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

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Abstract

This paper 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.

Key words: Gender wage gap, Women's labor supply decisions, Locational effect, Highly-educated women **JEL Codes:** J22, J31

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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

[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.

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 ratio (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 analysis 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.

[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.

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 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

[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.

[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.

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 individual. 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]

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

3 Descriptive facts

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

$$ln(w_e^g) = \sum_j \left[ln(w_{j,e}^g) \times \left(\frac{emp_{j,e}^g}{\sum_j emp_{j,e}^g} \right) \right] \tag{1}$$

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 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.

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

[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.

[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.

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 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 MSA*j* and, conversely, the relationship between women's emp/pop and men's wage in each MSA*j*.[10] To control local demand shocks, I include local unemployment rate in 2016 (X) as a control variable.

$$men's(women's)\ emp/pop_{\ j} = \beta_0 + \beta_1\ MSA\ women's(men's)\ log\ wage_j + X_j + \epsilon_j \qquad (2)$$

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

[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.

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 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.

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

[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.

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]

3.3.1 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 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

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

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.

3.3.2 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 per-

[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).

cent 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 subsample. 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 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

[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.

[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.

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.

3.3.3 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:

$$y_{ij} = \alpha + \beta MSA\ men's\ wage_j + \eta(spouse's\ education \times marriage)_i + \gamma X + \epsilon_i \tag{3}$$

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.

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):

$$ln(w_e^g) = \sum_j \left[\underbrace{ln(w_{j,e}^g)}_{A} \times \underbrace{\left(\frac{emp_{j,e}^g}{\sum_j emp_{j,e}^g} \right)}_{B} \right] \tag{4}$$

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?

$$ln(w_e^W)^P = \sum_{j=1}^{84}\left[ln(w_{j,e}^W) \times \underbrace{\left(\frac{emp_{j,e}^M}{\sum_j emp_{j,e}^M}\right)}_{B'}\right] \tag{5}$$

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 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

[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.

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

$$A = ln(w_{j,e}^{Mar}) \times \underbrace{\left(\frac{\sum_j emp_{j,e}^{Mar}}{\sum_j emp_{j,e}^{Mar} + \sum_j emp_{j,e}^{NMar}}\right)}_{C} + ln(w_{j,e}^{NMar}) \times \underbrace{\left(\frac{\sum_j emp_{j,e}^{NMar}}{\sum_j emp_{j,e}^{Mar} + \sum_j emp_{j,e}^{NMar}}\right)}_{D}. \quad (6)$$

And equation (4) becomes

$$ln(w_e^W)^P = \sum_{j=1}^{84} \underbrace{\left[ln(w_{j,e}^{Mar}) \times \underbrace{\left(\frac{\sum_j emp_{j,e}^{Mar}}{\sum_j emp_{j,e}^{Mar} + \sum_j emp_{j,e}^{NMar}}\right)}_{C} + ln(w_{j,e}^{NMar}) \times \underbrace{\left(\frac{\sum_j emp_{j,e}^{NMar}}{\sum_j emp_{j,e}^{Mar} + \sum_j emp_{j,e}^{NMar}}\right)}_{D}\right]}_{A} \times \underbrace{\left(\frac{emp_{j,e}^{NMar}}{\sum_j emp_{j,e}^{NMar}}\right)}_{B''}. \quad (7)$$

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 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

[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.

[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.

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.

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).

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

[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,

$$I_j = \frac{w_j^{women}}{w_j^{men}} = \frac{e(p_j, u^{women})}{e(p_j, u^{men})}, \tag{8}$$

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.

to measure the gender wage inequality:

$$ln(w_i) = \beta_0 + \beta_1 I_{M,i} + X + \epsilon_i \tag{9}$$

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 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:

$$ln(w_i) = \beta_0 + \beta_1 I_{M,i} + X + region_i + metro_i + \epsilon_i. \tag{10}$$

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]

$$ln(w_{ij}) = \beta_0 + \beta_1 I_{M,ij} + X + \theta_j + \epsilon_{ij}. \tag{11}$$

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

[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 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.

