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

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A Supplements to Empirical Analysis

A.1 Dramatic Gender-specific Structural Changes

A.1.1 Gender Sectoral Employment Gap

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

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

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

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

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

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

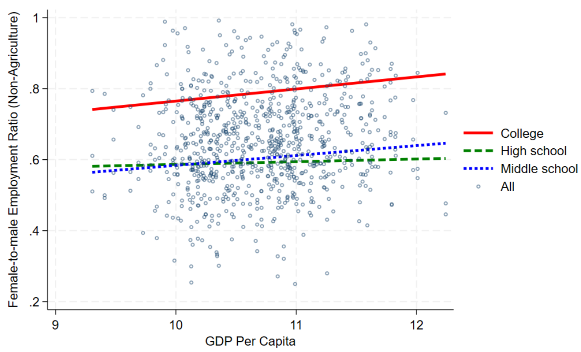
Education	Sector	2000		2005		2010		2015	
		Male	Female	Male	Female	Male	Female	Male	Female
College and Above	Manufacturing	24.69%	17.24%	26.03%	19.61%	37.54%	23.92%	27.68%	14.53%
	Service	46.05%	51.43%	51.23%	52.07%	44.37%	52.27%	54.07%	58.99%
High School	Manufacturing	21.24%	17.39%	26.32%	20.17%	37.32%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

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

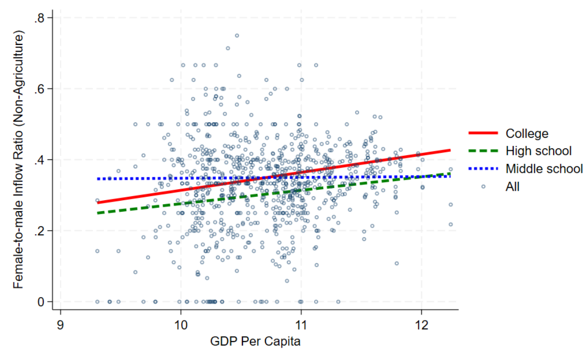
A.1.2 Gender Spatial Employment Gap

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

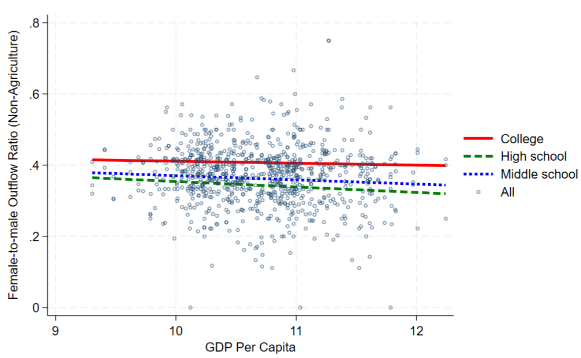
Figure A1: Gender Non-agricultural Employment Gap by Skills



