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Sex and the City: Demographics, Spatial Sorting, and the Marriage Market

Min Fang[1,2] | Zibin Huang[3,4] | Yushi Wang[5] | Yu (Alan) Yang[6]

[1]Department of Economics and Decision Sciences, China Europe International Business School, Pudong, Shanghai, China | [2]Lanzillotti Public Policy Research Center, University of Florida, Gainesville, Florida, USA | [3]College of Business, Shanghai University of Finance and Economics, Shanghai, China | [4]Shanghai Institute of International Finance and Economics, Shanghai, China | [5]International Business School, Hainan University, Haikou, China | [6]Guanghua School of Management, Peking University, Beijing, China

Correspondence: Yu (Alan) Yang (alanyang@gsm.pku.edu.cn)

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ABSTRACT

We study how the interaction between demographic changes and spatial sorting affects marriage matching across space. Using data from China, we first present stylized facts on the diverging spatial distribution of singlehood characterized by a high singles rate for females (males) in more (less) developed cities. We then build a quantitative spatial equilibrium model. It reveals that more highly educated women sort into the service sector in more developed cities than men. With persistent social norms of hypergamy, this results in more failed marriage matches for females (males) in more (less) developed cities, thereby lowering the national marriage rate.

JEL Classification: O14, R23, R13, J12

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 child-rearing 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 of family policies aimed at increasing marriage and fertility rates are generally understudied.

In this paper, we argue that the above spatial dispersion and gender- and skill-based mismatch in the marriage market are two interconnected facets of the outcomes of the same demographic changes and spatial sorting, which we refer to as **spatial demographic changes**, involving joint demographic shifts in education, economic sectors, and geographic location that are **gender-specific**. First, women out-educate men over time.[2] Second, more women than men are moving into the service sector. Third, compared with higher-skilled men, relatively more higher-skilled women work in the service sector, which is disproportionately concentrated in more developed cities. However, social norms in marital preferences or marriage-market frictions remain persistent, particularly stronger preferences or frictions among women (men) for upward (downward) matches. In essence, the joint spatial and skill shifts create a **squeeze effect** in all cities: In developed cities, the pool of acceptable

All authors contributed equally and are listed in alphabetical order.

higher-skilled men grows too slowly relative to the rising number of higher-skilled women, while in less developed areas the opposite imbalance occurs for lower-skilled men. Together, these factors lead to a spatial mismatch in 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 demographic changes while marriage and fertility rates have almost halved in the last two decades. We first present stylized facts on the potential causes of dramatic gender-specific spatial demographic changes and persistent social norms in the marriage market. We then build a quantitative spatial general equilibrium model with migration, multisector and multiskill production, and local marriage markets. After estimating the spatial model for China in 2015, we examine the effects of spatial demographic changes, project future changes, and assess the effectiveness of the current marriage subsidy policy.

In the first step, we show stylized facts regarding (1) the dramatic gender-specific spatial demographic 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 the share of service employment 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 level of economic development, especially among the higher educated, while it decreases among men, particularly the 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, multisector and multiskill 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; Ma and Xican 2020; Fang et al. Forthcoming). 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-skilled labor as inputs to produce final goods, whereas the agricultural sector uses undifferentiated labor as an input. Workers gain utility from the corresponding local wage income spent on final goods and local housing consumption. In addition, workers form families and gain utility from the local marriage market if they marry. 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 estimate the model quantitatively, combining calibration, log-linearization, and the contraction algorithm across several steps. Our estimation results on marriage-market social norms and spatial and sectoral allocation costs highlight the race between spatial demographic changes and social norms, as documented in the data and discussed in the context of fertility by Goldin (2025). Regarding marriage-market social norms, estimates indicate that the match value of marrying up is notably higher for females than for males, especially among higher-skilled females. Regarding spatial demographic changes, estimates of spatial and sector allocation costs indicate that allocation costs to service sectors in more developed cities are lower for females than for males, especially among high-skilled females. These parameter estimates are consistent with the observed stylized facts.

We then conduct a quantitative equilibrium analysis to understand the role of gender-specific spatial demographic changes in national and regional marriage rates, and simulate counterfactual policies to examine the aggregate implications. When removing gender-specificity from spatial demographic changes, we find that the national singles rates 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 regions. For example, the singles rate of college-educated women would decrease by more than 50%. Decomposition reveals that the narrowing and then reversal in the trend in college attainment for females relative to males explains one-third of the change in the singles rate, and the spatial sorting of females into service in more developed regions accounts for roughly the remaining two-thirds. In contrast, aggregate national demographic change from the agricultural to nonagricultural sectors does not substantially affect marriage matching. We also project continued gender-specific spatial demographic changes from 2015 to 2030 and find substantial further increases in the national and regional singles rates, driven by larger spatial mismatches in local marriage markets.

Finally, we examine a widely discussed and adopted family policy to increase marriage rates across 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 demographic 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 that can directly target spatial gender imbalance by subsidizing migration by particular genders and skills, or by balancing sectoral growth across regions. However, such policies raise concerns about gender equity and economic or political feasibility.

Literature Review. We contribute to the literature by empirically and quantitatively highlighting the interactive role of demographic changes and economic geography in the decline in marriage rates. Specifically, our work relates to four strands of literature on gender sorting in migration, demographic changes interacted with spatial sorting, marriage matching, and quantitative spatial modeling.

The first strand of literature documents and explains 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. The 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. 2025), and (2) better marriage opportunities in urban cities (Weiss et al. 2018; Dupuy 2021; Xiong 2023). We leverage this literature and embed both of the 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 concerns demographic changes and spatial sorting. The higher educational attainment of women and the rise of female employment in the service sector are related to various socioeconomic trends, including the rise of relative advantage 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). The spatial sorting of workers with different skills has been attributed to the diverging location amenity (Diamond 2016), the role of skill complementarities in production and mobility across cities (Eeckhout et al. 2014), and spatial structural changes (Eckert and Peters 2022).[4] Our paper bridges the two topics as spatial demographic changes and explores their interactions. This is related to the fact that single women are more likely to migrate than single men, especially at younger ages (Koh et al. 2025), social norms requiring males to pay for housing, and the resulting higher housing prices, have significantly discouraged low-educated male migrants (Wei and Zhang 2011; Wei et al. 2017), and the gender wage gap among married migrants is significantly smaller in larger cities (Xing et al. 2022), among others. Such demographic changes are also highly correlated with structural changes and are remarkably rapid in China (Chen et al. 2023). As shown by Ager et al. (2026), gender-biased technological change and structural changes have pushed rural young women to cities, where they acquired more education and found better-paying, skilled employment. We show that spatial demographic changes, along with 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.

The third strand of literature examines the marriage market and sorting 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), as documented in lab experiments (Fisman et al. 2006), US data (Schwartz and Mare 2005; Bertrand et al. 2015), and, more recently, Chinese data (Rossi and Xiao 2026).[5] Our paper shows that the above marital assortative matching patterns are also substantial in China, both within and across cities, 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.

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 significant fraction focuses on the consequences of the spatial classification of worker skills (Fajgelbaum and Gaubert 2020; Couture et al. 2024; Giannone 2017; Ma and Tang 2019; Hong 2025, 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 (2025) on assortative matching and geographic sorting of marriage. These studies primarily focus on how marriage affects the spatial distribution of skills or vice versa. Our paper focuses on the distinct impact of the interaction between spatial sorting and spatial demographic changes on regional and national marriage rates.

In summary, our study contributes to the literature by empirically and quantitatively examining the effect of spatial, gender-specific, demographic changes in education and the sector on local marriage markets across cities. By combining comprehensive individual-level and prefecture-level data sets, 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 reforms in China since 1978 have ushered in one of the most rapid periods of structural transformation and urbanization in modern economic history, triggering massive domestic migration and spatial demographic changes—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 is 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 in 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. Instead, 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 | Data Sets

The main data set 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 intercensal 1% 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 Census wave, 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 Census data from 2000 to 2015 to establish the stylized facts presented in the next section and focus on 2015 as the baseline to construct prefecture-level migration flows, sectoral employment choices, and marriage-matching outcomes for our quantitative 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).[6] 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 use the prefecture-level average housing prices per square meter in 2015.

3 | Stylized Facts

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

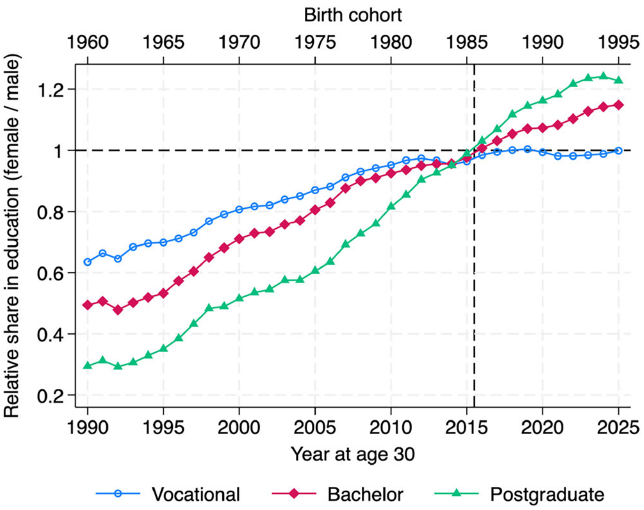


FIGURE 1 | Gender educational gap over time.
Notes: This figure presents the female-to-male relative share in education by birth cohort. A ratio of 1 means the number of females having the same degree equals that of males. The top x-axis marks the birth year, and the bottom x-axis shows the year they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

3.1 | Dramatic Gender-Specific Spatial Demographic Changes

We first highlight the dramatic gender-specific spatial demographic 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 more developed cities has been decreasing for females, particularly among those with higher education levels.

Gender Educational Gap. Our first perspective examines the gender gap in education. 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 is equal to 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 demographic 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

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%

Note: 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 sectoral gender employment gap by subtracting the overall gender employment gap. Data source: Population Census 2000, 2005, 2010, and 2015.

in the marriage market around 2015, at approximately age 30. The reversed education gap is even more 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 gender educational gap in the marriage market.

