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Labor Market Dynamics in Urban China and the Role of the State Sector*

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Abstract

This paper studies the effect of state-owned enterprises on the dynamics of the Chinese urban labor market. Using longitudinal monthly panel data, we document very low dynamics in the labor market, especially in the state sector. We develop and calibrate an equilibrium search and matching model with three differences between the state and the non-state sector: labor productivity, labor adjustment cost, and workers' bargaining power. Counterfactual analysis shows that the lack of dynamics is mainly driven by the strong bargaining power of state-sector workers. Eliminating the differences between the two sectors substantially reduces the unemployment rate and long-term unemployment rate.

Keywords: state sector; labor market dynamics; search and matching; China; long-term unemployment.

JEL codes: J64, J45, P23.

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1 Introduction

State-owned enterprises (SOEs) hold the key to understanding various aspects of the Chinese economy, which has become increasingly integrated and influential in the world. In this paper, we study the effect of China's SOEs on its labor market using an equilibrium search and matching framework. Jobs in SOEs are colloquially termed "iron rice bowls," as they tend to pay more and are more secure than non-SOE jobs (see, e.g., Meng, 2012 and Ge and Yang, 2014). However, as we show in this paper, areas with a higher concentration of SOEs, such as China's interior region, are also more likely to have higher levels of unemployment and higher long-term unemployment rates compared to the coastal area with fewer SOEs. This observation may be best understood in a general equilibrium framework, as the higher wages in SOEs may hinder job creation, thereby reducing the overall dynamics in the labor market and raising unemployment. This is precisely what we find in this paper using high-frequency monthly labor force data.

Our study adds to the large literature on China's SOEs (e.g., Brandt and Zhu, 2001, Hsieh and Song, 2015, and Berkowitz et al., 2017). Specifically, we complement the macro models of SOEs, which emphasize capital market distortions (Song et al., 2011, Brandt et al., 2013) and usually ignore the labor market or assume it to be competitive and frictionless. Our study fills this void by developing and calibrating a two-sector model incorporating key differences between the state and non-state sectors. The study of labor market impacts on the state sector is essential for properly formulating further SOE reform policies. Our empirical results suggest that it is important to lower the bargaining power of SOE workers to improve overall labor market efficiency. This is consistent with some recent major government initiatives that call for curtailing wage growth in the state sector.[1]

[1] The State Council issued a directive on reforming the wage-setting mechanism of SOEs in May 2018, calling for the alignment of SOE wages with market-prevailing levels and warning against wage increases unaccompanied by SOE productivity growth.

We first report new stylized facts on Chinese urban labor market dynamics using longitudinally matched monthly panel data from the Urban Household Survey (UHS) during 2003–2006, a period when labor market structural reforms were completed and mass layoffs at SOEs stopped (Feng et al., 2017). The UHS collects high-frequency monthly labor force data that are representative of urban China, and to the best of our knowledge we are the first to have access to the internal monthly UHS data. We show that the urban labor market is characterized by very low dynamics and a high prevalence of long-term unemployment. This applies to all age/education groups and regions, suggesting that it is a generic feature of the Chinese labor market. When we divide employment into two distinct statuses, state and non-state, we find much smaller flows into and out of the state sector compared with the non-state sector. These empirical regularities call for a deeper understanding of the role SOEs play in the inefficiencies of the overall labor market.

To that end, we extend the Diamond-Mortensen-Pissarides equilibrium search and matching framework by incorporating two different sectors: state and non-state. Building on the existing literature, we explicitly model three differences between SOEs and non-SOEs. First, the labor productivity levels of SOEs may be different from those of non-SOEs.[2] Second, SOEs are unable to lay off workers even when workers become unproductive.[3] Third, the bargaining power of workers is allowed to differ between the two sectors.[4] State sector and non-state sector firms maximize profits subject to these institutional differences, and they

[2]Productivity differences may arise from many factors, including differences in total factor productivity, industrial distributions, access to credit, and market power, as well as corruption and inefficiency losses in SOEs; these are all widely discussed in the literature (see, e.g., Lin and Tan, 1999, Brandt and Zhu, 2000, and Song et al., 2011).

[3]Lin and Tan (1999) and many other studies discuss the redundant-worker problem in SOEs, which typically results from the inability to fire workers or extremely high cost of doing so in the state sector. Cooper et al. (2015) use a dynamic labor demand model and find empirical support for much higher firing costs in SOEs. Berkowitz et al. (2017) estimate that the political pressure on SOEs to hire excess labor still accounted for 26.1% of a unit of profits in 2007.

[4]Unions and collective contracts are more common and effective in SOEs and may increase the bargaining power of SOE workers, as Yao and Zhong (2013) show using data on Chinese firms. In a socialist country such as China, the government may also intentionally give SOE workers more bargaining power to cultivate political support (see, e.g., Shleifer and Vishny, 1994, Brandt and Zhu, 2001, and Wang, 2017).

compete for workers in the same labor market. Workers are allowed to search and match with both types of employers when unemployed or on-the-job. When a worker and a firm form a match, wages are determined by bargaining over the surplus created. The model then derives the flows among the three labor force statuses: unemployment, the state sector, and the non-state sector. In equilibrium, such flows are translated into important labor market outcomes, including the unemployment rate, the long-term unemployment rate, and the state-sector employment share.