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 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]

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

[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 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.

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 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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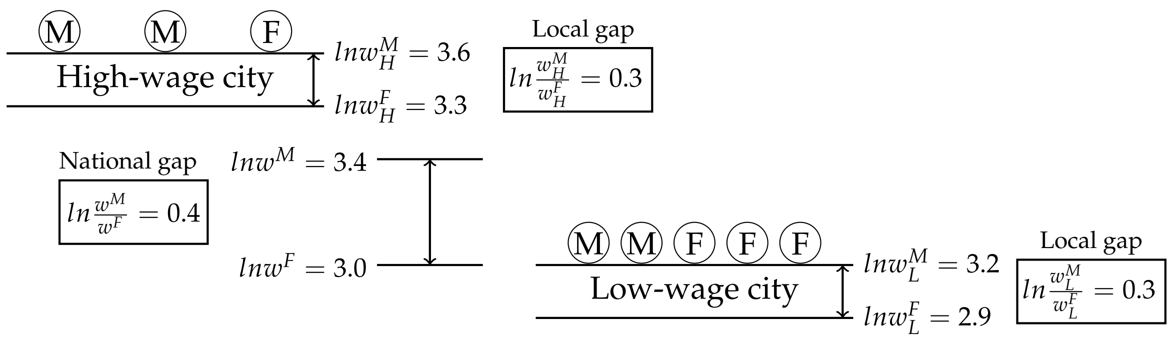
Figure 1: Log Wage Variations across MSAs by Education Level

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

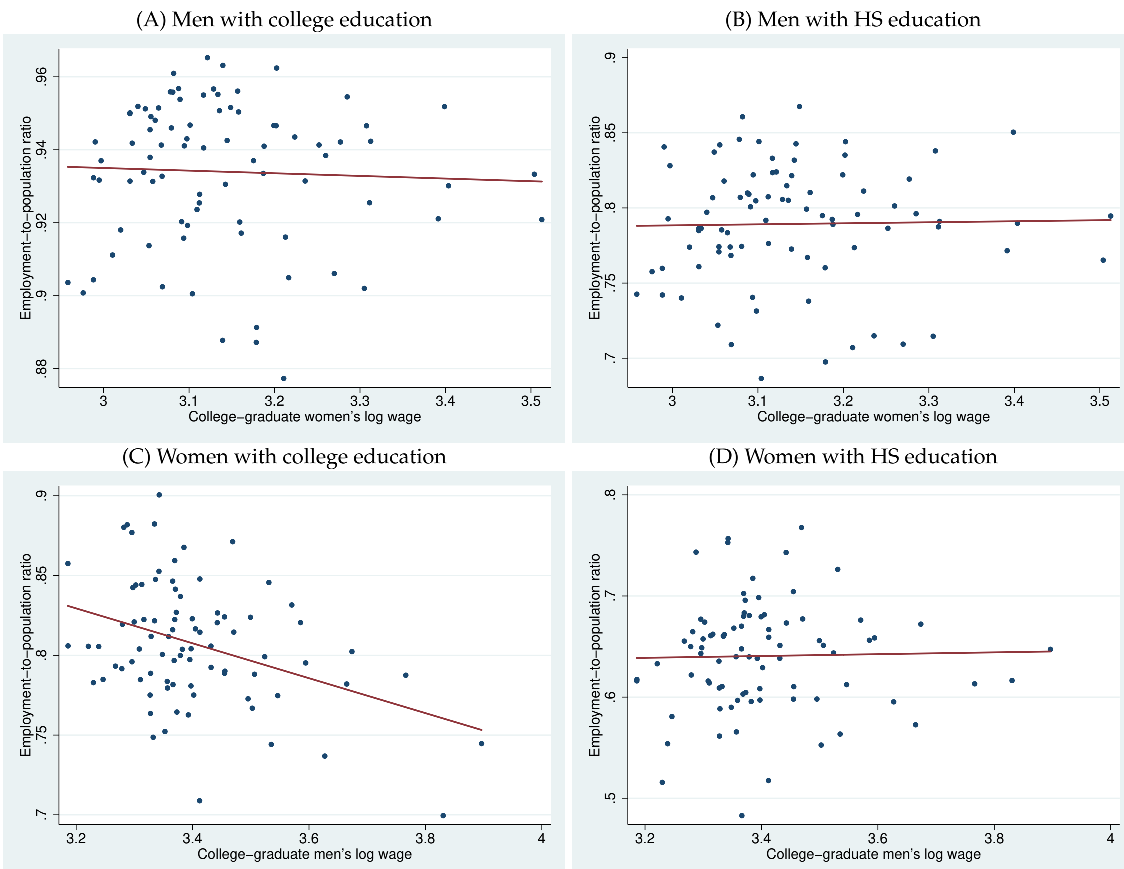
Notes: Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs. The unit of observation is an MSA.