Gender Sectoral Employment Gap. We then investigate gender-specific demographic changes in the gender employment gap across sectors and education levels. Let H be the number of employed workers. The gap for education level e in sector k and year t is calculated as follows:

$$\text{gap}_{kt}^{e} = \frac{H_{kt}^{\text{female,e}} - H_{kt}^{\text{male,e}}}{H_{kt}^{\text{male,e}}} - \frac{H_{t}^{\text{female}} - H_{t}^{\text{male}}}{H_{t}^{\text{male}}}, \quad (1)$$

where $\frac{H_{kt}^{\text{female,e}} - H_{kt}^{\text{male,e}}}{H_{kt}^{\text{male,e}}}$ is the difference between the number of female and male workers, divided by the number of male workers at the education-sector-year level. To account for differences in labor participation, we adjust the gender employment gap in each sector by subtracting the overall gender employment gap $\frac{H_{t}^{\text{female}} - H_{t}^{\text{male}}}{H_{t}^{\text{male}}}$ in year t.[7]

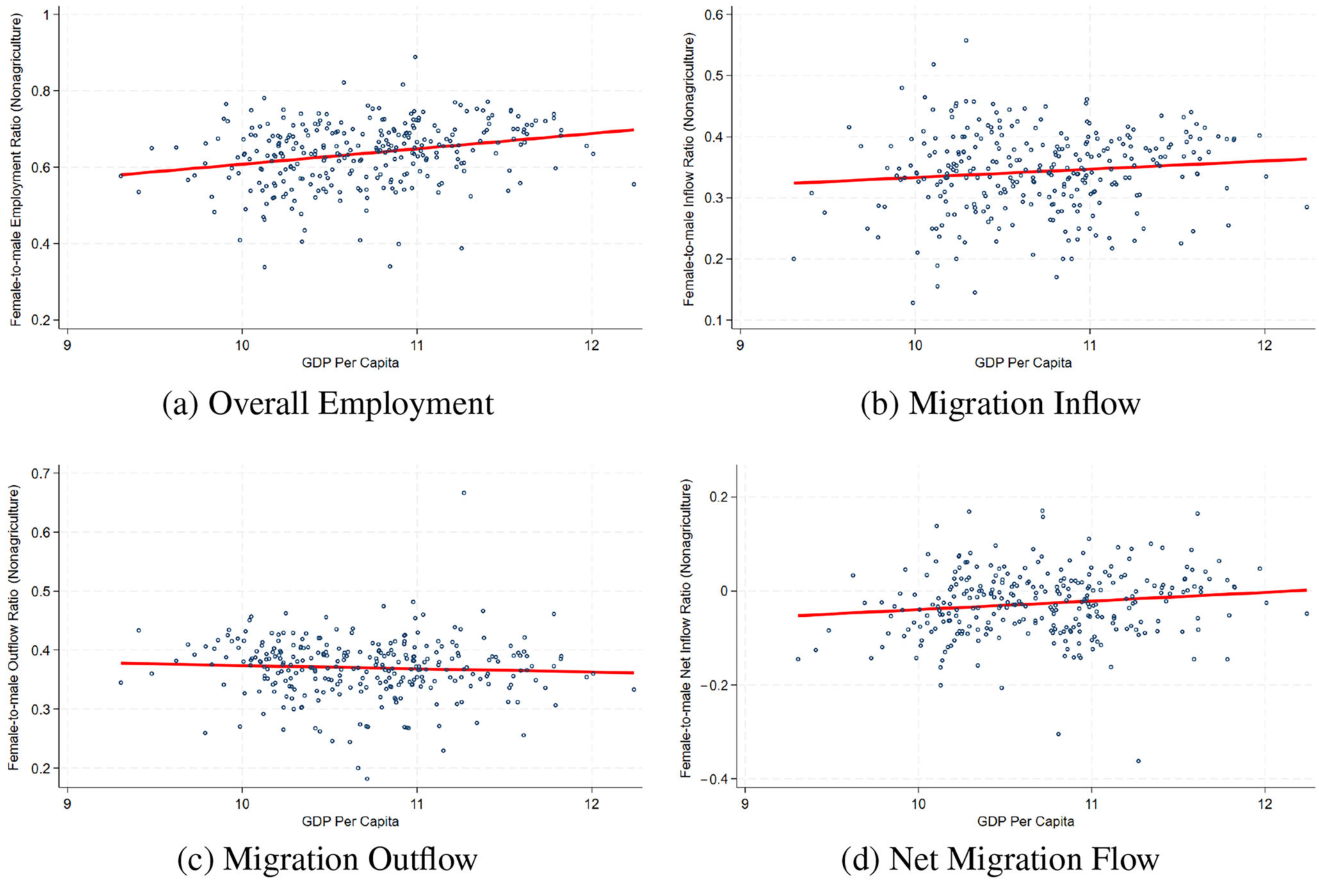
Table 1 presents the results. A positive number indicates that there are relatively more females than males in the specific sector for a given education level, after adjusting for the overall gender labor-participation gap. These results can be summarized into three key patterns. First, there has been a dramatic shift of females from the agriculture and manufacturing sectors to the service sector. This shift can be driven by an increase in the share of skilled females, who are more likely to work in the service sector, or by skilled females increasingly choosing employment in the service sector. Second, this pattern holds across all education levels. Therefore, the transition occurs not only across educational levels but also within each educational category. 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 cities, such as Shanghai, Beijing, or Shenzhen, following patterns of spatial demographic change similar to those in Eckert and Peters (2022).[8] **Gender Spatial Employment Gap**. We further investigate the relationship between prefecture-level GDP per capita and the gender spatial employment gap in the nonagricultural sector in 2015. Figure 2 shows the results for overall employment, migration inflow, migration outflow, and net migration inflow, respectively. In each subfigure, the log of GDP per capita is on the x-axis. On the y-axis, we have female nonagricultural employment (or different measures of 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 nonagricultural 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 for the migration outflow. All these patterns indicate a stronger spatial sorting of female workers into the modern sectors in more developed cities than of male workers. We further plot the gender employment gap for each educational level in Figure A1 in Online Appendix A.1 and find that the trend of more females working in the nonagricultural sector in more developed cities is the strongest for the college-educated group.

Summary. Therefore, the dramatic gender-specific spatial demographic 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 are higher in more developed cities in the nonagricultural sectors.

3.2 | Persistent Social Norms in the Marriage Market

We then highlight the persistent social norms in the marriage market, in which females are more likely to "marry up" and



(a) Overall Employment

(b) Migration Inflow

(c) Migration Outflow

(d) Net Migration Flow

FIGURE 2 | Gender nonagricultural employment gap by spatial development level.

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 nonagricultural 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.

males are more likely to "marry down" in terms of SES, driven by either marital preferences or marriage-market frictions. Since we do not have Census data on individual income, we rely on education as the primary proxy for SES in both the empirical analysis and the model. We demonstrate these patterns through (1) a comparison of the relative SES between married and never-married individuals and (2) an analysis of the relative SES between married husbands and their wives.

Relative Statuses between Married and Never-married. First, we compare the characteristics of older, never-married males and females (aged over 35) with those of 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 the two measures of SES. First, married males consistently have higher SES than 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. We further show that the results of the relative gap between married and never-married individuals hold across regions with different development levels in Online Appendix Table A3.

Relative Statuses within Married Couple. We further examine married couples in our Census data to analyze relative SES differences between husbands and wives. "Females marry up" in terms of college degrees or years of education refers to a situation in which 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.[9] Online Appendix Table A4

TABLE 2 | Relative socioeconomic status gap of married versus never-married.

Census year	2000		2005		2010		2015	
	Male (1)	Female (2)	Male (3)	Female (4)	Male (5)	Female (6)	Male (7)	Female (8)
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

Note: 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.

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%

Note: This table shows the relative socioeconomic status (SES) for married couples, using two measures of SES: college degree attainment and years of education. In college degree attainment, "Females marry up" refers to the proportion of couples in which a wife without a college degree marries a husband with one. In education, "Females marry up" refers to the proportion of couples in which the wife has fewer years of education than her husband. Conversely, "Females marry down" refers to a wife having a higher SES (a college degree or more years of education) than 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 when we set an age restriction for the matched couple to 35–40. Data source: Population Census 2000, 2005, 2010, and 2015.

further illustrates that these two conclusions hold in regions with different development levels.

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 demographic 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 demographic 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 30–45 across living locations. We consider individuals aged 30 or older because most Chinese people make their marriage choices before this age. We focus on individuals aged under 45 to examine cohorts who married around the 2000s and 2010s. Cities shaded in red indicate a higher male singles rate relative to the female singles rate, while those shaded in blue indicate a lower male singles rate relative to the female singles rate. 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). Online Appendix A.3.1 provides the singles rate for males and females separately.

City Characteristics and the Singles Rate. Finally, we present the relationship between the singles rate and city development levels in Figure 4. The figure shows that the singles rate among males is significantly lower in cities with higher levels of development, as indicated by higher GDP per capita. Conversely, in these more developed cities, the singles rate of females is substantially higher. In Online Appendix A.3.2, 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 Online Appendix A.3.3.