In the empirical analysis, we calibrate our model using the UHS data and conduct counterfactual experiments to better understand the effect of each of the three modeled differences between SOEs and non-SOEs.[5] Our calibration exercise has the following findings. First, SOEs' productivity is approximately two-thirds that of non-SOE firms.[6] However, increasing SOEs' productivity to the level of non-SOE firms only slightly reduces the average unemployment duration from 38 months to 36 months. Second, allowing SOEs to fire unproductive workers leads to a negligible decrease in the average unemployment duration, from 37.8 months to 37.6 months. Third, state-sector workers have much higher bargaining power than private-sector workers.[7] Reducing the bargaining power of state-sector workers to the level of private-sector workers leads to a substantial decline in the average unemployment duration, from 38 months to 30 months, and a decline in the long-term unemployment rate (unemployment with duration longer than six months) from 85.2% to 81.5%. Finally, combining all three channels reduces the average unemployment duration by 13 months (from 38 month to 25 months) and the long-term unemployment rate by 7.2 percentage points (from 85.2% to 78.0%). Moreover, it also reduces the unemployment rate by 2.6 percentage points,

[5] To be consistent with our model, we use only prime-age men in the analysis, for whom labor market participation is less of an issue.

[6] Using firm-level data, Hsieh and Song (2015) find that the state sector's labor productivity is lower than that of the private sector after adjusting for worker quality during 1998–2005.

[7] Sheng and Lu (2017) estimate workers bargaining power using firm-level data. They find that bargaining power is significantly higher in SOEs than in private firms during the 1999 to 2007 period.

from 9.0% to 6.4%. Therefore, the results suggest that institutional differences between the state and non-state sectors, especially the higher bargaining power of SOE workers, are important in explaining the low dynamics of the Chinese labor market.

In addition to contributing to the literature on China's state sector and labor market, our paper is related to the recent body of research on two-sector search models that capture either the public and private sectors in developed countries (see, e.g., Algan et al., 2002, Quadrini and Trigari, 2007, Hörner et al., 2007, Burdett, 2012, Bradley et al., 2017, Gomes, 2014, Gomes, 2015, Albrecht et al., 2017) or the formal and informal sectors in Latin American countries (see, e.g., Albrecht et al., 2009, Bosch and Esteban-Pretel, 2012, and Meghir et al., 2015). These models are characterized by the specific institutional background of the economic system under study. Our contribution is to build a two-sector model that captures salient features of the Chinese economic system with the coexistence of SOEs and non-SOEs. Specifically, unlike other models, we allow wages in both sectors to be endogenously determined and workers to switch employers when a better match appears.

The remainder of the paper proceeds as follows. The next section provides background information regarding the Chinese urban labor market and reviews the related literature. Section 3 introduces the UHS monthly data. Section 4 reports the main stylized facts on unemployment duration and labor market dynamics in urban China, as well as the different patterns for SOEs and non-SOEs. In Section 5, we develop a two-sector equilibrium search and matching model that incorporates three key institutional differences between SOEs and non-SOEs. This is followed by a discussion of the calibration strategies in Section 6, and the main results reported in Section 7. The last section concludes and discusses some caveats of this research. For brevity, some technical details regarding the data and additional empirical results, including robustness checks and subgroup results, are relegated to the Appendix.

2 Background and Literature Review

In Maoist China, the urban labor market was dominated by state-sector employment. Workers were guaranteed lifetime employment, and there was very minimal labor mobility across employers. Despite the economic reforms initiated in the late 1970s and early 1980s, the urban labor market did not change much until the mid-1990s (Dong and Putterman, 2003; Meng, 2012), when the SOE reform was initiated. The SOE reform was aimed at improving SOEs' financial situation and making them more competitive in the product market. Therefore, layoffs of redundant workers became inevitable (Cai, 2002). In the process, many small state-owned firms were privatized or closed. Large state-owned firms were corporatized and merged into large industrial groups under the control of the Chinese government. From 1995 to 2001, an estimated 34 million workers were laid off from the state sector (Giles et al., 2006). These layoffs, together with the private sector's development and the rising number of rural-to-urban migrants (to whom only private-sector jobs are typically available), resulted in a persistent decline in the state sector's share of employment. In fact, 1995 was the first year with no absolute growth in state-sector employment.[8]

Since the early 2000s, the Chinese urban labor market has transformed into one that is mainly market driven. Even in SOEs, employment relationships are based on contracts, and employment practices have become much more flexible. Worker mobility has also increased significantly. In general, however, state-sector employees still enjoy higher wages and more generous benefits and are better protected by labor laws and collective labor contracting systems (Demurger et al., 2012).