Figure 2: The relation between national gender wage gap and local gender wage gaps



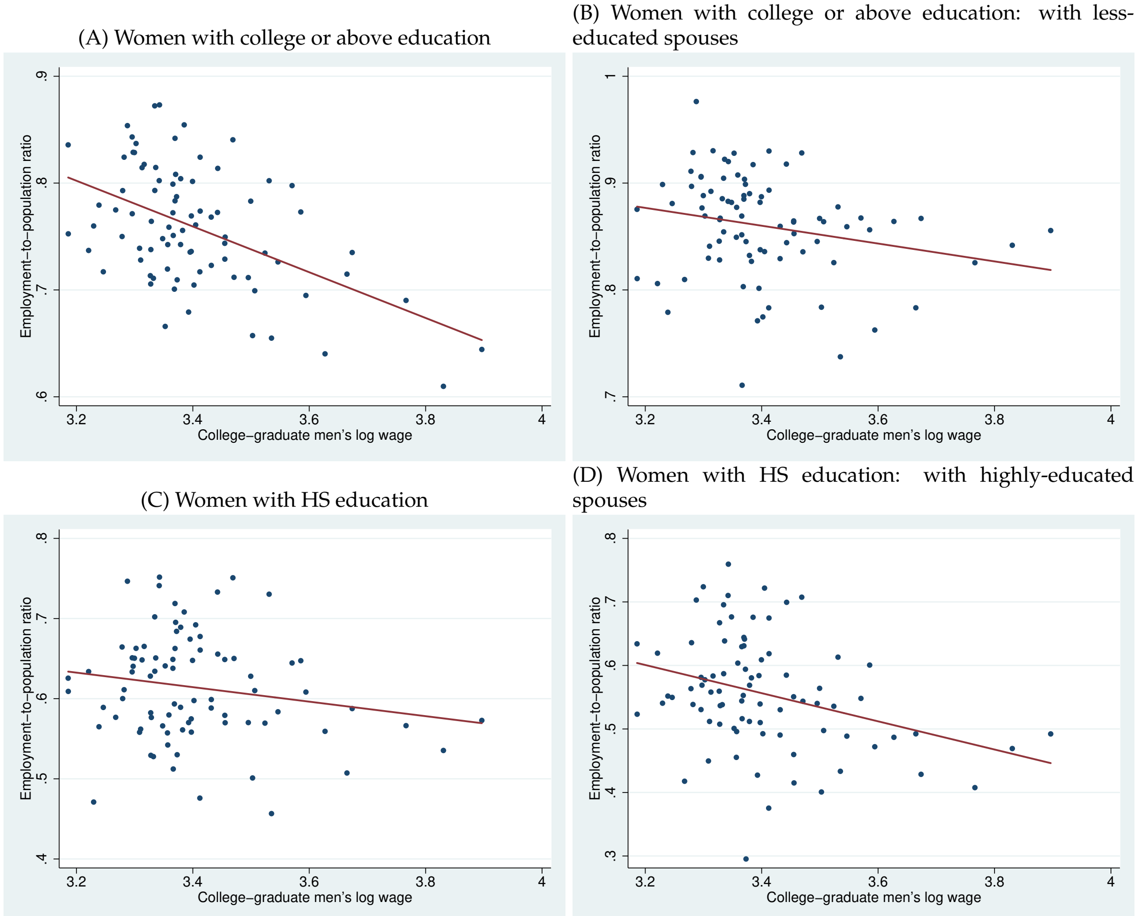
Notes: M refers a male worker and F refers a female worker. Suppose there are two cities—high-wage city and low-wage city and the local log wage differences between men and women are 0.3, which is the same for both cities. National weighted log wage for men would be 3.4, because two male workers work 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 3: The Relationship between emp/pop and log wage across MSAs