3.4 | Summary of the Stylized Facts

We document three sets of stylized facts: (1) dramatic gender-specific spatial demographic 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 into the spatial mismatch in the marriage market. As female educational attain-

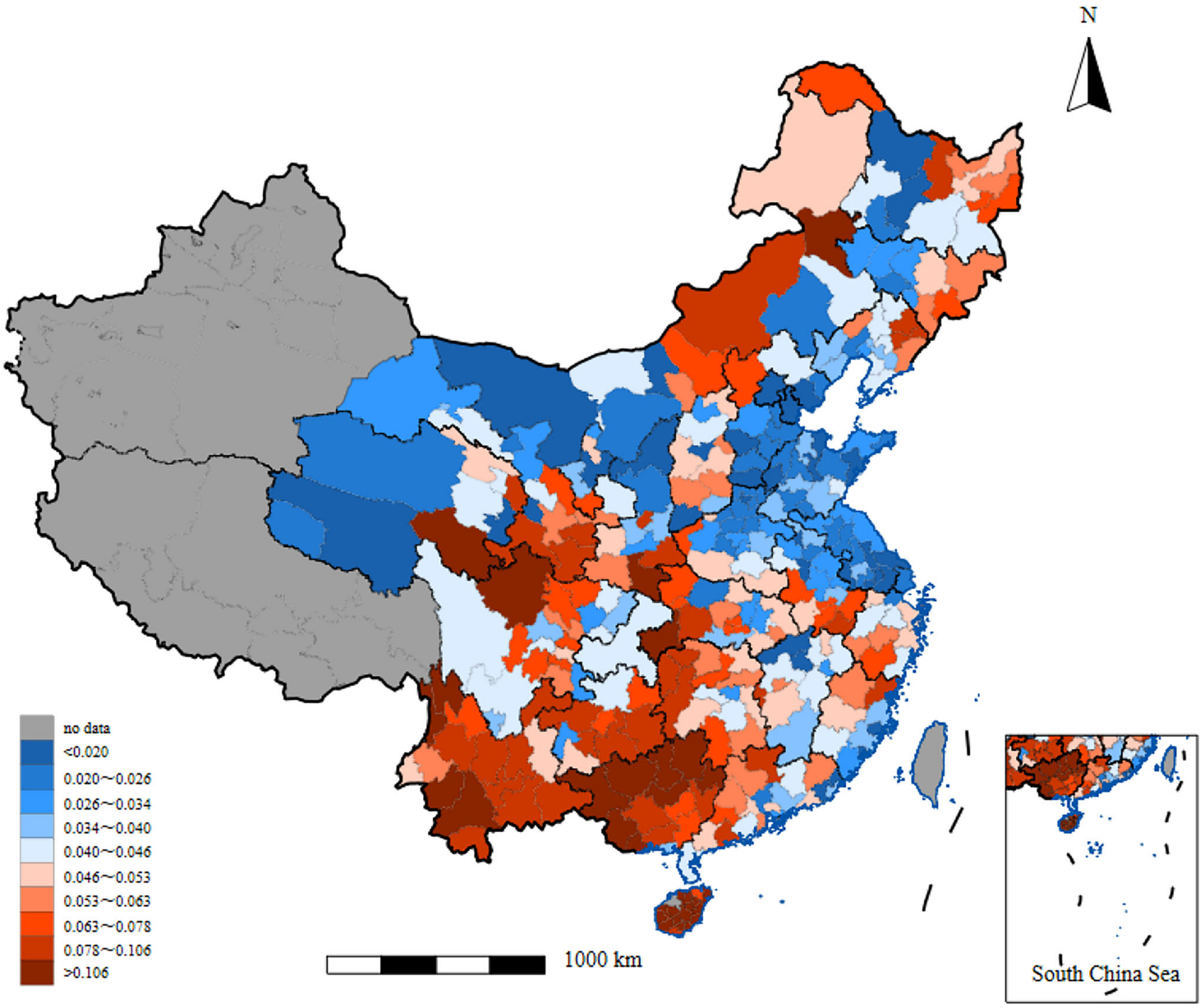


FIGURE 3 | Male-female singles rate gap across living locations in 2015.
Notes: This figure illustrates the singles rate gap between males and females aged 30–45 across different cities in 2015. Cities shaded in red (blue) indicate a higher (lower) male singles rate compared to the female singles rate. Data source: Population Census 2015.

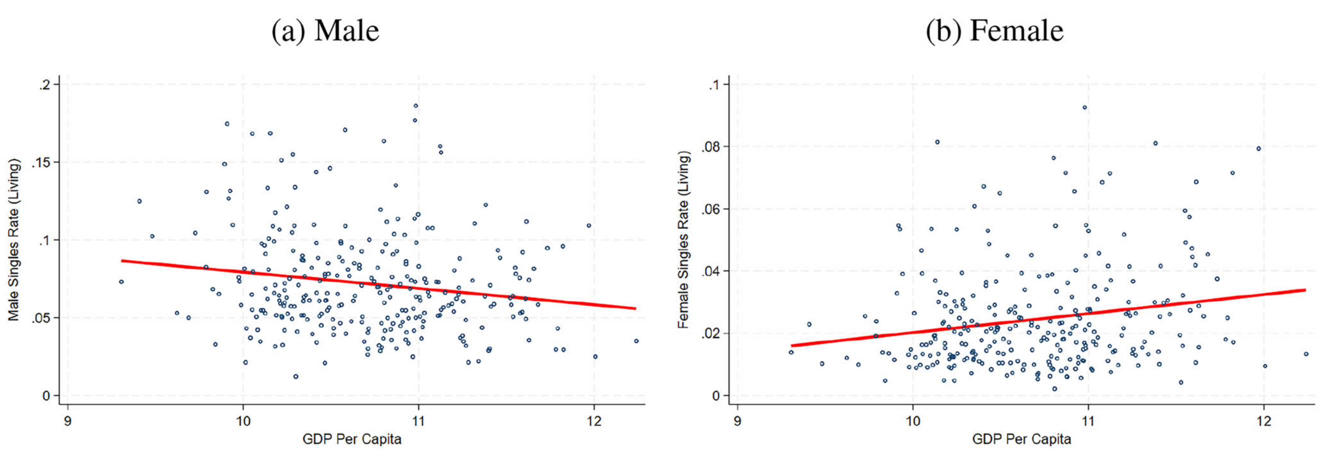


FIGURE 4 | GDP and singles rate of age over 30 in 2015.
Notes: This figure illustrates the relationship between GDP per capita and the singles rate (aged 30–45) at the living city level. Subfigure (a) presents the results for the male singles rate, while subfigure (b) shows the results for the female singles rate. Data source: Population Census 2015.

ment rises and the service sector expands rapidly in developed cities, women increasingly migrate to these areas in search of 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; Ma and Xican 2020; Fang et al. Forthcoming). 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 "modern sectors," employ a combination of high-, middle-, and low-skilled labor as inputs to produce final goods, whereas the agricultural sector uses all skills indifferently. There is a measure of H workers in this economy. Each worker o is characterized by gender g (male or female), 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 their workplace. 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, location, and sector allocation costs, and an unobserved location-preference shock. Their utility from marriage depends on the nonpecuniary 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 viewed 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 location and sector 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 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 through a given construction technology. The demand and supply of floor space in each prefecture determine the housing costs in each location.[10]

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

$$U^o_{i,jk} = \frac{z^o_{i,jk}}{\tau^{ge}_{i,jk}} \overline{V}^{ge}_{jk}, \tag{2}$$

where the term $\overline{V}^{ge}_{jk}$ 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 $\overline{V}^{ge}_{jk}$ in more detail in the next subsection.

The term $\tau^{ge}_{i,jk}$ 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 $\overline{\tau}^{ge}_k$, and the spatial-sectoral heterogeneity $\varepsilon^{ge}_{i,jk}$ that captures the differential cost of working in the sector k in a particular destination j as follows:[11]

$$\tau^{ge}_{i,jk} = \exp\left(G(d_{i,j}) + \overline{\tau}^{ge}_k + \varepsilon^{ge}_{i,jk}\right), \tag{3}$$

where $\overline{\tau}^{ge}_k$ captures the average gender- and education-specific national demographic sectoral change frictions to allocate to sector k and $\varepsilon^{ge}_{i,jk}$ 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 demographic changes, which we will discuss later. Note that, for the same destination sector k, the allocation cost can differ by gender and skill, so that the variation within a sector, such as high- versus low-skill service occupations, is implicitly accounted for.

The term $z^o_{i,jk}$ is an idiosyncratic Fréchet distributed location-preference shock:

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

where ϵ controls the dispersion of the shock. After the realization of the idiosyncratic location-sector preference shock $z^o_{i,jk}$ 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 $\pi^{ge}_{i,jk}$ denote the share of workers with gender g, skill e, and Hukou origin i migrating to sector k in city j for work. The gravity equation is given by

$$\pi^{ge}_{i,jk} = \frac{(\tau^{ge}_{i,jk})^{-\epsilon}(\overline{V}^{ge}_{jk})^{\epsilon}}{\sum_{j'k'}(\tau^{ge}_{i,j'k'})^{-\epsilon}(\overline{V}^{ge}_{j'k'})^{\epsilon}} \equiv \frac{\Phi^{ge}_{i,jk}}{\Phi^{ge}_{i}}. \tag{4}$$

This gravity equation describes the spatial and sectoral distribution of workers in the model, conditioned on 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 those in other cities, and we consider only marriages between opposite-gender individuals. 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 remain single consume their own income without any transfer or marriage utility. 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

$$V^o_{jk}(e') = \ln\left\{\underbrace{\left[\left(\frac{c^{ge}_{jk}(e')}{\beta}\right)^{\beta}\left(\frac{h^{ge}_{jk}(e')}{1-\beta}\right)^{1-\beta} \Big/ (1+\chi)\right]}_{\text{marital economic utility}} \cdot \underbrace{m^o_j(e')}_{\text{other marital utility}}\right\}, \tag{5}$$

where $c^{ge}_{jk}(e')$ and $h^{ge}_{jk}(e')$ 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 $\{g', e'\}$, and the parameter $(1 + \chi)$ captures the economies of scale from marriage relative to being single. Upon marriage, the couple forms a new household and shares their total income $(w^{ge}_{jk} + E_{k'}[w^{g'e'}_{jk'}])$ where $E_{k'}[w^{g'e'}_{jk'}]$ stands for the expected spouse's income with education e' in all potential sectors k'. 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:

$$c^{ge}_{jk}(e') = \beta(w^{ge}_{jk} + E_{k'}[w^{g'e'}_{jk'}]),$$

$$h^{ge}_{jk}(e') = \frac{(1-\beta)(w^{ge}_{jk} + E_{k'}[w^{g'e'}_{jk'}])}{q_{jk}},$$

where q_{jk} is the housing cost. The first part of Equation (5) captures marital economic utility. First, married households pool labor income, as total consumption depends on the combined earnings of both spouses. Second, married households have economies of scale in household consumption, which summarize shared housing and public goods within the household. Together, these channels parsimoniously capture the primary economic gains from marriage, which could potentially reflect pooling income to cover risks or saving for a down payment. While our static framework does not explicitly model dynamic considerations such as intertemporal risk sharing and wealth accumulation, these forces are captured in reduced form through the marriage utility premiums.

