City Size, Family Migration, and Gender Wage Gap: Evidence from Rural-Urban Migrants in China

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Abstract

Finding suitable employment in a city is more challenging for married than unmarried migrants. This paper provides empirical evidence that the denser and more diversified labor markets in large cities help alleviate the colocation problem of married couples. Using data from China, we show that the gender wage gap among married migrants is significantly smaller in larger cities, and this is mainly because large cities have higher employer and population densities. Large cities make married women more likely to be employed and to secure suitable jobs after family migration. We find no evidence for alternative explanations for the correlation between city size and married women's relative wages.

Keywords: city size, family migration, colocation choice, gender gap.

JEL Classification: J31, R12, R23, O15.

1 Introduction

In the past half-century, billions of rural residents in developing countries migrated to cities and disproportionately concentrated in high-density regions. China is an extraordinary example. Its urbanization rate rose sharply from 17.9% in 1978 to 64.7% in 2021 due to

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massive rural-urban migration. By 2018, mainland China had the most megacities (i.e., city agglomerations with over 10 million population) worldwide (United Nations 2019). We argue that, when family members migrate together, diversified labor markets in large cities make it easier for married women to find suitable jobs. Accordingly, the husbands are willing to accept lower-paid jobs when they move to large cities but demand higher wages in small ones. Therefore, city size is positively correlated with married women's wages relative to married men's. We show this correlation and explore the underlying mechanisms in the context of China, focusing mainly on rural migrants in urban areas.

To illustrate the mechanism formally, we first construct a spatial equilibrium model with two cities of unequal size, which is in the same spirit as Mincer (1978). We assume that the large city has a thicker labor market and provides better-matched jobs than the small one and that men earn more than women. We show that when workers migrate individually, the gender wage gap is independent of city size. However, women have higher relative wages when relocating with their husbands to the large than the small city. The intuition is as follows: In a society where the husband is the primary income earner, a married couple moves to a small city with a lower average income most likely because the husband finds a good job. Otherwise an identical couple would choose the large city, even when the husband has a relatively low wage job, because the wife can find a better-matched job there.

Using a nationally representative population survey, we show that the gender wage gap is negligible or small among unmarried migrants but reaches over 30% for married ones. Both individual and city level regressions indicate that the gender wage gap for married migrants is lower in larger cities. The relative wage of married women is over seven percentage points lower in the 10^{th} than in the 90^{th} percentile city. To alleviate endogeneity issues due to reverse causality and omitted variables, we use historical city population as an instrumental variable for the current population.

The most plausible mechanism underlying our finding is the interaction between the thickness of the labor market and the colocation problem of a migrant family, as illustrated in our theoretical model. We show that the positive correlation between city size and the relative wage of married female migrants can be largely explained by the density of employers and population within a city. Furthermore, married women's employment rate is higher in large cities. We also find that married male migrants are more likely to earn lower wages when their wives have a job, and migrant wives are more likely to be household heads (an indication of higher status within the households) in large cities.

There are several competing hypotheses about the city size effect. The first is the potential sorting of married migrants across cities of different sizes. We refute this explanation by showing that (1) our results are robust to correction of selection on unobserved individual characteristics and (2) the degree of assortative marriage by education is independent of city size. One also wonders whether children make a difference. For example, migrant couples may tend to leave their children behind in home villages when moving to large cities, or they may more easily find childcare services in larger cities which allow married women to participate more in the labor market. We rule this out by showing that married migrants in larger cities are equally likely to bring their children with them and that our main findings still hold after controlling for the presence of children. In addition, one might suspect that tighter labor market regulations in larger cities is the reason. For example, China's minimum wages are higher in large cities. If women are more likely to be supported by the wage floors, the regulation may reduce the gender wage gap in large cities. However, such regulations should also affect unmarried migrants, for whom we find no effects of city size on the gender wage gap.

Our research is related to three strands of literature. First, we contribute to the literature on family migration pioneered by Mincer (1978). Mincer (1978) emphasizes that "net family gain rather than personal gain motivates migration of households." He predicts that urban areas will be more attractive as wives' job motivation grows. Subsequent studies find further evidence that city size is a significant factor in attracting family migrants. Costa and Kahn (2000) show that in the United States, college-educated couples are increasingly located in large cities. Their explanation is that these "power couples" pursue dual careers and large cities help solve their colocation problems. In a follow-up study, Compton and Pollak (2007) question the colocation hypothesis. They find that the increasing concentration of power couples in large cities is mainly driven by a higher formation rate of power couples in those areas. Family migration has also generated considerable research interest among noneconomists such as sociologists and geographers. They emphasize the effect of gender-role beliefs and provide evidence that wives are reluctant to relocate for better jobs or likely to follow their husbands as "tied movers" (see, e.g., Bielby and Bielby 1992, Boyle et al. 2001, Cooke 2008, and Sorenson and Dahl 2016).[1] Benson (2014), on the other hand, argues that families tend to relocate for husbands' careers mainly because women have sorted into geographically dispersed occupations and have less locational constraints than men. Our study focuses on family migration in the unique context of China. The large population and rapid urbanization in China provide us a large analysis sample, which has clear advantages over the existing literature. For example, we have a large number of unmarried migrants to compare with married migrants; we also have substantial variation in destination cities that

[1] In the Chinese context, Xing and Zhang (2017) show that rural-urban migrants prefer larger cities, even with reduced wages. One possible explanation is that one household member (presumably the husband) gives up some personal income in exchange for better job opportunities for another family member (the wife in most cases). We provide supportive evidence for this conjecture.

allows for the exploration of heterogeneity along many dimensions.

Second, our paper connects with the literature on city-size wage premium. It is well known that workers are more productive and thus earn higher wages in larger cities. A series of influential studies have investigated potential determining factors of this city-size wage premium, including sorting of more capable workers into larger cities, selection of more productive firms due to tougher competition in larger cities, and learning advantages of larger cities (e.g., Glaeser and Maré 2001, Henderson 2003, Combes et al. 2008, Baum-Snow and Pavan 2012, Combes et al. 2012, De La Roca and Puga 2017, and Eckert et al. 2022).[2] Most related to our study is prior work emphasizing the benefits of a thicker labor market and better firm-worker match quality in larger cities (Helsley and Strange 1990, Wheeler 2001, Gan and Zhang 2006, Fu 2007, Bleakley and Lin 2012). We take the thick-market benefit of large cities as given and investigate how it helps solve the colocation problem for migrant couples. Unlike Costa and Kahn (2000) who infer colocation concerns from the locational distributions of couples, we directly examine migrant couples. For a large subsample of married migrants, we have information about when the migration occurred and when the couple got married, thus avoiding the criticism of Compton and Pollak (2007). By showing the mitigating effect of city size on the gender wage gap among married migrants, we provide a new angle to understand the benefits of working in larger cities.

Third, this study helps us better understand the gender wage gap. Worldwide, women earn less than men in the labor markets. Researchers have examined many factors that could potentially explain the gender wage gap, including gender differences in labor force participation, human capital, returns to skill, and psychological attributes or noncognitive skills; occupational segregation by gender; discrimination against women; and labor market regulations. Blau and Kahn (2017) provide a comprehensive review of this vast literature.[3] However, research on migrants' gender wage gap is scarce, and spatial factors have rarely been featured in this literature. We have only encountered two studies that take a spatial approach to understanding gender wage gaps. Liu and Su (2020) emphasize the fact that women are more willing to trade off earnings for short commutes than men. Using data from the American Community Survey, they show that given the distribution of jobs and residential locations, the gender difference in commuting preferences contributes substantially to gender

[2]For studies of the relationship between city size and wages in China, see Ning (2014), Wang and Li (2015), and Zong and Zhou (2015).

[3]Unlike the narrowing gender wage gap observed in some industrialized countries, the gap in China has widened significantly in recent years (see, for example, Wang and Cai 2008, Zhang et al. 2008, Song et al. 2017). Li et al. (2018) document a rising contribution of gender to urban wage inequality (measured in Gini), from 1.7% in 1995 to 3.5% in 2013. For understanding the gender wage gap in China, see also Maurer-Fazio and Hughes (2002), Zhang et al. (2008), Meng (1998), Chi and Li (2008), Wang and Cai (2008), Li and Dong (2011), Dong and Zhang (2009), Magnani and Zhu (2012), and Li and Ma (2015).

wage gaps. Using data from Denmark, Sorenson and Dahl (2016) document that dual-earner couples tend to live in places with higher expected wages for the man than for the woman. They show that this better job match for men could account for up to 36 percent of the gender wage gap in Denmark. Like Sorenson and Dahl (2016), in this study, we also argue that women tend to be the tied movers in family migration. We provide evidence that labor markets in larger cities help reduce the sacrifice of women as tied movers.

This paper proceeds as follows. In section 2, we construct a simple model to illustrate how a thicker labor market in large cities alleviates the tension of spouses' colocation choice. Section 3 introduces and describes the data we use. Section 4 establishes the fact that the gender wage gap for married migrants is smaller in large cities. Section 5 provides some ancillary evidence in support of our model's predictions. Section 6 explores alternative explanations of the relationship between city size and gender wage gap. Section 7 concludes with a few remarks.