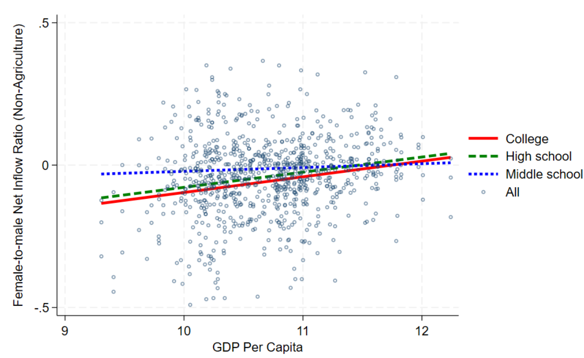
(a) Overall Employment



(b) Migration Inflow



(c) Migration Outflow



(d) Net Migration Flow

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

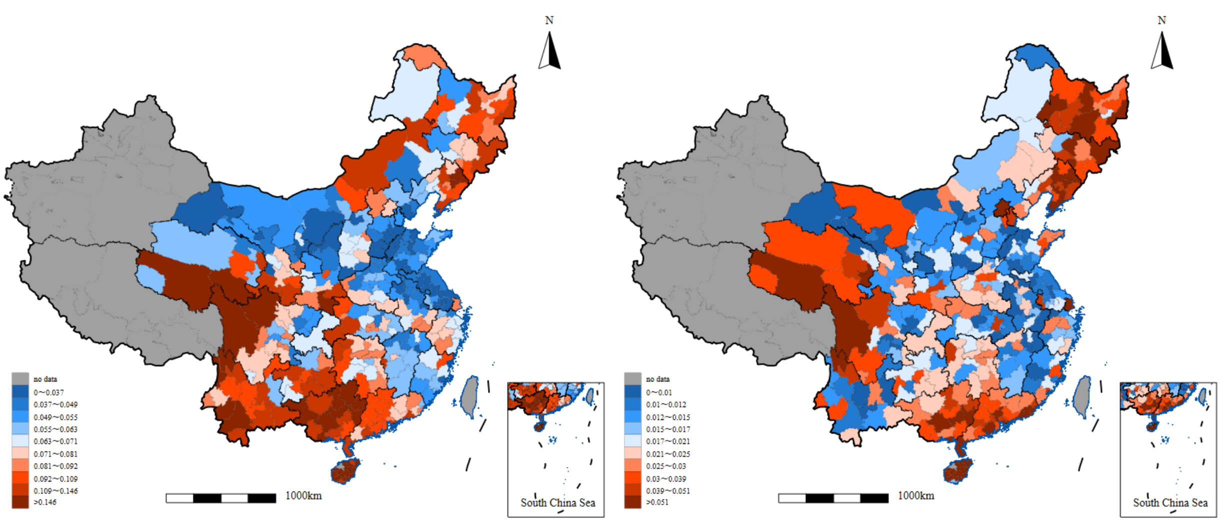
A.2 The Spatial Distributions of Singlehood

A.2.1 Visualization of the Spatial Distribution

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

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

(a) Male (b) Female



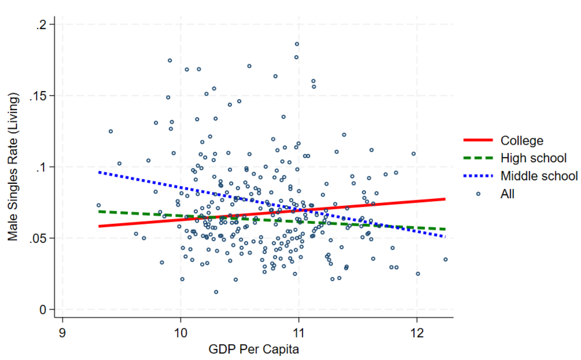
Notes: This figure illustrates the singles rate of males and females aged 30 to 45 across different cities in 2015. Subfigure (a) presents the male singles rate, while subfigure (b) shows the female singles rate. In both panels, cities shaded in red (blue) indicate a higher (lower) singles rate. Data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

A.2.2 Singles Rate by Education Level

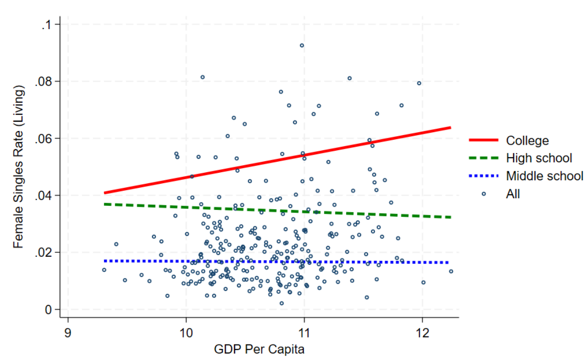
In this section, we also show the relationship between GDP per capita and the singles rate (ages 30 to 45) by education level at the living city level in Figure A3. The red solid line represents the fitted line for college-educated individuals. The green dashed line represents the fitted line for high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