Individuals can match across sectors within a location for marriage. The other marital utility for individual o to select a spouse of type e' is specified as:

$$m^o_j(e') = \exp\left[\tilde{\mu}^{ge}_j + \mu^{ge}(e') + \delta^{ge}_j(e') + \xi^o_j(e')\right], \tag{6}$$

where $\tilde{\mu}^{ge}_j$ represents the overall deterministic value of not being single in location j.[12] $\mu^{ge}(e')$ represents the deterministic match value of marrying with a specific type e' (relative to being single). $\delta^{ge}_j(e')$ denotes the within-marriage equilibrium transfer in the local marriage market j. This transfer satisfies $\delta^{ge}_j(e') = -\delta^{ge'}_j(e)$, implying a zero-sum bargaining outcome between spouses. This can be considered as the local marriage-market price. The term $\xi^o_j(e')$ is an idiosyncratic preference shock for partner type, following a Type I Extreme Value (T1EV) distribution with a dispersion parameter σ_ξ. The second part of Equation (5) captures other marital utility. The remaining marital utility premiums $(\tilde{\mu}^{ge}_j + \mu^{ge}(e'))$ could capture additional pecuniary benefits, including income risk sharing, precautionary savings, and credit constraints, or nonpecuniary benefits, including social recognition, emotional utility, and other cultural returns to marriage. However, we do not explicitly model these features but aim to back out the overall levels of these premiums $(\tilde{\mu}^{ge}_j + \mu^{ge}(e'))$ from the observed marriage matching in our equilibrium.[13]

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

$$\begin{aligned} V^o_{jk}(e') = {} & \ln(w^{ge}_{jk} + E_{k'}[w^{g'e'}_{jk'}]) - \ln((1+\chi)q^{1-\beta}_{jk}) + \tilde{\mu}^{ge}_j \\ & + \mu^{ge}(e') + \delta^{ge}_j(e') + \xi^o_j(e'). \end{aligned} \tag{7}$$

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

$$V^o_{jk}(\varnothing) = \ln(w^{ge}_{jk}) - \ln(q^{1-\beta}_{jk}) + \xi^o_j(\varnothing). \tag{8}$$

Using the properties of the T1EV distribution, we derive logit-form probabilities for marriage-market decisions. Denote $\widetilde{V}^{ge}_{jk}(\cdot)$ as the deterministic part in $V^o_{jk}(\cdot)$ specified above. First, the probability of choosing to marry a spouse of type e' is

$$P^{ge}_{jk}(e') = \frac{\exp(\widetilde{V}^{ge}_{jk}(e')/\sigma_\xi)}{\exp(\widetilde{V}^{ge}_{jk}(\varnothing)/\sigma_\xi) + \sum_{e''}\exp(\widetilde{V}^{ge}_{jk}(e'')/\sigma_\xi)}. \tag{9}$$

Second, the probability of choosing to stay single is

$$P^{ge}_{jk}(\varnothing) = \frac{\exp(\widetilde{V}^{ge}_{jk}(\varnothing)/\sigma_\xi)}{\exp(\widetilde{V}^{ge}_{jk}(\varnothing)/\sigma_\xi) + \sum_{e''}\exp(\widetilde{V}^{ge}_{jk}(e'')/\sigma_\xi)}. \tag{10}$$

Finally, the ex ante expected utility of living and working in destination jk, $\overline{V}^{ge}_{jk}$, is given by

$$\overline{V}^{ge}_{jk} = E\left[\max_{(e')} \widetilde{V}^{ge}_{jk}(e')\right]$$
$$= \sigma_\xi \gamma + \sigma_\xi \ln\left[\exp(\widetilde{V}^{ge}_{jk}(\varnothing)/\sigma_\xi) + \sum_{e'} \exp(\widetilde{V}^{ge}_{jk}(e')/\sigma_\xi)\right], \tag{11}$$

where γ is 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:

$$Y_{jM} = [(A^h_{jM}H^h_{jM})^{\frac{\sigma_M-1}{\sigma_M}} + (A^m_{jM}H^m_{jM})^{\frac{\sigma_M-1}{\sigma_M}} + (A^l_{jM}H^l_{jM})^{\frac{\sigma_M-1}{\sigma_M}}]^{\frac{\sigma_M}{\sigma_M-1}} \tag{12}$$

$$Y_{jS} = [(A^h_{jS}H^h_{jS})^{\frac{\sigma_S-1}{\sigma_S}} + (A^m_{jS}H^m_{jS})^{\frac{\sigma_S-1}{\sigma_S}} + (A^l_{jS}H^l_{jS})^{\frac{\sigma_S-1}{\sigma_S}}]^{\frac{\sigma_S}{\sigma_S-1}}, \tag{13}$$

where we denote the subscript M as manufacturing and the superscript m as middle-skill. The production function is a CES combination of high-skill H^h_{jM}, middle-skill H^m_{jM}, and low-skill labor H^l_{jM} multiplied by their corresponding city-level efficiencies A^h_{jM}, A^m_{jM}, and A^l_{jM} (similar for services S). In rural regions, 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 price of final goods to unity. In equilibrium, A_{jR} equals the agricultural wage w_{jR} in rural sector R of city j, for workers of all skills.[14]

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):

$$w^e_{jM} = (A^e_{jM})^{\frac{\sigma_M-1}{\sigma_M}}(Y_{jM})^{\frac{1}{\sigma_M}}(H^e_{jM})^{-\frac{1}{\sigma_M}}, \quad \text{for } e = \{h, m, l\}. \tag{14}$$

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:

$$H^e_{jk} = \sum_{gi} \pi^{ge}_{i,jk} H^{ge}_i, \tag{15}$$

where H^{ge}_i denotes the total number of workers with gender g and skill level e from location i. The term $\pi^{ge}_{i,jk}$ represents the migration probability of a worker with gender g and skill level e from home location i to destination location-sector jk. Lastly, within the total labor supply H^e_{jk}, the number of female workers is further discounted by a factor r^e_{jk} to be measured in effective labor units, to parsimoniously reflect the gender wage gap and labor participation gap for each skill e in jk observed in the data, which we assume to be exogenous and fixed in each specific city.

Essentially, Equation (14) shows that the spatial distribution of workers with different skills across sectors is shaped by migration probabilities and the Hukou population of specific types. In the service sector, for example, the number of workers of skill type e in a particular city j is jointly shaped by the skill-specific allocation costs from all origin cities and the availability of workers of specific skills from all origin cities. In particular, high- and low-skilled service workers have different productivities, are not fully substitutable in production, and incur different allocation costs to move to city j. Such a combination of the CES production function and city-pair skill-sector-gender-specific allocation costs provides us with the flexibility to capture the realistic spatial distribution of workers.

4.4 | Housing Market Clearing

Modern Sectors. We consider the manufacturing and service sectors as modern sectors compared to the agricultural sector in each city. 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. Denote ω as each household (both married and single), and the set of households in the modern sectors in j as Ω_{ju}. Using utility maximization for each worker and taking expectations over the distribution of idiosyncratic utility, this residential land market clearing condition can be expressed as

$$S_{ju} = \int_{\Omega_{ju}} h^{ge}_{jk}\, d\omega. \tag{16}$$

We assume that the construction sector supplies the floor space S. It converts geographic land L to floor space S with a regulated density of development ϕ_j (the ratio of floor space to land): $S_{ju} = \phi_j L^u_j$. This aligns with the fact that the housing and land markets in China are highly regulated (Yu Forthcoming; Deng et al. 2020; Fang et al. Forthcoming).

Agricultural Sector. Housing markets in the agricultural sector are simpler. We assume that rural housing costs are a fixed fraction of urban costs 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 $\{\beta, \epsilon, \chi, \sigma_\xi, \sigma, \eta\}$ 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 $\{Y_{jk}, H^{ge}_{jk}, c^{ge}_{jk}, h^{ge}_{jk}, P^{ge}_{jk}, S_{ju}\}$*, 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* $\{\tau^{ge}_{i,jk}, A^e_j, \phi_j, L_j, H^{ge}_i\}$ *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* $\{A^e_{jk}\}$ *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* $\{q_{ju}, w^e_{jk}\}$*, equilibrium floor space* S_{ju}*, and equilibrium output* Y_{ju}.
- *iv.* **[Marriage-Market Clearing]** *For all possible marriage matching types* (g, e) *versus* (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 Demographic Changes in the Model's View

Before estimating and fitting the model to microdata, we first demonstrate how the structural model that matches the cross-sectional spatial mismatch of marriage could inform us about the gender-specific spatial demographic changes in the time series in Section 3.1. The observed patterns in the gender educational gap, gender sectoral employment gap, and gender spatial employment gap are jointly governed by three key modeling components that are gender-specific: the gender-specific education distributions in the population at each hometown location H^{ge}_i, and the gender- and skill-specific allocation costs associated with moving from origin i to each destination sector k in each destination location j, denoted by $\{\bar{\tau}^{ge}_k, \varepsilon^{ge}_{i,jk}\}$, where $\bar{\tau}^{ge}_k$ represents the national average sectoral allocation costs and $\varepsilon^{ge}_{i,jk}$ denotes location-pair-specific spatial and sectoral allocation frictions. The model is static and would only provide cross-sectional estimates of these endogenous variables, reflecting the spatial mismatch in marriage in 2015 that our estimations in the next section also show. Later, in the counterfactuals, we conduct the analysis by simulating changes in core model elements that capture these key shifts over time and assess their role in shaping the marriage market.

The interaction of three primary trends drives the gender-specific spatial demographic 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, $H^{\text{female},e}_i / H^{\text{male},e}_i$. Second, we observe rapid growth in highly educated female employment in the service sector, which corresponds to a substantial decline in the relative allocation costs, $\bar{\tau}^{\text{female},e}_s / \bar{\tau}^{\text{male},e}_s$, 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 cost $\varepsilon^{\text{female},e}_{i,jk} / \varepsilon^{\text{male},e}_{i,jk}$ for educated females in destination cities j. Together, these changes represent the gender- and skill-specific spatial demographic changes captured in our stylized facts, which can be summarized in the following components: (1) A national educational shifter in relative female education: $H^{\text{female},e}_i / H^{\text{male},e}_i$; (2) A national sectoral shifter in relative female allocation costs: $\bar{\tau}^{\text{female},e}_s / \bar{\tau}^{\text{male},e}_s$; and (3) Spatial-sectoral shifters in relative female allocation costs: $\varepsilon^{\text{female},e}_{i,jk} / \varepsilon^{\text{male},e}_{i,jk}$.