2 A Simple Model

To provide a framework for empirical analysis, we present a simple model to illustrate the mechanism that governs the relationship between city size and gender wage gap. In the model, it is a spatial equilibrium outcome that earnings of married women migrants are relatively higher in large cities. Consider an economy with two cities. One city (L) is larger and provides $N(>1)$ times job positions as the other (S). N reflects the relative size, which can be endogenously determined. Each city has an equal number of jobs available for male and female workers. An equal number of male and female workers decide whether to work in the large or the small city. Workers of each gender are endowed with the same level of ability with A_m for males and A_f for females. We assume $A_m > A_f$, which may reflect real difference (e.g., male workers have more physical strength than female workers) and/or perceived difference due to gender discrimination.

A worker living in city $i \in \{L, S\}$ obtains the following utility $U^i = w^i + a^i - c^i$, where w^i is the wage income earned in city i, a^i is the urban amenity in city i, and c^i is the cost of living in city i. A worker will choose to live in the small city if and only if $U^L < U^S$. While a^i and c^i are exogenous parameters in an individual or couple's location choice, they are endogenously determined in this model in that they will adjust to establish a spatial equilibrium. For simplicity, we do not explicitly model the behaviors of a^i and c^i. Intuitively, when a city experiences population growth, the amenity value will decrease due to congestion, and the cost of living will increase as housing prices rise. These changes, which reflect the supply elasticities of city infrastructure and housing, will bring equilibrium and define the relative size of the large and small cities.

A worker's wage income is determined by his/her ability and the matching quality of the job, which is related to the thickness of the labor market. The large city has a thick labor market where every worker can find a job that perfectly matches his or her skill set. Thus, male and female workers in the large city earn $w_m^L = A_m$ and $w_f^L = A_f$, respectively. The small city has a thin labor market where workers' skills may not be perfectly matched with jobs. For example, a Python programmer can always find a job that requires her exact skills in the large city, but she may have to work as a Java programmer in the small city because not all kinds of jobs are available there. As a result, the worker's productivity will be lower in the small city. To capture this feature of a thin labor market, we assume that male and female workers in the small city earn $w_m^S = \gamma_m A_m$ and $w_f^L = \gamma_f A_f$, where γ_m and γ_f are random draws from a uniform distribution over $[\theta, 1]$ with $0 < \theta < 1$. We can also interpret γ as a result of discrimination against migrant workers. It is probable that discrimination against migrant workers is stronger in small than in large cities and that the degree of discrimination is randomly determined for individual workers. In this sense, job matching quality reflects discrimination as well.

Case 1: Each worker makes an independent location choice

We assume that a worker has one chance to draw a γ (i.e., conduct a job search) and decide whether to work in the small city, knowing that her wage in the large city fully reflects her ability. Let γ^* be the value of γ_m at which a male worker is indifferent between working in the small and the large city, then $A_m + a^L - c^L = \gamma^* A_m + a^S - c^S$. It is obvious that any male worker who draws a γ_m greater than γ^* will choose to work in the small city. Since spatial equilibrium requires that $\frac{1}{N+1}$ of the male workers choose the small city, and given that γ_m follows a uniform distribution over $[\theta, 1]$, it follows that $\gamma^* = \frac{N(1-\theta)}{N+1}$. The same is true for female workers; any female worker who draws a γ_f greater than γ^* will choose to work in the small city (see the illustration in panel A of Figure 1).

Define the gender wage gap as the difference in average log wages.[4] The gap in the large city is:

$$E(\ln A_m) - E(\ln A_f) = \ln A_m - \ln A_f. \tag{1}$$

Given the uniform distribution of γ, this gap in the small city is:

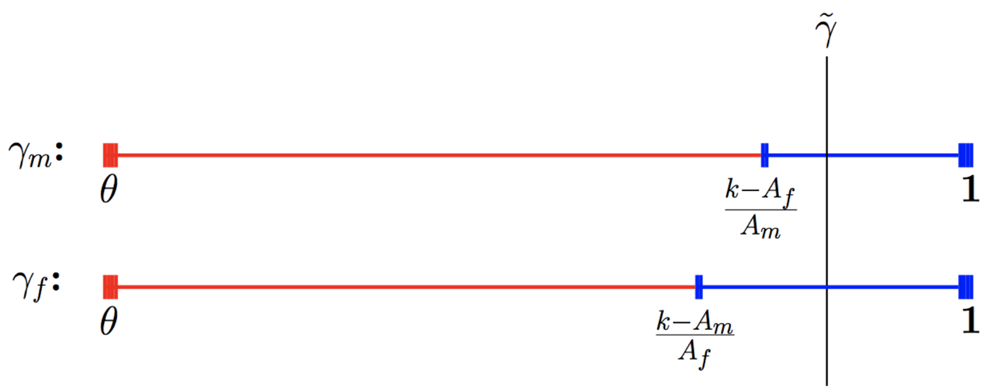
$$\begin{aligned} &E[\ln(\gamma_m A_m)|\gamma_m > \gamma^*] - E[\ln(\gamma_f A_f)|\gamma_f > \gamma^*] \\ &= \ln A_m + \int_{\gamma^*}^{1} \frac{lnt}{1-\gamma^*} dt - \ln A_f - \int_{\gamma^*}^{1} \frac{lnt}{1-\gamma^*} dt = \ln A_m - \ln A_f. \end{aligned} \tag{2}$$

[4] This is consistent with the empirical specification. In log wage regressions, the coefficient of the female dummy is the difference between average log wages for men and average log wages for women.

Figure 1: Job matching quality and the choice of city

A. Each worker makes an independent location choice

B. Married couples make a joint location choice



Note: Workers who draw a match quality (γ) in the blue region will end up in the small city.

Therefore, the gender wage gap among unmarried individuals is independent of city size.

Case 2: Each couple makes a joint location choice

In this case, a married couple makes independent draws of γ_m and γ_f (from the same uniform distribution as before),[5] and will choose to work in the small city if and only if

$$A_m + A_f + 2a^L - 2c^L < \gamma_m A_m + \gamma_f A_f + 2a^S - 2c^S. \tag{3}$$

We here assume that the married couple will enjoy twice as much urban amenity and pay twice as much living costs as an individual does, implying no gains or losses due to joint consumption. This is innocuous because the amenity and living-costs terms will always adjust to achieve spatial equilibrium and have no bearing on any of the arguments we are making below.

Rewrite the above condition (for a couple to choose the small city) as

$$\gamma_m A_m + \gamma_f A_f > k \tag{4}$$

where $k \equiv A_m + A_f + 2(a^L - a^S) - 2(c^L - c^S)$ is a constant in equilibrium.[6] Note that $k < A_m + A_f$; otherwise, no couple will choose to live in the small city. By assuming $\gamma_f = 1$, we find the minimum of the husband's γ_m to be $\frac{k-A_f}{A_m}$ at the small city. Similarly, among all couples living in the small city, the lower bound of the wife's γ_f is $\frac{k-A_m}{A_f}$. Since $A_m > A_f$ and $k < A_m + A_f$, it is easy to verify $\frac{k-A_f}{A_m} > \frac{k-A_m}{A_f}$. Although γ_m and γ_f are drawn from the same uniform distribution, as the result of sorting, the minimum γ_m is bigger than the minimum γ_f among all of the married couples observed in the small city (see panel B of Figure 1).

In this case, the gender wage gap (defined as the difference in average log wages between male and female migrants) in the large city is still the same as in equation (1). Let $\mu_m = E(\ln \gamma_m | \text{living in the small city})$ and $\mu_f = E(\ln \gamma_f | \text{living in the small city})$. Then the gender wage gap in the small city is:

$$\ln A_m + \mu_m - \ln A_f - \mu_f > \ln A_m - \ln A_f. \tag{5}$$

The inequality holds because $\mu_m > \mu_f$, which is proved in the Appendix. Therefore, in this case, the gender wage gap among married individuals is bigger in the small city.

Notice that if we calculate the gender wage gap for unmarried and married individuals in

[5] The assumption of independence between the couple's two draws of γ is not absolutely necessary. But it does help simplify our exposition.

[6] The exact size of k, which is determined by all model parameters, is irrelevant here. We only need the fact that it is a constant in equilibrium.

the whole economy (in both cities), the gender wage gap for unmarried individuals will be smaller than that for married individuals. This is because in the large city, the gender wage gap among married individuals is the same as unmarried individuals; however, in the small city, the gender wage gap among married individuals is larger than that among unmarried individuals.

In sum, the model has two predictions:
(i) *In the whole economy, the gender wage gap for unmarried individuals is smaller than that for married individuals.*
(ii) *The gender wage gap for unmarried individuals is independent of city size; the gender wage gap for married individuals is negatively correlated with city size.*

The key intuition is the following: In an economy where the husband is the main income earner and smaller cities' average wages are lower, a married couple moves to a smaller city most likely because the husband finds a good job opportunity there. As a result, we should expect to see a bigger gender wage gap among married migrants in a smaller city. To see this through the model, let $\tilde{\gamma}$ be a value of γ_m and γ_f such that a couple will be indifferent between the large and the small city, i.e., $\tilde{\gamma}A_m + \tilde{\gamma}A_f = k$. The wage gap between this couple is the same as in the large city even if they move to the small city. Now consider two more couples with the following random draws of matching quality: (1) $(\gamma_m, \gamma_f) = (\tilde{\gamma} + \varepsilon, \tilde{\gamma} - \varepsilon)$; (2) $(\gamma_m, \gamma_f) = (\tilde{\gamma} - \varepsilon, \tilde{\gamma} + \varepsilon); \varepsilon > 0$ is an arbitrarily small number. Obviously, these two sets of random draws are equally likely. However, the first couple will move to the small city because $(\tilde{\gamma} + \varepsilon)A_m + (\tilde{\gamma} - \varepsilon)A_f > k$ and the second couple will stay in the large city. Notice that the first couple in the small city will contribute to a gender wage gap greater than the gap in the large city. The second couple, if choosing the small city, will help bring the gender wage gap down in the small city. Yet they will not move to the small city because a negative shock to the husband's matching quality counts more than the positive shock to the wife's.