Feng et al. (2017) provide the first comprehensive picture of China's unemployment rate from 1988 to 2009 using annual UHS data. They break this period into three sub-periods based on the stages of China's labor market development: the SOE period (1988–1995), the

[8]Based on the China Statistical Yearbook and also cited by Giles et al. (2006).

labor market reform period (1996–2002), and the post-reform period (2003–2009). During the SOE period, the urban labor market was characterized by state-assigned jobs and lifetime employment. In the reform period, the estimated unemployment rate climbed rapidly, mainly driven by mass layoffs at SOEs and the acceleration of rural-to-urban migration. In the last period (2003–2009), the unemployment rate plateaued and became more sensitive to macroeconomic fluctuations. The rising unemployment trend stopped after 2002, partly as a result of China's entry into the World Trade Organization, which increased the demand for labor, and partly as a result of a major expansion in college enrollment, which improved the overall labor quality.

While Feng et al. (2017) focus on levels of unemployment, to date, little is known about the dynamics of unemployment in urban China. We are aware of only a few studies that touch upon the issue of unemployment duration and long-term unemployment rates.[9] These studies all rely on retrospective information that may suffer from recall bias, and all focus on the period of labor market reform (1995-2002), when SOEs carried out mass layoffs. Due to the regime shift, however, the post-reform period is more relevant to today's policy discussions, and it is the focus of this paper.

Finally, our paper is related to the literature on the intersection of SOEs and the labor market. Many studies analyze differences in wage distributions in SOEs and non-SOEs and usually find a significant SOE wage premium.[10] Most recently, Ge and Yang (2014) comprehensively examine the wage structures in the Chinese labor market and find that the

[9] Appleton et al. (2002) and Knight and Li (2006) use the 1999 China Academy of Social Science (CASS) Household Survey, which covers 4,000 households in 13 Chinese cities, and estimate an average unemployment duration of four years for workers laid off during the SOE reform period in the late 1990s; the durations were longer for workers with health problems, those with less education, and female workers with children. Giles et al. (2006) use data from the China Urban Labor Survey conducted in five large Chinese cities at the end of 2001 and show that only 34.8% of unemployed workers were re-employed within 12 months; the re-employment rate was particularly low for older and less-educated workers.

[10] See, e.g., Gordon and Li (1999), Gordon and Li (1999), Dong and Bowles (2002), Maurer-Fazio et al. (1999), Dong and Bowles (2002), and Rozelle et al. (2002).

state-sector wage premium increased during 1992–2007, mainly driven by the restructuring of the state sector. A few studies focus on labor adjustments using firm-level data. Using the Annual Survey of Industrial Firms (ASIF) from 1998 to 2007, Cooper et al. (2015) study the dynamic labor demand of manufacturing plants in China and find that SOEs have much higher adjustment costs than private plants. They also find that SOEs maximize the discounted present value of profits without a soft budget constraint. Cooper et al. (2017) extend their previous work and develop a two-sector general equilibrium model with costly labor adjustments. However, they assume a competitive labor market and do not model workers' search frictions. To date, no studies have jointly analyzed state sector wages and job flows in a coherent framework, as we do in this paper using the search and matching model.

3 Data

We use monthly UHS data collected by the National Bureau of Statistics (NBS) of China for the 2003–2006 period. The survey design of the UHS is similar to that of the Current Population Survey (CPS) in the United States, which is the source of official U.S. unemployment statistics. The NBS probabilistically draws a first-stage sample of households from selected cities and towns in each province in a multistage fashion. The NBS starts from cities and towns and then goes to districts, residential communities, and finally housing units. A final sample is then randomly selected from the first-stage sample for monthly detailed interviews and diary keeping. Each year, a portion of the households in the final sample is replaced by other households from the first-stage sample.

The NBS interviewers conduct the survey every month. The annual UHS data to which the research community typically has access are aggregated from internal UHS monthly data. For variables such as total wages and income, the annual data reflect the total numbers compiled from all 12 monthly data files. For variables such as labor force status, the annual data file uses information from the December monthly file (Feng et al., 2017). For the first time, we were given access to the internal monthly UHS data from January 2003 to December 2006. The monthly data are structured in the same way as the corresponding annual data. We merge individuals from January to December of each year from 2003 to 2006 to form 12-month panel data. We do not match individuals across years because a large proportion of households is replaced every January. In addition, we detect some reuse of household IDs every January, as households with the same ID in December and January show very different characteristics (in terms of the gender, education, and age of the household head as well as family size); this makes us doubt the reliability of using household ID to match the same household across years. The 12-month panel data that we were able to generate are sufficient for our analysis, as we focus on monthly transition rates and long-term unemployment with a duration greater than six months. We also tried merging individuals across years to conduct a robustness check and our results remain quite similar.

In all of the subsequent analyses, we use only a homogenous group of males aged 25 to 54, for whom the issue of labor force participation is not a major concern. This allows us to focus on the transition between the two labor force statuses of employment and unemployment, which we formally model in this paper. We impose two further restrictions on the sample. First, we exclude those without local-urban-*hukou*, or official household registration status. Almost all existing studies using UHS data make the same restriction because the UHS is not representative of non-*hukou* migrants. This restriction has the additional advantage of making our sample a more homogenous group, as migrants may have very different labor market behaviors than local-urban-*hukou* people.[11] Second, we exclude government-sector workers, i.e., those who have ever worked in the government sector during the survey period,

[11] In a robustness check reported in the Appendix, we do include all migrants in the UHS sample.

as our focus is SOEs that are assumed to be profit maximizers, at least conditional on the institutional restrictions we model explicitly.[12]

