Sex and the City:
Spatial Structural Changes and the Marriage Market*

Min Fang — U Florida
Zibin Huang — SUFE
Yushi Wang — Peking U
Yu (Alan) Yang — Peking U

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Abstract

Marriage and fertility are declining globally. We study the impact of spatial structural changes on marriage matching and quantify their aggregate implications for national marriage rates. Using data from China, we first present stylized facts on the joint patterns of dramatic gender-biased spatial structural changes, persistent marital social norms, and the diverging spatial distribution of singlehood characterized by a high singles rate for females (males) in more (less) developed cities. We then build a prefecture-level spatial equilibrium model with multi-sector and multi-skill production, migration, and local marriage markets. The model reveals that, without gender-specific spatial structural changes, the singles rate would be 30% lower for average women and over 50% lower for college-educated women. The key mechanism is that spatial structural changes lead more highly educated women to sort into the service sector in more developed cities than men. However, social norms remain persistent, particularly the strong preference for hypergamy. This results in more failed marriage matches for females (males) in more (less) developed cities, thereby lowering the national marriage rate. Counterfactual analysis shows that subsidizing marriage is costly and relatively ineffective amid continuing gender-specific spatial structural changes.

Keywords: Structural change; migration; marriage rate; spatial sorting; China.
JEL Codes: O14, R23, R13, J12.

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Fang: Department of Economics, University of Florida. Email: min.fang.ur@gmail.com. Huang: College of Business, Shanghai University of Finance and Economics; Shanghai Institute of International Finance and Economics. Email: huangzibin@mail.shufe.edu.cn. Wang: Guanghua School of Management, Peking University. Email: 2001110907@gsm.pku.edu.cn. Yang: Guanghua School of Management, Peking University. Email: alanyang@gsm.pku.edu.cn.

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1 Introduction

The marriage rate is declining globally (United Nations, 2019; Davidson and Hannaford, 2023), and so is fertility (Bhattacharjee et al., 2024), especially in countries where births outside marriage are culturally less acceptable.[1] The dramatic decline in the marriage rate and its consequences for subsequent fertility and childrearing are concerning and draw attention both in academia and among policymakers. The focus, however, is usually single-sided on females or males: Why are there so many single high-skilled women in developed cities (Edlund, 2005; Ong et al., 2020; Koh et al., 2025) or why are there so many single low-skilled men in underdeveloped rural areas (Jin et al., 2013; Edlund et al., 2013)? Furthermore, the aggregate implications for family policies to increase marriage and fertility rates are generally understudied.

In this paper, we argue that the above spatial dispersion and mismatch by gender and skill in the marriage market are the two sides of the same **spatial structural changes**, involving joint shifts in education, economic sector, and geographic location that are **gender-specific**. First, women out-educate men over time.[2] Second, compared to higher-skilled men, relatively more higher-skilled women work in the service sector, disproportionately located in more developed cities. However, marital social norms remain persistent, particularly the stronger preference among women (men) for upward (downward) matches. Together, these factors lead to a spatial mismatch of marriage: more failed marriage matches for higher-skilled women (lower-skilled men) in more (less) developed cities, thereby lowering the national marriage rate.

We study the above mechanism and quantify its aggregate implications in China, where the economy experienced rapid spatial structural changes while marriage and fertility rates almost halved in the last two decades. We first show stylized facts on the potential causes of such observations regarding dramatic gender-specific spatial structural changes and persistent social norms in the marriage market. We then build a quantitative spatial general equilibrium model with migration, multi-sector and multi-skill production, and local marriage markets. After estimating the spatial model for China in 2015, we show the effects of spatial structural changes, project

[1] One prominent region is East Asia, where out-of-wedlock birth is rare (Bongaarts and Casterline, 2022), marriage rate is declining, and fertility rate is the "lowest low" around the world (Goldin, 2024).

[2] The narrowing and reversing female-to-male educational gap is a global trend. See Feng et al. (2025) for an analysis of 83 countries across the spectrum of economic development.

changes in the future, and study the effectiveness of the current marriage subsidy policy.

In the first step, we show stylized facts regarding (1) the dramatic gender-specific spatial structural changes in our data from 2000 to 2015 in China, (2) the persistent social norms in the marriage market, and (3) the spatial mismatch of marriage. We first show a large increase in female educational attainment and employment share in service among higher-skilled female workers, and these trends are more pronounced in more developed cities. We then find that the relative socioeconomic status (SES) within married couples, with husbands having higher SES than wives, is almost unchanged over time. Finally, we show the spatial distribution of singlehood. The singles rate increases with the city's economic development for women, especially higher-educated, while decreases for men, especially lower-educated. We find similar spatial correlations between singlehood and the local share of the service sector.

Motivated by these facts, we build a prefecture-level spatial equilibrium model with migration, multi-sector and multi-skill production, and local marriage markets to understand and quantify the underlying mechanisms. The model embeds a marriage matching model with transferable utility à la Choo and Siow (2006) into a quantitative spatial equilibrium migration model in the context of China (Tombe and Zhu, 2019; Fan, 2019; Fang et al., 2022). Each prefecture comprises three sectors: agriculture, manufacturing, and service. The manufacturing and service sectors, considered "modern sectors," employ a combination of high-, middle-, and low-skill labor as input to produce final goods, whereas the agricultural sector uses undifferentiated labor as input. Workers gain utility from the corresponding local wage income spent on final goods and local housing consumption. In addition, workers gain utility from the local marriage market if they get married. The marital return consists of the overall value of marriage relative to singlehood, the match value of marrying a specific type of spouse, and the within-marriage equilibrium transfer.

Using various data sources from 2015, we solve and estimate the model quantitatively, combining calibration, log-linearization, and the contraction algorithm in several steps. Our estimation results on marriage market preferences and spatial and sector allocation costs highlight the race between spatial structural changes and social norms, as documented in the data and discussed in the context of fertility by Goldin (2024). Regarding social norms, the estimation of marriage market preferences shows that the match value of marrying up is notably higher for females compared to males, especially among high-skilled females. Regarding spatial structural changes, the estimation of spatial and sector allocation costs shows that the allocation costs into service sectors in more developed cities are lower for females than males, especially among high-skilled females. These parameter estimates are well consistent with the observed stylized facts.

We then conduct the quantitative equilibrium analysis to understand the role of gender-specific spatial structural changes in national and regional marriage rates and simulate counterfactual policies to study the aggregate implications. When removing the gender specificity in spatial structural changes, we find that the national singles rate decreased by about 30% and 12% for females and males, respectively. Such declines in singles rate are mainly due to higher-educated females in more developed cities and lower-educated males in less developed cities. Decomposition reveals that the narrowing and then reversing trend in college attainment of female relative to male explains one-third of the change in singles rate, and the spatial sorting of females into service in more developed regions accounts for roughly the remaining two-thirds. In contrast, the aggregate national structural change from agriculture to non-agriculture sectors does not substantially affect the marriage matching. We also project the continued gender-specific spatial structural changes from 2015 to 2030 and find substantial further increases in the national and regional singles rate due to larger spatial mismatch in the future in local marriage markets.

Finally, we study a widely discussed and adopted family policy to increase marriage rates in various countries: marriage subsidies.[3] Counterfactual analyses show that marriage subsidies have a limited effect despite the enormous potential fiscal costs. The main reason is that they do not address the root cause—skewed spatial distribution by gender and skill, shaped by gender-specific spatial structural changes. Even with a marriage subsidy as large as 10% of lifetime income, it is difficult to incentivize marginal individuals to marry when they lack an adequate local matching pool of marriage candidates. In contrast, our decomposition points to potentially more effective policies if they can directly target spatial gender imbalance to subsidize migration by particular gender and skill, or balance the sectoral growth across regions. However, such policies raise concerns about gender equity and economic or political feasibility.

[3]Although we do not model fertility, children are implicitly incorporated in the value of marriage. Therefore, the marriage subsidy in this paper is broadly defined and can also include the fertility subsidy and other preferable policies to married couples over singles.

Literature Review We contribute to the literature by highlighting the spatial perspective of the decline of the marriage rate empirically and quantitatively. Specifically, our work is related to four strands of literature on gender sorting in migration, demography, and marriage matching, spatial structural changes, and quantitative spatial modeling.

The first strand of literature documents and explains the observation of gender sorting in migration worldwide. Since Edlund (2005), various papers have documented the fact that young women outnumber men in urban areas, including Leibert (2016) for Germany, and Ong et al. (2020) and Koh et al. (2025) for China, among others. Literature generally shows two motives for such gender-skewed migration for females: (1) higher income opportunities in urban cities (Bacolod, 2017; Liu and Su, 2024; Elass et al., 2024), and (2) better marriage opportunities in urban cities (Weiss et al., 2018; Dupuy, 2021; Xiong, 2023). We leverage this literature and embed both above motives of gender sorting in migration into a quantitative spatial general equilibrium model to show that such gender sorting in migration could result in spatial marriage mismatch.

The second strand of literature studies demography and marriage matching patterns. Focusing on marriage within a single marriage market, the literature generally explains who marries whom and why (Weiss, 1997; Choo and Siow, 2006). Various studies have shown substantial patterns of marital assortative matching (Hitsch et al., 2010; Abramitzky et al., 2011; Dupuy and Galichon, 2014), and such marital assortative matching is particularly strong in education (Eika et al., 2019; Ashraf et al., 2020). Moreover, women generally prefer upward marriage matching more than men (hypergamy), documented in lab experiments (Fisman et al., 2006) and the US data (Schwartz and Mare, 2005; Bertrand et al., 2015). Our paper shows that the above marital assortative matching patterns are also substantial in China, especially the asymmetric hypergamy between men and women, consistent with evidence from the online dating experiment in Ong and Wang (2015). We then introduce this marital assortative matching into the quantitative spatial general equilibrium model and find that its interaction with gender, skill, and sector sorting in migration leads to spatial marriage mismatch.

The third strand of literature is related to (spatial) structural changes. The (non-spatial) structural changes regarding the rise of the service sector are related to various socioeconomic trends, including the rise of women in the high-skilled labor market (Cortes et al., 2018), the narrowing of gender gaps in employment and earnings (Ngai and Petrongolo, 2017; Autor et al., 2019; Kuhn et al., 2024), and the overall declining trends of marriage and fertility (Greenwood et al., 2017; Doepke et al., 2023). Such structural changes are particularly fast in China (Chen et al., 2023). However, the spatial patterns of such structural changes, such as the one analyzed in Eckert and Peters (2022) and shown to be important in Desmet and Rossi-Hansberg (2014), are still understudied. We show that such spatial structural changes in China are disproportionately urban-biased and drive gender- and skill-specific migration into more developed urban cities, eventually shaping the spatial distribution of marriage matching.

Finally, our paper relates to the quantitative spatial models that study the uneven distribution of economic and social activities (Redding and Rossi-Hansberg, 2017), among which a large fraction of the literature focuses on the consequences of spatial classification of worker skills (Fajgelbaum and Gaubert, 2020; Couture et al., 2024; Giannone, 2017; Hong, 2024, among others). Within the literature, a smaller but growing fraction focuses on spatial marriage, including Fan and Zou (2021) on the dual spatial labor market of two-parent families, Alonzo (2022) on the interplay between labor markets and marriage markets, Alonzo et al. (2023) on spatial assortative matching and inequality, and Mao and Wen (2024) on assortative matching and geographic sorting of marriage. These studies focus primarily on how marriage affects spatial distributions of skills or vice versa. Our paper focuses differently on how the interaction of such spatial sorting with spatial structural changes affects regional and national marriage rates.

In summary, our study contributes to the literature by empirically and quantitatively examining the effect of spatial gender-specific structural changes in education and sector on the local marriage markets across cities. By combining comprehensive individual-level and prefecture-level datasets, we provide a detailed analysis of the effects of spatial sorting on the local marriage market and quantify its aggregate implications in China.

2 Background and Data

2.1 Background

The economic reform in China since 1978 has ushered in one of the most rapid periods of structural transformation and urbanization in modern economic history, triggering massive domestic migration flows—from rural to urban areas, from less developed inland regions to more developed coastal cities, and from agriculture to manufacturing and services. A disproportionate share of these migrants are young, educated, unmarried women seeking improved socioeconomic conditions and opportunities, including better prospects for marriage. This dramatic demographic shift has significantly reshaped local marriage markets, particularly in both the most developed urban regions and the least developed rural regions.

As a result, two highly concerning socioeconomic issues have come to the forefront of Chinese society. First, the number of older unmarried men in rural areas has risen sharply (the so-called *"rural bare branches"*), a phenomenon attributed to both the imbalanced sex ratio at birth and the out-migration of young women (Jin et al., 2013). Meanwhile, the number of older unmarried women in urban areas has also increased substantially (referred to as *"urban leftover women"*), driven in part by the influx of young women into more developed urban regions (Ong et al., 2020; Koh et al., 2025). These two phenomena have sparked heated public debates and widespread media and academic attention. However, discussions typically focus on only one side of the issue or specific socioeconomic outcomes—such as rising housing prices—while the broader economic implications remain underexplored, particularly in relation to the rapid decline in marriage rates.

Another important fact is that most of these young individuals do not actively choose to remain single. Rather, they remain unmarried due to difficulties in the marriage market matching process. According to the 2022 China Family Panel Survey (CFPS), among unmarried young individuals, fewer than 4% reported no desire to marry. Regarding preferred marriage age, 95.5% expressed a desire to marry before age 35, and 91.2% hoped to marry before age 30.

2.2 Datasets

The main dataset we use is the Chinese Population Census for the years 2000, 2005, 2010, and 2015. The National Bureau of Statistics of China conducts a decennial census in years ending in zero and an inter-censal one-percent population survey (mini-census) in years ending in five. For simplicity, we refer to both the decennial and mini-census as the "Census data". For each wave of the Census, we use the individual-level random samples publicly released by the statistical bureau, which cover approximately 0.15% to 1% of the Chinese population. These data provide detailed individual-level information on gender, age, education, Hukou location, current residential location, employment sector and occupation, marital status, and other relevant variables. We use four waves of the Census data from 2000 to 2015 to establish the stylized facts presented in the next section and focus on the year 2015 as the baseline to construct prefecture-level migration flows, sectoral employment choices, and marriage matching outcomes for our quantitative spatial general equilibrium analysis.

We further supplement the Census data with information from the China Urban Statistical Yearbook, the City Statistical Yearbooks of each prefecture, and administrative housing cost data. From the Urban Statistical Yearbook, we extract prefecture-level GDP growth and urban land area. Since we do not directly observe land quotas at the prefecture level, we use the already-built urban land area as a proxy for land supply in our quantitative analysis and perform sensitivity checks using province-level land quota data. From the City Statistical Yearbooks, we obtain prefecture-industry-level wage data and impute prefecture-skill-sector-level wages following the method in Fang and Huang (2022).[4] Housing cost data are obtained from the China Real Estate Information (CREI), a data platform administered by the State Information Center of the central government. For our analysis, we used the prefecture-level average housing prices per square meter in 2015.

[4]The imputation combines each individual's industry and skill information from the Census data with the average wage for each industry from the City Statistical Yearbooks. We assign this industry-level average wage to each individual in the Census based on their prefecture and industry to obtain imputed individual wages. We then compute the average wage at the prefecture-skill level using these imputed values. A detailed description of the imputation procedure is provided in Appendix B.1.

3 Stylized Facts

In this section, we document stylized facts concerning (1) gender-specific spatial structural change in education and sectors, (2) social norms in the marriage market, and (3) spatial distributions of marriage and singlehood. First, we highlight the dramatic gender-specific structural changes in the educational gap, the sectoral employment gap, and the spatial employment gap between females and males. Next, we present the persistent and strong social norms in the marriage market, where females tend to marry up, and males tend to marry down in socioeconomic statuses, as proxied by education. Finally, we illustrate the spatial distributions of singlehood.

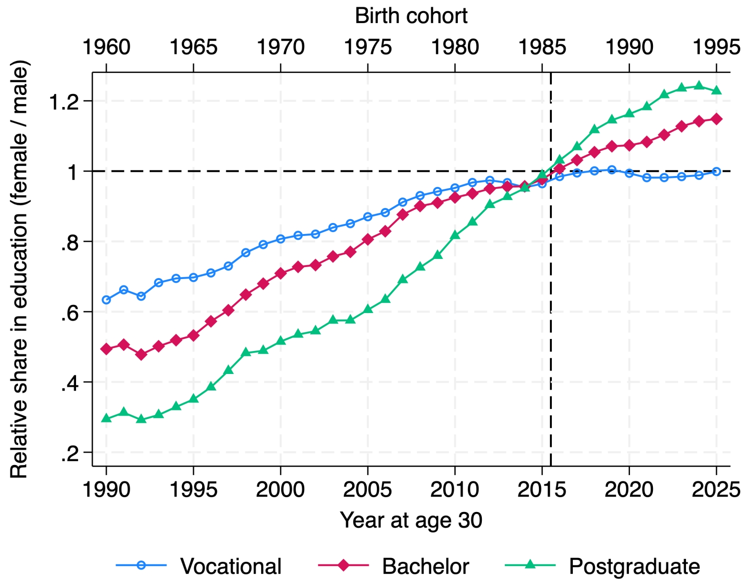
3.1 Dramatic Gender-Specific Spatial Structural Changes

We first highlight the dramatic gender-specific spatial structural changes between females and males from three perspectives: (1) the gender educational gap for females has been narrowing and even reversing over time; (2) the gender sectoral employment gap in the service sector has been decreasing for females, particularly among those with higher education levels; and (3) the gender spatial employment gap in the more developed cities has been decreasing for females, particularly among those with higher education levels.

Gender Educational Gap Our first perspective examines the gender educational gap. Figure 1 illustrates the female-to-male educational gap by birth cohort using data from the 2020 Population Census. We categorize terminal education degrees into three groups: postgraduate (above college), bachelor's (college), and vocational (high school). We calculate the education rates for each category and compare the proportions of females to males. A ratio of 1 indicates that the proportion of females with this degree equals that of males, while a ratio greater than 1 signifies a higher proportion of females than males in that category.

Figure 1 highlights the dramatic, gender-specific structural changes in educational attainment. The key takeaway is that the female-to-male education gap has narrowed substantially over time and has even reversed for the cohort born around 1985. This cohort entered the labor and marriage markets around 2005 at approximately age 20 and became a dominant group in the marriage market around 2015 at approximately age 30. The reversed education gap is even more

Figure 1: Gender Educational Gap Over Time



Notes: This figure presents the female-to-male relative share in education by birth cohort. A ratio of 1 means the number of females having the same degree equals that of males. The top x-axis marks the birth year, and the corresponding bottom x-axis shows the year when they are at age 30, around the prime age of marriage. Data source: Population Census 2020.

pronounced for later-born cohorts—such as those born in 1995—particularly at the postgraduate level. As younger cohorts continue to enter the marriage market, we expect to observe an increasingly reversed educational gap reflected in the marriage market.

Gender Sectoral Employment Gap We then investigate the gender-specific structural changes in the gender employment gap by sector and education. The gap is calculated as the difference between the number of female and male workers, divided by the number of male workers at the sector-year-education level. To account for differences in labor participation rates, we adjust the gender employment gap in each sector by the gender labor participation gap.[5]

Table 1 presents the results. A positive number indicates that there are relatively more females than males in the specific sector for a given education level, adjusted for the overall gender labor participation gap. These results can be summarized into three key patterns. First, there has been

[5]Since the male population is larger than the female population, and the male labor participation rate is higher, the gender employment gap is consistently negative across sectors, education levels, and years. Appendix A.1 provides the original population data and the detailed method used to calculate these ratios.