We have assumed that workers in the large city earn deterministic wages, and the wages of workers in the small city are determined by the matching quality, which is a random draw from a uniform distribution. We can also assume that workers in the small city have deterministic wages and those in the large city enjoy a city size premium randomly drawn from a specified distribution. Under reasonable conditions, this setup produces essentially the same conclusions: The gender gap is independent of city size when workers choose cities individually, and it is smaller in large cities for spouses who migrate together. In this case, some spouses will move to the large city even when the husband has a relatively low wage job because the wife can find a better-matched job, leading to a lower gender wage gap in the large city. Finally, although the model is agnostic about left-behind spouses (or children) and labor force participation, it has implications for such choices, which we will also examine empirically in sections 5-6.

3 Data and Key Facts

For empirical analysis of gender wage gap among migrants and its relation with city size, we use a one-fifth random sample of the 2005 one percent population survey (also known as the "mini census") conducted by the National Bureau of Statistics (NBS) of China.[7] This data set is unique for its information on individuals' monthly income. Other rounds of census or mini census of China, including more recent ones of 2010, 2015, and 2020, have no income information. The raw data cover over 2.5 million individuals from all provincial level jurisdictions (provinces, autonomous regions, and direct-control municipalities) of mainland China. Its comprehensive geographic coverage and large sample size are essential for this study to estimate each city's gender wage gap. The data also collect rich information on individual characteristics and family structure.

We use the household registration (Hukou) record to identify migrants. Under the Hukou system, Chinese citizens must register in a specific location. The Hukou status is primarily determined by birth, inheriting a parent's Hukou. Population movement was tightly controlled by the Hukou system under the planned regime, but it has become common in recent decades following the economic reform. In this paper, migrants are those who have left a rural Hukou registration location for more than six months and are currently living in cities and towns. Although population movement was possible and relatively easy under the reformed Hukou policy, cases of changing Hukou registration were rare in 2005. Most workers from rural areas were regarded as "temporary" migrants even after they had worked in urban areas for a long time. Therefore, the migrant sample is a stock rather than an annual flow, including individuals who moved to cities years ago.[8] When workers with urban Hukou migrate across cities, they face similar Hukou constraints. However, moves of urban-Hukou migrants are often initiated by employers, have specific job-related destinations, and may be properly compensated. Thus, this study focuses on rural-to-urban migrants to ensure a more homogeneous analysis sample.

[7] As far as we know, all academic researchers who have access to this data have only one fifth of the sample.

[8] Although our definition of rural migrants is standard in the literature (see, e.g., Xing and Zhang 2017), given the focus of this study, we need to be conscious about its implications for family migration. For example, if two individuals (say, two college students) came from different rural areas and got married in the city they met, they would be classified as a migrant couple. However, this is not exactly the type of joint family migration decision we set out to model. As a preliminary check, we find that in 91.7 percent of the migrant couples both spouses come from the same prefectures and that only 0.35 percent of the migrant couples both have post-secondary degrees, suggesting that marriage after migration is unlikely a serious concern. We will examine this issue more carefully below in section 6.

Table 1: Summary statistics for migrants (with positive wages)

	Married				Unmarried			
	Male		Female		Male		Female	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Ln(hourly wage)	2.912	0.608	2.574	0.590	2.782	0.542	2.706	0.491
Age	35.40	7.365	33.58	7.294	22.95	5.532	21.10	4.421
Education level								
Illiterate	0.014	0.118	0.049	0.216	0.005	0.074	0.004	0.066
Primary school	0.186	0.389	0.282	0.450	0.078	0.267	0.061	0.239
Middle school	0.614	0.487	0.557	0.497	0.655	0.475	0.704	0.457
High school	0.167	0.373	0.099	0.299	0.227	0.419	0.200	0.400
Professional college	0.016	0.127	0.012	0.107	0.027	0.162	0.027	0.162
College & above	0.003	0.054	0.001	0.036	0.008	0.089	0.004	0.065
Obs.	35,727		24,312		17,405		16,484	

We keep observations aged between 16 and 55 and classify them into two groups according to their marital status: *married* and *unmarried*.[9] The unmarried observations also include those divorced and widowed, with these two subgroups constituting 2.16 percent of the *unmarried* group.[10] Hourly wages are calculated using the monthly income divided by hours worked per month. The gender-gap patterns observed in this paper remain if we consider monthly wages. City size and some other city characteristics are from the 2006 City Statistical Yearbook of China (which publishes statistics for 2005). Table 1 reports summary statistics for migrants with positive income by marital status and gender. Not surprisingly, married migrants are older and less educated than unmarried migrants.[11] The gender difference in log wage is very small among unmarried migrants: 2.782 for men and 2.706 for women. In contrast, this gender difference is markedly larger for married migrants: 2.912 vs. 2.574.

Next, we visualize the gender wage gap for migrants of different marital status. Panels A and B of Figure 2 plot average wages by gender and age for unmarried and married samples separately. Although the gender gap exists among unmarried migrants, it is much smaller than that for the married. The gender wage gap reaches around 0.4 log points for the latter group, and the gap is relatively stable across ages. The gender wage gap shows a similar pattern when alternatively we examine the unmarried and married migrants across different

[9]The legal retirement age for most Chinese women is 55.

[10]We have also tried dropping all of the divorced and widowed individuals from our analysis sample. The results are similar.

[11]Relative to local residents, whose summary statistics are not reported, rural migrants are significantly younger and less educated.

education levels (panels C and D of Figure 2). These results suggest that the gender wage gap among married migrants is key to understanding the overall gender wage gap among all rural migrants.

To visualize the relationship between gender wage gap and city size, we calculate each city's wage gap. It is defined as the difference in log wages between male and female migrants, holding other personal characteristics constant. Specifically, we regress rural urban migrants' log wage on age, education level dummies, origin province dummies, and a female dummy for each prefecture-level city. The absolute value of the estimated coefficient on the female dummy is the city's gender wage gap. To ensure relatively accurate estimates, we consider only cities with more than 40 observations in the wage regressions.[12] Figure 3 shows the relationship between the gender wage gap and city size by marital status. Among the married migrants (panel B), there is a clear negative relationship between city size and gender wage gap. In contrast, the correlation is much less evident for unmarried migrants (panel A).[13] We next explore this relationship in a more rigorous way.

4 Gender Wage Gap of Rural Migrants and City Size

This section estimates the relationship between gender wage gap and city size and explores the underlying mechanisms. First, we use data on individual rural migrants, regressing log wage on the interaction of a female dummy and log city size together with some standard control variables. The coefficient of the interaction term shows how gender wage gap varies with city size. Panel A of Table 2 shows the results for married rural migrants. Column 1 indicates that married women have significantly lower wages than men. In a median-sized city (log population = 4.48), women earn 33% less than men.[14] The coefficient of the interaction term is 0.052, suggesting that women's relative wages are higher in larger cities. In column 2, we control for an individual's age, education, origin province, and destination province, and the results are similar.

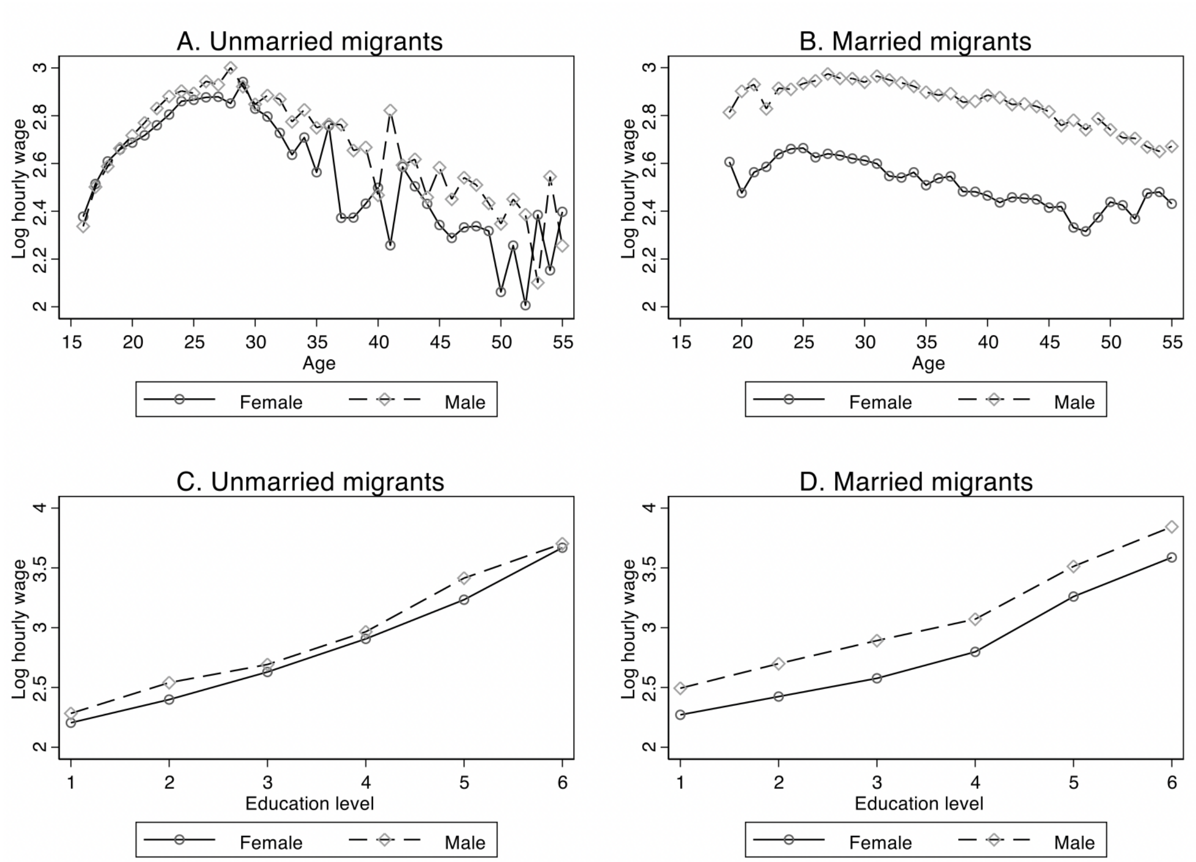
Ordinary least squares (OLS) regression is subject to potential endogeneity issues. First, unobserved city characteristics may affect both city size and (relative) wages, leading to omitted variables bias. For example, some regional demand shocks may have gender bias (Qian 2008). Second, wage levels may affect city size, resulting in reverse causality. Following