Some researchers (e.g., Ge and Yang, 2014) have cautioned that the UHS may over-sample workers from the state sector. We believe this is more of a concern for UHS samples prior to 2002 and less of a concern for our sample period of 2003–2006, as a 2002 redesign of the UHS resulted in stricter implementation of a residence-based sampling procedure.[13] We calculate that the state sector employment share is 53% in our analysis sample and 46% for the weighted sample,[14] as compared to 42% based on the 2005 mini-Census data for comparable sample restrictions. This seems consistent with statistics reported by other researchers using other data sources. For example, Meng (2012) writes "the share of (urban *hukou*) workers in state employment started to decline...further to 50 percent by 2008-09." Overall, we are confident that over-sampling of SOE workers is not a major concern for our analysis.

4 Labor Market Dynamics in Urban China

In this section, we use the 2003–2006 UHS monthly data to describe the basic patterns of labor market dynamics in urban China. The data can be longitudinally matched to study labor dynamics that are representative of urban China. We focus on two statistics: the month-to-month transition probabilities and the long-term unemployment rate, i.e., the proportion of long-term unemployed among all unemployed workers. We show that in general, the Chinese urban labor market has very low mobility and a very high prevalence of long-term unemployment, and these features generally hold for different demographic groups and regions. We then provide some suggestive evidence that SOE employment might play an

[12]We report results including government-sector employees in the Appendix.

[13]Most existing studies based on the UHS disproportionally use samples prior to 2002. For example, Ge and Yang, 2014 use data from 1992-2007, and Cai et al. (2010) cover the 1992-2003 period.

[14]We describe our weighting procedure and report detailed weighted results in the Appendix.

important role. By treating state-sector and private-sector employment as two distinct labor force statuses, we show that the state sector has noticeably lower mobility.[15]

Table 1 shows the transitional probabilities between employment and unemployment and contrasts them with U.S. data.[16] Overall, we see that mobility in the Chinese urban labor market is quite low. The probability of moving from unemployment to employment after 11 months is 16.4% in China compared with 59.4% in the U.S. Similarly, the probability of moving from employment to unemployment is also much lower in China. Only 0.9% of employed workers become unemployed after three months, while the corresponding percentage in the U.S. is 1.9%. The China–U.S. gap in short-term dynamics is even larger. The probability of moving from unemployment to employment after one month is 2.6% in China compared with 28.8% in the U.S., and the probability of moving from employment to unemployment after one month is only 0.2% in China compared with 1.1% in the U.S. Although the statistics may not be fully comparable, they suggest the low-mobility nature of the Chinese labor market.

One may argue that the U.S. is not suitable for comparison as it features very high labor market dynamics compared with the rest of the world. This is indeed a feature of the U.S. labor market, as one can see from Appendix Table C1, which presents unemployment rates and long-term unemployment rates for several transitional and developed countries. For a fairer comparison, we then compare the long-term unemployment rate between China and the countries listed in Appendix Table C1.

Table 2 shows the results on the duration of unemployment for all those who are unemployed in a given month up to that month, which is how long-term unemployment is typically measured. For any month i between June and December of year 2003–2006, we

[15] In the Appendix, we provide detailed descriptions of the UHS monthly data, its longitudinal matching, and the definitions of different labor force statuses.

[16] We use the CPS to generate U.S. statistics for the same time period to ensure comparability between China and the U.S.

first identify those who are unemployed in month i and then calculate the proportion who have been unemployed for at least k months (where k can be three or six). To calculate the proportion of unemployment spells lasting at least three months, we only use observations that have stayed in the UHS sample starting from at least month i-2. Therefore, we throw out the left-censored spells. However, left-censoring should be orthogonal to the distribution of unemployment spells, as the timing of entering the UHS sample is usually January.[17]

As shown in Table 2, the proportions of the unemployed that have been unemployed for at least three and six months are 96.0% and 90.7%, respectively. These ratios are high not just in relation to the U.S. but to all other countries listed in our Appendix Table C1.[18] The long-term unemployment rates, measured as unemployment lasting longer than six months, were high for some developed European countries (e.g., 71% for Germany and 72% for Greece) and transitional European countries (e.g., 75% for the Czech Republic and 84% for Slovak Republic). However, China has the highest long-term unemployment rate (91%), suggesting that the problem is quite severe there.

Table 2 also shows results by demographic group and region. We find that college-educated and older people are generally more likely to have shorter unemployment spells. Nevertheless, even for the group with the lowest long-term unemployment rate—males aged 40–54 with a college degree—the proportion unemployed for at least six months is still high, at 86.8%. When we compare different regions, we find that the inland area has a larger proportion of long-term unemployment compared to the coastal area.[19] The proportion of the unemployed out of work for at least six months is 92.9% in the inland area compared

[17] In Appendix Table C2, we include left-censored spells and report lower bounds and upper bounds on the corresponding proportions. We define all left-censored labor force statuses as unemployment to generate the upper bound and none as unemployment to generate the lower bound. In all cases, the proportions reported in Table 2 lie within the range suggested by Appendix Table C2.