The key to generating the three trends in the observed gender-specific spatial demographic changes lies in the three shifters above, especially at higher education levels ($e = h$). The national educational shift is clearly evident in the Census data. However, we acknowledge that the shifters and the underlying forces in the allocation costs are not explicitly modeled due to data limitations. We provide detailed explorations of the potential sources of these three trends in spatial demographic changes, along with associated empirical evidence, in Online Appendix B.6.

Finally, we argue that considering the goods market, trade, nonhomothetic preferences, and sector- or region-specific prices will not affect our marriage-market mechanism in the paper. Since our paper focuses on migration and local marriage markets, we do not explicitly model the goods market with three sectors or trade across regions, or nonhomothetic preferences across sectoral goods. We provide a detailed discussion of how incorporating goods-market and sector- or region-specific prices does not change our main results on marriage matching in Online Appendix B.7. The labor-market side with the goods market would be almost identical to our spatial demographic changes in the model. For the goods market, trade, nonhomothetic preferences, and sector- or region-specific prices, we show that incorporating these is nearly equivalent to introducing two wedges. First, an overall local price wedge between workers' consumption, c^{ge}_{jk}, and wage income, w^{ge}_{jk}, into our current model, which could shift the overall level of utility but does not affect the marriage-matching. Second, a subsistence consumption wedge in total consumption utility, which would further reinforce the tendency for workers to marry up rather than down, potentially strengthening the model's main mechanism.

5 | Model Calibration, Estimation, and Solution

In this section, we recover the model parameters and solve for the model equilibrium variable values in four steps. First, we calibrate a set of conventionally used parameters from the literature. Second, we estimate the marriage-market parameters. Third, we solve for all unobserved internal model variables. Fourth, we estimate the allocation cost components based on the above solutions. Our method combines calibration, log-linearization, and a contraction algorithm.

5.1 | Calibration of Fixed Parameters

In the first step, we calibrate a set of conventionally used fixed parameters based on the related literature. Table 4 summarizes all externally calibrated parameters used in the model. 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

TABLE 4 | Summary of external calibration.

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)

Note: This table summarizes all externally calibrated parameters from literature. β equals 0.77, reflecting the share of final goods consumption in total family consumption, based on data from the Urban Household Survey. ϵ equals 1.5, following Tombe and Zhu (2019). The household consumption economies-of-scale parameter χ equals 0.7 based on Greenwood et al. (2016) and OECD (2013). η equals 0.34, using the relative rural-to-urban housing rent from the 2010 China Population Census. σ equals 4, as shown recently in Bils et al. (2024). We also check for the robustness of these parameters.

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).

5.2 | Estimation of the Marriage-Market Parameters

In the second step, after calibrating the fixed parameters, we estimate the marriage-market parameters using the Generalized Method of Moments (GMM). We have four sets of parameters to pin down: the shape parameter of the marriage-preference shock σ_ξ; the overall deterministic marriage value $\tilde{\mu}_j^{ge}$, the match value with a specific type $\mu^{ge}(e')$; and marriage transfer $\delta_j^{ge}(e')$. Similar to the approach in Mao and Wen (2025), we first log-linearize Equations (9) and (10), and then subtract (9) by (10) to have:

$$\ln\left[P_j^{ge}(e')\right] - \ln\left[P_j^{ge}(\varnothing)\right] = \frac{1}{\sigma_\xi}\left[\tilde{\mu}_j^{ge} + \mu^{ge}(e') + \delta_j^{ge}(e') + \ln\left(\frac{W_j^{ge} + W_j^{g'e'}}{W_j^{ge}(1+\chi)}\right)\right], \tag{17}$$

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 the estimated moments. We then use the GMM to match them and estimate our target parameters.

By leveraging variations across local marriage markets across cities, the Choo and Siow (2006) type of marriage-matching models can be separately identified. The intuition behind the identification strategy stems from the three components of utility from marriage. (1) A location-specific value of marriage $\tilde{\mu}_j^{ge}$ captures the overall surplus from marriage relative to remaining single for each worker type in each location. This term is identified by the overall singlehood rate for each worker type in each location. It captures the overall attractiveness of being married in location j, which helps match cross-city variation in marriage rates. (2) A type-specific match value $\mu^{ge}(e')$ denotes the match value for a specific spouse pair (e, e'), which is constant across locations. It can be identified using the national-level spouse match shares across different types. (3) An equilibrium transfer $\delta_j^{ge}(e')$ represents the location-specific marriage-market transfer for each match pair (e, e') in location j and can be identified from the match shares of different spouse types across locations. It is endogenously determined to clear local marriage markets, which are matched to assortative matching patterns 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, leading to an overidentified GMM system.

Results of the Marriage-Market Estimation. Table 5 reports the estimation results for the type-specific match values $\mu^{ge}(e')$. We normalize the match value of being single to be zero. Such type-specific match values reflect social norms in the marriage market, potentially in both marital preferences, such that females or males prefer partners with higher or lower education, and marriage-market frictions, such that females or males have different probabilities to interact with partners with higher or lower education. The essence of these estimates lies in the *relative* differences between genders in Table 5, rather than their absolute values, providing evidence for social norms in marital matching. 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. Marriage to someone with a different level of education results in a relative loss of utility. However, there is a significant gender asymmetry in preferences. Males are more willing, or more likely, to marry down in education, while females are more willing, or more likely, to marry up. Specifically, for males, the utility loss from marrying up is substantial, whereas for females, this loss is much smaller across all skill levels. Again, these *relative* differences between genders, not their absolute values, show the asymmetric norm in marital matching. More details of the marriage matching estimation are provided in Online Appendix B.4.

Model Fit of the Marriage-Market Estimation. Since our GMM system is overidentified, we validate the model fit by

TABLE 5 | Nonpecuniary marital return by own and spouse types.

(a) Male value				**(b) Female value**			
Male type	**Wife type**			**Female type**	**Husband type**		
	l-skill	**m-skill**	**h-skill**		**l-skill**	**m-skill**	**h-skill**
l-skill	3.312	−0.672	−3.589	l-skill	5.253	2.373	−0.277
m-skill	2.615	2.654	0.106	m-skill	2.707	3.850	2.280
h-skill	0.651	1.770	3.175	h-skill	−0.101	1.411	3.794

Note: This table presents the estimation results for the type-specific match values $\mu^{ge}(e')$. We normalize the value of being single to be zero. 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.

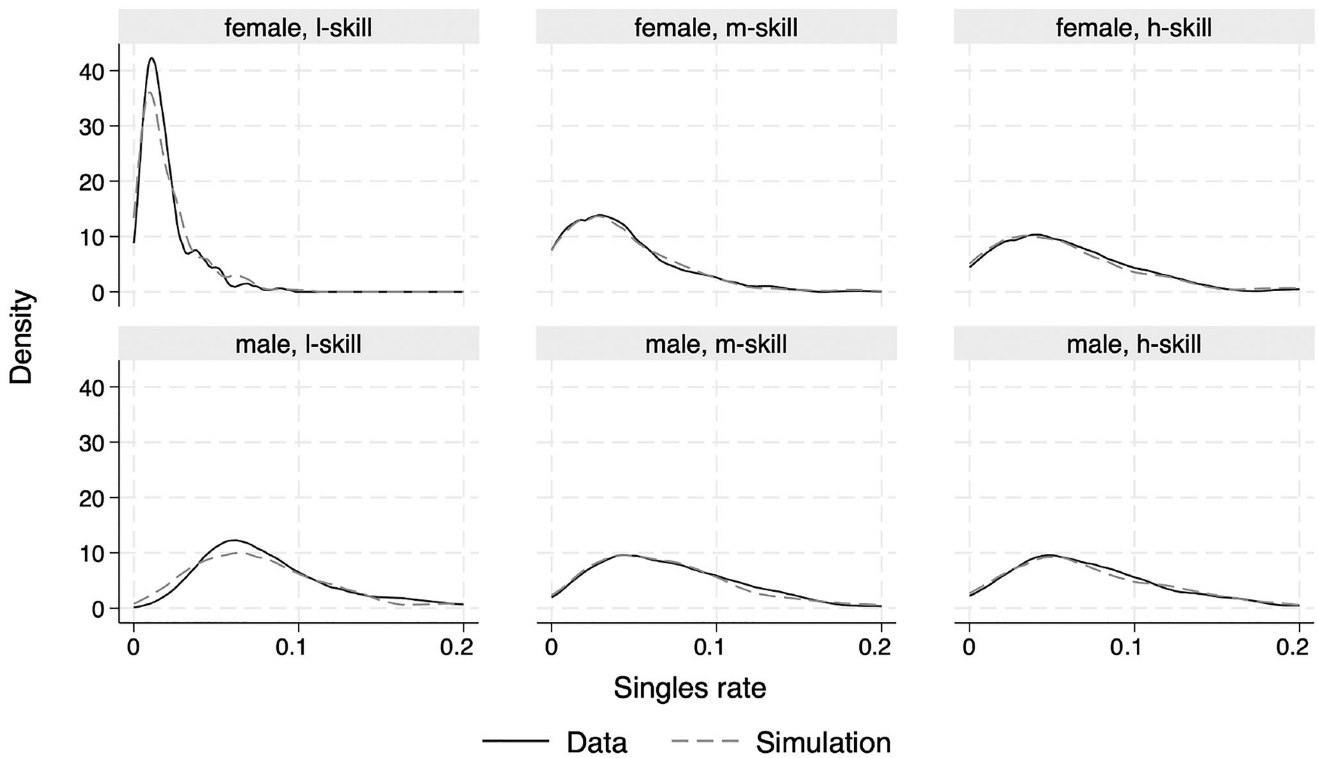


FIGURE 5 | Model fit of the city-level singles rate.
Notes: This figure plots the density of the city-level singles rate for each gender and skill. Solid lines are the data, and dashed lines are simulated results. The estimated model also shows that marital utility is an important component of workers' total utility, accounting for about 27% of an average worker's total utility.

examining the distributions of city-level singles rates for each skill group and gender in Figure 5. The estimated marriage-preference parameters yield a consistent model fit to 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. Online Appendix Figures B2 to B5 further validate the model by comparing the model-simulated match shares $(\ln[P_j^{ge}(e')] - \ln[P_j^{ge}(\varnothing)])$ and those in the data for each combination of male and female types. We can closely fit these matching outcomes as well. The estimated model also shows that marital utility is an important component of workers' total utility, accounting for about 27% of an average worker's total utility.