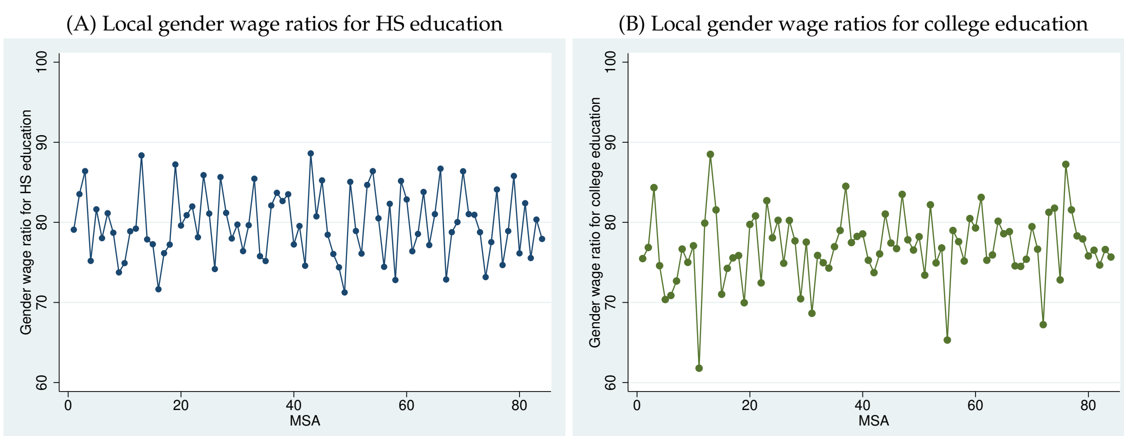
Notes: Data is from the 2016 ACS 5-year aggregate. The sample consists of non-Hispanic white workers aged 25-55 years with non-imputed data in 84 MSAs. The unit of observation is an MSA.

Figure 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 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: 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 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 3: The relationship between emp/pop and log wage for each MSA

Panel A. Dependent variable: men's emp/pop in each MSAs				
	(1) Advanced degree	(2) College	(3) Some college	(4) High school
Log wage of men with college education	-0.010	-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 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) Without children	(2) With children	(3) Without children	(4) With children
Log wage of men with college education	-0.081** (0.038)	-0.246*** (0.038)	0.003 (0.023)	-0.107*** (0.037)
Unemployment rate	-0.004 (0.005)	-0.015** (0.006)	-0.013*** (0.004)	-0.019*** (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) Without children	(2) With children	(3) Without children	(4) With children
Log wage of men with college education	0.002 (0.048)	-0.117*** (0.039)	0.040 (0.037)	0.099* (0.055)
Unemployment rate	-0.026*** (0.009)	-0.032*** (0.007)	-0.033*** (0.006)	-0.036*** (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 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 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***	-0.086***	-0.063**	-0.038
	(0.019)	(0.020)	(0.030)	(0.049)
Some college$_{sp}$ ×marriage	-0.012***	-0.009*	-0.043***	-0.005
	(0.004)	(0.005)	(0.005)	(0.005)
College graduates$_{sp}$ ×marriage	-0.065***	-0.108***	-0.106***	-0.063***
	(0.004)	(0.006)	(0.006)	(0.007)
Advanced degree$_{sp}$ ×marriage	-0.114***	-0.198***	-0.203***	-0.150***
	(0.006)	(0.009)	(0.009)	(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 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)× 100. Predicted wage ratio is exp(predicted women's log wage minus men's log wage)×100.