Table 1: Gender Employment Gap by Sector and Education

Education	Sector	2000	2005	2010	2015
College and Above	Agriculture	-45.0%	-32.3%	-16.2%	-13.2%
	Manufacturing	-34.6%	-26.9%	-23.3%	-22.7%
	Service	**-16.6%**	**-1.4%**	**+12.0%**	**+21.2%**
High School	Agriculture	-39.5%	-38.6%	-24.3%	-17.5%
	Manufacturing	-22.1%	-28.9%	-29.8%	-33.1%
	Service	**-0.4%**	**-3.4%**	**+1.1%**	**+4.1%**
Middle School and Below	Agriculture	+14.9%	+17.8%	+19.0%	+18.6%
	Manufacturing	-18.6%	-18.0%	-17.7%	-24.1%
	Service	**-14.6%**	**-11.2%**	**+4.7%**	**+9.3%**

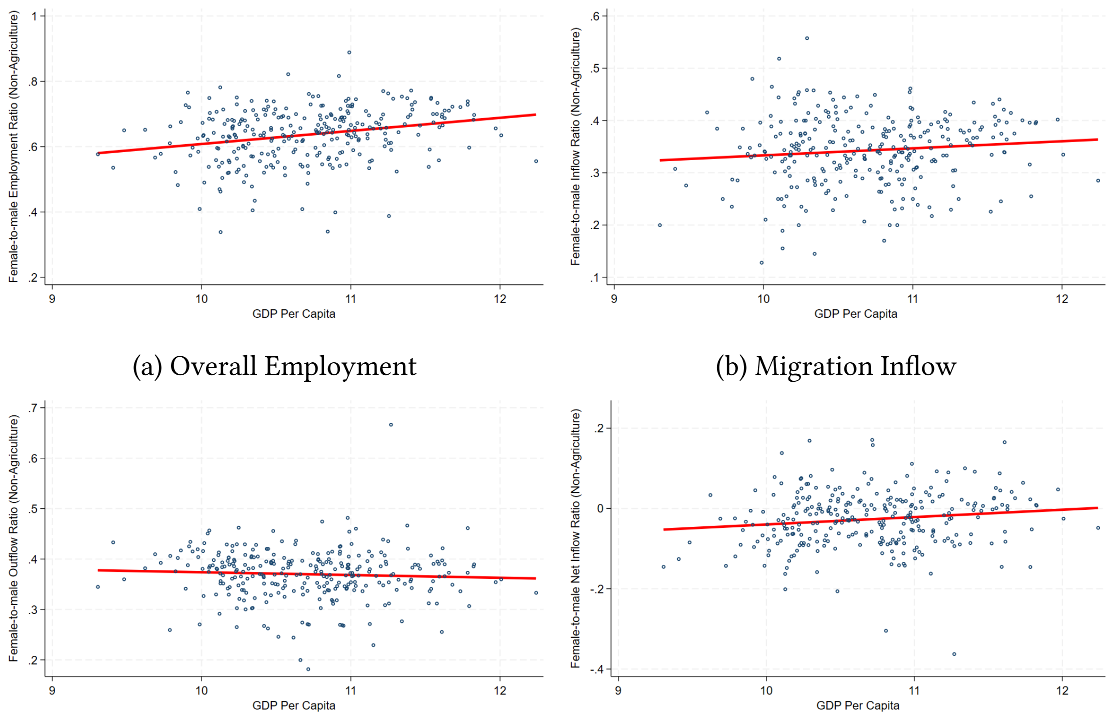
Notes: This table shows the adjusted gender employment gap across sectors for each Census year and education level. The gap is calculated as the difference between the number of female and male workers, divided by the number of male workers at the sector-year-education level. We then adjust the gender employment gap in each sector by the gender labor participation gap. That is, we have $gap_{adj} = gap_s - gap_{lp}$. Data source: Population Census 2000, 2005, 2010, and 2015.

a dramatic shift of females from the agriculture and manufacturing sectors to the service sector, irrespective of education level. Second, the female-to-male gender employment gap in the service sector shrank significantly for lower-skilled female workers, improving from approximately -15% in 2000 to about $+9\%$ in 2015. Third, this pattern is particularly pronounced for highly educated college females, with the gap improving from approximately -17% in 2000 to $+21\%$ in 2015. These changes are likely concentrated in more developed urban cities, such as Shanghai, Beijing, or Shenzhen, following similar patterns of spatial structural changes as in Eckert and Peters (2022).[6]

Gender Spatial Employment Gap We further investigate the relationship between prefecture-level GDP per capita and the gender spatial employment gap in the non-agricultural sector in 2015. Figure 2 shows the results for overall employment, migration inflow, migration outflow, and net migration inflow, respectively. In each subfigure, we have the log of GDP per capita on the x-axis. On the y-axis, we have female non-agricultural employment (or different measures of

[6]Table A2 in the appendix further provides insights into the sectoral migration of workers with rural Hukou. The values are computed as the proportion of rural Hukou workers employed in the manufacturing or service sectors relative to the total number of rural Hukou workers (for each gender-education type). The results indicate that the migration rate of rural workers into service sectors has steadily increased from 2005 to 2015 across all education levels for both males and females. In contrast, the migration rate into the manufacturing sector grew from 2000 to 2010 but declined between 2010 and 2015.

Figure 2: Gender Non-agricultural Employment Gap by Spatial Development Level



(a) Overall Employment

(b) Migration Inflow

(c) Migration Outflow

(d) Net Migration Flow

Notes: This figure illustrates the relationship between the spatial development level, proxied by the log of GDP per capita, and the gender employment gaps in the non-agricultural sector in 2015. Subfigures (a), (b), (c), and (d) present the results for measuring $\frac{\text{Female } x}{\text{Female } x + \text{Male } x}$ in four different variables x, including the overall employment, within migration inflow, within migration outflow, and within net migration inflow, respectively. Data source: Population Census 2015.

migration flows) divided by that of total employment (or different measures of migration flows).

Figure 2 Panel (a) shows that the overall gender employment gap in the non-agricultural sector is smaller in more developed cities, reflected in the positive slope of the female-to-male employment ratio against the GDP per capita of cities. This observation is accompanied by positive slopes of the migration inflow or the net migration flow in Panels (b) and (d), respectively. On the contrary, Panel (c) shows a negative slope of the for the migration outflow. All these patterns indicate a strong spatial sorting of female workers into the modern sectors in more developed cities, relative to male workers. We further plot the gender employment gap for each educational level in Figure A1 in Appendix A.1 and find that the trend of more female working in the non-agricultural sector in more developed cities is the strongest for the college-educated group.

Summary Therefore, the dramatic gender-specific spatial structural changes encompass three key components: (1) a dramatic increase in female educational attainment, particularly at higher levels, (2) a significant rise in female employment within the service sector, especially among higher-skilled female workers, and (3) female employment and migration net inflow is higher in more developed cities in the non-agricultural sectors.

3.2 Persistent Social Norms in the Marriage Market

We then highlight the persistent social norms in the marriage market, where females tend to "marry up" and males tend to relatively "marry down" in socioeconomic status, as proxied by education. Since we do not have data on individual income in the Census, we rely on education as the primary proxy for socioeconomic status, both in the empirical analysis and the model. We demonstrate these patterns through (1) a comparison of the relative socioeconomic status between married and never-married individuals and (2) an analysis of the relative socioeconomic status between married husbands and their wives.

Table 2: Relative Socioeconomic Status Gap of Married versus Never-married

Census Year	2000		2005		2010		2015	
	Male	Female	Male	Female	Male	Female	Male	Female
College Degree	+0.05	-0.09	+0.04	-0.12	+0.04	-0.08	+0.06	-0.14
Education Year	+2.41	-0.56	+2.13	-0.62	+1.33	-0.69	+1.49	-0.66

Notes: This table shows the relative socioeconomic status (SES) gap between married and never-married individuals of the same gender using two measures of SES: college degree attainment and years of education. In all comparisons, the mean SES of never-married individuals is subtracted from the mean SES of married individuals. Therefore, a positive value indicates that, for this gender in the given year, the average SES is higher for married individuals than for never-married ones. Columns (1), (3), (5), and (7) report the SES gap for married males relative to never-married males across different Census years. Columns (2), (4), (6), and (8) report the SES gap for married females relative to never-married females in the same Census years. We set an age restriction for the sample between 35 and 40 to ensure they have already made their marriage decisions. Data source: Population Census 2000, 2005, 2010, and 2015.

Relative Statuses between Married and Never-married First, we compare the characteristics of older, never-married males and females (aged over 35) to their married counterparts. Table

2 presents the relative SES gap between married and never-married individuals of the same gender, using two measures: college degree attainment and years of education. In all comparisons, the mean SES of never-married individuals is subtracted from the mean SES of married individuals. A positive value indicates that, for this gender in the given year, the average SES is higher for married individuals compared to never-married individuals.

Table 2 reveals a persistent and pronounced pattern of marriage sorting across all three measures of SES. First, married males consistently exhibit higher SES compared to their never-married counterparts. Specifically, married males are 5% more likely to hold a college degree and have approximately 1.5 to 2.5 more years of education than never-married males. Second, the patterns for females show the opposite trend. Married females are 9% to 14% less likely to hold a college degree and have about 0.6 fewer years of education compared to their never-married counterparts. Finally, these patterns remain highly persistent over time with an increasing trend.

Table 3: Relative Socioeconomic Status of Married Couples

Census Year	2000	2005	2010	2015
Panel A. College Degree				
Females marry up	3.44%	4.10%	3.87%	3.97%
Females marry down	0.86%	1.31%	1.48%	1.80%
Equal	95.70%	94.60%	94.65%	94.23%
Panel B. Education Year				
Females marry up	38.61%	37.90%	30.01%	28.33%
Females marry down	9.29%	9.67%	8.96%	9.77%
Equal	52.10%	53.23%	61.04%	61.90%

Notes: This table shows the relative socioeconomic status (SES) for married couples, using two measures of SES: college degree attainment and years of education. For college degree attainment, "Females marry up" indicates the proportion of couples where a wife without a college degree marries a husband with a college degree. For education, "Females marry up" refers to the proportion of couples where the wife has fewer years of education than her husband. Conversely, "Females marry down" is defined as the wife having higher SES (a college degree or more years of education) compared to her husband. "Equal" represents the proportion of couples where the wife and husband have the same SES. We do not set age restrictions in this table as long as the couples reach the legal marriage age in China. The results are very similar if we set an age restriction for the matched couple to be between 35 and 40. Data source: Population Census 2000, 2005, 2010, and 2015.

Relative Statuses within Married Couple We further examine the married couples in our Census data to analyze the relative SES between husbands and wives. "Females marry up" regarding college degrees or years of education is defined as a scenario where the husband has more education than the wife. Table 3 highlights a persistent and strong marriage sorting pattern. First, while most matches are equal, the proportion of females marrying up consistently outweighs that of females marrying down. Second, the tendency of females to marry up based on college degrees has remained remarkably stable, showing no significant changes over time.[7]

Summary In summary, we identify three main findings regarding social norms in the marriage market in China. First, married males exhibit higher SES than unmarried males, whereas married females have lower SES than unmarried females. Second, in married couples, females are more likely to marry up in SES than down. Third, these social norms remain persistent and robust despite the significant gender-specific structural changes observed over time.

3.3 Diverging Spatial Distributions of Singlehood

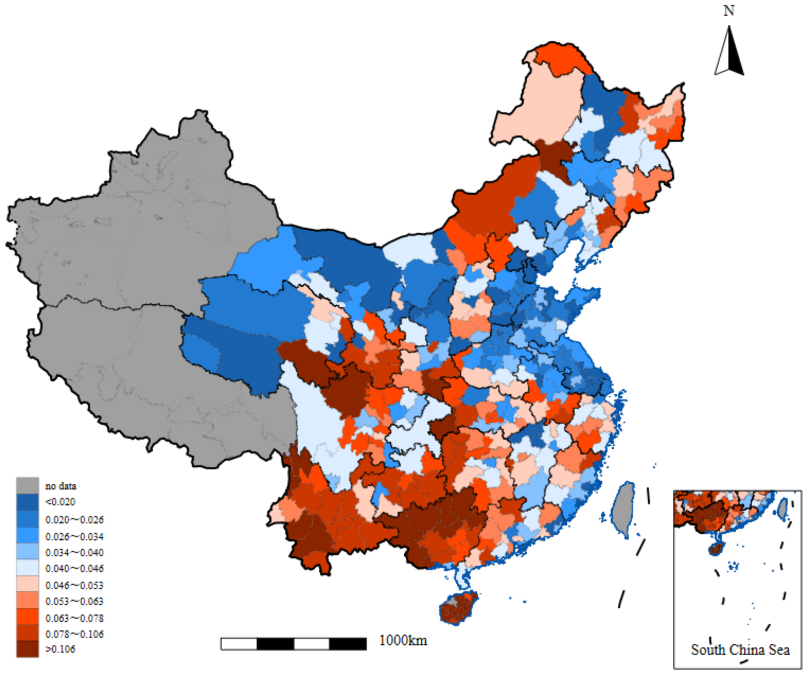
Finally, we present the third set of stylized facts on the spatial distribution of singlehood in 2015, shaped by the interplay between the dramatic "gender-specific structural changes" and the persistent and strong "social norms in the marriage market."

Visualization of the Spatial Distributions Figure 3 visualizes the spatial distribution of singlehood based on the 2015 Census data, using the singles rate gap between males and females aged 30 to 45 across living locations. We consider individuals aged over 30 because most Chinese people complete their marriage choices before this age. We focus on individuals aged under 45 to examine cohorts who completed their marriages around the 2000s and 2010s. Red means a large gap and blue means a small gap. The figure shows that the male-to-female singles rate gap is particularly high in less developed inland cities, such as Yunnan and Guizhou, while it is close to zero in more developed coastal cities, such as the Yangtze River Delta Region (Shanghai, Suzhou, Hangzhou, and Wuxi) and the Pearl River Delta Region (Guangzhou, Shenzhen, Hong Kong, and Zhuhai). Appendix A.2.1 provides singles rate for males and females separately.

City Characteristics and the Singles Rate Finally, we present the relationship between singles rate and city development levels in Figure 4. The figure shows that the singles rate of males

[7]The tendency of females to marry up based on education year has been decreasing due to the switch into equal matches. If we focus on females marry down in education year, the measure is roughly constant over time.

Figure 3: Male-Female Singles Rate Gap across Living Locations in 2015

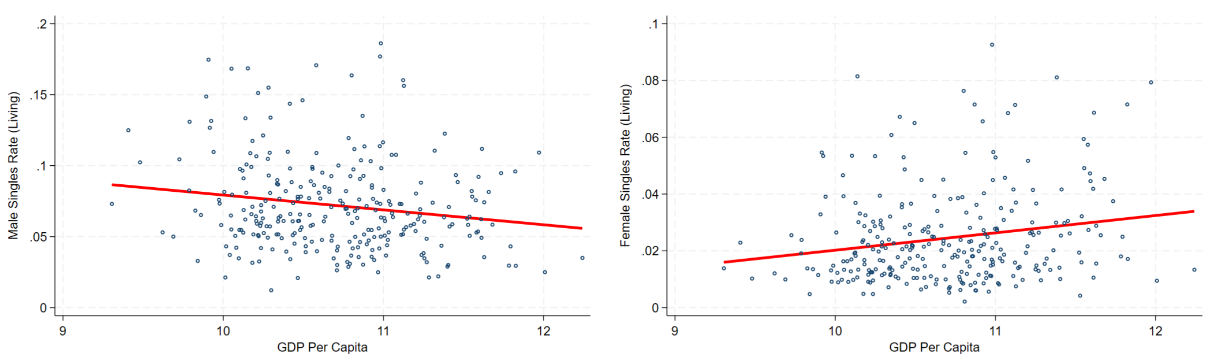


Notes: This figure illustrates the singles rate gap between males and females aged 30 to 45 across different cities in 2015. Cities shaded in red (blue) indicate a higher (lower) male singles rate compared to the female singles rate. Data source: Population Census 2015.

Figure 4: GDP and Singles Rate of Age over 30 in 2015

(a) Male

(b) Female



Notes: This figure illustrates the relationship between GDP per capita and the singles rate (aged 30-45) at the living city level. Subfigure (a) presents the results for the male singles rate, while subfigure (b) shows the results for the female singles rate. Data source: Population Census 2015.

is significantly lower in cities with higher development levels, as indicated by higher GDP per capita. Conversely, in these more developed cities, the singles rate of females is substantially higher. In Appendix Section A.2.2, we further show this relationship by education level. Among males, the negative relationship between GDP per capita and the overall singles rate is primarily driven by low-skill individuals. In contrast, for females, the positive relationship between GDP per capita and the overall singles rate is driven by high-skill individuals. We also change the measure for city development level to the nightlight index and the share of the service sector in GDP. We show the results to be robust in Appendix A.2.3.

3.4 Summary of the Stylized Facts

We document three sets of stylized facts: (1) dramatic gender-specific spatial structural changes in education and sectors; (2) persistent social norms in marriage; and (3) diverging spatial distributions of marriage and singlehood. These patterns underscore our central insight on the spatial mismatch in the marriage market. As female educational attainment rises and the service sector expands rapidly in developed cities, women increasingly migrate to these areas for employment opportunities. However, persistent social norms in marriage remain: women tend to prefer partners with higher SES, while men tend to prefer partners with lower SES. As a result, two distinct groups are disproportionately left unmatched: low-SES males from underdeveloped regions and high-SES females from developed areas. To explore the underlying mechanisms and driving forces behind these facts, we develop a quantitative spatial model and decompose China's marriage market dynamics into different channels.

4 A Spatial Equilibrium Model of Migration and Marriage

The model embeds marriage matching with transferable utility as in Choo and Siow (2006) into a quantitative spatial equilibrium model in the context of China (Tombe and Zhu, 2019; Fan, 2019; Fang et al., 2022). The economy consists of a set of prefectures indexed by $i = 1, \ldots, K$. Each prefecture comprises three sectors: agricultural, manufacturing, and service. The manufacturing and service sectors, considered as "modern sectors," employ a combination of high-, middle-, and low-skilled labor as inputs to produce final goods, whereas the agricultural sector uses undifferentiated labor as input. There is a measure of H workers in this economy. Each worker o is characterized by gender g (male m or female f), skill level e (high h, middle mid, low l) based on education, and hukou location i (hometown). Workers are single and participate in the local marriage market at the location where they work. Once matched and married, workers stay in their marriage. Divorce decisions are not modeled, given China's relatively low divorce rate.

Workers' utility is determined by their final goods consumption, housing consumption, marriage status, compounded allocation costs of location and sector, and an unobserved location preference shock. Their utility derived from marriage depends on the non-pecuniary match value, the marital transfer, and an idiosyncratic marriage preference shock. Equilibrium conditions in the local marriage market determine the marital transfer, which can be considered as a marriage market price. To marry a highly sought-after candidate, a worker must pay a higher transfer, whereas a worker with more desirable characteristics has greater bargaining power and receives this transfer.

Workers sequentially make three decisions. First, after their location preference shocks are realized, they choose their working locations based on the expected utility in each location, which depends on local wages, housing costs, compounded allocation costs of location and sector, and marriage market conditions. Second, their marriage preference shocks are realized, and they select their matching strategy in the local marriage markets. Finally, workers decide on the final good and housing consumption. Each prefecture i has a fixed land supply L_i, which can be converted to residential floor space S_{iu} through a given construction technology. The demand and supply of floor space in each prefecture determine the housing costs in each location.

4.1 Location Preferences and Worker Allocations

For a worker o from hukou city i allocating to sector k in living city j, the utility function is:

$$U^o_{i,jk} = \frac{z^o_{i,jk}}{\tau^{ge}_{i,jk}} \bar{V}^{ge}_{jk}, \tag{1}$$

where the term $\bar{V}_{jk}^{ge}$ denotes the expected utility value of choosing location j and sector k, which is determined by the expected final goods consumption, the housing consumption, and the marriage utility. We will explain $\bar{V}_{jk}^{ge}$ in more detail in the next subsection.

The term $\tau_{i,jk}^{ge}$ represents the compounded allocation costs for a worker with gender g, skill e, moving from city i to sector k in city j for employment. If $i = j$, then the worker is only allocated to sector k without migration; otherwise, the worker is both migrated from city i to city j and allocated to sector k. More specifically, the compounded allocation costs consist of the costs of the distance between the origin and the destination $G(d_{i,j})$, the overall relative costs of finding a job in a specific sector $\overline{\tau}_k^{ge}$, and the spatial sectoral heterogeneity $\varepsilon_{i,jk}^{ge}$ that captures the differential cost of working in the sector k in a particular destination j as follows:[8]

$$\tau_{i,jk}^{ge} = \exp\left(G(d_{i,j}) + \overline{\tau}_k^{ge} + \varepsilon_{i,jk}^{ge}\right), \tag{2}$$

where $\overline{\tau}_k^{ge}$ captures the average gender- and education-specific national structural sectoral change frictions to allocate to sector k and $\varepsilon_{i,jk}^{ge}$ captures the gender- and education-specific spatial sectoral frictions to allocate to sector k in city j. Both factors jointly govern the gender- and education-specific spatial structural changes, which we will discuss later.

The term $z_{i,jk}^{o}$ is an idiosyncratic Fréchet distributed location preference shock:

$$F(z_{i,jk}^{o}) = e^{-{z_{i,jk}^{o}}^{-\epsilon}}, \quad \epsilon > 1,$$

where ϵ controls the dispersion of the shock. After the realization of the idiosyncratic location preference shock $z_{i,jk}^{o}$ for each possible option, each individual chooses a location-sector pair jk to work in, based on the expected utility of each choice, which will be detailed later.

With the Fréchet distribution for the preference shock, we obtain a gravity equation for worker allocation flows. Let $\pi_{i,jk}^{ge}$ denote the share of workers with gender g, skill e, and hukou

[8]The spatial component $\varepsilon_{i,jk}^{ge}$ may also contains the tightness of migration policies and the costs of amenities between i and jk.

origin i migrating to sector k in city j for work. The gravity equation is given by:

$$\pi_{i,jk}^{ge} = \frac{(\tau_{i,jk}^{ge})^{-\epsilon}(\bar{V}_{jk}^{ge})^{\epsilon}}{\sum_{j'k'}(\tau_{i,j'k'}^{ge})^{-\epsilon}(\bar{V}_{j'k'}^{ge})^{\epsilon}} = \frac{\Phi_{i,jk}^{ge}}{\Phi_{i}^{ge}} \tag{3}$$

This gravity equation describes the spatial and sectoral distribution of workers in the model concerning gender g, skill e, and hometown i. Workers are more likely to allocate to city-sector pairs with higher expected utility values and lower allocation costs.

4.2 Utility and Local Marriage Market

Utility follows a log-linear functional form, incorporating final goods consumption, housing consumption, and marriage market value as its components. The local marriage market in city j is segmented from other cities, and we only consider marriages between the opposite genders. Individuals can either marry a specific type of spouse in city j or stay single. Married couples then form a new household, share their incomes and consumption with a certain family economy of scale, and engage in within-marriage transfers as a result of marriage market bargaining. In contrast, individuals who stay single consume their own incomes without any transfer or marriage utility value. Below, we detail the utility functions of both cases.

For an individual of type $\{g, e\}$ in location and sector $\{j, k\}$ who chooses to marry an opposite gender spouse of type $\{g', e'\}$, the utility function is given by:

$$V_{jk}^{o}(e') = \ln\left\{\left[\left(\frac{c_{jk}^{ge}(e')}{\beta}\right)^{\beta}\left(\frac{s_{jk}^{ge}(e')}{1-\beta}\right)^{1-\beta}\Big/(1+\chi)\right]\cdot m_{jk}^{o}(e')\right\} \tag{4}$$

where $c_{jk}^{ge}(e')$ and $s_{jk}^{ge}(e')$ denote final goods and housing consumption for an individual o of type $\{g, e\}$ in location and sector $\{j, k\}$ who marries a spouse of type $\{g', e'\}$. Upon marriage, the couple forms a new household and shares their total income $(w_{jk}^{ge} + E_{k'}[w_{jk'}^{g'e'}])$ where $E_{k'}[w_{jk'}^{g'e'}]$ stands for the expected spouse's income with eduction e' in all potential sectors k'. The parameter $(1 + \chi)$ captures the economies of scale from marriage relative to being single.