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 the estimated parameters in above two steps, we can calculate all unobserved variables: productivities $\{A^l_{jk}, A^m_{jk}, A^h_{jk}\}$, compounded allocation costs ($\tau^{ge}_{i,jk}$), 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^h_{jk} and A^m_{jk} as a function of A^l_{jk} using the first-order conditions

$$A^h_{jk} = A^l_{jk}(H^h_{jk}/H^l_{jk})^{1/(\sigma_k-1)}(w^h_{jk}/w^l_{jk})^{\sigma_k/(\sigma_k-1)}$$

$$A^m_{jk} = A^l_{jk}(H^m_{jk}/H^l_{jk})^{1/(\sigma_k-1)}(w^m_{jk}/w^l_{jk})^{\sigma_k/(\sigma_k-1)}.$$

Plugging A^h_{jk} and A^m_{jk} into the definition of Y_{jk}, we have

$$Y_{jk} = A^l_{jk}H^l_{jk}\left[\frac{w^h_{jk}H^h_{jk} + w^m_{jk}H^m_{jk} + w^l_{jk}H^l_{jk}}{w^l_{jk}H^l_{jk}}\right]^{\frac{\sigma_k}{\sigma_k-1}} \equiv A^l_{jk}H^l_{jk}(\Xi^l_{jk})^{-\frac{\sigma_k}{\sigma_k-1}},$$

where $\Xi^l_{jk} = \frac{w^l_{jk}H^l_{jk}}{w^h_{jk}H^h_{jk}+w^m_{jk}H^m_{jk}+w^l_{jk}H^l_{jk}}$ is the share of labor income distributed to low-skill workers. We also assume that agricultural productivity equals agricultural wages $A^e_{jr} = w_{jr}$, for all $e = \{h, m, l\}$. Intuitively, higher wages or skill shares require higher skill e 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 (4) to solve for the compounded allocation costs between cities and sectors:

$$\Phi^{ge}_i = \frac{(\overline{V}^{ge}_{ir})^{\epsilon}}{\pi^{ge}_{i,ir}} \tag{18}$$

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

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 (3). Specifically, we take the log of both sides of the equation and run a simple OLS regression to decompose the three components.

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

which includes a third-order polynomial in prefecture pair distance $G(d_{i,j})$, capturing standard migration frictions related to geographic separation, which is matched to migration flows across location pairs with different distances; a set of gender-education-sector fixed effects $\overline{\tau}^{ge}_k$, capturing average relative barriers to working in sector k for workers of type (g, e), which is matched to aggregate sectoral employment shares; and a set of location-pair gender-education-sector residuals $\varepsilon^{ge}_{i,jk}$, capturing destination-sector-specific heterogeneity, such as local labor market conditions, hiring frictions, networks, and amenities, which is matched to spatial variations in sectoral sorting patterns by gender and education. We emphasize that the sectoral allocation cost $\overline{\tau}^{ge}_k$ reflects all the national average gender- and education-specific allocation costs for sector k, and the location-pair specific spatial and sectoral allocation costs $\varepsilon^{ge}_{i,jk}$ reflects all the residual gender- and education-specific allocation costs for sector k between origin city i and destination j. The estimation results are summarized in Tables 6 and 7 for $\overline{\tau}^{ge}_k$ and $\varepsilon^{ge}_{i,jk}$, respectively.

Table 6 summarizes the relative sectoral allocation cost $\overline{\tau}^{ge}_k$ 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 nonagricultural 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 than for males. 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 demographic 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 $\varepsilon^{ge}_{i,jk}$ 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, 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 of assigning

TABLE 6 | Relative sectoral allocation costs by gender and skill.

	Male			Female		
$\bar{\tau}_k^{ge}$	**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

Note: This table summarizes the relative sectoral allocation cost by gender and skill ($\bar{\tau}_k^{ge}$), estimated from Equation (3) with our 2015 Census data for the model. The sectoral allocation cost of high-skill females in the service sector is normalized to 0 for comparison.

TABLE 7 | Relative spatial sectoral allocation costs by gender and skill.

	Male			Female		
Average $\varepsilon_{i,jk}^{ge}$	**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

Note: This table summarizes the relative locational allocation cost by gender and skill (average $\varepsilon_{i,jk}^{ge}$), estimated from Equation (3) 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.

higher-skilled workers to more developed cities is notably lower for female workers. This is consistent with Ager et al. (2026), who argue that gender-biased technological change alleviated allocation inefficiencies associated with intersectoral mobility costs, thereby improving women's economic status relative to men. 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 demographic changes in the gender spatial employment gap from Section 3.1 are likely reflected mainly in changes in these relative spatial allocation costs. More details on the spatial allocation costs are provided in Online Appendix B.5.

5.5 | Summary of Internal Estimation and Model Solution

Finally, to maintain clear tracking of the estimation and solution procedures, Table 8 provides a summary of the internally estimated parameters and solved variables. Each panel in the table maps to a corresponding section with the identification sources. Panel A is from the marriage-market matching in Section 5.2, Panel B from the unobserved model equilibrium variables in Section 5.3, and Panel C from the allocation cost decomposition in Section 5.4.

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 demographic changes on both national and regional singles rates and decompose their contributions into three key components: education, sectoral allocation costs, and spatial-sectoral allocation costs. We then examine how continued gender-specific spatial demographic changes would further influence marriage rates in China in the future.

6.1 | The Effects of Gender-Specific Spatial Demographic Changes

We begin by investigating the effects of gender-specific spatial demographic changes on national and regional singles rates. In addition, we quantify the contribution of each component of these demographic changes to the observed singles rates at both the national and regional levels. To achieve this, we use the estimated model and remove gender-specificity by equalizing the corresponding gender-specific parameters between males and females and computing the resulting counterfactual equilibria. In this way, we capture the dramatic gender-specific changes in education, migration, and sectoral employment observed in earlier empirical facts, although not necessarily mapping a specific time period, to more fundamentally understand the role of these shifters in shaping the marriage-market equilibrium across space. 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.

Table 9, Panel A, reports the overall effects of gender-specific spatial demographic changes 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-SDCs," shows the counterfactual in

TABLE 8 | Summary of internal estimation and model solution.

Notation	Description	Identification source
Panel A: Estimated parameters in marriage matching		
$\tilde{\mu}_j^{ge}$	Overall marriage value in j	Overall singlehood rate in j
$\mu^{ge}(e')$	Type-specific matching value	National-level type-specific matching rate
$\delta_j^{ge}(e')$	Local marriage equilibrium transfer	Match shares of spouse types across locations
Panel B: Recovered variables in model equilibrium		
A_{jk}^e	Location-sector-skill-specific productivity	Corresponding wages and worker shares
S_{jr}	Rural floor space in j	Rural housing expense and rent prices
S_{ju}	Urban floor space in j	Urban housing expense and rent prices
ϕ_j	Urban construction intensity	Urban floor space and land supply
$\tau_{i,jk}^{ge}$	Compounded allocation cost	Indirect utility and migration flow matrix
Panel C: Estimated parameters in allocation cost		
$G(d_{i,j})$	Distance effect in allocation cost	Correlation between distance and allocation cost
$\bar{\tau}_k^{ge}$	Sector-specific allocation cost	Sectoral average allocation cost
$\varepsilon_{i,jk}^{ge}$	Location-sector-specific allocation cost	Structural residual of total allocation cost

Note: This table provides a summary of the internally estimated parameters and solved variables. Each panel in the table maps to a corresponding section with the identification sources. Panel A is from the marriage-market matching in Section 5.2, Panel B from the unobserved model equilibrium variables in Section 5.3, and Panel C from the allocation cost decomposition in Section 5.4.

TABLE 9 | The effects of gender-specific spatial demographic changes on singles rates.

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-SDCs	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%

Note: 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-SDCs" shows the counterfactual in which all gender-specificity in education, sectoral, and spatial-sectoral allocation costs are all averaged out. The regions are defined by the prefecture's GDP per capita quartile. In Panel B, we sequentially decompose the percentage change in the singles rates by adding the changes for each component. The contributions of these three components sum to 100%.

which all gender-specificity in the three components is 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 demographic changes leads to a substantial reduction in the national singles rate for both females and males, by 29.19% and 11.75%, respectively. Second, these effects are particularly pronounced in more developed cities: the top quartile experiences a 38.90% reduction in the female singles rate and a 26.39% reduction for males.[15] These results underscore the crucial role of gender-specific spatial demographic changes in shaping local marriage markets, contributing to both national and regional marriage mismatches and elevated singles rates.

Panel B of Table 9 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

TABLE 10 | The effects of gender-specific SDCs 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-SDCs	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%

Note: 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-SDCs" shows the counterfactual in which all gender-specificity in education, sectoral, and spatial-sectoral allocation costs are all averaged out.

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. [16]

We further explore the role of gender-specific spatial demographic changes by analyzing singles rates across skill groups in Table 10. It again reports the singles rates and the percent changes between the baseline and the counterfactual scenario in which gender-specificity in spatial demographic changes is removed. The results align with the narrative of spatial mismatch in the marriage market, driven by the race between gender-specific demographic 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.

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 Online 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 demographic changes continue to follow the observed trends documented in Section 3.1. Specifically, we project a counterfactual scenario for 2030 based on the 2015 equilibrium in our model and extrapolate the 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 aged 30 in 2030 (i.e., those born in 2000) holding a bachelor's degree or higher. 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.[17]

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, and extending it forward 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 demographic 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 top- and bottom-quartile cities. We hold constant the costs for moving to other industries and to cities in the middle two quartiles. Additional technical details of this projection are provided in Online Appendix C.2.