[12] We also consider other thresholds (such as 20, 30, 50, and 100), and the results are not sensitive.

[13] Because there are more married than unmarried migrants, applying the same threshold of 40 observations leads to a smaller sample of cities in panel A than in panel B. Dropping cities absent in panel A from panel B still produces a (slightly weaker) positive correlation between women's relative wages and city size. On the other hand, using a lower threshold (e.g., 20) and thus more cities produces a stronger positive correlation in panel B.

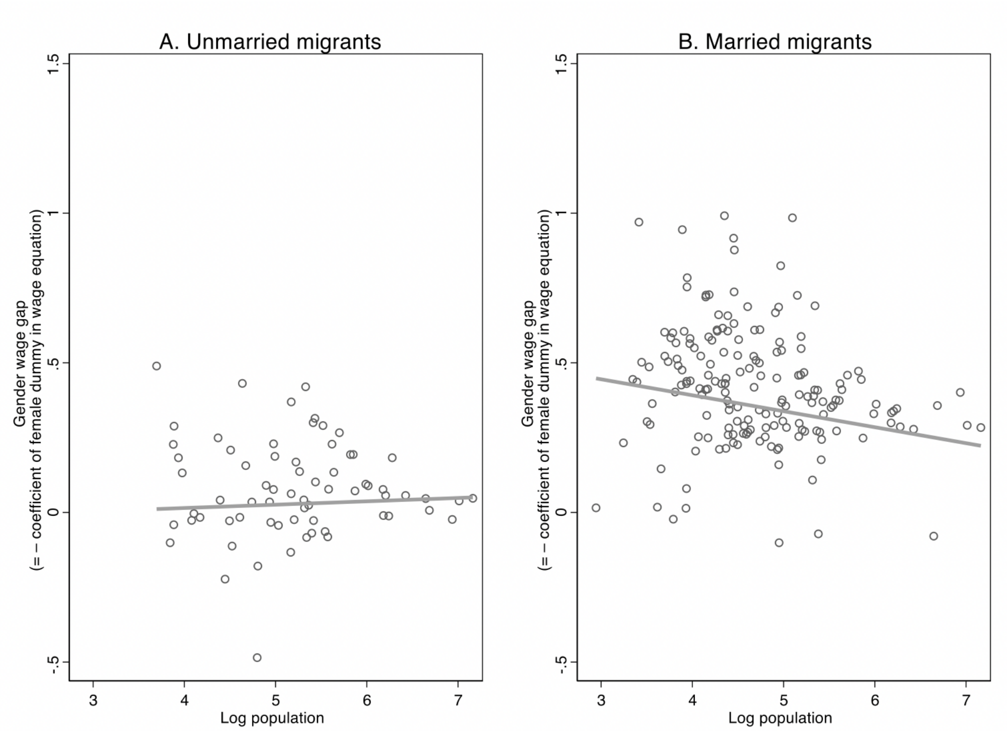
[14] $33\% = 1 - \exp(-0.634 + 0.052 * 4.48)$.

Figure 2: Wage profiles by gender and marital status



Notes: Education levels in panels C and D are: 1 - illiterate, 2 - primary school, 3 - middle school, 4 - high school, 5 - professional college, and 6 - college & above. In panels A and C, unmarried migrants also include divorced and widowed individuals. In panels B and D, married migrants include those who are married but migrate alone and leave their spouses back at home; we have also constructed panels B and D using the sample of couples who migrate together, and the results are similar. We have also made these plots using log monthly wage instead of log hourly wage, and the patterns are the same (see the online appendix here: https://wordpress.clarku.edu/juzhang/files/2022/06/OnlineAppendix.pdf).

Figure 3: The gender wage gap and city size for rural migrants



Notes: The gender wage gaps are for rural-to-urban migrants. We regress log hourly wage on age, education level dummies, origin province dummies, and a female dummy for each prefecture-level city. Gender wage gap is the absolute value of the coefficient on the female dummy. The fitted line is estimated using the number of migrants as weight. We also made a version of panel B using the same sample of cities as in panel A, and the results are similar. We have also made these plots using log monthly wage instead of log hourly wage, and the patterns are the same (see the online appendix here: https://wordpress.clarku.edu/juzhang/files/2022/06/OnlineAppendix.pdf).

Table 2: Gender wage gap and city size: individual level analysis

Dependent variable: ln(hourly wage)	(1)	(2)	(3)	(4)
	OLS		IV (2SLS)	
A: Married sample				
Female	-0.634***	-0.624***	-0.620***	-0.579***
	(0.115)	(0.365)	(0.124)	(0.100)
Ln(population)	0.094***	0.021	0.059	-0.045
	(0.025)	(0.021)	(0.053)	(0.053)
Ln(population)×Female	0.052**	0.056**	0.050*	0.048**
	(0.024)	(0.023)	(0.026)	(0.023)
Additional controls	No	Yes	No	Yes
Kleibergen-Paap rk Wald F statistic			20.42	28.72
Obs.	60,039	60,039	60,039	60,039
Adjusted R^2	0.110	0.230	0.107	0.226
B: Unmarried sample				
Female	-0.101	-0.061	0.022	0.060
	(0.069)	(0.068)	(0.090)	(0.111)
Ln(population)	0.101***	0.0387*	0.059	0.005
	(0.032)	(0.020)	(0.059)	(0.039)
Ln(population)×Female	0.005	0.004	-0.017	-0.018
	(0.011)	(0.010)	(0.015)	(0.018)
Additional controls	No	Yes	No	Yes
Kleibergen-Paap rk Wald F statistic			17.16	28.67
Obs.	33,889	33,889	33,889	33,889
Adjusted R^2	0.039	0.260	0.030	0.258

Note: In columns 2 and 4, we control for age dummies, education level dummies, origin province dummies, and destination province dummies. Standard errors clustered at the city level are in parenthesis. Ln(population) of 1985 and its interaction with the female dummy are used as instrumental variables in the IV estimation. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Au and Henderson (2006), we use city population in 1985 and its interaction with the female dummy as the instrumental variables for the 2005 city size and its interaction with the female dummy. The logic is that the Hukou system tightly controlled migration in the early years, and the city population in the 1980s was mainly determined by the planning regime. The historical population influences current city size but is likely to be independent of unobserved productivity that affects rural migrants' relative wages. The instrumental variables (IV) results reported in columns 3 and 4 are similar to those from the OLS regressions: The coefficient of the city size and female dummy interaction term reduced only slightly, from 0.056 to 0.048, in the specification with additional controls.

Our model also predicts that the gender wage gap of unmarried migrants is independent of city size. Panel B of Table 2 shows the corresponding results using individual-level data of unmarried migrants. The model specification is the same as that used for married migrants in panel A, and we are interested in the coefficient on the interaction term between female and log city size. The OLS results show that the gender wage gap for unmarried migrants is insignificant and much smaller than that of married migrants. Notably, the coefficient of the city size and female dummy interaction term is close to zero and statistically insignificant. In the IV regressions in columns 3 and 4, the coefficient of this interaction term even turns negative, although still not statistically different from zero. Comparing the results in panels A and B, the difference between married and unmarried migrants suggests that marital status is vital for city size to influence female migrants' relative wages.[15]

Next, we examine the effect of city size on the gender wage gap of married migrants using a set of regressions at the city level. (Unmarried migrants are not considered here because the gender wage gap of this group is statistically indistinguishable from zero across cities.) We first use information on married migrants to estimate a separate wage equation for each city, regressing log hourly wage on age, education level dummies, origin province dummies, and a female dummy. The coefficient on the female dummy represents (the negative of) gender wage gap in the city, adjusted by individual characteristics. We then regress this wage gap measure on log city size and some other city characteristics, using the number of married migrants in each city as weights. The advantage of this alternative approach is that by successively adding different city characteristics to the regression, we will be able to see which city characteristics can explain away the city size effect.