The log-linear utility function also implies that the household spends a fraction β of its income on final goods consumption and $1-\beta$ on housing consumption:

$$c_{jk}^{ge}(e') = \beta(w_{jk}^{ge} + E_{k'}[w_{jk'}^{g'e'}]), \tag{5}$$

$$s_{jk}^{ge}(e') = \frac{(1-\beta)(w_{jk}^{ge} + E_{k'}[w_{jk'}^{g'e'}])}{q_{jk}}. \tag{6}$$

The marriage utility value for individual o to select a spouse of type e' is specified as:

$$m_{jk}^{o}(e') = \exp\left[\tilde{\mu}_j^{ge} + \mu^{ge}(e') + \delta_j^{ge}(e') + \xi_{jk}^{o}(e')\right], \tag{7}$$

where $\tilde{\mu}_j^{ge}$ represents the overall deterministic value of not being single in location j. $\mu^{ge}(e')$ represents the deterministic match value of marrying with a specific type e' (relative to being single). $\delta_j^{ge}(e')$ denotes the within-marriage equilibrium transfer in the local marriage market j. This transfer satisfies $\delta_j^{ge}(e') = -\delta_j^{ge'}(e)$, implying a zero-sum bargaining outcome between spouses. This can be considered as the local marriage market price. The term $\xi_{jk}^{o}(e')$ is an idiosyncratic preference shock for partner type, following a Type I Extreme Value (T1EV) distribution with a dispersion parameter σ_ξ.

We now derive the final expressions for both married and single individuals. Substituting the optimal consumption choices and the marriage utility value into the utility function, the location utility for married individuals is:

$$V_{jk}^{o}(e') = \ln(w_{jk}^{ge} + E_{k'}[w_{jk'}^{g'e'}]) - \ln((1+\chi)q_{jk}^{1-\beta}) + \tilde{\mu}_j^{ge} + \mu^{ge}(e') + \delta_j^{ge}(e') + \xi_{jk}^{o}(e'). \tag{8}$$

For individuals choosing to stay single, we normalize the deterministic marriage value to zero. So the location utility for single individuals is:

$$V_{jk}^{o}(\varnothing) = \ln(w_{jk}^{ge}) - \ln(q_{jk}^{1-\beta}) + \xi_{jk}^{o}(\varnothing). \tag{9}$$

Using the properties of the Type I Extreme Value distribution, we derive the logit-form probabilities for marriage market decisions. First, the probability of choosing to marry a spouse of type e' is:

$$P_{jk}^{ge}(e') = \frac{\exp(V_{jk}^{ge}(e')/\sigma_\xi)}{\exp(V_{jk}^{ge}(\emptyset)/\sigma_\xi) + \sum_{e''} \exp(V_{jk}^{ge}(e'')/\sigma_\xi)}. \tag{10}$$

Second, the probability of choosing to stay single is:

$$P_{jk}^{ge}(\emptyset) = \frac{\exp(V_{jk}^{ge}(\emptyset)/\sigma_\xi)}{\exp(V_{jk}^{ge}(\emptyset)/\sigma_\xi) + \sum_{e''} \exp(V_{jk}^{ge}(e'')/\sigma_\xi)}. \tag{11}$$

Finally, the ex-ante expected utility of living and working in destination jk is given by:

$$\begin{aligned}\bar{V}_{jk}^{ge} &= E\Big[\max_{(e')} V_{jk}^{ge}(e')\Big] \\ &= \sigma_\xi \gamma + \sigma_\xi \ln \Big[\exp(V_{jk}^{ge}(\emptyset)/\sigma_\xi) + \sum_{e'} \exp(V_{jk}^{ge}(e')/\sigma_\xi)\Big]. \end{aligned} \tag{12}$$

where γ is the Euler's constant.

4.3 Production and Local Labor Market

We assume that a single final good Y is traded costlessly. There are two modern sectors: manufacturing (M) and service sectors (s). Their production functions have the same form with all high-, middle-, and low-skill workers as inputs:

$$Y_{jM} = [(A_{jM}^h H_{jM}^h)^{\frac{\sigma_M - 1}{\sigma_M}} + (A_{jM}^m H_{jM}^m)^{\frac{\sigma_M - 1}{\sigma_M}} + (A_{jM}^l H_{jM}^l)^{\frac{\sigma_M - 1}{\sigma_M}}]^{\frac{\sigma_M}{\sigma_M - 1}} \tag{13}$$

$$Y_{js} = [(A_{js}^h H_{js}^h)^{\frac{\sigma_s - 1}{\sigma_s}} + (A_{js}^m H_{js}^m)^{\frac{\sigma_s - 1}{\sigma_s}} + (A_{js}^l H_{js}^l)^{\frac{\sigma_s - 1}{\sigma_s}}]^{\frac{\sigma_s}{\sigma_s - 1}} \tag{14}$$

We denote subscript M as manufacturing sector and superscript m as middle skill. The production function is a CES combination of high-skill H_{jM}^h, middle-skill H_{jM}^m, and low-skill labor H_{jM}^l multiplied by their corresponding city-level efficiencies A_{jM}^h, A_{jM}^m, and A_{jM}^l (similar for services s). In rural cities, production is simply $Y_{jr} = A_{jr} H_{jr}$. Since we are not focusing on trade or substitution between goods and services, we assume that Y_r, Y_M, and Y_s are perfect substitutes and normalize the final goods price to unity. In equilibrium, A_{jr} equals the agricultural wage w_{jr} in rural sector r of city j, for both high- and low-skilled workers: $w_{jr}^h = w_{jr}^l = w_{jr}$.

Firms from urban sectors choose their labor inputs to maximize profits, taking productivity, factor prices, and decisions of other firms and workers as given. From the first-order conditions, we obtain the following equations for manufacturing (similar for services s):

$$w_{jM}^e = (A_{jM}^e)^{\frac{\sigma_M - 1}{\sigma_M}} (Y_{jM})^{\frac{1}{\sigma_M}} (H_{jM}^e)^{-\frac{1}{\sigma_M}}, \quad \text{for } e = \{h, m, l\} \tag{15}$$

Given the gravity equation as above, the local total labor supply of skill level e in sector k at location j is determined by the summation of the labor supply from all different hometowns i:

$$H_{jk}^e = \sum_{gei} \pi_{i,jk}^{ge} H_i^{ge}. \tag{16}$$

where H_i^{ge} denotes the total number of workers with gender g and skill level e from location i. The term $\pi_{i,jk}^{ge}$ represents the migration probability of a worker with gender g and skill level e from home location i to destination location-sector jk.

4.4 Housing Market Clearing

Modern Sectors Residential housing market clearing implies that the demand for residential floor space equals the supply of floor space allocated to residential use in each location. Using utility maximization for each worker and taking expectations over the distribution for idiosyncratic utility, this residential land market clearing condition can be expressed as:

$$S_{ju} = E[s_{ju}]H_{ju} = (1 - \beta) \frac{E[v_{ju}]H_{ju}}{q_{ju}} \tag{17}$$

where u includes both modern sectors $\{m, s\}$. We assume that the floor space S is supplied by a construction sector. It converts geographic land L to floor space S with a regulated density of development ϕ_j (the ratio of floor space to land): $S_{ju} = \phi_j L_j^u$. This aligns with the fact that the housing and the land markets are highly-regulated in China (Fang et al., 2022).

Agricultural Sector Housing markets in the agricultural sector are simpler. We assume that rural housing costs are a fixed fraction of urban cost in the same prefecture $q_{jr} = \eta q_{ju}$. Therefore, the price q_{jr} is the cost of building a unit of floor space on rural land. Given the cost, rural residents choose the optimal amount of floor space to build.

4.5 Definition of Spatial General Equilibrium

We now define and characterize the properties of a spatial general equilibrium given the model's fixed parameters $\{\beta, \epsilon, \chi, \mu, \sigma_{\xi}, \sigma, \eta\}$ as follows.

A ***Spatial General Equilibrium*** *for this economy is defined by a set of exogenous variables* $\{\tau^{ge}_{i,jk}, A^{e}_{j}, \phi_j, L_j, H^{ge}_{i}\}$*, a list of endogenous prices* $\{q_{ju}, w^{e}_{jk}, \delta^{ge}_{j}\}$*, quantities* $\{Y_{jk}, H^{ge}_{jk}, c^{ge}_{jk}, s^{ge}_{jk}, P^{ge}_{jk}, S_{ju}\}$*, and migration flow proportions* $\{\pi^{ge}_{i,jk}\}$ *that solve the firms' problem, workers' problem, floor space producers' problem, and market clearing such that:*

(i). ***[Worker Optimization]*** *Taking the exogenous economic conditions* $\{\tau^{ge}_{i,jk}, A^{s}_{j}, \phi_j, L_j, H^{ge}_{i}\}$ *and the aggregate prices* $\{q_{ju}, w^{e}_{jk}, \delta^{ge}_{j}\}$ *as given, workers' optimal migration choices pin down the equilibrium labor supply in each city* H^{ge}_{jk}*, the migration flow between each city pair* $\pi^{ge}_{i,jk}$*, and the marriage market outcomes.*

(ii). ***[Firm Optimization]*** *Taking the exogenous economic conditions* $\{A^{s}_{jk}\}$ *and local wages* $\{w^{e}_{jk}\}$ *as given, firms' optimal production choices pin down the equilibrium labor demand* H^{ge}_{jk}*.*

(iii). ***[Goods and Land Market Clearing]*** *For all cities, labor supply equals labor demand, and floor space supply equals floor space demand. This pins down the equilibrium aggregate prices* $\{q_{ju}, w^{e}_{jk}, \delta^{ge}_{j}\}$*, equilibrium floor space* S_{ju}*, and equilibrium output* Y_{ju}*.*

(iv). ***[Marriage Market Clearing]*** *For all possible marriage matching types* (g, e) *vs* (g', e') *in all cities, the marriage demand of type* (g, e) *on type* (g', e') *equals the marriage demand of type* (g', e') *on type* (g, e)*. This pins down the marriage market utility transfer* δ^{ge}_{j}*.*

4.6 Spatial Structural Changes in the Model's View

Before estimating and solving the model with microdata, we first demonstrate how the stylized facts in Section 3.1 connect to the structure of our model. The observed patterns in the gender educational gap, gender sectoral employment gap, and gender spatial employment gap are jointly governed by two key components: the gender-specific education distributions in the population at each hometown location H_i^{ge}, and the gender- and education-specific allocation costs associated with moving from origin i to each destination sector k in each destination location j, denoted by $\{\bar{\tau}_k^{ge}, \bar{\tau}_j^{ge}, \varepsilon_{i,jk}^{ge}\}$. Here, $\bar{\tau}_k^{ge}$ represents the national average sectoral allocation costs, $\bar{\tau}_j^{ge}$ captures the average spatial allocation costs by destination, and $\varepsilon_{i,jk}^{ge}$ denotes location-pair-specific spatial and sectoral allocation frictions.

The interaction of three primary trends drives the gender-specific spatial structural changes we observe. First, there has been a reversal in the gender educational gap across most locations, reflected in a greater increase in the relative population of highly educated female workers, H_i^{fe}/H_i^{me}. Second, we observe rapid growth in highly educated female employment within the service sector, which corresponds to a substantial decline in the relative allocation cost $\bar{\tau}_s^{fe}/\bar{\tau}_s^{me}$ for women. Third, we document significant migration of highly educated females to more developed cities, which is reflected in a small relative spatial-sectoral allocation costs $\varepsilon_{i,jk}^{fe}/varepsilon_{i,jk}^{me}$ for educated females in destination cities j.

Together, these changes represent the gender- and skill-specific spatial structural transformations captured in our stylized facts, which can be summarized in the following components:

- A national educational shifter in relative female education: H_i^{fe}/H_i^{me};
- A national sectoral shifter in relative female allocation costs: $\bar{\tau}_s^{fe}/\bar{\tau}_s^{me}$;
- Spatial-sectoral shifters in relative female allocation costs: $\varepsilon_{i,jk}^{fe}/\varepsilon_{i,jk}^{me}$.

5 Model Estimation and Solution

We estimate the model parameters and solve for the model equilibrium variable values in several steps, combining calibration, log-linearization, and a contraction algorithm.

5.1 Calibration of Fixed Parameters

In the first step, we calibrate a group of conventionally used parameters from related literature. The parameter β is calibrated to 0.77, reflecting the share of final goods consumption in total family consumption, based on data from the Urban Household Survey. The migration elasticity parameter ϵ is set to 1.5, following Tombe and Zhu (2019); we also check the robustness of our results using the alternative value of 1.9, as in Fang and Huang (2022). The household consumption economies of scale parameter χ is calibrated to 0.7 based on Greenwood et al. (2016) and OECD (2013). η is calibrated to 0.34, using the relative rural-to-urban housing rent from the 2010 China Population Census. Given our setup of three levels of skills, the skill complementarity parameter σ is calibrated to 4, as shown recently in Bils et al. (2024), and we also check robustness using the value of 1.4 following the more classical configuration in Katz and Murphy (1992). Table 4 summarizes all calibrated parameters used in the model.

Table 4: Fixed Parameters from the Literature

Parameter	**Description**	**Value**	**Source**
β	Share of consumption in utility	0.77	Urban Household Survey
ϵ	Migration elasticity	1.5	Tombe and Zhu (2019)
χ	Consumption economy of scale	0.7	Greenwood et al. (2016); OECD (2013)
η	Relative cost of rural housing	0.34	Population Census
σ	Elasticity of skill substitution	4.0	Bils et al. (2024)

Notes: This table summarizes all calibrated parameters.

5.2 Estimation of the Marriage Market Parameters

In the second step, after calibrating the fixed parameters, we estimate the marriage market parameter using the Generalized Method of Moments (GMM). We have four sets of parameters to pin down: shape parameter of the marriage preference shock σ_ϵ; overall deterministic marriage value $\tilde{\mu}_j^{ge}$, match value with a specific type $\mu^{ge}(e')$; and marriage transfer $\delta_j^{ge}(e')$. Same as the approach in Mao and Wen (2024), we first log-linearize equations (10) and (11), and then subtract

(10) by (11) to have:

$$\ln\left[P_j^{ge}(e')\right] - \ln\left[P_j^{ge}(\varnothing)\right] = \frac{1}{\sigma_\xi}\left[\tilde{\mu}_j^{ge} + \mu^{ge}(e') + \delta_j^{ge}(e') + \ln\left(\frac{W_j^{ge} + W_j^{g'e'}}{W_j^{ge}(1+\chi)}\right)\right] \tag{18}$$

where $P_j^{ge}(e'), P_j^{ge}(\varnothing), W_j^{ge}, W_j^{g'e'}$ are directly observed from data. Therefore, the left-hand side of this equation can be considered the target moments, and the right-hand side can be considered estimated moments. We then use the GMM to match them and estimate our target parameters.

Leveraging the variations across local marriage markets in different cities, the Choo and Siow (2006) type of marriage matching models can be separately identified. The intuition behind the identification strategy is as follows. $\widetilde{\mu}_j^{ge}$ captures the overall surplus from marriage relative to remaining single for each worker type in each location. This term can be identified by the overall singlehood rate of each worker type in each location. The term $\mu^{ge}(e')$ denotes the match value for a specific spouse pair (e, e'), which is assumed to be constant across locations. It can be identified using the national-level spouse match shares across different types. The term $\delta_j^{ge}(e')$ represents the location-specific marriage market transfer for each match pair (e, e') in location j, and it can be identified by the match shares of different spouse types across locations. Since marriage transfers are determined by a symmetric zero-sum bargaining process, we impose the restriction $\delta_j^{ge}(e') = -\delta_j^{ge'}(e)$. This constraint reduces the degrees of freedom and leads to an over-identified GMM system.

Table 5: Non-pecuniary Marital Return by Own and Spouse Types

(a) Male Value

Male Type	Wife Type		
	l-skill	m-skill	h-skill
l-skill	3.312	-0.672	-3.589
m-skill	2.615	2.654	0.106
h-skill	0.651	1.770	3.175

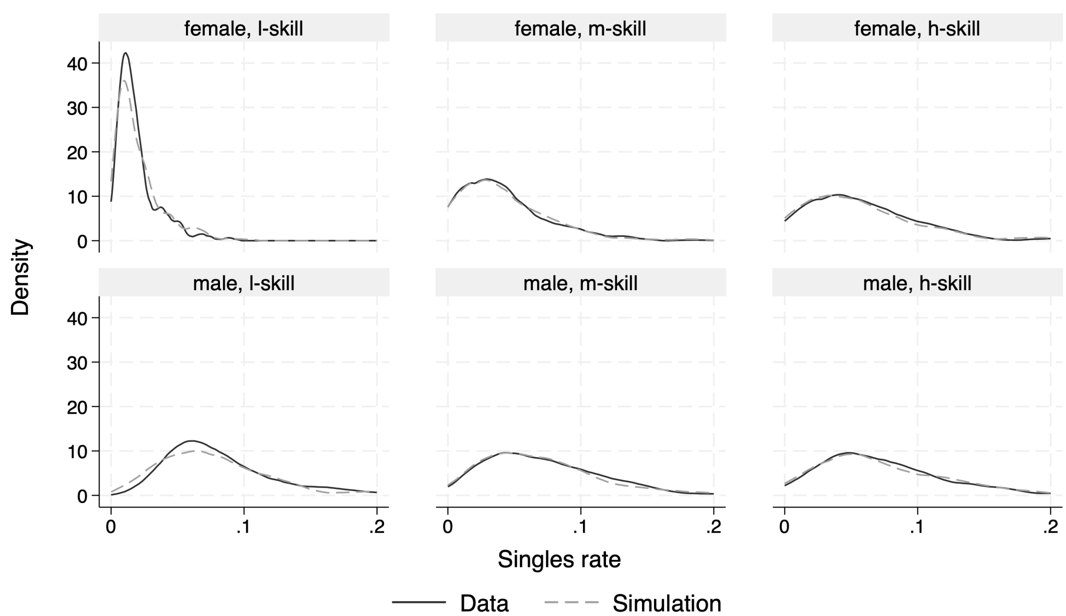
(b) Female Value

Female Type	Husband Type		
	l-skill	m-skill	h-skill
l-skill	5.253	2.373	-0.277
m-skill	2.707	3.850	2.280
h-skill	-0.101	1.411	3.794

Notes: This table presents the estimation results for the parameters of the marriage market. Panel (a) reports the parameters in the male utility function. Each row corresponds to the skill type of the male, and each column represents the skill type of his potential wife. Panel (b) reports the parameters in the female utility function. Similarly, each row corresponds to the skill type of the female, and each column represents the skill type of her potential husband.

Results of the Marriage Market Estimation Table 5 reports the estimation results for the type-specific match values $\mu^{ge}(e')$. We normalize the value of being single to be zero. Panels (a) and (b) present the results of the parameters in the male and the female utility function, respectively. Each row corresponds to the individual's own education type and each column corresponds to the spouse's education type. The results indicate that educational homogamy remains the dominant marriage pattern in China. Marrying someone with a different education level results in a utility loss. However, there is a significant gender asymmetry in preferences. Males exhibit a greater willingness to marry down in education, while females show a stronger preference for marrying up. Specifically, for males, the utility loss from marrying up is substantial, whereas for females, this loss is much smaller across all skill levels. More details of the marriage matching estimation are provided in Appendix B.4.

Figure 5: Model Fit of the City-level Singles Rate



Notes: This figure plots the density of the city-level singles rate for each gender and skill. Solid lines are the data, and dashed lines are simulated results.

Model Fit of the Marriage Market Estimation Since our GMM system is overidentified, we validate the model fit with the distribution of city-level singles rate of each skill group by gender in Figure 5. The estimated marriage preference parameters generate a consistent model fit of the city-level singles rate across all six population groups. The top panels show that as females climb the education ladder, the city-level singles rate is higher. The lower city-level singles rate is concentrated among low-skill females. However, the bottom panels show that such patterns do not exist for males across groups. On the contrary, low-skill males have a higher city-level singles rate. Appendix Figures B2 to B5 further validate the model by comparing the model simulated match shares ($\ln[P_j^{ge}(e')] - \ln[P_j^{ge}(\emptyset)]$) and those in the data for each combination of male and female types. We can closely fit these matching outcomes as well.

5.3 Solution of All Unobserved Variables

In the third step, based on the data we have on the observed equilibrium allocations and prices $\{H_i^{ge},\ H_{jk}^{ge},\ \pi_{i,jk}^{ge},\ w_{jk}^{e},\ q_{ju},\ q_{jr}\ \}$, and estimated parameters in above two steps, we can calculate all unobserved variables: productivities $\{A_{jk}^{l},\ A_{jk}^{m},\ A_{jk}^{h}\}$, compounded allocation costs ($\tau_{i,jk}^{ge}$), floor spaces $\{S_{ju}, S_{jr}\}$, and urban construction density (ϕ_i).