[18] Note that the level of unemployment in China was approximately 9% in 2006 according to Feng et al., 2017, which is comparable to many other countries in Appendix Table C1.

[19] The coastal area includes Liaoning, Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, and Hainan. The inland area includes all other provinces.

with 87.5% in the coastal area.

Overall, Tables 1 and 2 suggest very low mobility among labor force statuses and a high prevalence of long-term unemployment in the Chinese urban labor market. Further, the pattern holds for all demographic groups and for both coastal and inland areas, suggesting some common underlying forces. Given the important role of the state sector in the Chinese economy, including its large employment share in the labor market, we proceed to examine whether SOEs have played an important role in the dynamics of the overall labor market.

To start, we further divide employment status into state-sector employment and private-sector employment and re-examine labor force dynamics. Table 3 reports some basic transitional patterns among the four labor force statuses: state-sector employment (S), private-sector employment (P), unemployment (U), and out-of-labor-force (O). It is clear that S and P display quite distinct transitional patterns. If we compare S-U with P-U, we see that the risk of unemployment is much lower for those in the state sector. Conversely, when comparing U-S and U-P, we see that the unemployed have a much higher probability of getting a private-sector job than a state-sector job, even though the sizes of the two sectors are not much different in our sample.

Appendix Table C4 displays more detailed results by demographic group and region. In general, people with higher education and older people are more likely to move from unemployment to employment (both the state sector and the private sector) and less likely to move from employment to unemployment. This suggest that they may face more favorable labor market conditions than other groups. In addition, the coastal area has higher transition probabilities between employment and unemployment (as shown by U-S, U-P, S-U, and P-U) relative to the inland area, suggesting that the coastal area has much higher labor market mobility. These patterns are consistent with those of unemployment duration shown in Table

2.[20] Despite these differences, the state sector shows very low dynamics in all groups.

5 Theoretical Framework: A Two-sector Equilibrium Search and Matching Model

We follow the framework of the Diamond-Mortensen-Pissarides search and matching equilibrium model (DMP). We work in continuous time and assume that workers are homogeneous, risk neutral, and infinitely lived. We model labor market frictions using a matching function and assume that when a worker and a vacancy meet, a match productivity is drawn. There is free entry to vacancies such that, in equilibrium, the value of maintaining a vacancy equals zero. Match productivity is subject to idiosyncratic shocks, and the job arrival and job destruction rates are endogenous.

We extend the DMP model in two ways. First, we introduce two sectors in the economy: the state and the private sector. They differ in three aspects: productivity, firing cost, and workers' bargaining power. Second, we incorporate on-the-job search so that workers search both when unemployed and when employed. They receive competing offers from both sectors and are allowed to move across sectors. To deal with the problem that the axiomatic Nash bargaining solution is inapplicable because the set of feasible payoffs is nonconvex in models with on-the-job search (Shimer, 2006), we adopt the wage bargaining framework described in Cahuc et al. (2006) to allow for wage renegotiation when an outside offer arrives.

5.1 Setup

Two sectors exist in the economy: $j = 1$ denotes the state sector and $j = 2$ denotes the private sector. Each job is characterized by technology p_j, which is common to all firms in sector j, and a match-specific component z, which is an idiosyncratic shock drawn from

[20] In Appendix Tables C3 and C5, we re-produce Tables 2 and 3 by including people in the government sector. The results display similar patterns.

a distribution $G(z)$. We assume that the match quality distribution follows a log-normal distribution, or $\log z \sim N(0, \sigma^2)$, truncated at $\{\underline{z}, \bar{z}\}$. The output of a firm-worker match is $p_j z$.

For both sectors, each matched firm-worker pair has the same exogenous destruction rate δ. Moreover, in each period, the worker may receive a bad productivity shock with probability λ. For simplicity, we assume that once a worker is hit by the shock, his or her productivity permanently becomes zero for as long as the worker-firm match persists. Private firms always lay off a worker when he or she becomes unproductive. In contrast, SOEs are not allowed to fire the unproductive worker.[21] The literature on SOEs has discussed the redundant workers problem extensively and provided direct empirical evidence on the much higher firing cost faced by SOEs.[22]

5.1.1 Matching

We now describe the mechanism by which employers and workers match. The key variable is market tightness θ_j for $j = \{1, 2\}$, which is the ratio of vacancies to the number of workers searching for jobs, defined as follows.

$$\begin{aligned} \theta_1 &= \frac{v_1}{u + m_1 + m_2} \\ \theta_2 &= \frac{v_2}{u + m_1 + m_2} \end{aligned} \tag{1}$$

[21]The assumptions that private firms always fire unproductive workers and state firms always keep unproductive workers are not empirically restrictive. Think of an alternative model where the exogenous separation rate and productivity shock arrival rate are $\tilde{\delta}$ and $\tilde{\lambda}$, respectively. In this alternative model, we assume that private firms fire unproductive workers with probability ψ_1, while state firms fire unproductive workers with probability ψ_2, with $\psi_1 > \psi_2$; i.e., private firms are more likely to fire unproductive workers. Our model can be thought of as a recharacterization of this alternative model with $\delta = \tilde{\delta} + \psi_2 \tilde{\lambda}$ and $\lambda = (\psi_1 - \psi_2)\tilde{\lambda}$.