Again, since the OLS regression may be contaminated by endogeneity, we use city population in 1985 as the instrumental variable for city population in 2005. Table 3 shows the IV estimation results. The first column in panel A indicates that a one log point increase in

[15] Although not reported here, we have rerun regressions in panel A of Table 2 by dropping married individuals who have migrated alone and left their spouses back at home. The results are similar.

city size is associated with a 0.041 log point increase in women's relative wages. To evaluate the magnitude of this coefficient, notice that the 10^{th} and 90^{th} percentile difference in log city size is 1.77 (=5.52-3.75) in 2005. The regression result implies that the typical married woman's relative wage would increase by 7.3 percentage points if she moved from the 90^{th} to the 10^{th} percentile city.

What are the possible factors underlying this relationship? First, the economic structure may influence both the gender wage gap and city size. Column 2 in panel A of Table 3 shows that controlling for the economic structure (secondary and tertiary sector employment shares) increases rather than decreases the coefficient of city size. Second, we control for average education levels (share of migrants with high school degrees or above) in column 3 because the gender wage gap may vary across education levels. The result shows that adding the education control has no significant impact on the coefficient of city size. Thus married women have relatively higher wages in larger cities not because large cities are more attractive to educated couples as suggested by Costa and Kahn (2000). Third, the number of firms per square kilometer of built-up area and city population density (both in logarithms) are positively correlated with women's relative wages. Including them in the regression reduces the coefficient of city size close to zero (column 4). This seems to suggest that gender wage gap is lower in larger cities because those cities have higher employer and population densities. Column 5 includes all control variables; the city size coefficient is statistically insignificant.

One might be concerned that unobserved characteristics of married migrants were different in large cities than in small cities. For example, migrant women in large cities might be more similar to their husbands in unobservable characteristics. We employ Dahl's (2002) method to correct potential selection bias due to unobservables when estimating the gender wage gap for each city. Dahl (2002) assumes that the probability of the first-best choice is the only information needed for correcting the selection bias. If individual i has migrated to city j, city j is the first-best choice. Dahl (2002) proposes to estimate the probability of person i migrating to city j (P_{ij}) nonparametrically based on actual migration flows. Approximated by its linear expansions, an unknown function of P_{ij} is added to the city-specific wage equation to correct the selection bias.

To nonparametrically estimate P_{ij}, the key to implementing Dahl's approach, we first divide all married migrants into different cells based on home region, education level, age, and gender.[16] The gender dummy allows the probability of choosing a city to differ for men

[16] We divide China into seven different regions: North, Northeast, East, Central, South, Northwest, and Southwest. Within each of the seven home regions, individuals are divided into three education groups (primary and below, middle school, and high school and above), seven age groups, and two gender groups.

Table 3: Gender wage gap and city size: city level analysis (IV estimation)

	(1)	(2)	(3)	(4)	(5)
A. Second stage results (DV: Estimated city-level gender wage gap)					
Ln(population)	0.041***	0.061***	0.038***	0.012	0.026
	(0.012)	(0.014)	(0.012)	(0.020)	(0.023)
Share of secondary sector		0.001			-0.005
		(0.003)			(0.004)
Share of tertiary sector		-0.003			-0.009**
		(0.004)			(0.004)
Share of educated			-0.316		-0.182
			(0.212)		(0.236)
Ln(# of firms/built-up area)				0.020	0.002
				(0.014)	(0.015)
Ln(population density)				0.056**	0.067**
				(0.025)	(0.029)
Obs.	174	174	174	174	174
Adjusted R^2	0.133	0.235	0.135	0.168	0.232
B. Second stage results (DV: City-level gender gap corrected for selection bias)					
Ln(population)	0.037***	0.059***	0.035***	0.010	0.030
	(0.014)	(0.016)	(0.014)	(0.023)	(0.027)
Obs.	174	174	174	174	174
Adjusted R^2	0.104	0.198	0.102	0.156	0.206
C. First stage results for excluded IV					
Ln(population_1985)	0.615***	0.543***	0.632***	0.432***	0.393***
	(0.036)	(0.037)	(0.035)	(0.031)	(0.034)
F statistic	298.64	213.65	320.86	196.62	136.60

Notes: In panel A, the gender wage gap is estimated by running regressions of log hourly earnings on age, education dummies, origin province dummies, and a female dummy for each city. The coefficient on the gender dummy is used as the dependent variable. In panel B, the dependent variable of gender gap is estimated by running regressions of log hourly earnings on a female dummy, controlling for age and education dummies and a quartic polynomial of an individual's predicted probability of migrating to the current city. The probability is estimated nonparametrically based on an individual's age, gender, education levels, and origin region. Only cities with more than 40 married migrants are considered. Regressions in this table are weighted using the number of migrants as weights. Regressions in panels B and C include the same controls as in panel A, although not reported here. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

and women. For each individual i in city j, we find the cell to which he/she belongs. The predicted probability of i choosing j, $\hat{P_{ij}}$, is the fraction of all the individuals in that cell who migrated to city j. For each city j, we regress log wage on a female dummy, a vector of individual characteristics, and a quartic polynomial of $\hat{P_{ij}}$ to obtain women's relative wage. We then regress this selection-corrected relative wage on city size together with various controls. The key coefficient on city size is presented in panel B of Table 3. We see that the city size effects are similar to those in panel A. Therefore, selection bias cannot explain the negative relationship between city size and the gender wage gap among married migrants.

Overall, results in Tables 2-3 show that among married migrants, gender wage gap is smaller in larger cities. Explorations in Table 3 suggest that this city size effect comes from higher densities of population and employers in larger cities; the city size effect disappears once we control for those densities. This is consistent with the notion that larger cities provide a better job-skill match for female migrants.

5 Ancillary Evidence

5.1 Employment rate and city size

The wage gap is only one aspect of gender inequality; we consider employment rate in this section. Suppose large cities alleviate the colocation problem of married couples due to diversified labor markets. Then we should observe a higher employment rate for married women in larger than in smaller cities. We first calculate the employment rate for different groups in each city and regress them on city size and control variables. Observations with positive wages are treated as being employed in the labor market. Panel A of Table 4 shows that, for married migrants (columns 1-2), the employment rate is higher in larger cities, and the correlation is much stronger for women. For married female migrants, a one unit increase in log city population raises the employment rate by 2.7 percentage points (IV result in column 1); for their male counterparts, the effect is 0.9 percentage points.[17] Such a positive correlation is absent for unmarried migrants (see columns 3-4).[18] If anything, unmarried women seem to have a slightly lower employment rate in larger cities. Therefore,

[17]Self-selection into the labor market has been studied as a determining factor of the gender wage gap (Blau and Kahn 2017). If women with higher earning potential (e.g., better education or higher innate ability) are more likely to enter the labor market, then all else being equal a higher employment rate implies lower average earnings for women, resulting in a larger gender wage gap. Therefore, women's higher employment rate in larger cities actually weighs against finding a smaller gender wage gap in such cities.

[18]Our further exploratory analysis shows that the positive coefficient on city size for married women migrants can be explained away by the number of firms per unit of built-up area and log population density, similar to the findings in Table 3. See also Lu et al. (2012) who examine the effect of city size on employment rate for urban residents of different skill levels.

Table 4: Effect of city size on employment rate and probability of being household head (OLS and IV estimations)

Dependent variable	A: Employment rate				B: share of female migrants as household heads
	Married migrants		Unmarried migrants		
	women	men	women	men	
	(1)	(2)	(3)	(4)	(5)
OLS					
Ln(population)	0.037***	0.008***	-0.001	0.005	0.011***
	(0.008)	(0.002)	(0.005)	(0.004)	(0.002)
Obs.	223	221	116	130	230
Adjusted R^2	0.084	0.077	-0.009	0.003	0.124
IV					
Ln(population)	0.027***	0.009***	-0.011	-0.0004	0.007***
	(0.010)	(0.002)	(0.007)	(0.005)	(0.002)
Obs.	223	221	116	130	230
Adjusted R^2	0.077	0.074	-0.038	-0.009	0.110
1st stage F	375.71	386.81	201.22	218.71	193.68

Note: Although not reported here, every regression includes a constant. To calculate the city level employment rate, we first regress the employment dummy on age dummies, education level dummies, and their interactions, and use the mean of the residuals to calculate the adjusted employment rate for each city. Similarly, we first regress the female household head dummy on age dummies, education level dummies, and their interactions, and use the mean of the residuals to calculate the adjusted female household share. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

in terms of employment rate, married migrants benefit from large city size more than other groups, and married women benefit more than married men.

In further exploratory analysis, we regress married male migrants' wages (in log) on individual and city characteristics, adding a control variable to indicate whether the migrant's wife is also employed in the city. We find that if the wife has a job, the husband's wage is 12.3% lower, holding individual and city characteristics constant. This suggests that a migrant husband is willing to accept a considerably lower wage if the wife can find a job in the destination city. Combined with the results in Table 4, it implies that migrant husbands tend to accept lower paying jobs in larger cities because their wives are more likely to find work in those cities. This explains why gender wage gaps among married migrants are lower in larger cities.