Productivities First, from profit maximization and zero profits, we can infer urban sectoral productivity from the data on employment and wages for $k = \{m, s\}$. First, we solve for productivity A_{jk}^{h} and A_{jk}^{m} as a function of A_{jk}^{l} using the first order conditions

$$A_{jk}^{h} = A_{jk}^{l}(H_{jk}^{h}/H_{jk}^{l})^{1/(\sigma_k-1)}(w_{jk}^{h}/w_{jk}^{l})^{\sigma_k/(\sigma_k-1)}$$

$$A_{jk}^{m} = A_{jk}^{l}(H_{jk}^{m}/H_{jk}^{l})^{1/(\sigma_k-1)}(w_{jk}^{m}/w_{jk}^{l})^{\sigma_k/(\sigma_k-1)}$$

Plugging A_{jk}^{h} and A_{jk}^{m} into the definition of Y_{jk}, we have:

$$Y_{jk} = A_{jk}^{l}H_{jk}^{l}\Big[\frac{w_{jk}^{h}H_{jk}^{h} + w_{jk}^{m}H_{jk}^{m} + w_{jk}^{l}H_{jk}^{l}}{w_{jk}^{l}H_{jk}^{l}}\Big]^{\frac{\sigma_k}{\sigma_k-1}} \equiv A_{jk}^{l}H_{jk}^{l}(\Xi_{jk}^{l})^{-\frac{\sigma_k}{\sigma_k-1}}$$

where $\Xi_{jk}^{l} = \frac{w_{jk}^{l}H_{jk}^{l}}{w_{jk}^{h}H_{jk}^{h}+w_{jk}^{m}H_{jk}^{m}+w_{jk}^{l}H_{jk}^{l}}$ is the share of labor income distributed to low-skill workers. We also assume that agricultural productivity equals agricultural wages $A_{jr}^{s} = w_{jr}$, for all $s = \{h, m, l\}$. Intuitively, higher wages or skill shares s require higher skill s productivity at equilibrium for urban sectors. We can then calculate the productivity for both skill types as follows:

$$A^l_{jk} = w^l_{jk}(\Xi^l_{jk})^{\frac{1}{\sigma_k - 1}}$$
$$A^m_{jk} = w^m_{jk}(\Xi^m_{jk})^{\frac{1}{\sigma_k - 1}}$$
$$A^h_{jk} = w^h_{jk}(\Xi^h_{jk})^{\frac{1}{\sigma_k - 1}}$$

where $\Xi^m_{jk} = \frac{w^m_{jk}H^m_{jk}}{w^h_{jk}H^h_{jk}+w^m_{jk}H^m_{jk}+w^l_{jk}H^l_{jk}}$ and $\Xi^h_{jk} = \frac{w^h_{jk}H^h_{jk}}{w^h_{jk}H^h_{jk}+w^m_{jk}H^m_{jk}+w^l_{jk}H^l_{jk}}$, respectively.

Land Market Clearing Second, from workers' first-order conditions for residential floor space and the summation of all workers residing in each prefecture and region jk, we can calculate both urban and rural floor space:

$$S_{ju} = \frac{1-\beta}{q_{ju}} \sum_k \left[w^l_{jk}H^l_{jk} + w^m_{jk}H^m_{jk} + w^h_{jk}H^h_{jk} \right], \qquad S_{jr} = \frac{1-\beta}{q_{jr}} \left[w_{jr}H_{jr} \right]$$

We can then back out the implied construction intensity $\phi_j = S_{ju}/L_j$.

Compounded Allocation Costs Normalizing the compounded allocation cost by staying at hometown i agriculture sector r $\tau^{ge}_{i,ir}$ to unity, we can directly invert the allocation gravity equation (3) to solve for the compounded allocation costs between cities and sectors:

$$\Phi^{ge}_i = \frac{(\bar{V}^{ge}_i)^{\epsilon}}{\pi^{ge}_{i,i}} \tag{19}$$
$$\tau^{ge}_{i,jk} = \frac{\bar{V}^{ge}_{jk}}{(\Phi^{ge}_i \pi^{ge}_{i,jk})^{\frac{1}{\epsilon}}} \tag{20}$$

5.4 Estimation of Allocation Cost Components

In the final step, we estimate the detailed components of allocation costs. The compounded allocation costs $\tau^{ge}_{i,jk}$ have already been solved in the previous section. We now recover the individual components of allocation cost using equation (2). Specifically, we take the log of both sides of the equation and run a simple OLS regression.

$$\log(\tau^{ge}_{i,jk}) = G(d_{i,j}) + \overline{\tau}^{ge}_k + \varepsilon^{ge}_{i,jk}$$

which includes a third-order polynomial in prefecture pair distance $G(d_{i,j})$, a set of sector fixed effects $\overline{\tau}_k^{ge}$, and a set of spatial sector residuals $\varepsilon_{i,jk}^{ge}$. More specifically, the average sectoral allocation cost $\overline{\tau}_k^{ge}$ reflects all the average gender- and education-specific allocation costs for sector k for the national average, and the location-pair specific spatial and sectoral allocation costs $\varepsilon_{i,jk}^{ge}$ reflects all the residual gender- and education-specific allocation costs for sector k between origination i and destination j. The estimation results are summarized in Tables 6 and 7 for $\overline{\tau}_k^{ge}$ and $\varepsilon_{i,jk}^{ge}$, respectively.

Table 6: Relative Sectoral Allocation Costs by Gender and Skill

$\bar{\tau}_k^{ge}$	Male			Female		
	l-skill	m-skill	h-skill	l-skill	m-skill	h-skill
Agriculture	0.398	0.821	1.581	0.319	0.857	1.785
Manufacturing	0.126	0.159	0.215	0.178	0.249	0.353
Service	0.290	0.189	0.080	0.224	0.097	0

Notes: This table summarizes the relative sectoral allocation cost by gender and skill ($\overline{\tau}_k^{ge}$), estimated from equation (2) with our 2025 data for the model. The sectoral allocation cost of high-skill females in the service sector is normalized to 0 for comparison.

Table 6 summarizes the relative sectoral allocation cost $\varepsilon_{i,jk}^{ge}$ in 2015, where the sectoral allocation cost of high-skill females in the service sector is normalized to 0 for comparisons. There are three takeaways. First, the sectoral allocation cost is relatively lower for participation in the service sector, regardless of skill and gender. Second, the sectoral allocation cost for participation in the service sector is notably lower for higher-skilled workers, regardless of gender. Third, the sectoral allocation cost for higher-skilled workers' participation in the service sector is notably lower for female workers. All these relative costs in the sectoral participation are reflected in the observed strong sectoral sorting of higher-skilled females into service sectors. The spatial structural change in the gender sectoral employment gap from Section 3.1 could be mainly reflected in changes in these relative sectoral allocation costs.

Table 7 summarizes the relative spatial sectoral allocation costs $\overline{\tau}_j^{ge}$ in 2015, where the spatial sectoral allocation cost of high-skill females in the most developed quartile of cities is normalized to 0 for comparisons. There are also three takeaways. First, the spatial sectoral allocation cost is relatively lower for allocation to more developed cities, regardless of skill and gender. Second,

Table 7: Relative Spatial Sectoral Allocation Costs by Gender and Skill

Average $\varepsilon^{ge}_{i,jk}$	Male			Female		
	l-skill	m-skill	h-skill	l-skill	m-skill	h-skill
Least Developed	0.463	0.488	0.592	0.473	0.564	0.629
Second Quartile	0.555	0.600	0.594	0.554	0.570	0.610
Third Quartile	0.448	0.445	0.417	0.439	0.425	0.399
Most Developed	0.171	0.104	0.034	0.171	0.079	0

Notes: This table summarizes the relative locational allocation cost by gender and skill (average $\varepsilon^{ge}_{i,jk}$), estimated from equation (2) with our 2015 data for the model. We group cities into four quartiles, divided by the level of development (GDP per capita). The locational allocation cost of high-skill females in the most developed region is normalized to 0 for comparison.

the spatial sectoral allocation cost for allocation to more developed cities is notably lower for higher-skilled workers, regardless of gender. Third, the spatial sectoral allocation cost for higher-skilled workers' allocation to more developed cities is notably lower for female workers. All these relative costs in the spatial sectoral allocation are reflected in the observed strong spatial sorting of higher-skilled females into more developed cities. The spatial structural change in the gender spatial employment gap from Section 3.1 could be mainly reflected in changes in these relative spatial allocation costs. More details on the spatial allocation costs are provided in Appendix B.5.

6 Quantitative Analysis

In this section, we conduct a quantitative analysis of the estimated model. We begin by assessing the effects of gender-specific spatial structural changes on both national and regional singles rates, and decompose the contributions of three key components: education, sectoral allocation costs, and spatial-sectoral allocation costs. We then examine how continued gender-specific spatial structural changes, following existing trends, would further influence marriage rates in China in the future.

6.1 The Effects of Gender-specific Spatial Structural Changes

We begin by investigating the effects of gender-specific spatial structural changes on national and regional singles rates. In addition, we quantify the contribution of each component of these structural changes to the observed singles rates at both the national and regional levels. To achieve this, we remove gender-specificity by equalizing the corresponding gender-specific parameters between males and females in the estimated model and computing the resulting counterfactual equilibria. Specifically, we consider the following three adjustments: (1) equalizing male and female education levels; (2) equalizing male and female sectoral allocation costs; and (3) equalizing male and female spatial-sectoral allocation costs. These adjustments only average out gender-specific differences, while preserving heterogeneity along other dimensions, such as differences in allocation costs across education groups, sectors, destinations, and hometowns.

Table 8: The Effects of Gender-specific Spatial Structural Changes on Singles Rate

National & Regional	Male			Female		
Singles Rate	National	Least Dev.	Most Dev.	National	Least Dev.	Most Dev.
Panel A: Singles Rate and Percentage Changes						
Baseline	8.17%	8.98%	8.11%	3.46%	2.36%	5.09%
No GS-SSCs	7.21%	8.03%	5.97%	2.45%	1.99%	3.11%
% Changes	-11.75%	-10.58%	-26.39%	-29.19%	-15.68%	-38.90%
Panel B: Decomposition of the Percentage Changes						
National Educational	32.29%	93.68%	-15.89%	31.68%	-18.92%	44.44%
National Sectoral	-1.04%	-41.05%	15.89%	0.00%	16.22%	-6.06%
Spatial Sectoral	68.75%	47.37%	100.00%	68.32%	102.70%	61.62%

Notes: This table lists the singles rate for each gender under different scenarios in Panel A. "Baseline" presents the equilibrium outcomes in the real world for 2015. "No GS-SSCs" shows the counterfactual in which all gender-specificities in education, sectoral, and spatial-sectoral allocation costs are all averaged out. The regions are defined by the prefecture quartile by GDP per capita. In Panel B, we decompose the percentage change in singles rates sequentially by adding the change of each component one by one. The contributions of these three components sum to 100%.

Table 8, Panel A, reports the overall effects of gender-specific spatial structural changes (GS-SSCs) on the singles rate, focusing on the national average, the least developed quartile of cities, and the most developed quartile of cities. The first row, “Baseline,” presents the equilibrium outcomes in the real world for 2015. The second row, “No GS-SSCs,” shows the counterfactual in which all gender-specificities in the three components are averaged out. The third row, “%

Changes," reports the relative percent change in the corresponding singles rate relative to the baseline equilibrium.

The main findings are as follows. First, eliminating gender-specificity in spatial structural changes leads to a substantial reduction in the national singles rate for both females and males—by 29.19 percent and 11.75 percent, respectively. Second, these effects are particularly pronounced in more developed cities: the top quartile experiences a 38.90 percent reduction in the female singles rate and a 26.39 percent reduction for males.[9] These results underscore the crucial role of gender-specific spatial structural changes in shaping local marriage markets, contributing to both national and regional marriage mismatches and elevated singles rates.

Panel B of Table 8 provides a sequential decomposition of the percentage changes reported in Panel A. The effects are broken down into three sources of gender-specificity: (i) national educational differences, (ii) national sectoral allocation differences, and (iii) spatial-sectoral allocation differences. The contributions of these three components sum to 100%.

The decomposition reveals several insights. First, gender-specific differences in education account for roughly one-third of the observed effects on national singles rates, while spatial-sectoral allocation differences explain the remaining two-thirds. In contrast, national sectoral allocation differences play a negligible role. When we further examine regional outcomes, the importance of education and spatial-sectoral sorting becomes even more prominent. These results indicate that gender-specific changes in education and sectoral spatial sorting are the key drivers of spatial mismatches in the marriage market, especially in more developed urban areas.

We further explore the role of gender-specific spatial structural changes by analyzing singles rates across skill groups in Table 9. Panel A again reports the singles rates and the percent changes between the baseline and the counterfactual scenario in which gender-specificity in spatial structural changes is removed. The results align with the narrative of spatial mismatch in the marriage market, driven by the race between gender-specific structural changes and persistent social norms. Specifically, when gender-specificity is eliminated, the singles rates decline most significantly for low-skilled males and high-skilled females.

[9] Due to China's historically skewed sex ratio at birth—largely driven by son preference—the male singles rate is persistently higher than the female rate. Therefore, we cannot totally erase singlehood by only equalizing gender-specific spatial structural change parameters.

Table 9: The Effects of Gender-specific SSCs on Singles Rate Across Skills

Singles Rate	Male			Female		
Across Skills	Low Skill	Mid Skill	High Skill	Low Skill	Mid Skill	High Skill
Baseline	8.71%	7.42%	6.91%	1.74%	4.25%	9.55%
No GS-SSCs	7.63%	6.38%	6.58%	1.85%	3.14%	4.46%
% Changes	-12.40%	-14.02%	-4.78%	6.32%	-26.12%	-53.30%

Notes: This table lists the singles rate for each gender-skill type under different scenarios. "Baseline" presents the equilibrium outcomes in the real world for 2015. "No GS-SSCs" shows the counterfactual in which all gender-specificities in education, sectoral, and spatial-sectoral allocation costs are all averaged out.

Our findings are robust to different orders of sequential decomposition and to decompositions that isolate each factor individually. These robustness checks, along with detailed breakdowns of singles rate changes by gender, skill, and region, are reported in Appendix C.1.

6.2 How about the Future? China in 2030

We next show how national and regional singles rates would evolve if gender-specific spatial structural changes continue to follow the observed trends documented in Section 3.1. Specifically, we project a counterfactual scenario for the year 2030 based on the 2015 equilibrium in our model and extrapolate time trends observed from 2000 to 2015.

The projection incorporates three shifters, as highlighted in the stylized facts. First, we account for continued gender-specific changes in education by calibrating the high-skill population share to reflect the share of individuals holding a bachelor's degree or higher among those aged 30 in 2030 (i.e., those born in 2000). According to the 2020 Census, 34.5% of women and 26.5% of men in this cohort obtained undergraduate or higher education, raising the female-to-male high-skill ratio from 1.15 in 2015 to 1.30 in 2030.[10]

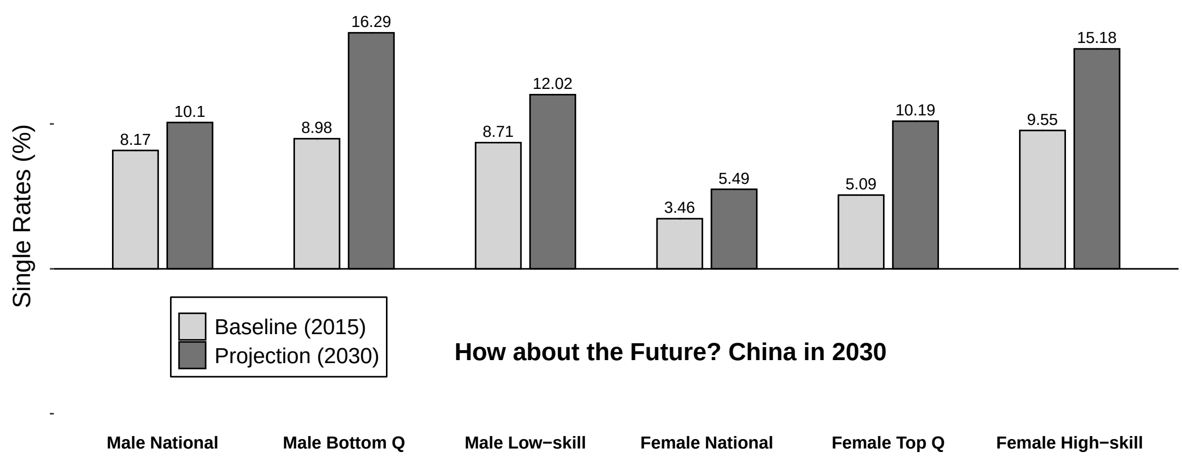
Second, we project continued gender-specific sectoral changes by linearly interpolating the gender employment gap in the service sector from 2000 to 2015, as reported in Table 1, forward

[10]College dropout is rare in China. In the baseline analysis, we define high-skill as any college education or above, including vocational college. However, due to the expansion of higher education, more than half of the cohort aged 30 in 2030 will have attended vocational or higher institutions. Thus, we redefine high-skill as a bachelor's degree or higher for this projection. Robustness checks using the original definition are provided in Appendix C.2.2.

to 2030. This increases the female-to-male employment gap to 46.61% (+25.41 percentage points) for high-skill, 8.45% (+4.35 p.p.) for medium-skill, and 36.47% (+27.17 p.p.) for low-skill groups. We match these targets by reducing the female sectoral allocation costs $\overline{\tau}_k^{ge}$ while holding male costs constant.

Third, we consider further spatial sectoral structural changes. Since no natural projection target exists for this dimension, we simulate an intensified spatial disparity by doubling the existing gap in spatial allocation costs $\varepsilon_{i,jk}^{ge}$ between moving to the service sector in the top and bottom quartile cities. We hold constant the costs for moving to other sectors and to cities in the middle two quartiles. Additional technical details of this projection are provided in Appendix C.2.

Figure 6: How about the Future? China in 2030



Notes: This figure plots the singles rate for each gender under different scenarios. "Baseline (2015)" presents the equilibrium outcomes in the real world for 2015. "Projection (2030)" shows the counterfactual in which the gender-specificities in education, sectoral, and spatial-sectoral allocation costs are projected into 2030 based on the trends between 2000-2015. "Bottom Q" and "Top Q" represent prefecture quartiles by GDP per capita.

Table 10 presents the results and their decomposition, while Figure 6 visualizes the key national and group-specific singles rates. Continued gender-specific spatial structural changes would substantially raise the national singles rate. Specifically, the national singles rate for females (males) is projected to increase by 58.67 percent (23.62 percent). Moreover, due to spatial mismatch, the impact is especially pronounced for males in the least developed quartile of cities

Table 10: The Effects of Continuing Gender-specific Spatial Structural Changes

Singles Rate	Male			Female		
by Groups	National	Least Dev.	Low Skill	National	Most Dev.	High Skill
Panel A: Singles Rate and Percentage Changes						
Baseline (2015)	8.17%	8.98%	8.71%	3.46%	5.09%	9.55%
Projection (2030)	10.10%	16.29%	12.02%	5.49%	10.19%	15.18%
% Changes	23.62%	81.40%	38.00%	58.67%	100.20%	58.95%
Panel B: Decomposition of the Percentage Changes						
National Educational	57.51%	25.31%	66.77%	57.14%	46.27%	56.66%
National Sectoral	1.55%	5.20%	1.51%	1.48%	0.00%	1.42%
Spatial Sectoral	40.93%	69.49%	31.72%	41.38%	53.73%	41.92%

Notes: This table lists the singles rate for each gender under different scenarios in Panel A. "Baseline (2015)" presents the equilibrium outcomes in the real world for 2015. "Projection (2030)" shows the counterfactual in which the gender-specificity in education, sectoral, and spatial-sectoral allocation costs are projected into 2030 based on the trends between 2000 and 2015. The regions are defined by the prefecture quartile by GDP per capita. In Panel B, we decompose the percentage change in singles rates sequentially by adding the change of each component one by one. The contributions of these three components sum to 100%.

and females in the most developed quartile of cities. In both cases, the singles rate nearly doubles. Among the contributing factors, the educational shift plays the largest role, though the continued spatial sectoral shift also contributes significantly. These results are robust to alternative specifications for projected trends in education and national/spatial sectoral changes, as discussed in Appendix C.2.

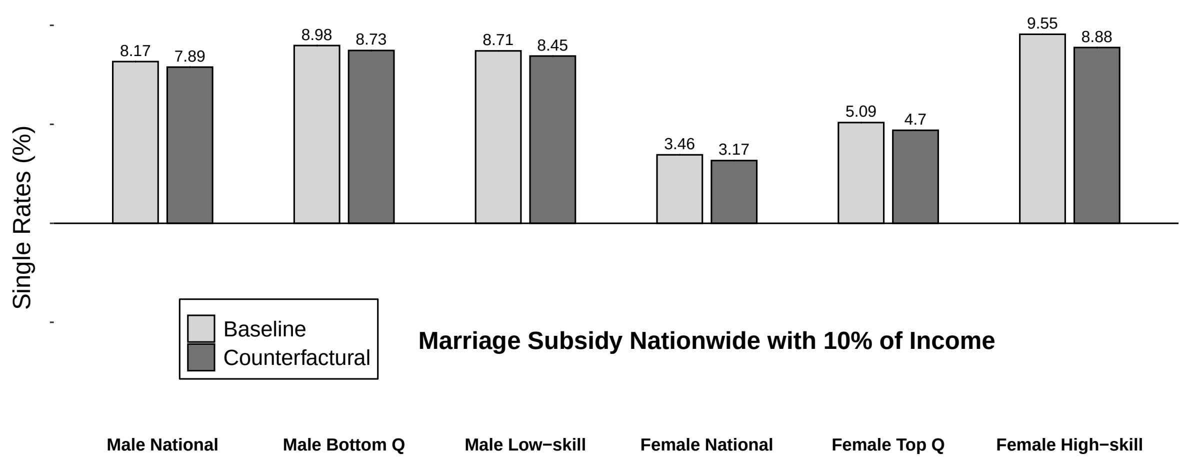
The projection for 2030 in Table 10 raises important concerns for economists and policymakers. Even under a more conservative assumption—where the speed of spatial structural change is halved—the projected increase in singles rates remains substantial, as shown in Table C8 of Appendix C.2. Policymakers in many countries, including China, should pay more attention to the declining marriage rates and actively pursue various family policies to encourage marriage.