[22]For example, using firm-level data, Cooper et al. (2015) show that the linear firing cost is only approximately 17% of the annual compensation to a worker in the private sector but is 161% of the annual compensation to a worker in the state sector.

where v_1 and v_2 are the number of vacancies in the state sector and the private sector, respectively. u is the number of unemployed workers. m_1 and m_2 are the number of employed workers in state-owned firms and private firms. We normalize $u + m_1 + m_2 = 1$.

The job-finding rate depends on θ_j according to an increasing function $f(\theta_j)$, and the recruiting rate is a decreasing function $q(\theta_j) = f(\theta_j)/\theta_j$. Define the flow of contacts by the matching function $f(\theta) = \mu\theta^\eta$. The arrival rates of jobs from the state sector and the private sector can be written as

$$f(\theta_j) = \mu\theta_j^\eta \quad \text{for } j \in \{1, 2\} \tag{2}$$

The recruiting rates of the state sector and the private sector are

$$q(\theta_j) = \mu\theta_j^{\eta-1} \quad \text{for } j \in \{1, 2\} \tag{3}$$

For simplicity, we assume that unemployed and employed workers have the same search intensity. We provide a robustness check in the Appendix, where we show that our qualitative results are not affected if we assume they have different search intensities.

5.1.2 Bargaining

When an unemployed worker and a firm form a match, they conduct Nash bargaining to split the surplus created. Let β_j denote the bargaining power of workers in sector j, i.e., the constant share of the match rent received by workers, U denote the lifetime utility of an unemployed worker, and $V_j(z)$ denote the value of a firm-worker match in sector j with match productivity z. For an unemployed worker who receives a job offer from a firm with match productivity z in sector j, he/she bargains with the firm with an outside option U and receives a value of $W_j(\phi_{j,0}(z), z)$, where $\phi_{j,0}(z)$ is the total compensation for a worker who enters a firm from unemployment.[23]

$$W_j(\phi_{j,0}(z), z) = U + \beta_j(V_j(z) - U) \tag{4}$$

In the case of on-the-job search, the axiomatic Nash bargaining solution and standard strategic bargaining solutions are inapplicable.[24] Therefore, we adopt the approach described in Cahuc et al. (2006), where wage renegotiations are allowed between a firm and a worker when the worker receives an outside offer. Essentially, they extend the Rubinstein micro-foundations for the Nash bargaining solution to a three-player game, namely, a game played by the worker, his current employer, and the poaching firm.

Specifically, when a worker in sector j with match productivity z encounters an outside offer from a firm with match productivity z' in sector j', the bargaining outcome is described as follows.

$$W_{j'}(\phi_{j',j}(z', z), z') = V_j(z) + \beta_{j'}(V_{j'}(z') - V_j(z)) \qquad \text{if } V_{j'}(z') > V_j(z) \tag{5}$$

$$W_j(\phi_{j,j'}(z, z'), z) = V_{j'}(z') + \beta_j(V_j(z) - V_{j'}(z')) \qquad \text{if } V_{j'}(z') \leq V_j(z) \tag{6}$$

where $\phi_{j',j}(z', z)$ is compensation a worker received when employed by a firm in sector j' with match-specific productivity z', but with a rejected competing offer from a firm in sector j with match-specific productivity z. $\phi_{j,j'}(z, z')$ is similarly defined.

In equation (5), the value of the match formed with the poaching firm $V_{j'}(z')$ is larger. Therefore, the poaching firm wins, and the worker switches to the new firm. In the bargaining game between the worker and the poaching firm, the outside option for the worker is $V_j(z)$,

[23]Total compensation includes wages and all fringe benefits.

[24]As pointed out in Shimer (2006), in the case of on-the-job search, the set of feasible payoffs is nonconvex, as an increase in the wage raises the duration of an employment relationship.

which is the entire surplus of the previous match or the maximum value that the incumbent firm is willing to offer to keep the worker. The worker and the poaching firm then split the surplus of the new match, which is $V_{j'}(z') - V_j(z)$, according to the bargaining power parameter $\beta_{j'}$.

Similarly in equation (6), when $V_{j'}(z') \leq V_j(z)$, the incumbent firm wins, and the worker stays in the incumbent firm. However, wage renegotiation happens, and the outside option for the worker becomes the maximum value that the poaching firm can offer, which is $V_{j'}(z')$. The worker then splits the surplus with the incumbent firm, which is $V_j(z) - V_{j'}(z')$ using the bargaining power parameter β_j.