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

(a) Male



(b) Female



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

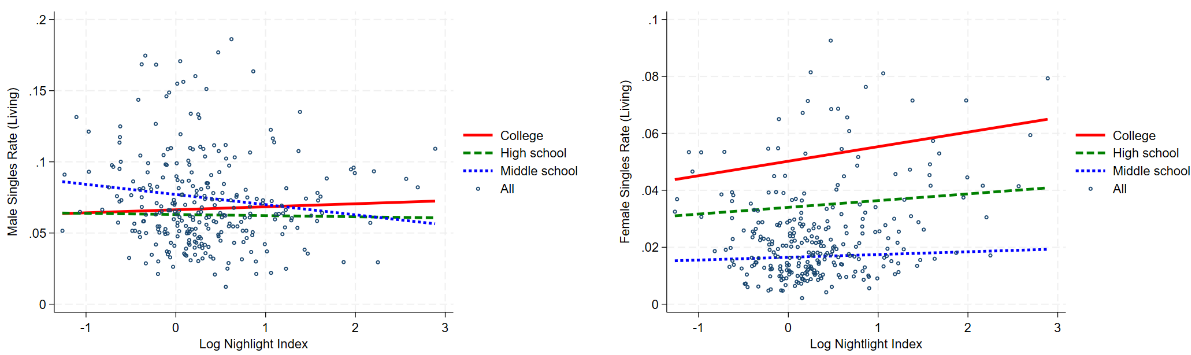
A.2.3 More City Characteristics and the Singles Rate

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

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

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

(a) Male (b) Female

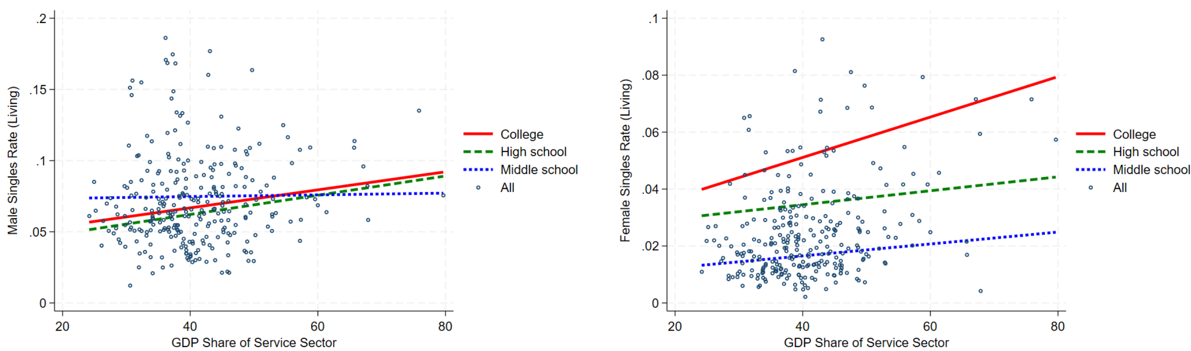


Notes: This figure illustrates the relationship between log nightlight index and the singles rate (aged 30-45) by education level at the living city level. Subfigure (a) presents the results for the male singles rate, while subfigure (b) shows the results for the female singles rate. The red solid line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

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

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

(a) Male (b) Female



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

B Supplements to Model and Estimation

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

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

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

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

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

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

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

Table B1: List of Cities

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

Table B2: List of Cities (Continued)

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

Table B3: List of Cities (Continued)

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

Table B4: List of Cities (Continued)

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

Table B5: List of Cities (Continued)