6.3 Counterfactual Policy of Marriage Subsidies

Economic incentives are widely adopted in East Asian and Nordic countries in response to declining marriage and fertility rates. Governments in China, South Korea, and Japan have introduced various measures such as housing subsidies for newlyweds, childbirth allowances, tax breaks for families, and childcare support to ease the financial burdens of family formation. Despite differences in welfare regimes, these policies share a common goal: to alter the economic calculus surrounding marriage and childbearing. Although such incentives may not directly reshape deep-seated social norms or mate preferences, they can indirectly influence matching behavior by mitigating structural barriers and shifting family life's perceived costs and benefits. However, the effectiveness of these measures remains mixed, particularly in societies where persistent gender norms and upward matching preferences continue to shape partner selection.

In counterfactual analysis, we first simulate a nationwide marriage subsidy of 10% of married couples' lifetime income, which is substantially higher than all current subsidy policies. For instance, local government in Busan, South Korea, offers up to a one-time payment of $15,000 for newly married couples, and local government in Guangzhou, China, offers a one-time fee of about $8,000 for newly married couples.[11] The amount of the nationwide marriage subsidy in our counterfactual would cost about 9% of the national GDP in our model. However, such a substantial marriage subsidy seems relatively ineffective, despite the significant scale of subsidies.

Figure 7: Marriage Subsidy Nationwide with 10% of Income



Notes: This figure plots the singles rate for each gender under different scenarios. "Baseline" presents the equilibrium outcomes in the real world for 2015. "Counterfactual" shows the simulation in which a marriage subsidy of 10% of married couples' lifetime income is provided nationwide. "Bottom Q" and "Top Q" represent prefecture quartiles by GDP per capita.

[11]See the references (https://www.sedaily.com/NewsView/2GQ6VDU8E8?utm_source=chatgpt.com) for South Korea and (https://www.cls.cn/detail/2016236?utm_source=chatgpt.com) for China.

Figure 7 shows the results on the marriage rates for the aggregate and selected regional or skill groups. First, the marriage subsidy of 10% of the couple's income only reduces the national female (male) singles rate from 3.46 p.p. (8.17 p.p.) to 3.17 p.p. (7.89 p.p.), with a corresponding 8.3 percent (3.4 percent) decrease. The effects are even smaller if we focus on females in the top quartile of the most developed cities and with high skill, or males in the bottom quartile of the least developed cities and with low skill. In other words, such a substantial marriage subsidy could only incentivize fewer than one percentage point more workers to get married because most workers who choose to stay single are inframarginal at both ends of the spatial marriage mismatch. The marriage subsidy cannot alter the fundamental trends in gender-specific spatial structural changes and is therefore largely ineffective.

Given the large fiscal burden of the nationwide marriage subsidy and relatively small effects, we further explore more targeted subsidies based on locations or educational groups. The effects are still very limited in promoting marriage formation for the same reason discussed above. Details of these counterfactual simulations are provided in Appendix C.4.

7 Further Policy Discussions

Finally, this section provides a general discussion of further policies. Essentially, the frictions that lead to the observed spatial mismatch of marriage are the race between gender-specific spatial structural changes and the persistent social norms in the marriage market. To mitigate the continuing decline in the national marriage rate, the key intervention is to reduce the gender-specificity in spatial structural changes or alter the social norms in the marriage market.

Policies that Reduce Spatial Gender Imbalances Our decomposition points to potentially more effective policies if they can directly target spatial gender imbalance to subsidize migration by particular gender and skill, or balance the sectoral growth across regions. For instance, the government could subsidize the movements of high-skill males into more developed cities or increase the migration barriers for high-skill females to more developed cities. Symmetrically, the government could subsidize the movements of high-skill females back to less developed cities or impose tax penalties for high-skill males in less developed cities. If the policies are wellexecuted, this class of policies could largely move the singles rate towards the case of no gender-specificity in spatial structural changes, as in Table 8. However, such policies raise concerns about gender equity and economic or political feasibility, especially when the subsidies or penalties are substantial. Furthermore, since all workers in the economy have already made their optimal marital decisions, including staying single, such subsidies or penalties may lead to significant welfare losses by distorting both the marriage and labor markets. This type of policy is rarely carried out in any country and is expected to be socially unpopular.

Policies that Reshape Martial Social Norms Alternatively, the government could influence the social norms in the marital matching to mitigate the gender marrying-up and marrying-down differences. This policy class could be grouped into "talk" or "walk" efforts. In terms of "talk" effort, the government could verbally propagandize female marrying down or male marrying up. However, the "talk" effort could hardly create any real effects since persistent social norms are potentially formed due to persistent discrimination against females. Females are urged to match males with better SES to mitigate such disadvantages. Moreover, the deeply rooted culture of gender-biased division of household responsibilities is difficult to change through propaganda alone, without appropriate economic incentives. In terms of "walk" effort, the government could design and carry out many other policies that are more gender-neutral, so that the social norms may eventually evolve towards more gender-balanced marital matching preferences. For instance, the social norms around the gender division of childcare, as in Zhou and Xi (2025). However, such endogenous changes in social norms may be relatively slow-moving and insufficient to mitigate the decline in marriage and fertility rates.

Summary To summarize, while marriage and fertility rates continue to decline in various countries, designing mitigating policies that are both effective and feasible presents a substantial challenge.

8 Conclusion

This paper studies the impact of structural change beyond direct economic outcomes and extends the focus to family formation. We investigate how gender-specific spatial structural changes shape local marriage markets and national marriage rates in China. Empirically, we document joint patterns of shifts of higher educational attainment towards females, persistent marital social norms, and an increasingly polarized spatial distribution of singlehood, marked by the rising singles rate among higher-educated women in more developed cities and lower-educated men in less developed areas.

To quantify these dynamics, we develop a spatial equilibrium model at the prefecture level that incorporates migration, multi-sector and multi-skill production, and endogenous local marriage markets. Our quantitative analysis finds that these gender-specific spatial changes explain roughly 30% of the national female singles rate and over 50% among higher-educated women as of 2015. We then project these trends to 2030 and find that the spatial mismatch in the marriage market will be exacerbated without intervention. Counterfactual policy analysis shows that broad-based interventions, such as gender-neutral marriage subsidies, are costly and have limited effectiveness without changing the skewed spatial distribution by gender and skill shaped by gender-specific spatial structural changes. In contrast, policies that can directly target spatial gender imbalance, such as subsidizing migration by particular gender and skill or balancing sectoral growth across regions, are potentially more effective but also challenging in economic or political feasibility.

Looking ahead, the spatial mismatch in the marriage market driven by ongoing gendered structural shifts will likely remain a key contributor to China's declining marriage and fertility rates. These trends in the education sector and spatial allocation are common in many other countries. Current policy tools in China and abroad appear insufficient to address this emerging demographic challenge. Tackling it will require more innovative, targeted, and perhaps politically difficult solutions that go beyond traditional approaches and directly engage with the underlying structural imbalances in education, labor, and geography.

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Online Appendix to "Sex and the City: Spatial Structural Changes and the Marriage Market"*

Min Fang	Zibin Huang	Yushi Wang	Yu (Alan) Yang
U Florida	SUFE	Peking U	Peking U

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A Supplements to Empirical Analysis

A.1 Dramatic Gender-specific Structural Changes

A.1.1 Gender Sectoral Employment Gap

Table A1 presents the raw data on gender employment by sector and education in 2000, 2005, 2010, and 2020. "NL" denotes no labor participation. We compute the gender employment gap (adjusted by the labor participation rate) in Table 1 based on the data from this table. Specifically, for each sector-education-year cell, we first subtract the number of employed females from the number of employed males, and then divide this gap by the number of employed males. This yields the original gender employment gap. Furthermore, we calculate the gender gap in total employment similarly (which gives us an overall gender employment gap for all sectors) and subtract this value from each original gender employment gap across all cells.

Is the significant rise in female employment in the service sector possibly driven solely by local workers? Table A2 provides further insight into the sectoral migration patterns of workers with rural *Hukou*. The values are calculated as the proportion of rural *Hukou* workers employed in the manufacturing or service sectors relative to the total number of rural *Hukou* workers (for each gender-education group). The results indicate that the migration rate of rural workers to the service sector steadily increased from 2005 to 2015 at all levels of education for both men and women. In contrast, the migration rate to the manufacturing sector rose from 2000 to 2010, but decreased between 2010 and 2015. These findings suggest that the employment gap results reported in the previous table are driven not only by local workers but also by migrants.

Table A1: Gender Employment by Sector and Education (Unit: 10 thousand)

Education	Sector	2000		2005		2010		2015	
		Male	Female	Male	Female	Male	Female	Male	Female
College and Above	Agriculture	44.46	16.09	63.52	31.03	132.21	79.46	106.99	62.51
	Manufacturing	490.63	228.71	671.96	364.07	1265.28	671.36	1298.22	635.71
	Service	1551.00	1001.27	2291.21	1827.19	3030.13	2677.52	3534.68	3281.43
	NL	141.61	118.84	282.57	313.09	433.78	608.47	845.10	1171.83
High School	Agriculture	1491.46	622.12	1259.83	535.52	1249.67	650.13	956.20	517.75
	Manufacturing	1728.54	1021.57	1814.35	948.31	2602.71	1210.04	2463.40	950.93
	Service	2359.25	1905.62	2498.59	1941.79	2895.49	2242.82	3233.17	2450.38
	NL	738.07	1077.63	943.05	1561.29	885.96	1665.19	1524.61	2307.06
Middle School and Below	Agriculture	19998.90	19224.09	16316.42	16138.91	13047.73	12440.46	8774.23	7921.86
	Manufacturing	5301.21	3318.47	5796.16	3658.31	10046.13	5892.98	7316.52	3480.67
	Service	3918.52	2609.60	4714.15	3295.70	6262.68	5071.73	5735.50	4645.78
	NL	2184.85	5341.69	2799.50	6704.04	2345.76	5951.38	3920.22	7928.44

Notes: This table shows gender employment across different sectors for each Census year and education level. "NL" means not in the labor market. All numbers are adjusted by the sampling rate of each Census. The unit is 10 thousand. Data source: Population Census from 2000, 2005, 2010, and 2015.

Table A2: Sectoral Migration of Rural Labors by Gender and Education

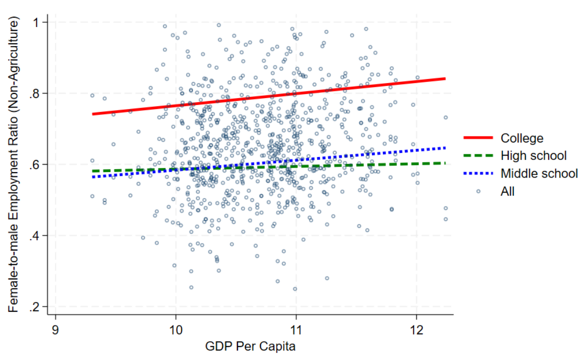
Education	Sector	2000		2005		2010		2015	
		Male	Female	Male	Female	Male	Female	Male	Female
College and Above	Manufacturing	24.69%	17.24%	26.03%	19.61%	37.54%	23.92%	27.68%	14.53%
	Service	46.05%	51.43%	51.23%	52.07%	44.37%	52.27%	54.07%	58.99%
High School	Manufacturing	21.24%	17.39%	26.32%	20.17%	37.32%	26.35%	32.26%	17.28%
	Service	20.48%	22.49%	25.11%	26.93%	28.58%	32.08%	34.45%	36.54%
Middle School and Below	Manufacturing	14.03%	9.17%	18.18%	11.85%	32.06%	20.74%	28.12%	14.62%
	Service	9.01%	5.81%	12.33%	8.29%	17.03%	14.84%	19.47%	16.68%

Notes: This table shows the sectoral migration patterns for each Census year and education level. The values are calculated as the proportion of workers in rural Hukou who are employed in the manufacturing or service sectors relative to the total number of workers in rural Hukou (for each gender-education type). Data source: Population Census from 2000, 2005, 2010, and 2015.

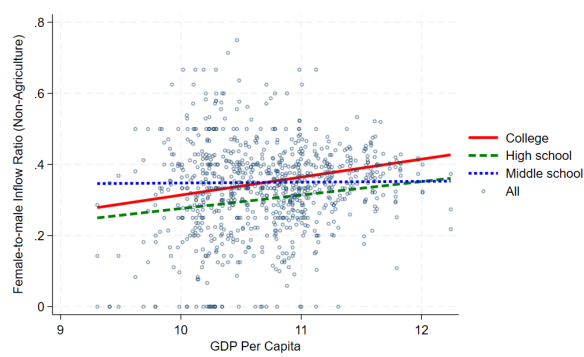
A.1.2 Gender Spatial Employment Gap

In the main text, Figure 2 plots the overall gender employment gap in the non-agricultural sector against local economic development. In Figure A1 below, we further plot these gaps calculated for each educational level. We find that the trend of more female working in the non-agricultural sector in more developed cities is strongest for the college-educated group.

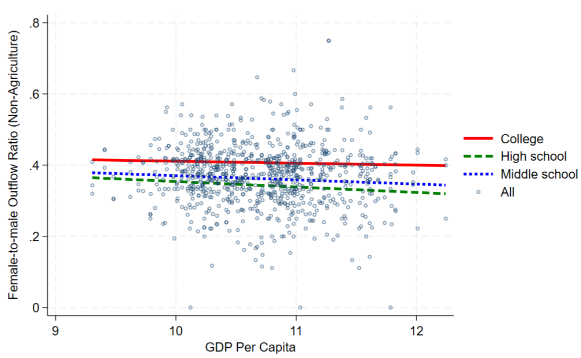
Figure A1: Gender Non-agricultural Employment Gap by Skills



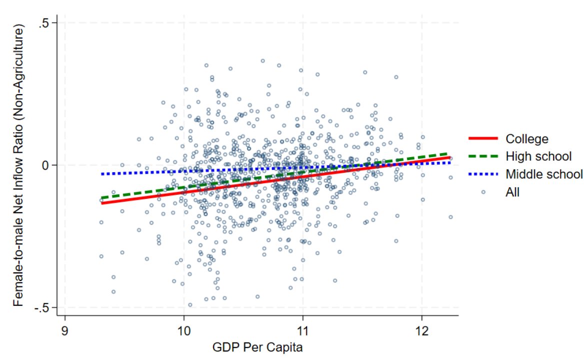
(a) Overall Employment



(b) Migration Inflow



(c) Migration Outflow



(d) Net Migration Flow

Notes: This figure illustrates the relationship between the spatial development level, proxied by the log of GDP per capita, and the gender employment gaps by education level in the non-agricultural sector in 2015. Subfigures (a), (b), (c), and (d) present the results for measuring $\frac{\text{Female } x}{\text{Female } x + \text{Male } x}$ in four different variables x, including the overall employment, within migration inflow, within migration outflow, and within net migration inflow, respectively. Data source: Population Census 2015.

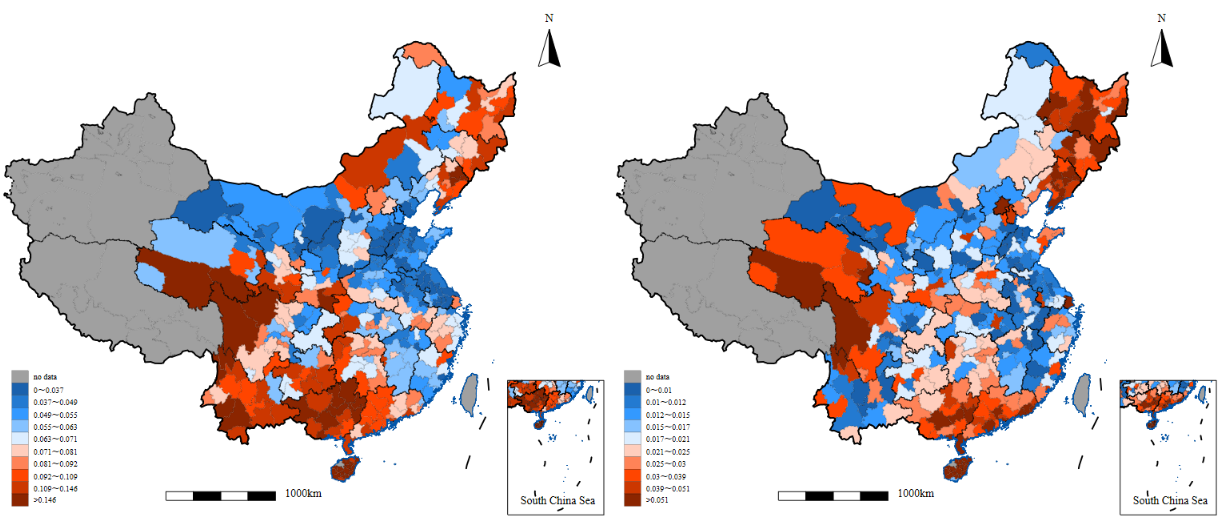
A.2 The Spatial Distributions of Singlehood

A.2.1 Visualization of the Spatial Distribution

We further show the spatial distribution of single males and females separately in Figure A2. Subfigure (a) shows that the singles rate for males is higher in inland provinces with low development levels and lower in coastal provinces with high development levels. In contrast, this pattern is reversed for females, as shown in Subfigure (b). The singles rate of females is low in underdeveloped regions, such as Yunnan and Guizhou, but high in the most developed regions, such as Shanghai and Beijing. Another noteworthy observation is the high number of older single females in the northeastern region, which may reflect the legacy of industrialization and socialist traditions in that area.

Figure A2: Prefecture-level Singles Rate of People over 30 in China

(a) Male (b) Female



Notes: This figure illustrates the singles rate of males and females aged 30 to 45 across different cities in 2015. Subfigure (a) presents the male singles rate, while subfigure (b) shows the female singles rate. In both panels, cities shaded in red (blue) indicate a higher (lower) singles rate. Data source: Population Census 2015.

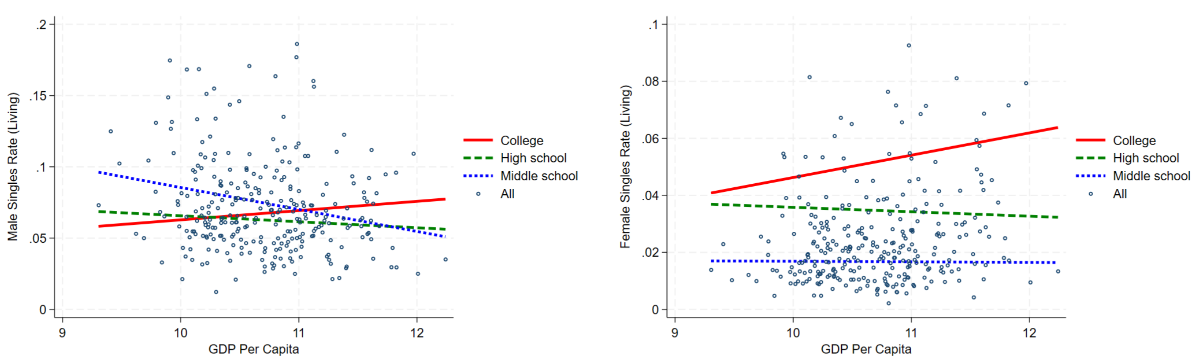
A.2.2 Singles Rate by Education Level

In this section, we also show the relationship between GDP per capita and the singles rate (ages 30 to 45) by education level at the living city level in Figure A3. The red solid line represents the fitted line for college-educated individuals. The green dashed line represents the fitted line for high school-educated individuals, and the blue dashed line corresponds to those with a middle school education or below. We observe an interesting asymmetry in these two subfigures. Among males, the negative relationship between GDP per capita and the overall singles rate is primarily driven by low-skilled individuals. In less developed cities, males with an education level below middle school are significantly more likely to remain single compared to their counterparts in more developed cities. In contrast, for females, the positive relationship between GDP per capita and the overall singles rate is driven by high-skilled individuals. In less developed cities, women with education above the college level are substantially less likely to be single compared to their counterparts in more developed cities.

Figure A3: GDP and Singles Rate of Age over 30 in 2015

(a) Male

(b) Female



Notes: This figure illustrates the relationship between GDP per capita and the singles rate (aged 30-45) by education level at the living city level. Subfigure (a) presents the results for the male singles rate, while subfigure (b) shows the results for the female singles rate. The red solid line represents the fit line for college-educated people. The green dashed line represents the fit line for high school-educated people. The blue dashed line represents the fit line for middle school (and below) educated people. Data source: Population Census 2015.

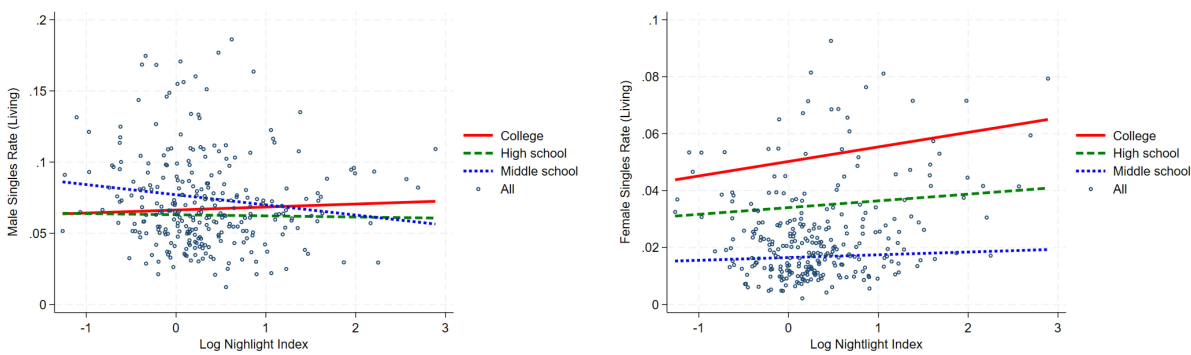
A.2.3 More City Characteristics and the Singles Rate

In this section, we further examine the relationship between the singles rate and additional city-level characteristics, including the nightlight index and the share of the service sector in GDP.