5.1.3 Value of Matches

We use $V_1(z)$ and $V_2(z)$ to denote the value of matches in the state sector and private sector with match productivity z, respectively. Firms and workers are assumed to have the same discount rate r. We first write the value of a match between a worker and a private firm, with match-specific productivity z.

$$\begin{aligned} rV_2(z) = p_2 z &+ (\delta + \lambda)(U - V_2(z)) \\ &+ f(\theta_1) \int_{\underline{z}}^{\bar{z}} 1\{V_2(z) < V_1(z')\} \beta_1 (V_1(z') - V_2(z)) dG(z') \\ &+ f(\theta_2) \int_{\underline{z}}^{\bar{z}} 1\{V_2(z) < V_2(z')\} \beta_2 (V_2(z') - V_2(z)) dG(z') \end{aligned} \tag{7}$$

In equation (7), a match between a worker and a private firm produces $p_2 z$. However, the match will terminate in three possible ways. In the first case, the worker either becomes unemployed for exogenous reasons (with probability δ) or is fired when a bad productivity shock happens (with probability λ). In this case, the total value of the worker and the firm will be U, and the change of the value of the match is $U - V_2(z)$. In the second case, the worker moves to another SOE. This happens when the worker receives an offer from the state sector (with probability $f(\theta_1)$) and draws a new match productivity z' which offers a higher value than the current match, i.e., when $V_1(z') > V_2(z)$. In this case, the change of value is $\beta_1(V_1(z') - V_2(z))$.[25] In the last case, the worker moves to a non-state sector job. This happens when the worker receives an outside offer from a private firm (with probability $f(\theta_2)$) and draws a match productivity z' such that $V_2(z') > V_2(z)$. The change of value is $\beta_2(V_2(z') - V_2(z))$ in this case.

A similar expression can be derived for the value of a match between a worker and a state-owned firm.

$$\begin{aligned} rV_1(z) &= p_1 z + \delta(U - V_1(z)) + \lambda(V_1^0(z) - V_1(z)) \\ &\quad + f(\theta_1) \int_{\underline{z}}^{\bar{z}} 1\{V_1(z') > V_1(z)\}\beta_1(V_1(z') - V_1(z))dG(z') \\ &\quad + f(\theta_2) \int_{\underline{z}}^{\bar{z}} 1\{V_2(z') > V_1(z)\}\beta_2(V_2(z') - V_1(z))dG(z') \end{aligned} \tag{8}$$

Note that the key difference between equation (8) and equation (7) is that when the bad productivity shock happens, the state-owned firm will not simply fire the worker. Rather, the match stays but becomes unproductive, with a value we denote as $V_1^0(z)$.

For an unproductive match between a worker and a state-owned firm, we have the fol-

[25] In this case, the incumbent firm loses the worker and receives a value of 0, but the worker gets $V_2(z) + \beta_1(V_1(z') - V_2(z))$. Therefore, the overall change of value is $\beta_1(V_1(z') - V_2(z))$.

lowing:

$$
\begin{aligned}
rV_1^0(z) = 0 &+ \delta(U - V_1^0(z)) \\
&+ f(\theta_1)\int_{\underline{z}}^{\bar{z}} 1\{V_1(z') > W_1(\phi_{1,0}(z), z)\} \\
&[\beta_1(V_1(z') - W_1(\phi_{1,0}(z), z)) + W_1(\phi_{1,0}(z), z) - V_1^0(z)]dG(z') \\
&+ f(\theta_2)\int_{\underline{z}}^{\bar{z}} 1\{V_2(z') > W_1(\phi_{1,0}(z), z)\} \\
&[\beta_2(V_2(z') - W_1(\phi_{1,0}(z), z)) + W_1(\phi_{1,0}(z), z) - V_1^0(z)]dG(z') \qquad (9)
\end{aligned}
$$

In the above equation, the match produces 0, as productivity becomes zero after the shock. We assume that when the bad productivity shock happens, SOEs have to keep the unproductive worker and pay him/her the minimum wage, which is equal to $\phi_{1,0}(z)$, the wage rate offered to an unemployed worker with match productivity z. Again, the match will end in three ways. First, the match ends exogenously with the worker becoming unemployed (with probability δ). Second, the worker receives an offer from another SOE and draws a new match productivity, which provides a value that is greater than the worker's current value $W_1(\phi_{1,0}(z), z)$. When this happens, the worker's value changes from $W_1(\phi_{1,0}(z), z)$ to $\beta_1(V_1(z') - W_1(\phi_{1,0}(z), z)) + W_1(\phi_{1,0}(z), z)$. The firm's value changes from $V_1^0(z) - W_1(\phi_{1,0}(z), z)$ to 0. Thus, the total change of value for the match is $\beta_1(V_1(z') - W_1(\phi_{1,0}(z), z)) + W_1(\phi_{1,0}(z), z) - V_1^0(z)$. The expression is similar for the last case, when the unproductive worker moves to a private firm.

5.1.4 Value of Workers

Unemployed workers receive the value of leisure b, which is taken as constant across individuals regardless of their employment history. The value of unemployment is thus

$$
\begin{aligned}
rU = b &+ f(\theta_1)(\int_{\underline{z}}^{\bar{z}} \max\{W_1(\phi_{1,0}(z), z), U\} dG(z) - U) \\
&+ f(\theta_2)(\int_{\underline{z}}^{\bar{z}} \max\{W_2(\phi_{2,0}(z), z), U\} dG(z) - U)
\end{aligned} \tag{10}
$$

where $\phi_{1,0}(z)$ and $\phi_{2,0}(z)$ are the compensations received by a worker with match productivity z when he/she enters a state firm or a private firm from unemployment, respectively.