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

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

B.3 Algorithm for Solving the Model Equilibrium and Counterfactuals

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

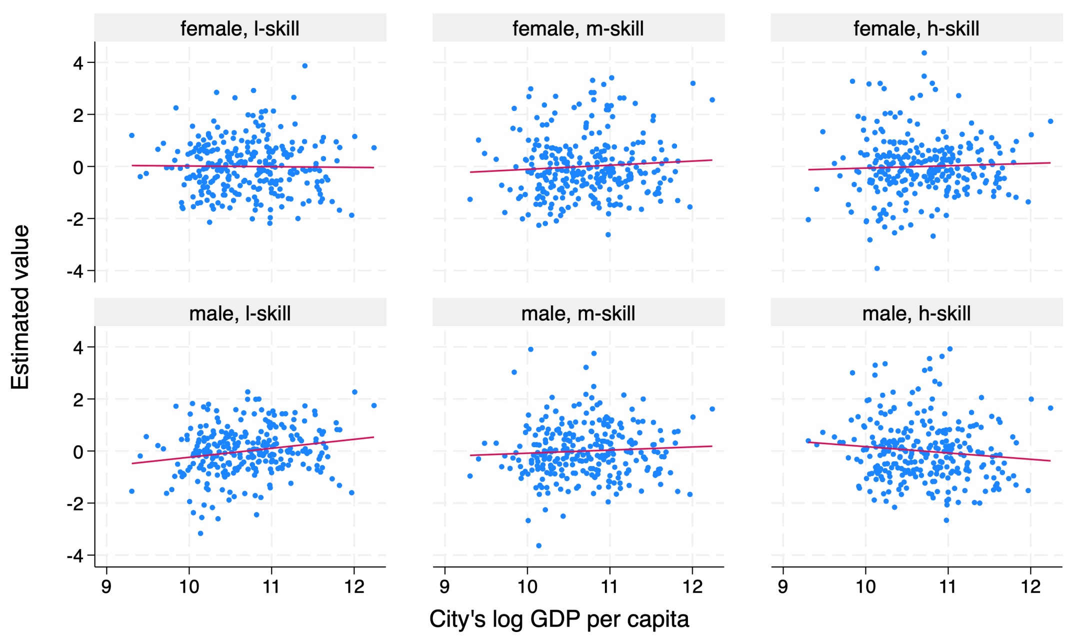
Iteration. At this stage, all endogenous variables have been updated once. We proceed to the next iteration by taking a weighted average of old and new values: $x^1 = (1-\lambda)x^0 + \lambda\hat{x}^0$. This iterative process continues until the difference between x^t and x^{t+1} falls below a convergence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

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

B.4 Details on Marriage Matching Estimation

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

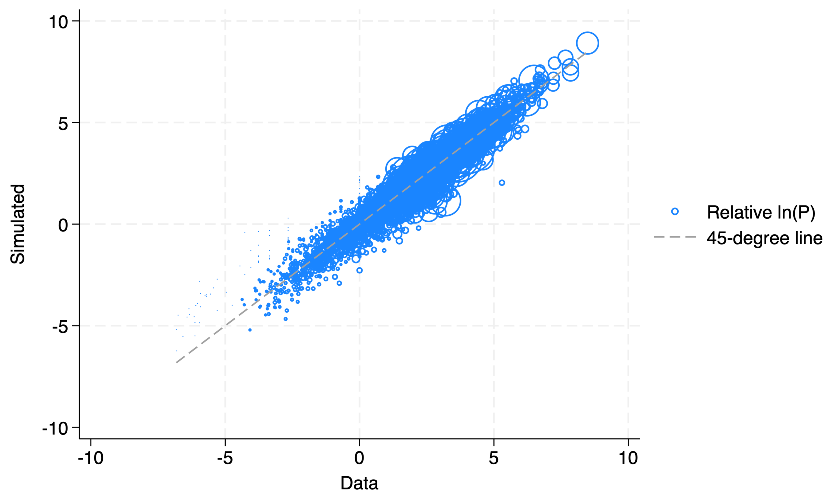
Figure B1: Non-pecuniary value of being married vs. GDP per capita