5.2 Female household head and city size

The status of being the household head represents the relative economic power of an individual within the household. On average, husbands earn more than their wives and are more likely to be the household heads (Xu and Huang 2018). In our married migrant households sample, only 13% of the household heads are women. Higher relative wages of women increase their chance of being household heads. To illustrate this point, we focus on married migrant households with both the husbands and wives having positive wages in cities and regress the wives' household head status (yes=1/no=0) on their relative wages ($= \ln(wage\_wife) - \ln(wage\_husband)$). The results indicate that a one unit increase in the wives' relative wages leads to a 3.7 percentage point higher probability of them becoming household heads.[19]

If moving to large cities increases the chance for women to earn relatively higher wages within households, we would expect more female household heads in such cities. Therefore, we examine the probability of being a household head for women in association with city size in the last column of Table 4. Here the analysis sample includes only married migrants with positive individual incomes,[20] and we further confine our sample to households with both spouses migrating. The results indicate that indeed female migrants are more likely to be household heads in larger cities.[21]

5.3 What do migrant wives do?

We next show some direct evidence that the job markets in larger cities provide a better occupational match for married female migrants. Taking advantage of more detailed information on occupations, here we rely on data from the 2016 wave of the China Migrants Dynamic Survey (CMDS). CMDS is an annual survey of migrant population in China, conducted by the National Health Commission starting in 2009. Each year, CMDS surveys a sample of about 200,000 migrant households all over the country, collecting detailed information on demographics, income, health, employment, etc.[22] Using the CMDS data, we find that compared with unmarried female migrants, married female migrants are significantly more likely to work in the low-end services sector: Whereas 64.22% of married female migrants work in low-end services, only 57.23% of unmarried female migrants work in this sector. Within low-end services, married female migrants are significantly more likely than unmarried female migrants to work in wholesale and retail (29.60% vs. 19.87%), janitorial service (2.94% vs. 0.35%), and domestic service (1.07% vs. 0.36%). We take these as evidence that married

[19]The coefficient is statistically significant at the 1% level. Controlling for host city dummies and personal characteristics has little impact on the results.

[20]We also tried including the married migrants without income and the results are similar.

[21]In addition to employment rate and the probability of being household head, we also explored the correlation between a few other outcomes and city size. We found that female migrants in larger cities tend to get married at a slightly older age, but neither the number of children female migrants have nor the age when they have the first child is statistically significantly correlated with city size.

[22]CMDS surveys oversample long-term migrants and only collect information about one household member. For these reasons, we cannot use the CMDS data for our baseline analysis.

Table 5: City size and occupations of married female migrants (OLS estimation)

	(1) Low-end service	(2) Wholesale and retail	(3) Janitorial service	(4) Domestic service
Ln(population)	-0.003	-0.002	0.003***	0.001
	-0.003	-0.002	-0.0007	-0.001
Female×Married	-0.226***	-0.062***	-0.053***	-0.006*
	(0.026)	(0.023)	(0.006)	(0.004)
Ln(population)×Female×Married	0.045***	0.011**	0.006***	0.003***
	(0.005)	(0.005)	(0.001)	(0.001)
Individual characteristics	Yes	Yes	Yes	Yes
City characteristics	Yes	Yes	Yes	Yes
Constant	0.408***	0.355***	0.050***	-0.013***
	(0.020)	(0.029)	(0.007)	(0.004)
Obs.	113,791	113,791	113,791	113,791
Adjusted R^2	0.063	0.029	0.035	0.009

Notes: In each column, the dependent variable is a dummy variable that equals to 1 if the migrant works in the occupation. Individual characteristics controls include gender, age and age squared, years of schooling, and ethnicity. City characteristics include the shares of FDI in GDP, fixed capital investment in GDP, in-budget fiscal expenditure in GDP, GDP per capita, ratio of tertiary to secondary industrial output, fraction of college educated population, housing prices, per capita areas of paved road and number of buses, and a dummy for provincial capital city. The standard errors are clustered at the city level and are reported in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

female migrants are more suited for jobs in these occupations, perhaps due to their age, experience, human capital endowment, and time constraints.

In Table 5, we regress a migrant's occupation on log city population, a female-married interaction, and a log-population-female-married interaction, controlling for individual and city characteristics. In all four columns, we find that in larger cities, married female migrants are more likely to be working in occupations more suitable for them. Such occupations are low-end services including particularly wholesale and retail, janitorial service, and domestic service. For example, in column (1), the coefficient of the three-way interaction term implies that when log city population increases by one unit, the share of married female migrants working in low-end services increases by 4.5 percentage points. This suggests that larger cities offer a higher-quality occupational match for married female migrants, consistent with our assumption in the model.

6 Alternative Explanations of the City-Size Effect on Gender Wage Gap

The empirical evidence shown above is consistent with the mechanism illustrated in Section 2. This section considers some alternative explanations for the city-size effect on the gender wage gap of married migrants.

6.1 Are assortative marriages driving our results?

Married migrant women's higher relative wages in large cities might result from the sorting of married migrants into different cities rather than better matching quality attributable to thick labor markets. One possible mechanism is that couples of positively assortative marriages (i.e., the husband and wife have similar traits) migrate to large cities, leading to a narrower gender wage gap there even without more diversified labor markets. Or, if negatively assortative marriage prevails in small cities, there will be a higher share of couples with husbands earning high wages and wives earning low wages or staying out of the labor market in small cities (Zhang and Liu 2003). Following the literature on assortative marriage (Greenwood et al. 2014, Eika et al. 2019), we run the following regression to examine whether educational assortative marriage varies with city size:

$$sch_{ci}^{h} = \alpha + \beta * sch_{ci}^{w} + \gamma * sch_{ci}^{w} * size_c + \delta * size_c + \varepsilon_{ci}. \tag{6}$$

Here sch_{ci}^{h} and sch_{ci}^{w} represent years of schooling for the husband and the wife of migrant couple i in city c; $size_c$ is log population of city c; β captures the correlation between the husband's and the wife's education in cities of size zero. The coefficient of the interaction term, γ, shows how the degree of assortative marriage varies with city size.

Column 1 of Table 6 reports the estimation results of equation (6). While both city size and wife's schooling have significantly positive coefficients, their interaction has an insignificant coefficient close to zero. Column 2 replaces the independent variable of city size with city dummies, and the results remain essentially unchanged. We also calculate Kendall's rank correlation coefficient, or Kendall's τ, between husband's and wife's education levels for each city to measure marriage assortativeness. Column 3 of Table 6 regresses Kendall's τ on city size, and the coefficient of city size is statistically indistinguishable from zero. Therefore, we do not find stronger assortative marriages in larger cities.[23]

[23]Sun and Zhang (2020) find that the surging housing markets increased assortative marriage in urban China. If housing prices grew more rapidly in large cities, one would expect large cities to have more assortative marriages. Unlike Sun and Zhang, whose focus is on urban residents, we examine rural migrants

Table 6: Assortative marriage and city size

Dependent variable	(1)	(2)	(3)
	Husband's years of schooling		City Kendall's τ of spousal education
Wife's schooling	0.415***	0.385***	
	(0.029)	(0.030)	
Ln(population)×wife's schooling	-0.005	-0.001	
	(0.005)	(0.005)	
Ln(population)	0.082**		0.006
	(0.041)		(0.008)
City fixed effects	No	Yes	No
Obs.	16,385	16,385	192
Adjusted R^2	0.224	0.234	-0.002

Notes: Observations of married rural migrants with both spouses moving are used. We assign years of schooling to individuals according to their education levels. When calculating the spousal correlation of education (Kendall's τ) at the city level, education levels are classified into three categories: primary and below, middle school, and high school and above. The regression of column (3) uses the number of married migrant couples as weight. Standard errors are in parentheses.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

6.2 Is marriage after migration driving our results?

One argument against the colocation explanation for the higher wages of married women in larger cities is that women may get married in urban areas after the migration (Compton and Pollak 2017). Suppose women earn higher wages in large cities and, at the same time, are more likely to get married in a thick marriage market. In that case, the positive correlation between women's relative wage and city size is not a result of the colocation decision of migrant couples. In this subsection, we show that (1) most of the married migrants move to urban areas after marriage, (2) when we confine our analysis to observations who migrate after getting married, the results are similar to what we obtained above, and (3) controlling for migration duration and marriage time does not greatly affect our results.

We use two pieces of information to identify those who migrate after getting married (or post-marriage migration): marriage date and migration duration when the survey was conducted. For example, if one individual has been married for more than one year and he/she has left the Hukou registration place for less than one year, he/she is considered a migrant who migrated after marriage.[24] We find that post-marriage migrants account

who are less likely to purchase housing in large cities because they cannot afford or are not allowed to do so.

[24]The migration duration is only given in intervals and is top coded at six years (half to one year, 1 to 2, 2 to 3, 3 to 4, 4 to 5, 5 to 6, and above six years). Therefore, we can only partially identify post-marriage migration, and we cannot determine for those who have migrated for over six years and have been married for over six years. We use two approaches to deal with the top coding issue: treating them as pre-marriage

Table 7: Gender gap and city size for those who migrated after marriage (IV estimation)

Dependent variable: ln(wage)	(1)	(2)	(3)	(4)
	Sample of post-marriage migrants			All married migrants
	Age: 16-55	16-30	31-55	
Ln(population)×Female	0.055*	0.034	0.062*	0.063**
	(0.029)	(0.027)	(0.033)	(0.028)
Female	-0.606***	-0.491***	-0.647***	-0.677***
	(0.132)	(0.138)	(0.152)	(0.131)
Ln(population)	0.050*	0.064**	0.046	0.046
	(0.030)	(0.032)	(0.030)	(0.042)
Marriage duration	No	No	No	Yes
Migration duration	No	No	No	Yes
Other controls	Yes	Yes	Yes	Yes
Kleibergen-Paap rk Wald F	31.092	30.162	30.881	32.685
Obs.	18,292	4,861	13,431	32,492
Adjusted R^2	0.178	0.188	0.175	0.208

Note: We use a migrant's marriage date and migration duration to determine whether one migrated after marriage. For example, if an individual has been married for more than one year and he/she left the Hukou registration place for less than one year, he/she is regarded as one who migrated after marriage. Since the migration duration is top coded at six years, we cannot determine and have thus excluded those observations with a migration and marriage duration longer than six years. Other controls include age dummies, education level dummies, and origin province dummies. Standard errors clustered at the city level are in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

for most married migrants. Among married migrants aged 16-30, the share of post-marriage migrants is about one-half. Among those aged 31-55, the share reaches 95% when we exclude observations whose marriage-migration timing cannot be determined due to top-coding of migration duration. The share of post-marriage migration is high because the Hukou system discourages marriage between migrants of different Hukou status.