Figure A4 displays the relationship between the singles rate and the logarithm of the nightlight index across cities. Overall, we observe a positive correlation between the nightlight index and the female singles rate, whereas a negative correlation is evident for the male singles rate. These correlations appear to be primarily driven by low-skilled males and high-skilled females. These patterns are consistent with our previous findings based on GDP per capita.

Figure A4: Nightlight Index and Singles Rate of Age over 30 in 2015

(a) Male (b) Female

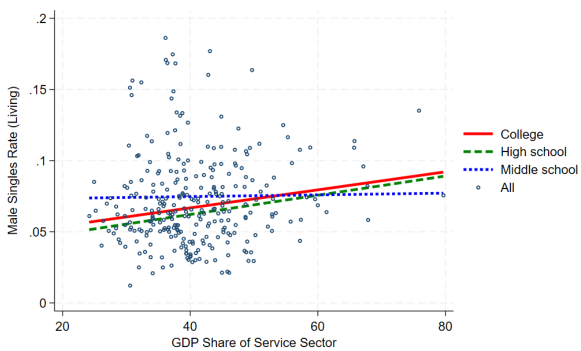


Notes: This figure illustrates the relationship between log nightlight index and the singles rate (aged 30-45) by education level at the living city level. Subfigure (a) presents the results for the male singles rate, while subfigure (b) shows the results for the female singles rate. The red solid line represents the fit line for college-educated people. The green dashed line represents the fit line for high school-educated people. The blue dashed line represents the fit line for middle school (and below) educated people. Data source: Population Census 2015.

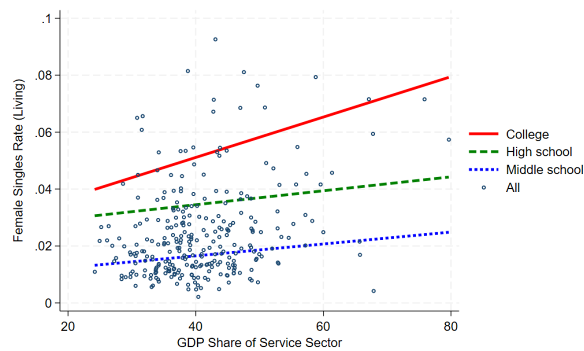
Figure A5 presents the relationship between singles rate and the service sector share in GDP across cities. Similar to the previous results, we find that females—particularly those with a college education—are more likely to be single in cities with larger service sectors. In contrast, we find a negative correlation for low-skilled males.

Figure A5: Service Sector GDP Share and Singles Rate in 2015

(a) Male



(b) Female



Notes: This figure illustrates the relationship between the share of the service sector in GDP and the singles rate (aged 30-45) by education level at the living city level. Subfigure (a) presents the results for the male singles rate, while subfigure (b) shows the results for the female singles rate. The red solid line represents the fit line for college-educated people. The green dashed line represents the fit line for high school-educated people. The blue dashed line represents the fit line for middle school (and below) educated people. Data source: Population Census 2015.

B Supplements to Model and Estimation

B.1 Imputation of the Prefecture-sector-skill-level Wage

In the quantitative model of this study, we need average wages for different skill groups (education levels) across various cities in 2015. However, no dataset directly provides skill-specific average wages at the city level. Ideally, if individual wage data were available in the population Census, we could compute the average wage for skill group s in city j as:

$$w_j^s = \frac{1}{N_j^s} \sum_i w_{ij}^s \tag{B1}$$

where w_j^s denotes the average wage of workers with skill s in city j, N_j^s is the number of such workers, and w_{ij}^s is the wage of individual i with skill s in city j.

However, the Census only contains individual wage data for 2005. Fortunately, the City Statistical Yearbooks report average wages by industry for each city. Moreover, the Census provides information on individuals' education and industry. This allows us to impute an individual's wage using the average wage in their corresponding city-industry cell. We then apply equation (B1) to compute average wages by city and skill.

Essentially, we construct city-skill-level wages by combining average city-industry wages with the distribution of education levels across industries. Since the City Statistical Yearbooks are compiled by local governments, we manually collect a large number of them for the year 2015. In a few cases where data for 2015 is unavailable, we use data from the closest available year and adjust wages based on city-level GDP growth. For example, if the 2015 yearbook for Beijing is missing but the 2014 version is available, we use the 2014 city-industry wages and scale them by Beijing's 2015 GDP growth rate to estimate the 2015 wages. The proportion of such replacements is very low.

B.2 List of Cities in the Model with Marriage Rates

Table B1: List of Cities

City Name	GDP Per Capita (RMB)	Male Singles Rate	Female Singles Rate	High-skilled Female Singles Rate	Low-skilled Male Singles Rate
Ordos	207163	0.035	0.013	0.043	0.022
Dongying	163938	0.025	0.010	0.021	0.024
Shenzhen	157985	0.109	0.079	0.103	0.105
Suzhou	136702	0.030	0.017	0.028	0.031
Guangzhou	136188	0.096	0.072	0.099	0.101
Baotou	132253	0.043	0.025	0.033	0.065
Wuxi	130938	0.030	0.018	0.028	0.045
Zhuhai	124706	0.095	0.038	0.096	0.085
Nanjing	118171	0.059	0.045	0.049	0.075
Changsha	115443	0.082	0.026	0.088	0.045
Hangzhou	112230	0.074	0.029	0.066	0.078
Changzhou	112221	0.036	0.016	0.034	0.042
Dalian	110682	0.112	0.069	0.105	0.119
Zhenjiang	110351	0.049	0.011	0.061	0.024
Daqing	110113	0.062	0.042	0.053	0.094
Foshan	108299	0.092	0.045	0.102	0.071
Tianjin	107960	0.054	0.047	0.031	0.075
Weihai	106922	0.053	0.027	0.042	0.035
Beijing	106497	0.076	0.057	0.043	0.082
Wuhan	104132	0.078	0.049	0.081	0.084
Shanghai	103796	0.082	0.059	0.047	0.110
Qingdao	102519	0.051	0.032	0.040	0.054
Ningbo	102374	0.064	0.016	0.063	0.040
Hohhot	101492	0.058	0.004	0.053	0.010
Wuhai	100871	0.063	0.019	0.065	0.056
Zhoushan	95113	0.089	0.026	0.071	0.064
Zhongshan	94030	0.093	0.031	0.107	0.080
Yantai	91979	0.059	0.030	0.057	0.043
Xiamen	90379	0.057	0.042	0.060	0.089
Shaoxing	90003	0.071	0.025	0.082	0.063
Yangzhou	89647	0.030	0.010	0.041	0.058
Zibo	89235	0.029	0.014	0.033	0.023
Shenyang	87734	0.123	0.081	0.084	0.123
Panjin	87351	0.064	0.030	0.069	0.061
Jinan	85919	0.044	0.020	0.046	0.030
Nantong	84236	0.022	0.013	0.026	0.006
Yichang	82360	0.111	0.017	0.123	0.061
Xinyu	81354	0.074	0.015	0.078	0.077
Taizhou	79479	0.021	0.010	0.025	0.013
Tangshan	78398	0.032	0.026	0.036	0.055
Jiayuguan	78336	0.049	0.013	0.061	0.034
Yulin	77267	0.035	0.015	0.036	0.031
Zhengzhou	77179	0.061	0.037	0.061	0.068
Jiaxing	76850	0.038	0.014	0.038	0.029
Nanchang	75879	0.037	0.026	0.031	0.080
Dongguan	75616	0.088	0.042	0.087	0.048
Fuzhou	75259	0.069	0.030	0.073	0.090
Panzhihua	75078	0.065	0.027	0.059	0.079
Chengdu	74273	0.062	0.026	0.065	0.064
Changchun	73324	0.080	0.052	0.066	0.123
Hefei	73102	0.054	0.022	0.041	0.072
Quanzhou	72421	0.059	0.019	0.061	0.074
Huzhou	70894	0.058	0.010	0.067	0.015

Table B2: List of Cities (Continued)

City Name	GDP Per Capita (RMB)	Male Singles Rate	Female Singles Rate	High-skilled Female Singles Rate	Low-skilled Male Singles Rate
Yinchuan	69594	0.066	0.014	0.058	0.035
Ezhou	68921	0.057	0.014	0.046	0.000
Sanming	67978	0.055	0.008	0.053	0.000
Fangchenggang	67972	0.156	0.037	0.145	0.061
Benxi	67656	0.160	0.071	0.157	0.192
Wuhu	67592	0.052	0.016	0.054	0.034
Xi'an	66938	0.073	0.042	0.076	0.086
Longyan	66863	0.051	0.011	0.058	0.040
Huizhou	66231	0.073	0.034	0.072	0.077
Anshan	64710	0.108	0.069	0.088	0.165
Taiyuan	63483	0.064	0.046	0.060	0.067
Hulunbuir	63131	0.067	0.019	0.075	0.068
Guiyang	63003	0.108	0.031	0.101	0.053
Jinhua	62480	0.073	0.016	0.077	0.018
Yingkou	61925	0.075	0.035	0.078	0.055
Shizuishan	61845	0.053	0.021	0.042	0.065
Xuzhou	61511	0.048	0.017	0.047	0.035
Binzhou	61189	0.044	0.008	0.051	0.051
Maanshan	60802	0.037	0.009	0.032	0.024
Xiangtan	60430	0.061	0.027	0.088	0.051
Xiangyang	60319	0.051	0.028	0.061	0.071
Tongliao	60123	0.063	0.023	0.057	0.081
Liaoyuan	59855	0.083	0.053	0.083	0.160
Kunming	59656	0.117	0.028	0.109	0.067
Harbin	59027	0.098	0.055	0.072	0.107
Taizhou	58917	0.064	0.015	0.058	0.020
Liuzhou	58869	0.186	0.045	0.203	0.052
Songyuan	58841	0.050	0.016	0.049	0.045
Zhuzhou	58661	0.073	0.021	0.089	0.042
Fushun	58597	0.177	0.093	0.138	0.103
Sanya	58486	0.114	0.017	0.127	0.067
Yancheng	58299	0.042	0.011	0.046	0.011
Rizhao	58110	0.056	0.015	0.054	0.083
Putian	57873	0.025	0.011	0.018	0.018
Tongling	57387	0.074	0.006	0.082	0.024
Lanzhou	56972	0.069	0.025	0.078	0.046
Tai'an	56490	0.050	0.012	0.058	0.034
Huai'an	56460	0.034	0.010	0.038	0.011
Jilin	56076	0.077	0.026	0.081	0.083
Weifang	55824	0.041	0.017	0.044	0.034
Sanmenxia	55681	0.086	0.022	0.111	0.034
Zhangzhou	55570	0.055	0.027	0.054	0.084
Yingtan	55568	0.036	0.009	0.043	0.051
Jiaozuo	54590	0.047	0.022	0.049	0.048
Langfang	54460	0.055	0.032	0.059	0.068
Yan'an	53924	0.045	0.020	0.054	0.059
Quzhou	53847	0.072	0.012	0.082	0.026
Baishan	53136	0.114	0.036	0.134	0.098
Bayannur	53000	0.052	0.006	0.054	0.023
Zaozhuang	52692	0.030	0.009	0.027	0.071
Haikou	52534	0.135	0.072	0.113	0.111
Chongqing	52321	0.064	0.024	0.059	0.066
Ningde	52006	0.104	0.018	0.107	0.020
Luoyang	51692	0.046	0.018	0.053	0.062
Lishui	51676	0.091	0.020	0.100	0.029
Yueyang	51429	0.076	0.023	0.083	0.063
Shuozhou	51256	0.036	0.008	0.032	0.000
Shijiazhuang	51043	0.043	0.028	0.045	0.048
Nanping	50932	0.070	0.015	0.089	0.041
Wenzhou	50790	0.063	0.023	0.055	0.068
Xuchang	50162	0.050	0.016	0.051	0.053
Yangjiang	49894	0.112	0.034	0.124	0.077

Table B3: List of Cities (Continued)

City Name	GDP Per Capita (RMB)	Male Singles Rate	Female Singles Rate	High-skilled Female Singles Rate	Low-skilled Male Singles Rate
Jiangmen	49608	0.097	0.055	0.105	0.067
Laiwu	49377	0.042	0.002	0.058	0.000
Xining	49197	0.060	0.020	0.077	0.038
Nanning	49066	0.164	0.076	0.187	0.183
Zhaoqing	48670	0.093	0.039	0.103	0.017
Jining	48529	0.031	0.009	0.031	0.038
Lianyungang	48416	0.047	0.013	0.054	0.028
Pingxiang	48133	0.120	0.024	0.123	0.023
Dezhou	48062	0.029	0.006	0.037	0.039
Jingmen	48000	0.066	0.010	0.091	0.020
Jinchang	47739	0.032	0.011	0.027	0.048
Baoji	47565	0.070	0.020	0.076	0.043
Mudanjiang	47356	0.082	0.039	0.073	0.092
Jingdezhen	47216	0.070	0.018	0.079	0.022
Changde	46408	0.073	0.019	0.084	0.053
Deyang	45701	0.076	0.018	0.080	0.038
Tonghua	45171	0.100	0.038	0.099	0.082
Jincheng	44994	0.043	0.007	0.058	0.022
Cangzhou	44819	0.030	0.005	0.035	0.000
Hebi	44778	0.040	0.022	0.031	0.095
Liaocheng	44743	0.026	0.007	0.027	0.000
Suqian	43853	0.035	0.010	0.041	0.041
Xianyang	43426	0.051	0.015	0.047	0.010
Chifeng	43269	0.047	0.024	0.042	0.067
Ulanqab	43221	0.093	0.023	0.088	0.030
Yangquan	42688	0.082	0.020	0.085	0.000
Chenzhou	42682	0.084	0.029	0.095	0.059
Liupanshui	41618	0.064	0.034	0.077	0.088
Zigong	41447	0.085	0.010	0.089	0.028
Xianning	41234	0.061	0.008	0.067	0.000
Dandong	40850	0.095	0.039	0.092	0.066
Qinhuangdao	40746	0.048	0.025	0.062	0.031
Maoming	40324	0.077	0.025	0.077	0.014
Leshan	39973	0.081	0.011	0.069	0.038
Jiujiang	39505	0.040	0.022	0.053	0.061
Shaoguan	39380	0.109	0.029	0.109	0.039
Guilin	39329	0.171	0.027	0.186	0.024
Huangshan	38794	0.086	0.007	0.106	0.000
Chengde	38505	0.058	0.015	0.067	0.027
Shiyan	38431	0.098	0.028	0.109	0.028
Tongchuan	38378	0.099	0.011	0.127	0.069
Bengbu	38267	0.047	0.022	0.044	0.048
Chizhou	38014	0.089	0.017	0.104	0.079
Luohe	37987	0.058	0.027	0.062	0.041
Siping	37714	0.065	0.045	0.071	0.039
Xuancheng	37610	0.077	0.006	0.090	0.000
Puyang	36842	0.043	0.018	0.045	0.031
Anyang	36828	0.039	0.013	0.040	0.050
Linyi	36656	0.049	0.010	0.052	0.014
Wuzhou	36104	0.146	0.065	0.154	0.136
Suizhou	35900	0.057	0.010	0.062	0.000
Mianyang	35754	0.078	0.014	0.087	0.049
Ziyang	35702	0.085	0.022	0.092	0.040
Baicheng	35571	0.055	0.021	0.049	0.024
Hengyang	35538	0.066	0.022	0.074	0.022
Kaifeng	35326	0.061	0.037	0.066	0.068
Zunyi	35123	0.061	0.020	0.066	0.080
Jiamusi	35069	0.077	0.026	0.057	0.052
Huaibei	35057	0.021	0.029	0.020	0.065
Changzhi	35029	0.078	0.017	0.096	0.048
Meishan	34379	0.053	0.008	0.052	0.036
Xinxiang	34340	0.045	0.022	0.047	0.143

Table B4: List of Cities (Continued)

City Name	GDP Per Capita (RMB)	Male Singles Rate	Female Singles Rate	High-skilled Female Singles Rate	Low-skilled Male Singles Rate
Yibin	34060	0.074	0.016	0.084	0.015
Pingdingshan	33984	0.051	0.028	0.052	0.078
Chaozhou	33954	0.061	0.049	0.056	0.050
Shantou	33732	0.088	0.053	0.092	0.090
Handan	33450	0.034	0.014	0.040	0.051
Loudi	33444	0.066	0.021	0.086	0.000
Qingyuan	33392	0.098	0.036	0.109	0.069
Chongzuo	33355	0.144	0.035	0.161	0.000
Zhanjiang	32933	0.110	0.067	0.112	0.092
Chuzhou	32634	0.040	0.010	0.043	0.043
Ya'an	32523	0.082	0.018	0.080	0.034
Neijiang	32080	0.061	0.011	0.067	0.019
Luzhou	31714	0.049	0.023	0.047	0.114
Jinzhong	31434	0.064	0.013	0.072	0.013
Jieyang	31255	0.077	0.061	0.075	0.111
Anqing	31101	0.063	0.012	0.089	0.029
Guang'an	31046	0.052	0.011	0.057	0.038
Hanzhong	31001	0.087	0.032	0.096	0.039
Datong	30989	0.061	0.014	0.073	0.026
Zhangjiakou	30840	0.090	0.014	0.095	0.023
Yiyang	30776	0.087	0.024	0.111	0.048
Zhangye	30704	0.052	0.007	0.044	0.061
Xinyang	30157	0.071	0.021	0.065	0.028
Xiaogan	29924	0.041	0.012	0.046	0.026
Wuzhong	29698	0.012	0.017	0.015	0.038
Qinzhou	29560	0.134	0.028	0.132	0.000
Fuxin	29491	0.081	0.023	0.056	0.083
Yichun	29457	0.057	0.011	0.072	0.043
Zhangjiajie	29425	0.109	0.022	0.144	0.018
Shuangyashan	29237	0.093	0.031	0.092	0.083
Ankang	29193	0.155	0.029	0.170	0.000
Yunfu	29078	0.105	0.039	0.111	0.026
Baoding	29067	0.049	0.017	0.052	0.040
Chaoyang	28852	0.057	0.020	0.066	0.053
Nanyang	28653	0.075	0.025	0.086	0.051
Heze	28350	0.053	0.014	0.063	0.055
Jixi	28222	0.121	0.053	0.116	0.211
Tieling	27885	0.072	0.030	0.067	0.022
Jingzhou	27875	0.060	0.021	0.070	0.086
Suining	27868	0.068	0.010	0.076	0.000
Zhongwei	27857	0.042	0.005	0.042	0.000
Fuzhou	27735	0.058	0.012	0.058	0.143
Hengshui	27543	0.033	0.013	0.032	0.000
Weinan	27452	0.050	0.012	0.052	0.012
Qingyang	27366	0.051	0.009	0.055	0.027
Baise	27363	0.151	0.027	0.153	0.075
Ji'an	27168	0.059	0.013	0.059	0.029
Anshun	27065	0.107	0.012	0.107	0.000
Qujing	27045	0.061	0.009	0.064	0.034
Zhumadian	27001	0.064	0.022	0.064	0.037
Heihe	26575	0.052	0.033	0.049	0.075
Haidong	26531	0.119	0.021	0.122	0.000
Shangluo	26415	0.117	0.015	0.132	0.000
Heyuan	26401	0.071	0.029	0.071	0.058
Huainan	26398	0.032	0.017	0.031	0.045
Linfen	26239	0.066	0.005	0.068	0.000
Yongzhou	26222	0.099	0.024	0.119	0.083
Huaihua	26060	0.109	0.023	0.129	0.036
Laibin	25667	0.169	0.033	0.192	0.030
Yulin	25444	0.101	0.030	0.093	0.102
Baiyin	25410	0.081	0.013	0.056	0.025
Shanwei	25283	0.133	0.082	0.134	0.071

Table B5: List of Cities (Continued)

City Name	GDP Per Capita (RMB)	Male Singles Rate	Female Singles Rate	High-skilled Female Singles Rate	Low-skilled Male Singles Rate
Huanggang	25262	0.062	0.011	0.071	0.000
Lvliang	25003	0.069	0.018	0.065	0.060
Hegang	24981	0.091	0.037	0.093	0.122
Shangqiu	24940	0.053	0.019	0.061	0.135
Qitaihe	24823	0.097	0.019	0.090	0.022
Tongren	24712	0.089	0.015	0.100	0.029
Shangrao	24633	0.055	0.010	0.060	0.022
Qiqihar	24430	0.098	0.054	0.089	0.195
Xingtai	24256	0.035	0.013	0.036	0.040
Nanchong	23881	0.042	0.009	0.044	0.030
Zhoukou	23728	0.051	0.016	0.050	0.068
Guangyuan	23263	0.080	0.013	0.084	0.059
Hezhou	23178	0.168	0.039	0.185	0.200
Ganzhou	23148	0.055	0.016	0.057	0.028
Suihua	23095	0.065	0.047	0.066	0.071
Wuwei	22931	0.037	0.010	0.048	0.000
Suzhou	22415	0.043	0.009	0.045	0.050
Yuncheng	22304	0.021	0.012	0.021	0.039
Bijie	22230	0.110	0.019	0.109	0.050
Meizhou	22155	0.082	0.027	0.092	0.045
Xinzhou	21731	0.058	0.015	0.070	0.000
Lu'an	21524	0.073	0.009	0.081	0.000
Baoshan	21444	0.076	0.013	0.074	0.000
Lijiang	20724	0.110	0.039	0.123	0.025
Yichun	20414	0.132	0.053	0.136	0.119
Guigang	20240	0.127	0.055	0.138	0.031
Lincang	20077	0.175	0.033	0.196	0.000
Puer	19789	0.149	0.012	0.164	0.020
Shaoyang	19156	0.065	0.014	0.074	0.034
Bozhou	18771	0.033	0.005	0.038	0.000
Pingliang	18490	0.068	0.014	0.072	0.036
Hechi	17841	0.131	0.024	0.148	0.116
Tianshui	16743	0.105	0.026	0.108	0.000
Fuyang	16121	0.050	0.010	0.048	0.047
Bazhong	15076	0.053	0.012	0.062	0.028
Zhaotong	13097	0.102	0.010	0.097	0.000
Longnan	12172	0.125	0.023	0.136	0.125
Dingxi	10987	0.073	0.014	0.071	0.095

Notes: This table displays the complete list of the 277 cities used in the quantitative model, sorted by the GDP per capita. The second column shows GDP per capita in 2015. The third and fourth columns show the male and female singles rate (aged 30-45) in 2015, respectively. The fifth and sixth columns show the singles rate of highly educated females and the singles rate of low-educated males (aged 30-45) in 2015, respectively.