Table 11 presents the results and their decomposition, while Figure 6 visualizes the key national and group-specific singles rates. Continued gender-specific spatial demographic changes would substantially raise the national singles rate. Specifically, the national singles rate for females (males) is projected to increase by 58.67% (23.62%). Moreover, due to spatial mismatch, the impact is especially pronounced for males in the least developed quartile of cities 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 most significant role, accounting for about 60%, while the continued spatial-sectoral shift also contributes significantly, accounting for about 40%. These results are robust to alternative specifications for projected trends in education and national/spatial-sectoral changes, as discussed in Online Appendix C.2.[18]

One point worth noting in the projection is that we abstract away the potential effect of the one-child policy (OCP) relaxation since 2016 in China, which may increase the marital surplus and attenuate the rise of the singles rate in the future. For a bound exercise, we instead calibrate an exogenous marriage-surplus shift that can increase the national marriage rate for women by 1.02% compared to the baseline, matching the effect of OCP removal found by Chen and Choo (2023). We then impose this marriage-surplus increase from the OCP relaxation into the 2030 projection exercise; thus, this is done in a nonstructural way. We find that the projected national singles rate for women in 2030 increases by 30.2% compared to the 58.7% that we projected previously when OCP relaxation was abstracted away. Given that Chen and Choo (2023) consider a single nationwide matching market in 2010 without spatial segregation or mismatch, and that the spatial-sectoral divergence in 2010 was less substantial

TABLE 11 | The effects of continuing gender-specific spatial demographic 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)	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%

Note: 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's GDP per capita quartile. In Panel B, we sequentially decompose the percentage change in the singles rate by adding the changes for each component. The contributions of these three components sum to 100%.

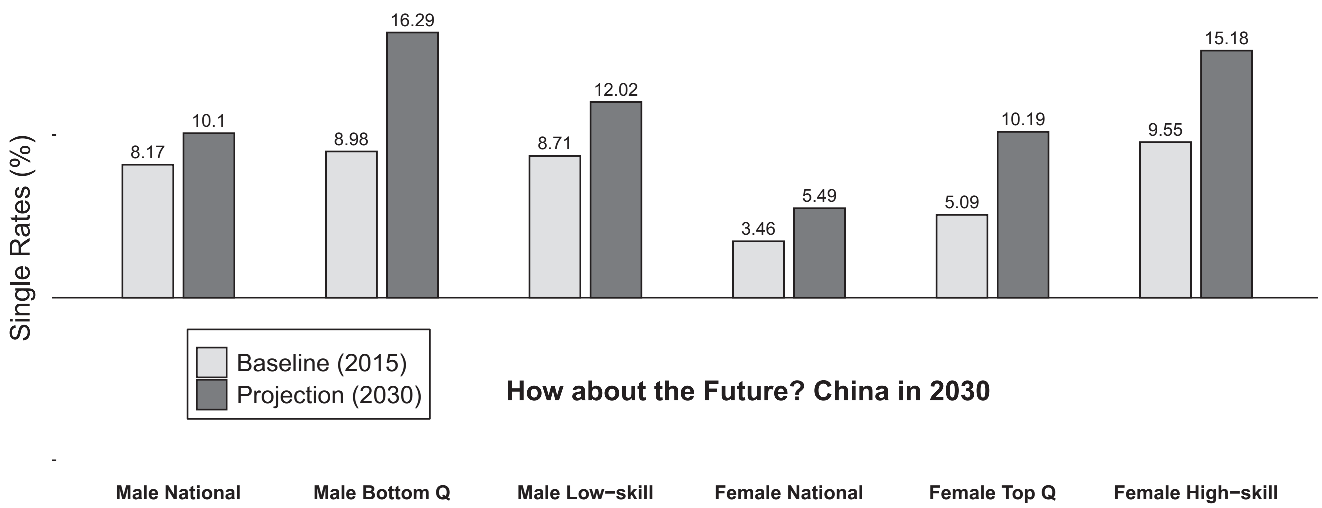


FIGURE 6 | How about the future? China in 2030.

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 and 2015. "Bottom Q" and "Top Q" represent prefecture quartiles by GDP per capita.

than in the projected year 2030, the effect of the higher expected marital surplus from the OCP removal on increasing marriage is likely to be smaller, especially for low-skilled men in less developed regions and high-skilled women in developed regions, for whom we project the highest increase in singles rate given the spatial mismatch. Therefore, we think the above simulated 30.2% increase in the national singles rate for women in 2030 would likely represent a lower bound, whereas the original 58.7% increase serves as an upper bound. In any case, this range of the singlehood increase is substantial.

The 2030 projection in Table 11 raises essential concerns for economists and policymakers. Even under a more conservative assumption—where the speed of spatial demographic changes is halved—the projected increase in singles rates remains substantial, as shown in Table C9 of Online Appendix C.2. Policymakers in many countries, including China, should pay closer attention to declining marriage rates and actively pursue family policies to encourage marriage.

6.3 | Counterfactual Policy of Marriage Subsidies

To address declining marriage and fertility rates, economic incentives are widely adopted in East Asian and Nordic countries. Governments in China, South Korea, and Japan have introduced various measures, including housing subsidies for newlyweds, childbirth allowances, tax breaks for families, and childcare support, to ease the financial burdens associated with family formation. Despite differences in welfare regimes, these policies

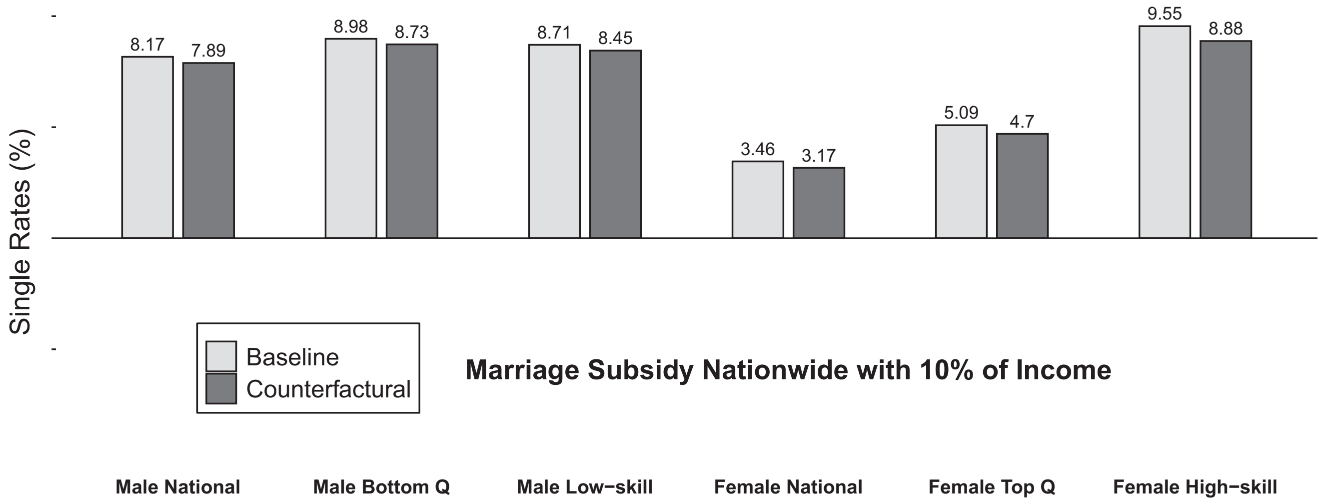


FIGURE 7 | Marriage subsidy nationwide with 10% of income.
Notes: This figure plots the singles rate for each gender under different scenarios. "Baseline" presents the equilibrium outcomes in the real world for 2015. "Counterfactual" shows the simulation in which a marriage subsidy of 10% of married couples' lifetime income is provided nationwide. "Bottom Q" and "Top Q" represent prefecture quartiles by GDP per capita.

share a common goal: to alter the economic calculus surrounding marriage and childbearing. Although such incentives may not directly alter deep-seated social norms or mate preferences, they can indirectly influence matching behavior by mitigating demographic barriers and shifting the perceived costs and benefits of family life. 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 equal to 10% of married couples' lifetime income, which is substantially higher than 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 up to $8000 for newly married couples. The amount of the nationwide marriage subsidy in our counterfactual would cost about 3.5% of the national GDP in our model. However, such a marriage subsidy appears relatively ineffective, despite its substantive scale.

Figure 7 shows the results of a 10% marriage subsidy 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 (8.17) percentage points to 3.17 (7.89) percentage points, with a corresponding decrease of 8.3% (3.4%). The effects are even smaller if we focus on females in the top quartile of the most developed cities and those with high skills, or males in the bottom quartile of the least developed cities and those with low skills. In other words, such a substantial marriage subsidy could only incentivize fewer than 1 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 gender-specific spatial demographic changes and is therefore largely ineffective.

We then extend this to a nationwide marriage subsidy equal to different levels of married couples' lifetime income, ranging from 5% to 100%. Figure 8 further plots the singles rate for males and females under different levels of national marriage subsidies, ranging from 0% (baseline) to 100% of a married couple's lifetime income. The slope of the relationship is nearly flat, indicating a very limited policy effect as the subsidy increases. Even when the subsidy doubles a couple's lifetime income, the male singles rate declines only modestly, from 8 percentage points to 6 percentage points. Overall, the national marriage subsidy appears costly yet 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 reasons discussed above. Details of these counterfactual simulations are provided in Online Appendix C.4.