Table 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)×100. Numbers are weighted by individual weights given by the ACS, then age-adjusted to control different age distributions across MSAs.

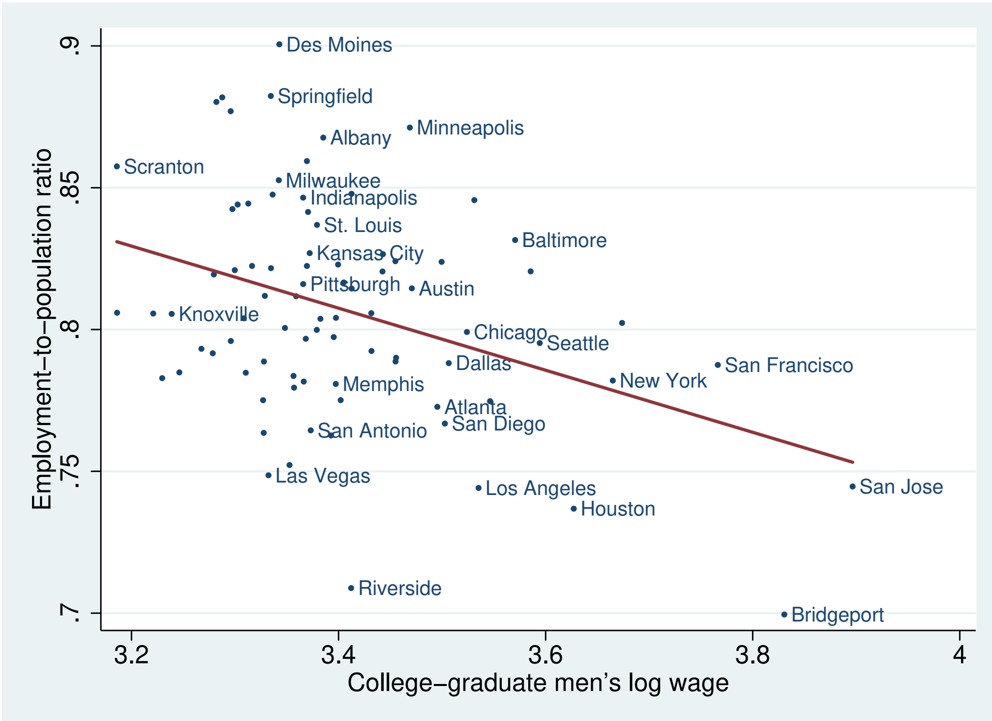
Table 9: Gender Wage Gaps in Log Hourly Wage

Panel A. 84 MSAs			
	(1)	(2)	(3)
	Total	HS education	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.

Appendix 1

Figure A1: 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: 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 A2: 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 A3: 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.

Appendix 2

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

$$-wu_1(w(1-\ell)+I(w),\alpha\ell)+\alpha u_2(w(1-\ell)+I(w),\alpha\ell)=0.^{28} \tag{12}$$

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

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

Then, we have

$$\frac{d\ell}{dw}=\frac{u_1+\{1-\ell+I'(w)\}(wu_{11}-\alpha u_{12})}{w^2u_{11}-2\alpha wu_{12}+\alpha^2u_{22}}. \tag{13}$$

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.

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.

[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.

[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.

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 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:

$$\frac{\partial \frac{d\ell}{dw}}{\partial \alpha} = \frac{\{ -(1-\ell+I'(w))u_{12} \overbrace{[den]}^{negative} \} - \{ \overbrace{[num]}^{positive}(-2wu_{12}+2\alpha u_{22})\}}{den^2} > 0. \tag{14}$$

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:

$$\frac{\partial \frac{d\ell}{dw}}{\partial \alpha} = \frac{\{ -(1-\ell+I'(w))u_{12} \overbrace{[den]}^{negative} \} - \{ \overbrace{[num]}^{negative}(-2wu_{12}+2\alpha u_{22})\}}{den^2}. \tag{15}$$

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.