B.3 Algorithm for Solving the Model Equilibrium and Counterfactuals

In this subsection, we describe the algorithm used to solve for the model counterfactuals. Given the set of exogenous variables and calibrated parameters, our objective is to compute the model-implied equilibrium, or the responses of endogenous variables to policy changes within the model framework. We focus on selecting the equilibrium that best replicates real-world observations. Accordingly, the initial values of model variables are calibrated to match data from 2015.

We begin by specifying the exogenous variables and the system of model equations. The exogenous variables are given by $\{\tau^{ge}_{i,jk}, A^e_j, \phi_j, L_j, H^{ge}_i\}$, where i indexes origin cities, j indexes destination cities, g denotes gender, and e indicates education groups. The system of equations consists of four primary blocks:

1. **Housing Block**: construction and market-clearing equations;
2. **Production Block**: production, wage, and floor space price equations;
3. **Migration Block**: worker income, utility values, and gravity equations;
4. **Marriage Block**: marriage market matching equations.

We next illustrate the contraction algorithm used to solve the model at the baseline equilibrium. The updating sequence proceeds from the housing block to the production block, followed by the migration block and finally the marriage block. Let x^t denote the value of an endogenous variable at the beginning of iteration t, and $\hat{x}^t$ its updated value during the same iteration. All initial values x^0 are directly derived from data.

Housing Block. We begin with the housing market. Given the initial land supply L^{0u}_j from data, we update the floor space supply $\hat{S}^0_j$ as:

$$\hat{S}^0_j = \phi_j L^{0u}_j \tag{B2}$$

With the updated floor space supply, along with the initial values for family income v^0_{ju} and population distribution H^0_{ju}, we compute the updated housing price $\hat{q}^0_{ju}$ using the housing market clearing condition (17):

$$\hat{q}^0_{ju} = (1-\beta)\frac{E[v^0_{ju}]H^0_{ju}}{\hat{S}^0_j} \tag{B3}$$

Production Block. Next, we update the production block. Given the initial working population distributions H^{0e}_{jM} and H^{0e}_{js}, we compute wages using the firms' first-order conditions in equation (15):

$$\hat{w}^{0e}_{jM} = (A^e_{jM})^{\frac{\sigma_M-1}{\sigma_M}}(\hat{Y}_{jM})^{\frac{1}{\sigma_M}}(H^{0e}_{jM})^{-\frac{1}{\sigma_M}}, \quad \text{for } e = \{h, m, l\} \tag{B4}$$

$$\hat{w}^{0e}_{js} = (A^e_{js})^{\frac{\sigma_s-1}{\sigma_s}}(\hat{Y}_{js})^{\frac{1}{\sigma_s}}(H^{0e}_{js})^{-\frac{1}{\sigma_s}}, \quad \text{for } e = \{h, m, l\} \tag{B5}$$

Migration Block. We then move to the migration block, using the updated wages and housing rents. The marriage market transfer is initialized to zero, i.e., $\delta^{0ge}_j(e') = 0$. Using the deterministic parts of equations (8) and (9), we compute the utilities associated with marriage and staying single:

$$\hat{V}^{0ge}_{jk}(e') = \ln(\hat{w}^{0ge}_{jk} + E_{k'}[\hat{w}^{0g'e'}_{jk'}]) - \ln((1+\chi)(\hat{q}^0_{jk})^{1-\beta}) + \mu^{ge}(e') + \delta^{0ge}_j(e') \tag{B6}$$

$$\hat{V}^{0ge}_{jk}(\varnothing) = \ln(\hat{w}^{0ge}_{jk}) - \ln((\hat{q}^0_{jk})^{1-\beta}) \tag{B7}$$

Next, we use equation (12) to compute the ex ante expected utility:

$$\hat{\bar{V}}^{0ge}_{jk} = \sigma_\xi\gamma + \sigma_\xi \ln\left[\exp(\hat{V}^{0ge}_{jk}(\varnothing)/\sigma_\xi) + \sum_{e'}\exp(\hat{V}^{0ge}_{jk}(e')/\sigma_\xi)\right] \tag{B8}$$

We then plug the utility values into the gravity equation (3) to derive migration shares:

$$\hat{\pi}^{0ge}_{i,jk} = \frac{(\tau^{ge}_{i,jk})^{-\epsilon}(\hat{\bar{V}}^{0ge}_{jk})^{\epsilon}}{\sum_{j'k'}(\tau^{ge}_{i,j'k'})^{-\epsilon}(\hat{\bar{V}}^{0ge}_{j'k'})^{\epsilon}} = \frac{\hat{\Phi}^{0ge}_{i,jk}}{\hat{\Phi}^{0ge}_{i}} \tag{B9}$$

The updated migration and population distribution is then computed using the labor supply equation (16):

$$\hat{H}_{jk}^{0e} = \sum_{gei} \hat{\pi}_{i,jk}^{0ge} H_i^{0ge} \tag{B10}$$

Marriage Block. With updated utility values and population distributions, we now update the marriage market transfers $\hat{\delta}_j^{0ge}(e')$. Starting with the initial guess $\delta_j^{0ge}(e') = 0$, and using $\hat{\hat{V}}_{jk}^{0ge}$ and $\hat{V}_{jk}^{0ge}(\varnothing)$, we compute the marriage choice probabilities from equations (10) and (11):

$$\hat{P}_{jk}^{0ge}(e') = \frac{\exp(\hat{V}_{jk}^{0ge}(e')/\sigma_\xi)}{\exp(\hat{V}_{jk}^{0ge}(\varnothing)/\sigma_\xi) + \sum_{e''} \exp(\hat{V}_{jk}^{0ge}(e'')/\sigma_\xi)}, \tag{B11}$$

$$\hat{P}_{jk}^{0gen}(\varnothing) = \frac{\exp(\hat{V}_{jk}^{0ge}(\varnothing)/\sigma_\xi)}{\exp(\hat{V}_{jk}^{0ge}(\varnothing)/\sigma_\xi) + \sum_{e''} \exp(\hat{V}_{jk}^{0ge}(e'')/\sigma_\xi)} \tag{B12}$$

Using these probabilities, we compute the demand and supply for each marriage pair (e, e') and calculate the sum of the squared distance between demand and supply as the objective function. Finally, we use the Nelder-Mead optimization algorithm to estimate the equilibrium transfer values by minimizing the objective value.

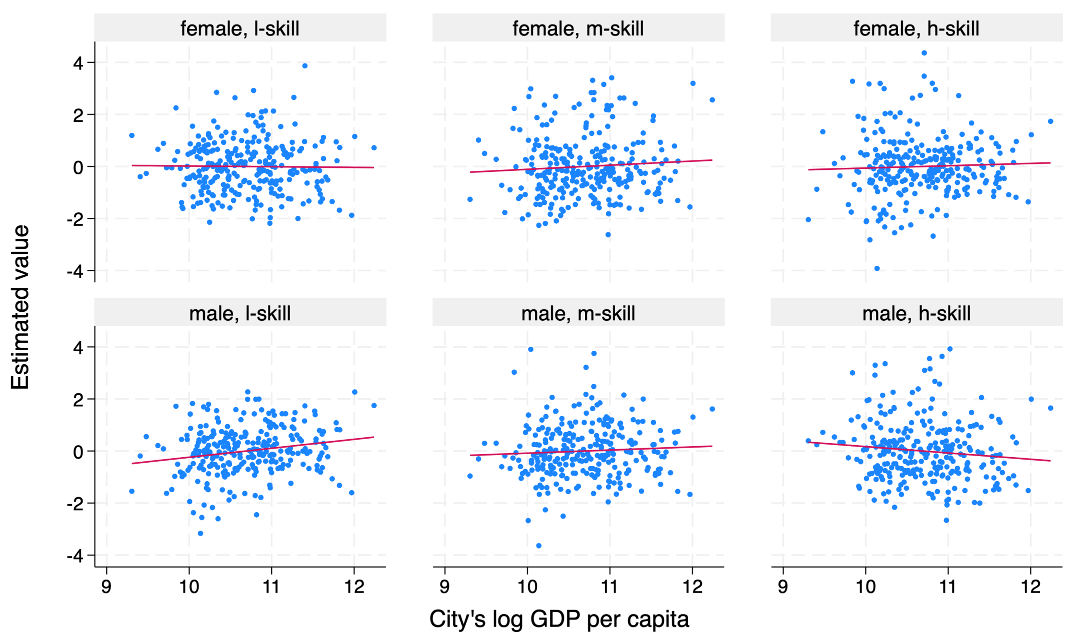
Iteration. At this stage, all endogenous variables have been updated once. We proceed to the next iteration by taking a weighted average of old and new values: $x^1 = (1 - \lambda)x^0 + \lambda\hat{x}^0$. This iterative process continues until the difference between x^t and x^{t+1} falls below a convergence threshold, that is, when the updating error for all variables is smaller than 1×10^{-6}.

For alternative counterfactual scenarios, the iteration may begin with a different block; however, the overall structure of the algorithm remains unchanged.

B.4 Details on Marriage Matching Estimation

In this section, we show additional details on the marriage matching estimation. Figure B1 plots the estimated parameter values of $\tilde{\mu}_j^{ge}$ from equation (18) for each gender and skill, which reflect the average value of getting married relative to being single in the city j, against city j's log GDP per capita. In general, we do not find that the non-pecuniary value of being married systematically varies by the economic development of the city. Therefore, most of the observed spatial dispersion of the singles rate by gender and skill is driven by the systematic marital preference and the relative supply of men and women of each type in local marriage markets.

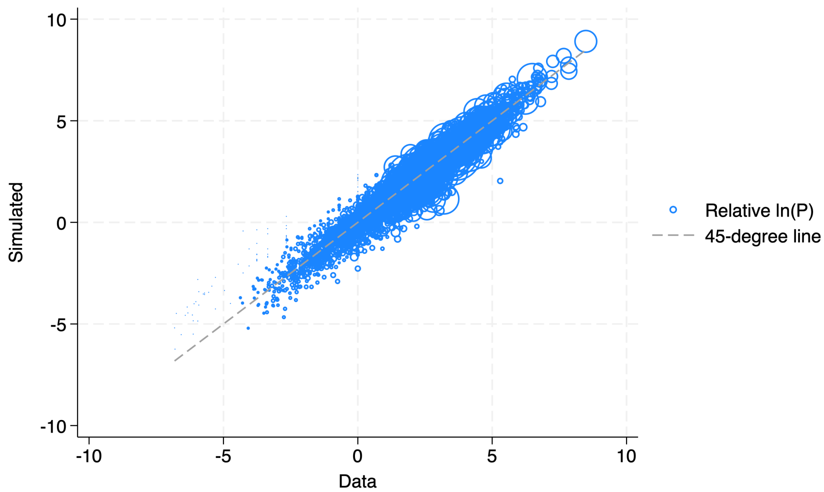
Figure B1: Non-pecuniary value of being married vs. GDP per capita



Notes: Figure B1 plots the estimated parameter values of $\tilde{\mu}_j^{ge}$ from equation (18) for each gender and skill. The estimated parameters are normalized to have mean zero in the whole sample.

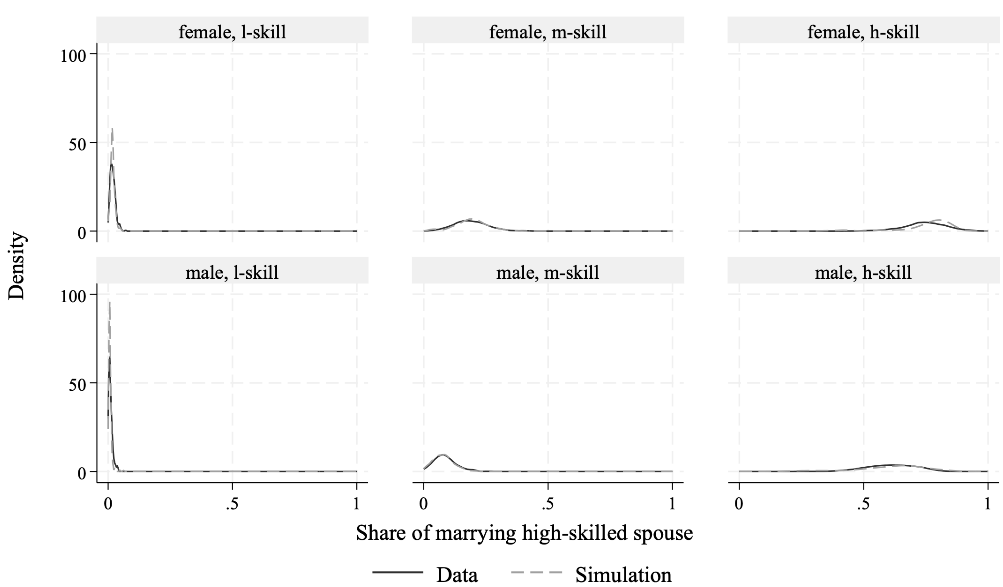
Figure B2 compares the data and the simulated match shares $(\ln[P_j^{ge}(e')] - \ln[P_j^{ge}(\emptyset)])$ of each gender g skill e with spousal types e', relative to the share of being single $\emptyset$. All observations are closely located around the 45-degree line. Figures B3, B4 and B5 further checks the model fit for the share of marrying a high-, middle-, and low-skilled spouse, each by gender and own skill type, by plotting the empirical density of the share across cities in the data and model simulation. These results suggest that we can reasonably fit the observed matching patterns across gender and skill types.

Figure B2: Model Fit of the Relative Match Shares



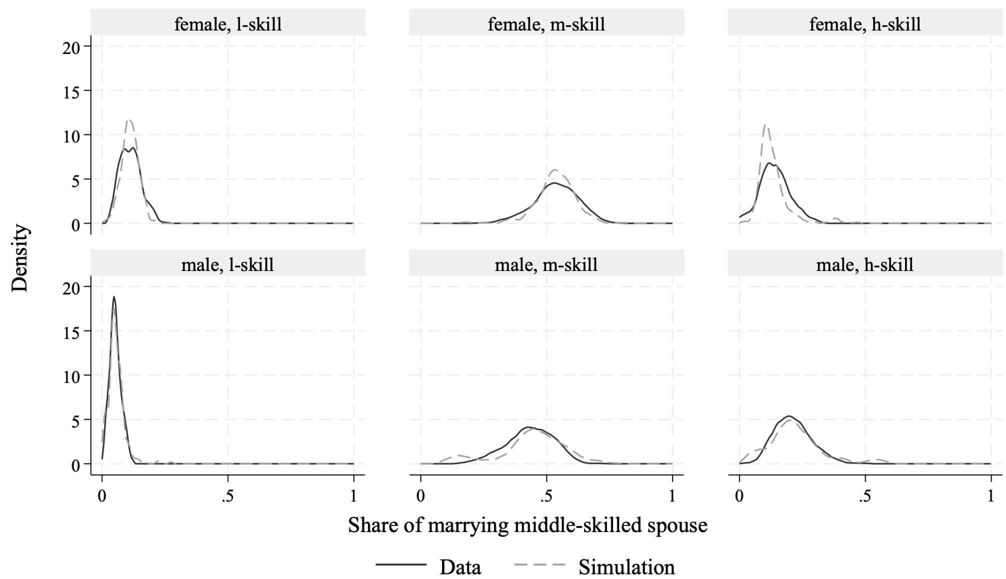
Notes: This figure compares the data and simulated relative match shares ($\ln[P_j^{ge}(e')] - \ln[P_j^{ge}(\varnothing)]$) between each combination of male and female types, including singlehood. The size of each dot is weighted by the population size in each type combination.

Figure B3: Model Fit of the Share of Marrying High-Skilled Spouse



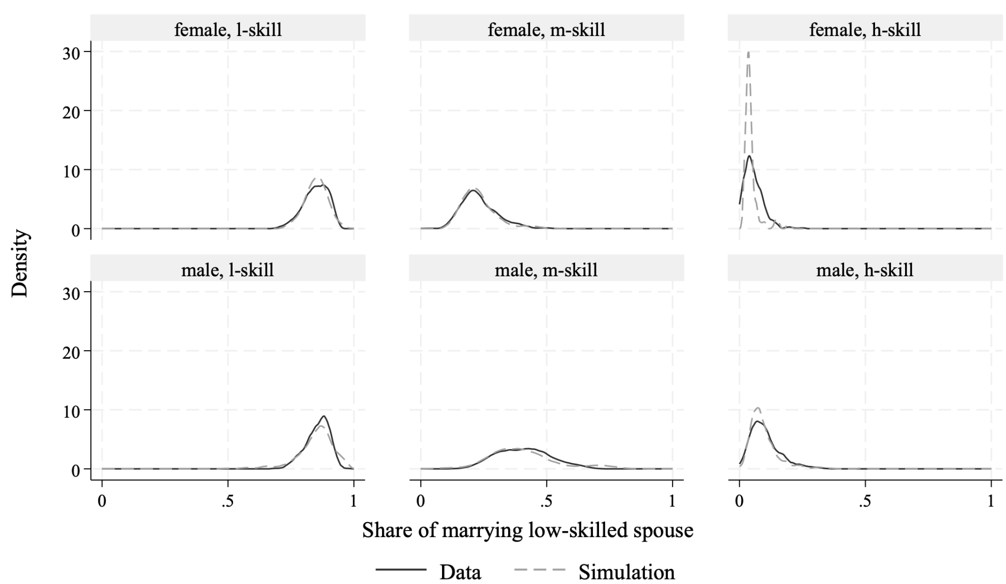
Notes: This figure plots the density of the city-level share of marrying a high-skilled spouse for each gender and own skill. Solid lines are the data, and dashed lines are simulated results.

Figure B4: Model Fit of the Share of Marrying Middle-Skilled Spouse



Notes: This figure plots the density of the city-level share of marrying a middle-skilled spouse for each gender and own skill. Solid lines are the data, and dashed lines are simulated results.

Figure B5: Model Fit of the Share of Marrying Low-Skilled Spouse



Notes: This figure plots the density of the city-level share of marrying a low-skilled spouse for each gender and own skill. Solid lines are the data, and dashed lines are simulated results.

B.5 Estimation on Allocation Costs in the Model

Table B6 re-organizes the relative spatial sectoral allocation costs originally reported in Table 7 in the main text (by gender and skill) and instead groups them by sector. Note that the overall sectoral cost (τ_k^{ge}) has been separated out, so here we focus on the comparison within each sector across regions, i.e. the further spatial distribution of each sector. We find that for agriculture, the allocation cost is the lowest in the least developed region, consistent with the high employment share of agriculture in those areas. On the contrary, the allocation costs to manufacturing and service decrease with local economic development, reflecting the opposite spatial distribution.

Table B6: Relative Spatial × Sectoral Allocation Cost

Average $\varepsilon_{i,jk}^{ge}$	Agriculture	Manufacturing	Service
Least Developed	0.070	0.499	0.411
Second Quartile	0.233	0.513	0.462
Third Quartile	0.247	0.317	0.317
Most Developed	0.441	-0.058	0

Notes: This table summarizes the residual allocation cost by region and sector (average $\varepsilon_{i,jk}^{ge}$), estimated from equation (2) with our 2015 data for the model. The allocation cost of service in the most developed region quartile is normalized to 0 for comparison.

Table B7 further provides the most detailed estimates of the relative spatial allocation cost by gender, skill, destination region, and sector. Again, this has removed the overall sectoral cost (τ_k^{ge}) for each gender and skill.

Table B7: Detailed Relative Spatial Sectoral Allocation Costs

$\varepsilon_{i,jk}^{ge}$	Male			Female		
	l-skill	m-skill	h-skill	l-skill	m-skill	h-skill
			Panel A: Agriculture			
Least Developed	0.123	0.100	0.332	0.243	0.140	0.374
Second Quartile	0.275	0.335	0.539	0.379	0.409	0.398
Third Quartile	0.368	0.416	0.356	0.411	0.398	0.323
Most Developed	0.604	0.668	0.420	0.577	0.782	0.595
			Panel B: Manufacturing			
Least Developed	0.580	0.624	0.719	0.581	0.879	0.913
Second Quartile	0.675	0.710	0.693	0.631	0.652	0.733
Third Quartile	0.526	0.489	0.408	0.493	0.427	0.417
Most Developed	0.179	0.094	0.046	0.129	-0.024	-0.079
			Panel C: Service			
Least Developed	0.546	0.542	0.589	0.529	0.502	0.529
Second Quartile	0.595	0.617	0.569	0.585	0.529	0.576
Third Quartile	0.475	0.448	0.458	0.421	0.393	0.381
Most Developed	0.213	0.117	0.032	0.180	0.075	0

Notes: This table reports the detailed relative locational allocation cost by gender, skill, destination region and sector ($\varepsilon_{i,jk}^{ge}$), estimated from equation (2) with our 2015 data for the model. We group cities into four quartiles, divided by the level of development (GDP per capita). The locational allocation cost of high-skilled females in the service sector in the most developed region is normalized to 0 for comparison.

C Supplements to Quantitative Analysis

C.1 Effects of Gender-specific Spatial Structural Changes

C.1.1 Additional Results on Detailed Effects

Table C1 provides the detailed singles rate for each gender and skill level along the decomposition path. The sequential decomposition starts from the baseline and removes the gender-specificity in national educational, national sectoral, and spatial sectoral components one by one in each row. Panel A is for the whole population, and Panels B and C list the results in the least and the most developed region quartile by GDP per capita.