The regression results using the post-marriage migrants show the same pattern as reported above (see columns 1-3 in Table 7). Married women earn a higher relative wage in larger cities: One more unit in log city size is associated with a 5.5 percentage point increase in women's relative wages. The effect is mainly driven by older migrants (aged 31-55). Finally, in an alternative specification, we do not restrict our sample to post-marriage migrants. Instead, we address the marriage-migration timing issue by controlling for migration

migration, which will underestimate the share of post-marriage migration; or, excluding these observations, which will probably overestimate the share of post-marriage migration. In either case, post-marriage migrants account for most married migrants (58% and 78%, respectively). Among those aged 31-55, excluding those with longer marriage and migration duration increases post-marriage migrants' share to 95%. It is also worth noting that using migration duration intervals rather than exact migration durations tends to underestimate the share of post-marriage migrants.

duration and marriage time. The results are similar (column 4 in Table 7).[25]

6.3 Is the presence of children driving our results?

Migrant couples in larger cities might have fewer children or be more likely to leave their children behind at home than those in smaller cities, enabling the wives in larger cities to participate in the labor market longer and earn a higher wage. To examine this possibility, for each migrant household we construct two dummy variables to indicate whether they have children aged 0-12 and whether they have children aged 0-5 living with them. In Table 8, we first estimate a linear probability model to check whether migrant households in larger cities are less likely to have children living in the household. Panel A examines children aged 0-12 and panel B children aged 0-5. Column (1) uses the sample of all married migrants and column (2) focuses on the married migrants with both the husband and the wife present in the household (i.e., they migrated together to the city). In all four regressions, the coefficient of log city population has a positive sign, although only one is (marginally) statistically significant. Thus there is no evidence that married migrants in larger cities are less likely in need of childcare; if anything, it is the opposite.

However, one may argue that even if married migrants in larger cities are equally or more likely to have children in the household, they may be less affected. Since larger cities tend to have more developed childcare markets, migrant parents may be able to use childcare services, allowing the wives to participate more in the labor market and thus earn higher wages. In panel C of Table 8, we directly examine how the presence of children affects the relationship between city size and gender wage gap. In column (1), we add the three-way interaction term, Ln(population)×Female×Children0-12, to the wage regression (where "Children0-12" represents the number of children aged 0-12). We find that the three-way interaction term has a positive coefficient that is not statistically significant. That is, while female migrants earn more (i.e., gender wage gap is smaller) in larger cities, this effect is not influenced by the number of children aged 0-12. The positive and statistically significant coefficient of Ln(population)×Female implies that the city size effect exists for migrants without small children. In column (2), instead of adding the three-way interaction term, we drop all married migrants with children aged 0-12. Again, the coefficient of Ln(population)×Female is positive and statistically significant (though somewhat lower than the baseline estimates in Table 2), suggesting that the city size effect is not driven by the presence of small children.

[25] Some studies emphasize the learning effect to explain the city size premium (e.g., De La Roca and Puga 2017). Female migrants' higher relative wages in larger cities might result from women's faster learning relative to men. We also estimate the regressions controlling for the interaction of the gender dummy and migration duration. The results remain essentially unchanged.

Table 8: Migrant children and city size (IV estimation)

	(1)	(2)
	Married migrant households	Married migrant households: both spouses moved
A: Dependent variable: Having migrant children aged 0 to 12 (yes=1/no=0)		
Ln(population)	0.008	0.003
	(0.013)	(0.007)
Obs.	76,106	16,377
Adjusted R^2	0.095	0.440
B: Dependent variable: Having migrant children aged 0 to 5 (yes=1/no=0)		
	Married migrant households	Married migrant households: both spouses moved
Ln(population)	0.011	0.013*
	(0.008)	(0.006)
Obs.	76,106	16,377
Adjusted R^2	0.077	0.273
C: Dependent variable: ln(wage)		
	Married migrant households	Drop obs. with migrant children aged 0-12
Female	-0.516***	-0.492***
	(0.107)	(0.106)
Ln(population)	-0.043	-0.037
	(0.053)	(0.047)
Ln(population)×Female	0.041*	0.038*
	(0.022)	(0.021)
Ln(population)×Female×Children0-12	0.016	
	(0.010)	
Obs.	60,039	45,327
Adjusted R^2	0.229	0.231

Notes: For panels A and B, we keep only the household heads for the regressions. Age, education, gender of household head, size of migrant household, migration duration, marriage duration, destination province dummies, and origin province dummies are included as control variables. The population size of 1985 is used as the instrumental variable. In panel C, we also control for the interaction between female and the number of children aged 0-12, Female×Children0-12. The population size of 1985 and its interactions with city size and number of children are used as instrumental variables. Constant terms are not reported. Standard errors clustered at the city level are in parentheses. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

6.4 Is nonrandom Hukou status conversion driving our results?

The literature on gender wage gap has long paid attention to potential sample selection bias (Lu et al. 2022). In our context here, one worries about nonrandom conversion of Hukou status. When rural migrants obtained local urban Hukou, they would drop out of our analysis sample. Before 2005, the year our population survey was conducted, it was almost certainly easier to get a local Hukou in smaller cities. Thus different cities would have different fractions of rural migrants missed from our analysis sample. One should be concerned with selection bias if, in each city, the rural migrants who have obtained local urban Hukou have a significantly different level of gender wage gap than those rural migrants who have not obtained local urban Hukou.

Unfortunately, our population survey data do not contain any information about Hukou status conversion. Instead, we use the 2002 wave of the China Household Income Project (CHIP) data to investigate this issue. The CHIP survey collects detailed information about Hukou status. For an urban resident, it asks whether this person used to have a rural Hukou, and if so, when and through which channel this person obtained the local urban Hukou. Using the CHIP data, we construct a sample of rural migrants who either still hold rural Hukou or have obtained local urban Hukou.

We regress log hourly wage on the urban Hukou dummy, female dummy, their interaction, and a city fixed effect, controlling for individual characteristics (including age, education level, marital status, and ethnicity). The urban Hukou dummy captures the effect of an urban Hukou that makes urban jobs more accessible to the migrant; the coefficient of the female dummy measures gender wage gap; and the interaction term indicates whether gender wage gap is significantly different for those who obtained local urban Hukou. Our results show that the coefficient of the interaction term is very small in magnitude and statistically insignificant. In an alternative specification, instead of controlling for city dummies, we control for log city population and its interactions with other variables. In particular, we include a triple interaction term, Obtained urban Hukou$\times$Female$\times$Ln(population). Its coefficient is also small and statistically insignificant, suggesting that the differential selection effect between female and male migrants obtaining urban Hukou (if it exists at all) does not depend on city size. We also rerun these regressions using the sample of married migrants only, and the results are similar. Therefore, these findings suggest that nonrandom conversion of Hukou status is unlikely to be driving our results.

6.5 Is higher minimum wage in larger cities an explanation?

Men and women might be affected by labor market regulations differently. For example, Li and Ma (2015) show that minimum wages are beneficial for low-wage women and help reduce the gender wage gap. Since minimum wages are usually higher in more prosperous regions, low-paid women may benefit more from this policy in larger cities, leading to a positive correlation between women's relative wages and city size for married migrants. If this is a valid explanation, minimum wages should also lead to higher relative wages for unmarried female migrants in larger cities. Recall that panel B of Table 2 examines how women's relative wages vary with the city size using individual-level data of unmarried migrants. Both OLS and two-stage least squares (2SLS) results show a small and statistically insignificant coefficient of the interaction of city size and the female dummy. As minimum wage regulation does not discriminate against migrants based on marital status, the results for unmarried migrants suggest that the relatively higher female wages for married migrants in large cities are unlikely a result of higher minimum wages (or better labor protection) there.

7 Conclusions

When married couples migrate, the individually optimal choices of location for the husband and the wife might differ. As a result, the wives are usually the *tied movers* who sacrifice their optimum to follow their husbands, leading to a larger gender wage gap among married migrants. This colocation problem is alleviated when they move to large cities that have dense and diversified labor markets. This paper illustrates this mechanism using a simple spatial equilibrium model, and provides empirical evidence in China's context of rapid urbanization.

Using a large nationally representative sample of rural-urban migrants, we show that the wages of married women relative to men are significantly higher in larger cities. This phenomenon can be explained mainly by the positive correlations between city size and employer and population densities. Married migrant women in larger cities are also found to have higher employment rates and are more likely to be in occupations most suited to them. All these suggest that given the benefit of thick and diversified labor markets in large cities, the husbands do not require a significant city size premium in wages. We consider several competing explanations, including sorting based on unobserved individual characteristics or assortative marriage and regional differences in labor regulations and childcare availability, which are proved to be empirically irrelevant or less important.

