	18.2	8.9
158	Special education teachers	17.6	0.7
96	Pharmacists	17.3	-14.7
163	Vocational and educational counsellors	17.1	3.9
155	Kindergarten and earlier school teachers	16.5	-3.3
95	Registered nurses	16.4	-1.8
177	Welfare service workers	14.2	-1.7
173	Urban and regional planners	13.6	2.2
184	Technical writers	13.4	-2.7
74	Atmospheric and space scientists	12.4	0.8
174	Social workers	12.0	3.2
227	Air traffic controllers	10.5	4.3
164	Librarians	9.3	2.8
98	Respiratory therapists	9.1	-5.3

Notes: occ1990dd is Dorn's (2009) occupation classification.

Table A2.3: Robustness tests on the relationship between the share of men working high-hours and women's average age at first birth: Occupation level

Panel A. Without Controls				
	(1)	(2)	(3)	(4)
	Num_children	Ratio($\geq$ one kid)	Ratio($\geq$ two kids)	Ratio($\geq$ three kids)
High-hours	0.360	0.239	0.155	-0.011
	(0.365)	(0.162)	(0.154)	(0.049)
Controls	No	No	No	No
Occupation FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	380	380	380	380
R^2	0.862	0.833	0.841	0.853

Panel B. With Controls				
	(1)	(2)	(3)	(4)
	Num_children	Ratio($\geq$ one kid)	Ratio($\geq$ two kids)	Ratio($\geq$ three kids)
High-hours	0.522**	0.270**	0.231**	0.033
	(0.249)	(0.109)	(0.105)	(0.036)
Controls	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	380	380	380	380
R^2	0.897	0.885	0.877	0.869

Notes: Clustered standard errors in parentheses,* p<0.10, ** p<0.05, *** p<0.01. The unit of observation is an occupation by year. Data is from the 1980 to 2000 US Census and the 2011 ACS three-year aggregate (2009-2011). The sample consists of native-born individuals aged 25–55 with at least a bachelor's degree who are working full time (35 hours or more) and for wages in reported week. Dependent variable is the number of children, ratio of having more than one child, two children, three children among married women aged 25–40, respectively. Control variables include log wages of men and women aged 25–55 and share of master's or doctoral degrees among married women aged 25–40 with children. Regression is weighted by the number of married women aged 25–40.

Table A2.4: The relationship between the share of men working high-hours and O*NET characteristics

O*NET characteristics	Share of men working high-hours in ACS		Differences in means
	Low	High	
Interpersonal relationships			
Contact with others	0.08	0.51	0.43**
	(0.90)	(0.46)	
Establishing and maintaining interpersonal relationships	-0.13	0.46	0.59*
	(1.11)	(0.85)	
Coordinate or lead others	-0.08	0.66	0.74***
	(0.82)	(0.94)	
Impact of decisions on co-workers or company results	-0.23	0.60	0.83***
	(1.05)	(0.78)	
Autonomy			
Structured vs. unstructured work	-0.45	0.54	0.99***
	(0.87)	(0.91)	
Freedom to make decisions	-0.16	0.43	0.59**
	(0.84)	(1.01)	
Frequency of decision making	-0.07	0.59	0.66**
	(1.08)	(0.66)	
Competitiveness			
Level of competition	-0.59	0.31	0.90***
	(0.85)	(1.02)	

Notes: Standard deviations are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01. Data is from the O*NET (Version 23.0, released in 2018) and the 2017 ACS five-year aggregate. Given the distribution of the share of men working high-hours across occupations, I extract two groups, on from below 25 percentile and the other from above 75 percentile. Each of the O*NET characteristics are normalized to have a mean of 0 and a standard deviation of 1.

Table A2.5: Changes in employment status after the first childbirth (NLSY97)

	O.L.F	Part-time	$Hours \geq 5hrs$	$Hours \geq 10\%$	$Change\_occ$	$Change\_selfemp$	O.L.F&part	O.L.F&5hrs	O.L.F&10%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High-hours·	0.074**	0.043	0.246***	0.199**	0.058*	0.064**	0.117*	0.320***	0.273***
delaying fertility	(0.036)	(0.050)	(0.075)	(0.082)	(0.034)	(0.028)	(0.062)	(0.081)	(0.090)
High-hours·	0.016	0.086	0.285***	0.245***	0.050*	0.039	0.102*	0.301***	0.261***
non delaying fertility	(0.029)	(0.054)	(0.071)	(0.080)	(0.027)	(0.027)	(0.060)	(0.073)	(0.084)
Non-high-hours·	0.056	0.176**	0.245***	0.234***	0.062	0.046	0.231***	0.300***	0.290***
non delaying fertility	(0.045)	(0.069)	(0.078)	(0.087)	(0.047)	(0.030)	(0.077)	(0.082)	(0.092)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	750	750	750	750	750	750	750	750	750

Notes: Data is from the NLSY97 (2003-20117). The sample consists of married women who have at least a bachelor's degree and had their first birth after at least age 22. The sample is limited to women who were working full time at the year of childbirth, except for those who are self-employed. Women who divorced, separated, or were widowed after the first childbirth are excluded from the sample. Control variables include age, age^2, vector of race dummies, number of children, and a dummy variable for having a graduate degree. The error term is clustered at the individual level and individual weights given by the NLSY97 are applied in regressions. Dependent variables in each column are as below:

- Column (1) O.L.F: drop out of the labor force
- Column (2) Part-time: working less than 35 hours per week
- Column (3) $Hours \geq 5hrs$: reducing working hours more than 5 hours
- Column (4) $Hours \geq 10\%$: reducing working hours more than 10 percent
- Column (5) $Change\_occ$: change both occupation and workplace
- Column (6) $Change\_selfemp$: change to self-employment
- Column (7): column (1) + column (2)
- Column (8): column (1) + column (3)
- Column (9): column (1) + column (4)

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B.B.A. & B.A., Economics, Sogang University, Seoul, South Korea	2006
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Graduate Assistantship, University of Missouri in St.Louis	2014-2016
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