Table C1: Detailed Effects of Gender-specific Spatial Structural Changes on Singles Rate

	Male				Female			
	All	L-skill	M-skill	H-skill	All	L-skill	M-skill	H-skill
	Panel A: National							
Baseline	8.17%	8.71%	7.42%	6.91%	3.46%	1.74%	4.25%	9.55%
−National Educational (NE)	7.86%	7.69%	7.19%	9.22%	3.14%	1.98%	4.26%	7.04%
−NE−National Sectoral (NS)	7.87%	7.76%	7.11%	9.11%	3.14%	1.97%	4.24%	7.14%
−NE−NS−Spatial Sectoral (SS)	7.21%	7.63%	6.38%	6.58%	2.45%	1.85%	3.14%	4.46%
	Panel B: Least Developed							
Baseline	8.98%	9.66%	7.66%	5.53%	2.36%	1.69%	3.61%	6.67%
−National Educational (NE)	8.09%	8.43%	7.11%	7.03%	2.43%	1.95%	3.77%	5.19%
−NE−National Sectoral (NS)	8.48%	8.85%	7.51%	7.34%	2.37%	1.86%	3.71%	5.19%
−NE−NS−Spatial Sectoral (SS)	8.03%	8.57%	7.52%	6.36%	1.99%	1.49%	2.83%	3.58%
	Panel C: Most Developed							
Baseline	8.11%	8.28%	8.35%	7.56%	5.09%	1.92%	5.05%	11.48%
−National Educational (NE)	8.45%	7.48%	8.39%	10.37%	4.21%	2.13%	4.89%	8.32%
−NE−National Sectoral (NS)	8.11%	7.15%	7.97%	10.06%	4.33%	2.22%	4.95%	8.55%
−NE−NS−Spatial Sectoral (SS)	5.97%	6.17%	5.24%	6.13%	3.11%	2.35%	3.49%	5.78%

Notes: This table lists the singles rate for each gender-skill type under the baseline and different counterfactual simulations. The panels are defined by the prefecture quartile by GDP per capita. Within each panel, the sequential decomposition starts from the baseline and removes the gender-specificity in each component one by one in each row.

C.1.2 The Roles of Individual Components of SSCs

In addition to the sequential decomposition that we analyze in Section 6.1 of the main text, we also conduct the decomposition and examine the role of each individual component among the national educational, national sectoral, and spatial sectoral, one at a time. Table C2 provides the results for the national average. Panel A provides the singles rate under the baseline and each decomposition, and Panel B calculates the percentage change in the singles rate in each decomposition compared to that in the baseline. Tables C3 and C4 further analyze the bottom and top quartile regions.

Table C2: Detailed Effects of Individual Components of SSCs - National

National:	Male				Female			
	All	L-skill	M-skill	H-skill	All	L-skill	M-skill	H-skill
	Panel A: Singles Rate							
Baseline	8.17%	8.71%	7.42%	6.91%	3.46%	1.74%	4.25%	9.55%
National Educational	7.86%	7.69%	7.19%	9.22%	3.14%	1.98%	4.26%	7.04%
National Sectoral	8.19%	8.78%	7.36%	6.83%	3.48%	1.74%	4.23%	9.69%
Spatial Sectoral	7.42%	8.42%	6.39%	4.63%	2.67%	1.66%	3.21%	6.46%
	Panel B: Percentage Change Compared to Baseline							
National Educational	-3.79%	-11.71%	-3.10%	33.43%	-9.25%	13.79%	0.24%	-26.28%
National Sectoral	0.24%	0.80%	-0.81%	-1.16%	0.58%	0.00%	-0.47%	1.47%
Spatial Sectoral	-9.18%	-3.33%	-13.88%	-33.00%	-22.83%	-4.60%	-24.47%	-32.36%

Notes: This table lists the singles rate for each gender-skill type under the baseline and each decomposition simulation that changes only one component at a time. Panel A provides the singles rate, and Panel B calculates the percentage change in the singles rate in each simulation compared to that in the baseline.

Table C3: Detailed Effects of Individual Components of SSCs - Least Developed

Least Developed:	Male				Female			
	All	L-skill	M-skill	H-skill	All	L-skill	M-skill	H-skill
				Panel A: Singles Rate				
Baseline	8.98%	9.66%	7.66%	5.53%	2.36%	1.69%	3.61%	6.67%
National Educational	8.09%	8.43%	7.11%	7.03%	2.43%	1.95%	3.77%	5.19%
National Sectoral	9.38%	10.10%	8.07%	5.78%	2.32%	1.62%	3.56%	6.66%
Spatial Sectoral	8.36%	9.46%	7.52%	4.42%	2.17%	1.34%	2.90%	5.25%
				Panel B: Percentage Change Compared to Baseline				
National Educational	-9.91%	-12.73%	-7.18%	27.12%	2.97%	15.38%	4.43%	-22.19%
National Sectoral	4.45%	4.55%	5.35%	4.52%	-1.69%	-4.14%	-1.39%	-0.15%
Spatial Sectoral	-6.90%	-2.07%	-1.83%	-20.07%	-8.05%	-20.71%	-19.67%	-21.29%

Notes: This table lists the singles rate for each gender-skill type under the baseline and each decomposition simulation that changes only one component at a time. Panel A provides the singles rate, and Panel B calculates the percentage change in the singles rate in each simulation compared to that in the baseline.

Table C4: Detailed Effects of Individual Components of SSCs - Most Developed

Most Developed:	Male				Female			
	All	L-skill	M-skill	H-skill	All	L-skill	M-skill	H-skill
				Panel A: Singles Rate				
Baseline	8.11%	8.28%	8.35%	7.56%	5.09%	1.92%	5.05%	11.48%
National Educational	8.45%	7.48%	8.39%	10.37%	4.21%	2.13%	4.89%	8.32%
National Sectoral	7.75%	7.91%	7.92%	7.30%	5.25%	2.01%	5.12%	11.82%
Spatial Sectoral	6.04%	6.80%	5.24%	4.27%	3.49%	2.12%	3.60%	8.38%
				Panel B: Percentage Change Compared to Baseline				
National Educational	4.19%	-9.66%	0.48%	37.17%	-17.29%	10.94%	-3.17%	-27.53%
National Sectoral	-4.44%	-4.47%	-5.15%	-3.44%	3.14%	4.69%	1.39%	2.96%
Spatial Sectoral	-25.52%	-17.87%	-37.25%	-43.52%	-31.43%	10.42%	-28.71%	-27.00%

Notes: This table lists the singles rate for each gender-skill type under the baseline and each decomposition simulation that changes only one component at a time. Panel A provides the singles rate, and Panel B calculates the percentage change in the singles rate in each simulation compared to that in the baseline.

C.1.3 Decomposition in Alternative Sequences

In the main analysis, we sequentially decompose the changes in singles rate into national educational, national sectoral, and spatial sectoral changes in gender-specificity. In this section, we check the robustness of alternative sequences of the decomposition. In Table C5, Panel A still gives the overall changes on the singles rate between the baseline and the counterfactual where all gender-specificity in all three components is averaged out. In Panel B, we decompose the above percentage change starting instead from the national sectoral component, followed by the spatial sectoral change, and the national educational component is added last. Overall, we find robust results that the gender-biased spatial sectoral distribution explains the largest portion of the observed singles rate changes. The gender educational trend contributes by roughly one-quarter to one-third, while the national structural change in gender-specificity plays almost no role at the aggregate level. Table C6 further provides detailed results for each gender and skill in different regions.

Table C5: The Effects of Gender-specific SSCs on Singles Rate - Alternative Sequence

National & Regional	Male			Female		
Singles Rate	National	Least Dev.	Most Dev.	National	Least Dev.	Most Dev.
	Panel A: Singles Rate and Percentage Changes					
Baseline	8.17%	8.98%	8.11%	3.46%	2.36%	5.09%
No GS-SSCs	7.21%	8.03%	5.97%	2.45%	1.99%	3.11%
% Changes	-11.75%	-10.58%	-26.39%	-29.19%	-15.68%	-38.90%
	Panel B: Decomposition of the Percentage Changes					
National Sectoral	-2.08%	-42.11%	16.82%	-1.98%	10.81%	-8.08%
Spatial Sectoral	79.17%	106.32%	79.91%	79.21%	40.54%	88.89%
National Educational	22.92%	35.79%	3.27%	22.77%	48.65%	19.19%

Notes: This table mimics Table 8 but changes the order of the sequential decomposition to first remove the gender-specificity in the national sectoral component, then followed by the spatial sectoral and national educational ones.

Table C6: Detailed Effects of Gender-specific SSCs on Singles Rate - Alternative Sequence

	Male				Female			
	All	L-skill	M-skill	H-skill	All	L-skill	M-skill	H-skill
				Panel A: National				
Baseline	8.17%	8.71%	7.42%	6.91%	3.46%	1.74%	4.25%	9.55%
−National Sectoral (NS)	8.19%	8.78%	7.36%	6.83%	3.48%	1.74%	4.23%	9.69%
−NS−Spatial Sectoral (SS)	7.43%	8.42%	6.40%	4.65%	2.68%	1.67%	3.22%	6.46%
−NS−SS−National Educational (NE)	7.21%	7.63%	6.38%	6.58%	2.45%	1.85%	3.14%	4.46%
				Panel B: Least Developed				
Baseline	8.98%	9.66%	7.66%	5.53%	2.36%	1.69%	3.61%	6.67%
−National Sectoral (NS)	9.38%	10.10%	8.07%	5.78%	2.32%	1.62%	3.56%	6.66%
−NS−Spatial Sectoral (SS)	8.37%	9.47%	7.54%	4.44%	2.17%	1.34%	2.91%	5.24%
−NS−SS−National Educational (NE)	8.03%	8.57%	7.52%	6.36%	1.99%	1.49%	2.83%	3.58%
				Panel C: Most Developed				
Baseline	8.11%	8.28%	8.35%	7.56%	5.09%	1.92%	5.05%	11.48%
−National Sectoral (NS)	7.75%	7.91%	7.92%	7.30%	5.25%	2.01%	5.12%	11.82%
−NS−Spatial Sectoral (SS)	6.04%	6.80%	5.24%	4.29%	3.49%	2.13%	3.61%	8.36%
−NS−SS−National Educational (NE)	5.97%	6.17%	5.24%	6.13%	3.11%	2.35%	3.49%	5.78%

Notes: This table lists the singles rate for each gender-skill type under the baseline and different counterfactual simulations. The panels are defined by the prefecture quartile by GDP per capita. Within each panel, the sequential decomposition starts from the baseline and removes the gender-specificity in each component one by one in each row.

C.2 Effects of Continuing Gender-specific Spatial Structural Changes

C.2.1 Specifications of the SSCs Projections in 2030

To study the effects of continued trends in gender-specific spatial structural change, we project a counterfactual scenario for the year 2030 based on the equilibrium year 2015 and the stylized fact trends from 2000 to 2015 discussed in Section 3.1. In this section, we provide detailed explanations for how we construct the projections for 2030 across the three key shifters.

First, we project the continued national educational changes by gender. According to the 2020 Census, 34.5% of women and 26.5% of men in the cohort born in 2000 (age 30 in 2030) attended undergraduate or higher programs, raising the female-to-male high-skill (h-skill) ratio to 1.30 from 1.15 in 2015. We calibrate the share of high-skilled individuals by gender and proportionally adjust the shares of low- (l-skill) and medium-skilled (m-skill) individuals to maintain the full population. After computing the updated national skill composition by gender and their relative ratios compared to 2015 (one ratio for each gender-skill group), we apply these rescaling factors to the initial population at each home location i. This approach preserves the spatial distribution of education while capturing national trends.

Second, we project the national sectoral changes by linearly interpolating the gender employment gap in the service sector, as shown in Table 1, from 2000–2015 to 2030. This projection increases the female-to-male service employment gap to 46.6% from 21.2% for h-skill, to 8.5% from 4.1% for m-skill, and to 36.5% from 9.3% for l-skill individuals. To achieve these targets, we adjust the female sectoral allocation costs $\overline{\tau}_k^{ge}$: decreasing the cost of entering the service sector and increasing the costs of entering agriculture and manufacturing, separately for each skill level. The magnitude of adjustment is symmetric and preserves the overall labor supply. The allocation costs for males $\overline{\tau}_k^{ge}$ remain unchanged. These cost adjustments feed into the gravity equation, altering females' sectoral employment shares relative to males.

Third, we simulate spatial sectoral change by modifying the spatial allocation costs $\varepsilon_{i,jk}^{ge}$ for females. While there is no straightforward empirical target for heterogeneous sectoral growth across space, we assume an intensification of the existing pattern. Specifically, we double the existing gap in spatial allocation costs for female migration to the service sector between the top and bottom quartile cities (ranked by GDP per capita). Concretely, for females of all skill levels and home locations, we reduce $\varepsilon^{ge}_{i,jk}$ by half when migrating to the service sector in top-quartile cities, and increase it by half for migration to the service sector in bottom-quartile cities. Spatial allocation costs to other sectors, as well as to the service sector in the middle two quartiles, are held constant.

C.2.2 Alternative Specifications of the SSCs Projections in 2030

In this section, we check the robustness of the specification for projecting the spatial structural change in 2030. First, for the continued national educational change, we redefine the high-skilled workers as those with at least a bachelor's degree in the main analysis. The main reason is that more than half of the new cohort of age 30 in 2030 attended vocational or above colleges due to continued college expansions in China; therefore, the relative classification of high versus lower skills becomes unbalanced compared to the baseline in 2015 (less than one-quarter). Here, we keep the previous classification of high-skill as vocational college and above, and redo the projection for 2030. For the 2030 cohort, 53.5% of men and 64.1% of women belong to this h-skill group.

Table C7 provides the projection result. In general, we find a qualitatively consistent result compared to the projection and decomposition in Table 10. The large group size of the high-skilled, especially female, leads to an even higher singles rate in 2030. This is partly because the relative marital preference for different spousal skills remains unchanged, making it less compatible with the new skill composition in 2030 and potentially exaggerating the increase in singles rate.

For national and spatial sectoral changes, we test robustness and smoothness of the effect by projecting them by half the size in our main analysis. The trend of the share of high-skills (bachelor's degree and above) is kept unchanged as in the main counterfactual case in Section 6.2 because the educational composition has been finalized for this new cohort as of now. The results are reported in Table C8. Even if we assume that the speed of the spatial structural change into 2030 is half of that specified previously, the projected decrease in marriage rate is still substantial.

Table C7: Continuing Gender-specific SSCs - Alternative Education

Singles Rate by Groups	Male			Female		
	National	Least Dev.	Low Skill	National	Most Dev.	High Skill
	Panel A: Singles Rate and Percentage Changes					
Baseline (2015)	8.17%	8.98%	8.71%	3.46%	5.09%	9.55%
Projection (2030)	12.48%	21.31%	17.72%	7.99%	13.21%	13.70%
% Changes	52.75%	137.31%	103.44%	130.92%	159.53%	43.46%
	Panel B: Decomposition of the Percentage Changes					
National Educational	76.57%	43.15%	84.24%	76.60%	65.27%	56.39%
National Sectoral	0.46%	1.38%	0.55%	0.44%	-1.23%	0.96%
Spatial Sectoral	22.97%	55.47%	15.21%	22.96%	35.96%	42.65%

Notes: This table defines the high-skilled group as vocational college and above, while in Table 10 it is defined as the bachelor's degree and above. Other specifications are the same as in Table 10.

Table C8: Continuing Gender-specific SSCs - Alternative National and Spatial Sectoral Changes

Singles Rate by Groups	Male			Female		
	National	Least Dev.	Low Skill	National	Most Dev.	High Skill
	Panel A: Singles Rate and Percentage Changes					
Baseline (2015)	8.17%	8.98%	8.71%	3.46%	5.09%	9.55%
Projection (2030)	9.62%	13.49%	11.41%	4.98%	8.80%	13.88%
% Changes	17.75%	50.22%	31.00%	43.93%	72.89%	45.34%
	Panel B: Decomposition of the Percentage Changes					
National Educational	76.55%	41.02%	81.85%	76.32%	63.61%	73.67%
National Sectoral	0.69%	3.77%	0.74%	0.66%	-1.08%	0.92%
Spatial Sectoral	22.76%	55.21%	17.41%	23.03%	37.47%	25.40%

Notes: This table defines the high-skilled group as vocational college and above, while in Table 10 it is defined as the bachelor's degree and above. Other specifications are the same as in Table 10.

C.3 Effects of Marriage Subsidies

Table C9 provides the detailed changes in singles rate by gender, skill and regions under the nationwide marriage subsidies (10% of household income).

Table C9: Detailed Effects of Counterfactual Marriage Subsidies

Singles Rate	Male				Female			
	All	L-skill	M-skill	H-skill	All	L-skill	M-skill	H-skill
	Panel A: National							
Baseline	8.17%	8.71%	7.42%	6.91%	3.46%	1.74%	4.25%	9.55%
Marriage Subsidy	7.89%	8.45%	7.14%	6.55%	3.17%	1.56%	3.87%	8.88%
	Panel B: Least Developed							
Baseline	8.98%	9.66%	7.66%	5.53%	2.36%	1.69%	3.61%	6.67%
Marriage Subsidy	8.73%	9.41%	7.41%	5.30%	2.13%	1.51%	3.27%	6.17%
	Panel C: Most Developed							
Baseline	8.11%	8.28%	8.35%	7.56%	5.09%	1.92%	5.05%	11.48%
Marriage Subsidy	7.78%	8.00%	8.00%	7.12%	4.70%	1.73%	4.61%	10.71%

Notes: This table lists the singles rate for each gender-skill type under the baseline and counterfactual simulations. The panels are defined by the prefecture quartile by GDP per capita.

C.4 Alternative Marriage Subsidy Policies

C.4.1 Location-specific Marriage Subsidy Policies

In this section, we incorporate the practical concern about fiscal capacity and instead simulate the location-specific marriage subsidy policy. On the one hand, given the potentially large fiscal burden of marriage subsidies, it is likely that only the local government of the more developed region is capable of implementing such policies. On the other hand, if the central government considers intergovernmental transfers, such transfers may be offered first to the least developed region where men's singles rate is especially high and suffers from high bride price in equilibrium.

We simulate the marriage subsidy, still equivalent to 10% of household income, provided only to the most or least developed quartile of cities. The results are reported in Table C10. In general, we find very limited policy effects on reducing singles rate.

Table C10: Effects of Location-specific Marriage Subsidies

Singles Rate	Male				Female			
	All	L-skill	M-skill	H-skill	All	L-skill	M-skill	H-skill
				Panel A: National				
Baseline	8.17%	8.71%	7.42%	6.91%	3.46%	1.74%	4.25%	9.55%
Subsidy Most Developed	8.05%	8.63%	7.28%	6.67%	3.33%	1.69%	4.09%	9.15%
Subsidy Least Developed	8.12%	8.65%	7.39%	6.89%	3.41%	1.70%	4.19%	9.49%
				Panel B: Least Developed				
Baseline	8.98%	9.66%	7.66%	5.53%	2.36%	1.69%	3.61%	6.67%
Subsidy Most Developed	9.01%	9.69%	7.68%	5.55%	2.35%	1.68%	3.60%	6.66%
Subsidy Least Developed	8.67%	9.34%	7.36%	5.27%	2.15%	1.52%	3.29%	6.19%
				Panel C: Most Developed				
Baseline	8.11%	8.28%	8.35%	7.56%	5.09%	1.92%	5.05%	11.48%
Subsidy Most Developed	7.71%	7.91%	7.93%	7.08%	4.73%	1.76%	4.66%	10.76%
Subsidy Least Developed	8.14%	8.31%	8.37%	7.57%	5.08%	1.91%	5.03%	11.46%

Notes: This table lists the singles rate for each gender-skill type under the baseline and different counterfactual simulations. The panels are defined by the prefecture quartile by GDP per capita.

C.4.2 Education-specific Marriage Subsidy Policies

Lastly, since we observe that the singles rate is much higher among low-skilled men and high-skilled women, we experiment with the marriage subsidy equivalent to 10% of household income, targeted to only low-skilled men or high-skilled women. The results are reported in Table C11. In general, we find very limited policy effects on reducing singles rate.

Table C11: Effects of Education-specific Marriage Subsidies

Singles Rate	Male				Female			
	All	L-skill	M-skill	H-skill	All	L-skill	M-skill	H-skill
	Panel A: National							
Baseline	8.17%	8.71%	7.42%	6.91%	3.46%	1.74%	4.25%	9.55%
Subsidy L-skill Male	8.09%	8.49%	7.62%	7.03%	3.37%	1.67%	4.14%	9.41%
Subsidy H-skill Female	8.12%	8.68%	7.37%	6.78%	3.40%	1.75%	4.28%	9.15%
	Panel B: Least Developed							
Baseline	8.98%	9.66%	7.66%	5.53%	2.36%	1.69%	3.61%	6.67%
Subsidy L-skill Male	8.87%	9.45%	7.89%	5.66%	2.27%	1.62%	3.50%	6.54%
Subsidy H-skill Female	8.94%	9.63%	7.62%	5.46%	2.34%	1.70%	3.63%	6.37%
	Panel C: Most Developed							
Baseline	8.11%	8.28%	8.35%	7.56%	5.09%	1.92%	5.05%	11.48%
Subsidy L-skill Male	8.05%	8.04%	8.54%	7.66%	4.99%	1.85%	4.93%	11.34%
Subsidy H-skill Female	8.03%	8.24%	8.27%	7.39%	4.98%	1.94%	5.09%	11.02%

Notes: This table lists the singles rate for each gender-skill type under the baseline and different counterfactual simulations. The panels are defined by the prefecture quartile by GDP per capita.