6.4 | Counterfactual Policy of Changing Marital Social Norms

Essentially, the observed spatial mismatch in marriage results from a race between gender-specific spatial demographic changes and the persistent social norms in the marriage market. Alternatively, the government could influence social norms to mitigate gender differences in marrying up and marrying down. This group of policies could be categorized into "talk" or "walk" efforts. In terms of the "talk" effort to shape marital preferences, the government could verbally propagandize for females marrying down or males marrying up. However, the "talk" effort could hardly create any real effects, as persistent social norms

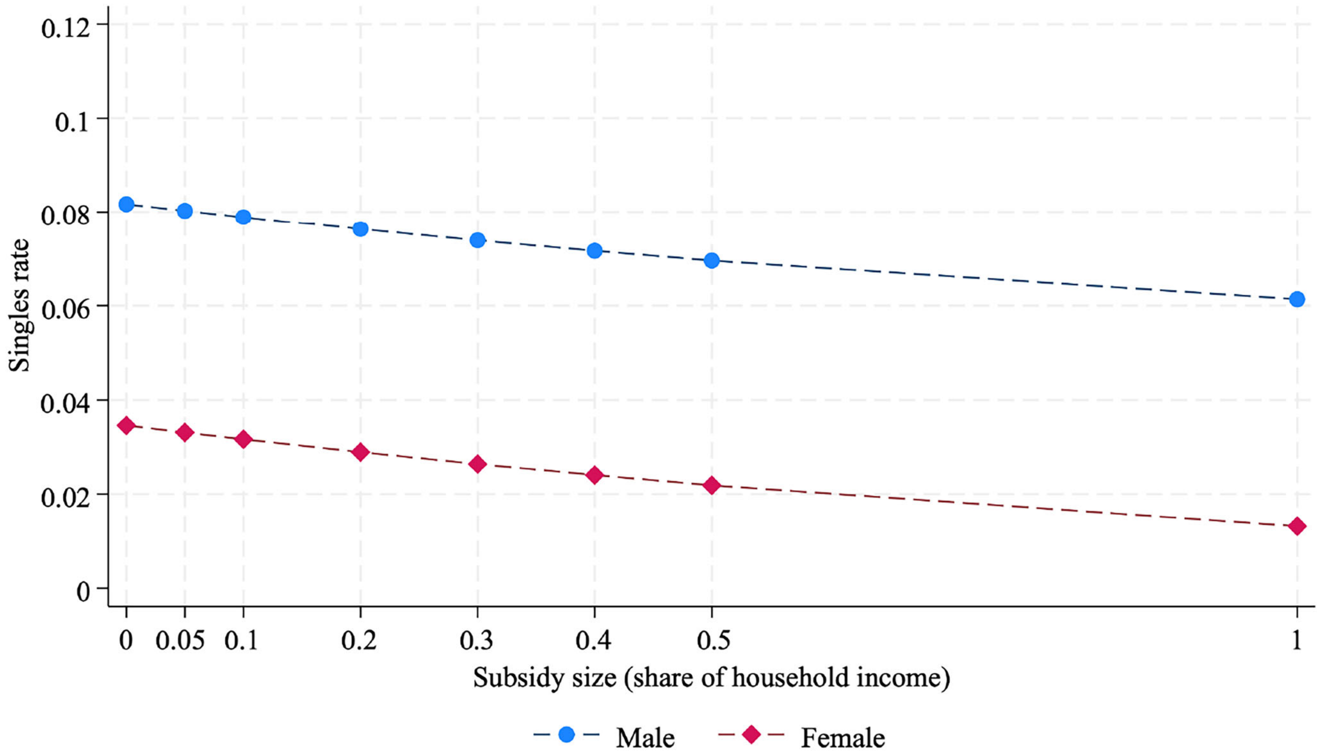


FIGURE 8 | Singles rates under various nationwide marriage subsidies.
Notes: This figure plots the singles rate for males and females under different levels of national marriage subsidies, ranging from 0% (baseline) to 100% of a married couple's lifetime income.

TABLE 12 | The effects of changing marital social norms.

Singles rate	**Male**			**Female**		
by groups	**National**	**Least dev.**	**Low skill**	**National**	**Most dev.**	**High skill**
Baseline	8.17%	8.98%	8.71%	3.46%	5.09%	9.55%
New norms	7.88%	8.29%	6.18%	3.16%	4.30%	5.46%
% Changes	−3.55%	−7.68%	−29.05%	−8.67%	−15.52%	−42.83%

Note: This table lists the singles rate for each gender under different scenarios. "Baseline" presents the equilibrium outcomes in the real world for 2015. "New norms" shows the counterfactual in which marital social norms are equalized between males and females within each educational group. The regions are defined by the prefecture's GDP per capita quartile.

are potentially formed due to persistent discrimination against females. Females are urged to pair with males of higher SES to mitigate these disadvantages. Moreover, the deeply rooted culture of gender-biased division of household responsibilities is difficult to change through propaganda alone.

In terms of "walk" effort to overcome marriage-market frictions, the government could design and implement many other policies that are more gender-neutral and help disadvantaged groups in the marriage market, so that social norms may eventually evolve toward more gender-balanced marital matching, 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.

Table 12 presents the results in which marital social norms are equalized between males and females within each educational group. Specifically, we equalize the nonpecuniary marital return for males in the left panel with the corresponding value for females in the right panel in Table 5, that is, $\hat{\mu}^{e,male}(e') = \hat{\mu}^{e,female}(e') = (\mu^{e,male}(e') + \mu^{e,female}(e'))/2$. For instance, a type e male (female) would have the same nonpecuniary marital return while matching a type e' female (male). The results show that changing marital social norms is quite effective in shaping SES sorting, as reflected in the substantial decline in the singles rates of low-skill males and high-skill females. The effects are comparable to those of the decomposed educational shifters in Table 9, as they address the same SES sorting issue. However, such a change in marital social norms could not resolve fundamental spatial gender imbalances driven by gender-specific spatial demographic changes.

6.5 | Discussions on Policies that Reduce Spatial Gender Imbalances

To mitigate the continuing decline in the national marriage rate, another intervention is to reduce the gender-specificity of spatial demographic changes. Our decomposition points to potentially more effective policies that can directly target spatial gender imbalances to subsidize migration by specific gender and skill groups, or to balance sectoral growth across regions. For instance, the government could subsidize the migration of high-skilled males into more developed cities or increase barriers to the migration of high-skilled females into those cities. Symmetrically, the government could subsidize the return of high-skilled females to less developed cities, or impose tax penalties on high-skilled males in those cities. If the policies are well-executed, this class of policies could largely move the singles rate toward the case of no gender-specificity in spatial demographic changes, as in Table 9.

However, such policies raise concerns about gender equity and economic or political feasibility, especially when the subsidies or penalties are substantial. Essentially, if not carefully designed or executed, such policies may eventually penalize women for their educational achievements and efforts to move into higher-paying jobs in more developed cities. Any gender-biased policy to address these issues needs to be carefully designed and implemented for feasibility. 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. To summarize, while marriage and fertility rates continue to decline across countries, designing practical, feasible mitigation policies poses a substantial challenge.

7 | Conclusion

We investigate how the interaction between demographic changes and spatial sorting shapes local marriage markets and national marriage rates in China. Empirically, we document joint patterns of gender-specific spatial demographic changes, 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 quantitative spatial equilibrium model at the prefecture level that incorporates migration, multisector and multiskill production, and endogenous local marriage markets. Our quantitative analysis finds that these gender-specific spatial changes contribute to roughly 30% of the change in 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 unless they address the skewed spatial distribution by gender and skill, shaped by gender-specific spatial demographic changes. In contrast, policies that can directly target spatial gender imbalance, such as subsidizing gender- and skill-based migration or balancing sectoral growth across regions, are potentially more effective but also challenging in terms of economic or political feasibility and raising gender inequality concerns.

Looking ahead, the spatial mismatch in the marriage market driven by ongoing gendered demographic 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 demographic imbalances in education, labor, and geography.

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Data Availability Statement

The microdata that support the findings of this study are available from the National Bureau of Statistics of China. Restrictions apply to the availability of these data, which were used under license for this study. Researchers interested in the data can follow the official procedure to obtain authorized access from NBS (http://www.stats.gov.cn/english/) with the permission of the National Bureau of Statistics of China. The files for replicating the empirical and quantitative results are available at the OpenICPSR Project (https://doi.org/10.3886/E250797V1).

Endnotes

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 2025).

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.

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 may also include the fertility subsidy and other preferential policies for married couples relative to singles.

The literature also includes spatial sorting and inequality (Baum-Snow and Pavan 2012; Diamond and Gaubert 2022; Ma and Tang 2019; Hong 2025), trade openness and internal migration (Fan 2019; Ma and Xican 2020), structural change and internal migration (Hao et al. 2020; Garriga et al. 2023), and innovation and internal migration (Guo et al. 2025).

Rossi and Xiao (2026) estimate a national-level Choo and Siow (2006) model and document that changes in the supply of educated men and women explain half of the decline in marriage in China between 1999 and 2019. The deterioration of the female-to-male ratio explains an additional 13% for men, and a decrease in marital surplus (the value of marriage) accounts for the remainder.

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 each individual in the Census an industry-level average wage 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 Online Appendix B.1.

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

Table A2 in the Online Appendix provides further insights into sectoral migration of workers with rural Hukou. The values are computed as the proportion of rural Hukou workers employed in manufacturing or services 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 increased from 2000 to 2010 but declined from 2010 to 2015.

The tendency of females to marry up based on education year has been decreasing due to the switch to equal matches. The proportion of females marrying down in education years remains roughly constant over time.

Although wages and housing costs are measured at an annual frequency, the marriage decision in the model reflects a one-time choice based on expected lifetime utilities in a stationary environment, consistent with standard static marriage matching frameworks as in Choo and Siow (2006).

The spatial component $\varepsilon^{ge}_{i,jk}$ may also contain the tightness of migration policies and the costs of amenities between i and jk, both of which could be skill- and gender-specific.

Note that the search friction and search cost are also implicitly (and negatively) incorporated in this term, for which we view as exogenous. They increase the relative value of being voluntarily single in location j by avoiding these costs of the marital search.

Explicitly modeling them would substantially increase model complexity while providing only limited insight into our main mechanism, which operates through gender-specific spatial sorting and marriage-market matching. These extensions would mainly affect the level of marriage incentives rather than the spatial and gender-specific mismatch that is central to our analysis.

We abstract from explicitly modeling land as an input in agricultural production, as our focus is on urban spatial sorting and marriage-market outcomes. Any cross-city variation in agricultural land productivity is captured by the location-specific productivity term A_{jR}.

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 wholly eliminate singlehood by equalizing only gender-specific spatial demographic change parameters.

We find that the major contribution to the role of spatial-sectoral allocation costs ($\varepsilon^{ge}_{i,jk}$) is at the jk-level instead of the ij-level, given that most of the variations in ij should have been captured by the flexible distance function $G(d_{ij})$. In a robustness check in Online Appendix Table C7, we further calculate the ij-fixed effect for each gender-skill in $\varepsilon^{ge}_{i,jk}$ and make these fixed effects all zero, thus removing these residual frictions at the ij-level (left in $\varepsilon^{ge}_{i,jk}$). We find very similar results in the decomposition analysis.

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

In counterfactuals and projections throughout the paper, we consider the case of keeping fundamentals in the marriage-market constant, including marital preference, the assumption of frictionlessness, and the value of singlehood in each location. Empirically, we find that the estimated value of singlehood is higher in locations with lower average allocation costs, though it is not directly correlated with local economic development. As a result, we may underestimate the singles rates when the costs of allocating to service in developed regions further reduce in the projection, even when they are already high in the current projection for 2030.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Data S1