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

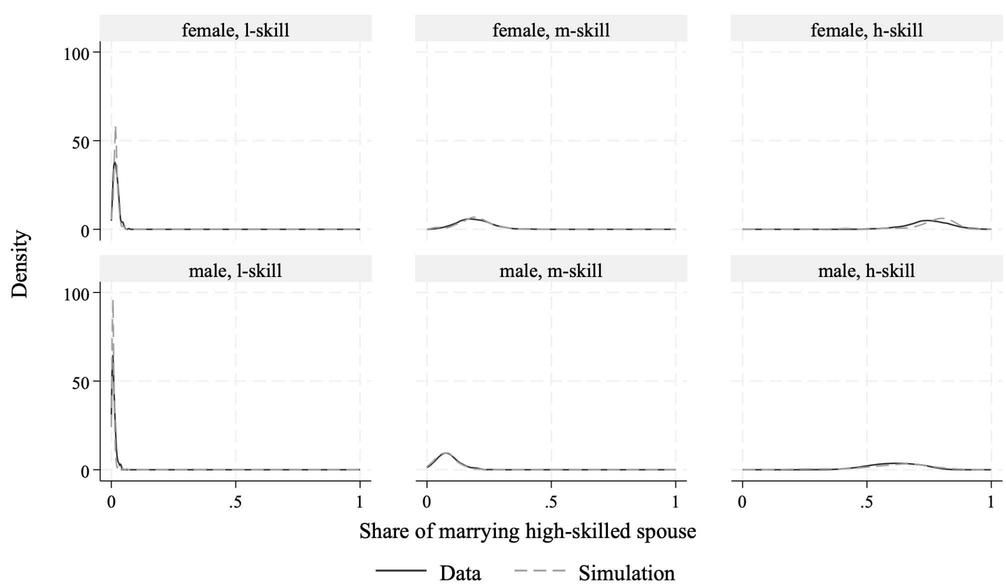
Figure B2 compares the data and the simulated match shares ($\ln[P_j^{ge}(e')] - \ln[P_j^{ge}(\emptyset)]$) of each gender g skill e with spousal types e', relative to the share of being single $\emptyset$. All observations are closely located around the 45-degree line. Figures B3, B4 and B5 further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

Figure B2: Model Fit of the Relative Match Shares



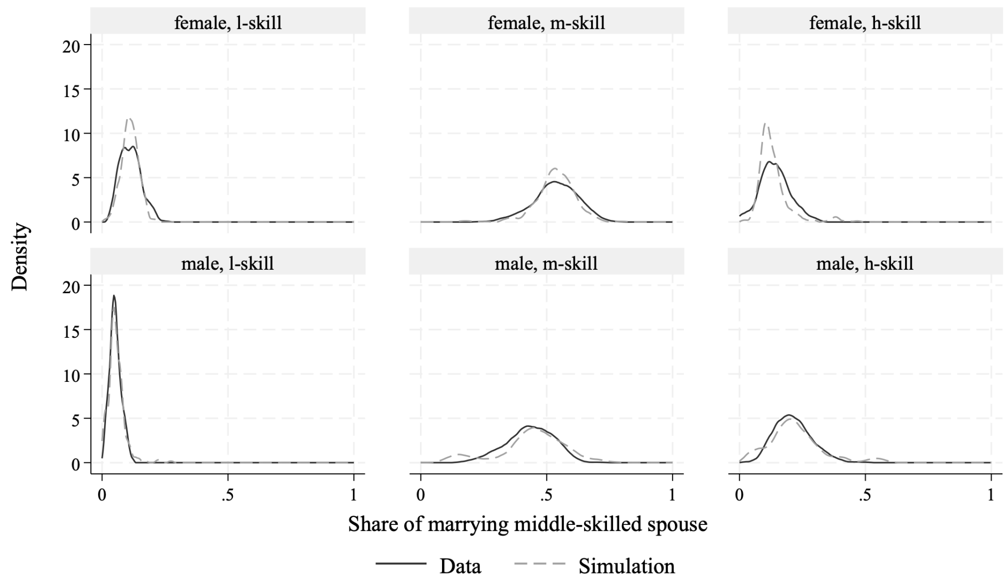
Notes: This figure compares the data and simulated relative match shares ($\ln[P_j^{ge}(e')] - \ln[P_j^{ge}(\emptyset)]$) between each combination of male and female types, including singlehood. The size of each dot is weighted by the population size in each type combination.