Our research sheds new light on the rising gender wage gap in China. We argue that when migrant couples face difficulty in finding suitable employment in destinations cities, the wives are more likely to sacrifice their careers to follow their husbands, resulting in a higher gender wage gap. This implies that the gender wage gap will continue to rise as family migration happens on a large scale. On the other hand, large cities alleviate the tension of migrant couples' colocation problem, which provides an explanation for the attractiveness of large cities in China as well as in other developing countries. We show that large and diversified labor markets increase married women's wages and create a higher premium for married women than men. This gender perspective provides a more nuanced understanding of the city size premium.

This paper has some shortcomings. First, our main empirical evidence comes from one wave of cross-sectional data in 2005. This large population survey in China is the only data set we know of that allows us to estimate the gender wage gap for rural migrants in a large number of cities. Although sufficient for our baseline analysis, this data lacks a few features that only panel data or repeated cross-sectional data could offer. For example, we believe that the city size effect on gender wage gap will be more convincingly estimated in individual fixed effects models. We are also interested to know how the relationships we identified in this study vary over time. For these, we will need more and better data.

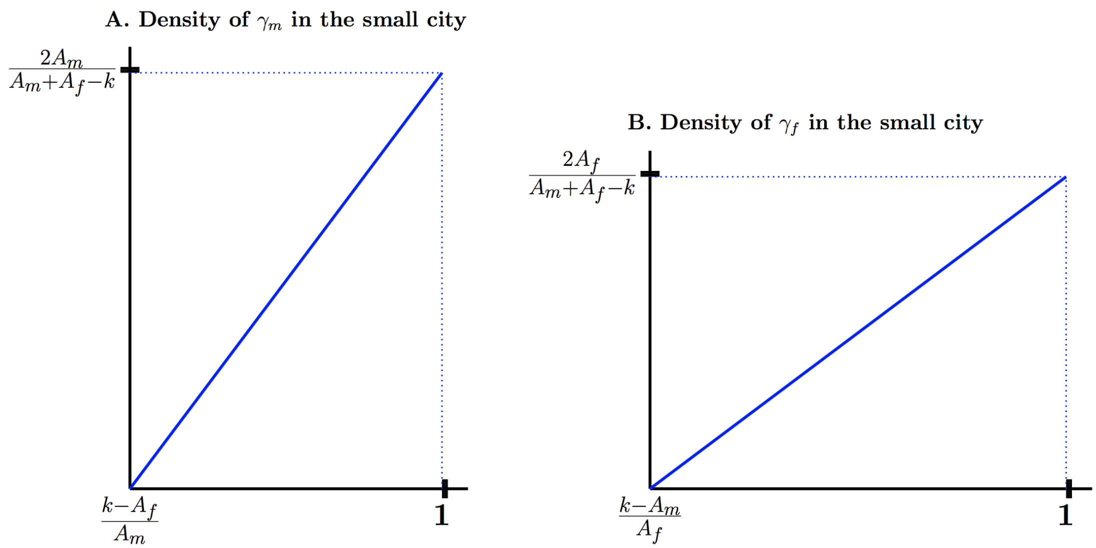
Second, although labor force participation, wages, and occupation, as we already considered, reflect employment quality, direct evidence of job matching quality is still scarce. Of particular interest in the Chinese labor markets is discrimination against rural migrants for their lack of local Hukou. Suppose discrimination against migrants is more severe in small cities due to lack of competition and thin labor markets, and the extent of discrimination one encounters is randomly determined. Then married migrants face the same colocation problems as in our model, rendering the discrimination explanation entirely compatible with our matching quality hypothesis. Ideally one would like to isolate the contribution of discrimination to married women's higher relative wages in large cities from the effect of matching qualities in urban labor markets. We leave this for future research.

Appendix: Proof

Let $\mu_m = E(\ln \gamma_m | \text{living in the small city})$ and $\mu_f = E(\ln \gamma_f | \text{living in the small city})$. We need to prove that $\mu_m > \mu_f$.

Note that "γ_m|living in the small city" and "γ_f|living in the small city" are not uniformly distributed. Certain random draws of γ_m and γ_f, although above their respective lower bounds, are not observed in the small city simply because the spouse has an unlucky draw. For example, if the wife draws a $\gamma_f < \frac{k-A_m}{A_f}$, even if the husband draws a $\gamma_m = 1$, they will not move to the small city and thus this $\gamma_m = 1$ will not be observed there.

Figure A.1: Density of γ_m and γ_f in the small city



From the discussion in the main text, we know that conditional on living in the small city, the range of γ_m is $(\frac{k-A_f}{A_m}, 1]$. When $\gamma_m = \frac{k-A_f}{A_m}$, the probability that this husband will be observed in the small city is 0. In general, if the husband's draw of γ is $\gamma_m^{'} > \frac{k-A_f}{A_m}$, he will move to the small city only if his wife's draw is greater than $\frac{k-\gamma_m^{'} A_m}{A_f}$, which occurs with probability $\frac{1-\frac{k-\gamma_m^{'} A_m}{A_f}}{1-\theta} = \frac{\gamma_m^{'} A_m+A_f-k}{A_f(1-\theta)}$. This probability is linearly increasing with $\gamma_m^{'}$. Thus, conditional on living in the small city, γ_m has a linear probability density function. Since the function's integral (i.e., area below it) over $(\frac{k-A_f}{A_m}, 1]$ has to be 1, its height at 1 should be $\frac{2A_m}{A_m+A_f-k}$ (as depicted in panel A in Figure A.1). For similar reasons, conditional on living in the small city, γ_f has a linear probability density function over $(\frac{k-A_m}{A_f}, 1]$ with the height at 1 equal to $\frac{2A_f}{A_m+A_f-k}$ (as in panel B).

Thus the probability density function for γ_m is:

$$f(\gamma_m) = \frac{\frac{2\gamma_m A_m}{A_m+A_f-k} - \frac{2(k-A_f)}{A_m+A_f-k}}{1 - \frac{k-A_f}{A_m}} = \frac{(\gamma_m A_m + A_f - k)2A_m}{(A_m + A_f - k)^2}.$$

Similarly, the probability density function for γ_f is:

$$f(\gamma_f) = \frac{\frac{2\gamma_f A_f}{A_m+A_f-k} - \frac{2(k-A_m)}{A_m+A_f-k}}{1-\frac{k-A_m}{A_f}} = \frac{(\gamma_f A_f + A_m - k)2A_f}{(A_m+A_f-k)^2}.$$

Given the probability density functions, we have:

$$\mu_m = \int_{\frac{k-A_f}{A_m}}^{1} \frac{(tA_m + A_f - k)2A_m}{(A_m+A_f-k)^2} (\ln t)\, dt;$$

and

$$\mu_f = \int_{\frac{k-A_m}{A_f}}^{1} \frac{(tA_f + A_m - k)2A_f}{(A_m+A_f-k)^2} (\ln t)\, dt.$$

Since we are comparing these two expectations, we can drop the common positive constant term $\frac{2}{(A_m+A_f-k)^2}$ in the integrals. To simplify notation, let $x \equiv \frac{k-A_f}{A_m}$ and $y \equiv \frac{k-A_m}{A_f}$, $1 > x > y > 0$; thus $A_f - k = -xA_m$ and $A_m - k = -yA_f$. It follows that $\mu_m > \mu_f$ if and only if

$$\int_x^1 (tA_m^2 - xA_m^2)(\ln t)\, dt > \int_y^1 (tA_f^2 - yA_f^2)(\ln t)\, dt.$$

Since $\int t(\ln t)\, dt = \frac{t^2 \ln t}{2} - \frac{t^2}{4} + Constant$ and $\int \ln t dt = t\ln t - t + Constant$, to prove $\mu_m > \mu_f$ we need

$$A_m^2(\frac{t^2\ln t}{2} - \frac{t^2}{4} - xt\ln t + xt)|_x^1 > A_f^2(\frac{t^2\ln t}{2} - \frac{t^2}{4} - yt\ln t + yt)|_y^1,$$

which is equivalent to

$$\frac{1}{(1-x)^2}[(x-\frac{1}{4}) - (\frac{(3x^2)}{4} - \frac{x^2\ln x}{2})] > \frac{1}{(1-y)^2}[(y-\frac{1}{4}) - (\frac{(3y^2)}{4} - \frac{y^2\ln y}{2})],$$

given that $\frac{A_m}{A_f} = \frac{1-y}{1-x}$.

Note that the two sides of the inequality above have the same function form, so, given $x > y$, we only need to show $d\left\{\frac{1}{(1-x)^2}[(x-\frac{1}{4}) - (\frac{(3x^2)}{4} - \frac{x^2\ln x}{2})]\right\}/dx > 0$. This derivative is $\frac{1-x+x\ln x}{(1-x)^2} + \frac{2(x-\frac{1}{4}-\frac{(3x^2)}{4}+\frac{x^2\ln x}{2})}{(1-x)^3} = \frac{(1-x+x\ln x - x + x^2 - x^2\ln x)+(2x-\frac{1}{2}-\frac{3x^2}{2}+x^2\log x)}{(1-x)^3} = \frac{1-x^2+2x\ln x}{2(1-x)^3}$. Given $0 < x < 1$, $(1-x)^3 > 0$. Let $f(x) = 1 - x^2 + 2x\ln x$, then $f'(x) = 2 - 2x + 2\ln x$, and $f''(x) = \frac{2}{x} - 2$. Since $f''(x) = \frac{2}{x} - 2 > 0$, $f'(x) < f'(1) = 0$, and $f(x) > f(1) = 0$. Thus $\frac{1-x^2+2x\ln x}{2(1-x)^3} > 0$. This completes the proof.■

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