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



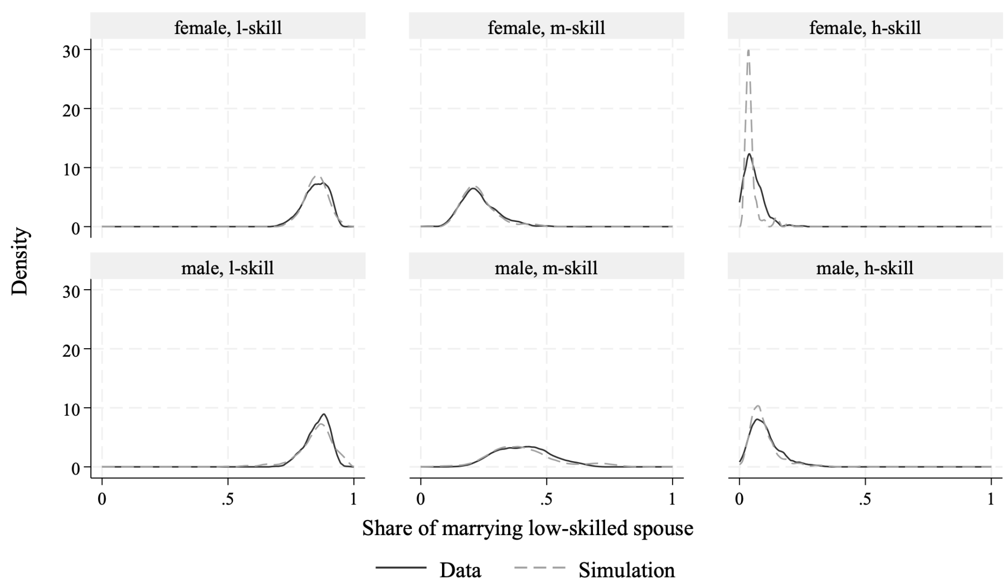
Notes: This figure plots the density of the city-level share of marrying a high-skilled spouse for each gender and own skill. Solid lines are the data, and dashed lines are simulated results.

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



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

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



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

B.5 Estimation on Allocation Costs in the Model

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

Table B6: Relative Spatial × Sectoral Allocation Cost

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

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

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

Table B7: Detailed Relative Spatial Sectoral Allocation Costs

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

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

C Supplements to Quantitative Analysis

C.1 Effects of Gender-specific Spatial Structural Changes

C.1.1 Additional Results on Detailed Effects

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

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

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

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

C.1.2 The Roles of Individual Components of SSCs

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

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

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

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

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

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

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

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

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

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

C.1.3 Decomposition in Alternative Sequences

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

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

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

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

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

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

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

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

C.2.1 Specifications of the SSCs Projections in 2030

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

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

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

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

C.2.2 Alternative Specifications of the SSCs Projections in 2030

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

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

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

Table C7: Continuing Gender-specific SSCs - Alternative Education

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

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

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

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

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

C.3 Effects of Marriage Subsidies

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

Table C9: Detailed Effects of Counterfactual Marriage Subsidies

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

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

C.4 Alternative Marriage Subsidy Policies

C.4.1 Location-specific Marriage Subsidy Policies

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

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

Table C10: Effects of Location-specific Marriage Subsidies

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

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

C.4.2 Education-specific Marriage Subsidy Policies

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

Table C11: Effects of Education-specific Marriage Subsidies

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

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