For a worker who newly enters a state-owned firm with match productivity z and compensation $\phi_{1,0}(z)$, his/her value of working is

$$
\begin{aligned}
& rW_1(\phi_{1,0}(z), z) = \phi_{1,0}(z) + \delta(U - W_1(\phi_{1,0}(z), z)) \\
& \quad + f(\theta_1) \int_{\underline{z}}^{\bar{z}} [1\{V_1(z') > V_1(z)\}(V_1(z) + \beta_1(V_1(z') - V_1(z))) \\
& \quad + 1\{V_1(z') \leq V_1(z)\} \max\{W_1(\phi_{1,0}(z), z), V_1(z') + \beta_1(V_1(z) - V_1(z'))\} - W_1(\phi_{1,0}(z), z)] dG(z') \\
& \quad + f(\theta_2) \int_{\underline{z}}^{\bar{z}} [1\{V_2(z') > V_1(z)\}(V_1(z) + \beta_2(V_2(z') - V_1(z))) \\
& \quad + 1\{V_2(z') \leq V_1(z)\} \max\{W_1(\phi_{1,0}(z), z), V_2(z') + \beta_1(V_1(z) - V_2(z'))\} - W_1(\phi_{1,0}(z), z)] dG(z')
\end{aligned} \tag{11}
$$

The worker receives a flow utility that equals his/her compensation $\phi_{1,0}(z)$. The worker becomes unemployed at rate δ. When the bad productivity shock arrives, the worker is not laid off. The worker also does not experience a reduction in the value of employment, as he/she is already paid at the minimum wage given his/her match productivity z; i.e., there is not yet any poaching firm to trigger the wage renegotiation. The worker receives an outside offer from a state-owned firm at rate $f(\theta_1)$ and draws a new match productivity z' from the distribution $G(z)$. When $V_1(z') > V_1(z)$, the worker moves to the poaching firm and gets $V_1(z) + \beta_1(V_1(z') - V_1(z))$. When $V_1(z') \leq V_1(z)$, the worker stays in the incumbent firm but may renegotiate with the incumbent firm if the outside offer is competitive enough; i.e., $V_1(z') + \beta_1(V_1(z) - V_1(z')) > W_1(\phi_{1,0}(z), z)$. If the renegotiation happens, the worker will get a pay increase, and the value rises from $W_1(\phi_{1,0}(z), z)$ to $V_1(z') + \beta_1(V_1(z) - V_1(z'))$. The expressions are similar when the worker receives an offer from a private firm.

For a worker who newly enters a private firm with match productivity z and compensation $\phi_{2,0}(z)$, his/her value of working is

$$
\begin{aligned}
rW_2(\phi_{2,0}(z), z) &= \phi_{2,0}(z) + (\delta + \lambda)(U - W_2(\phi_{2,0}(z), z)) \\
&+ f(\theta_1) \int_{\underline{z}}^{\bar{z}} [1\{V_1(z') > V_2(z)\}(V_2(z) + \beta_1(V_1(z') - V_2(z))) \\
&+ 1\{V_1(z') \leq V_2(z)\} \max\{W_2(\phi_{2,0}(z), z), V_1(z') + \beta_2(V_2(z) - V_1(z'))\} - W_2(\phi_{2,0}(z), z)]dG(z') \\
&+ f(\theta_2) \int_{\underline{z}}^{\bar{z}} [1\{V_2(z') > V_2(z)\}(V_2(z) + \beta_2(V_2(z') - V_2(z))) \\
&+ 1\{V_2(z') \leq V_2(z)\} \max\{W_2(\phi_{2,0}(z), z), V_2(z') + \beta_2(V_2(z) - V_2(z'))\} - W_2(\phi_{2,0}(z), z)]dG(z')
\end{aligned} \tag{12}
$$

The above expression is very similar to the case when an unemployed worker enters a state-owned firm. The only difference is that when the bad productivity shock arrives at rate λ, the worker will be laid off.

5.1.5 Value of Firms

For a firm with match productivity z in sector j, the value of hiring an unemployed worker is

$$J_j^0(z) = (1-\beta_j)(V_j(z) - U) \quad \text{for } j = 1,2 \tag{13}$$

The value of hiring a productive worker from sector j' with match productivity z' is

$$J_{jj'}^1(z,z') = (1-\beta_j)(V_j(z) - V_{j'}(z')) \quad \text{for } j = 1,2 \tag{14}$$

The value of hiring an unproductive worker from the state sector with match productivity z' is

$$J_{j1}^2(z,z') = (1-\beta_j)(V_j(z) - W_1(\phi_{1,0}(z'),z')) \quad \text{for } j = 1,2 \tag{15}$$

The value of posting a vacancy is:

$$\begin{aligned} q(\theta_j)[u \int_{\underline{z}}^{\bar{z}} \max\{J_j^0(z),0\}dG(z) + m_1^1 \int_{\underline{z}}^{\bar{z}} \int_{\underline{z}}^{\bar{z}} \max\{J_{j1}^1(z,z'),0\}dG(z)dM_1^1(z') \\ + m_1^0 \int_{\underline{z}}^{\bar{z}} \int_{\underline{z}}^{\bar{z}} \max\{J_{j1}^2(z,z'),0\}dG(z)dM_1^0(z') \\ + m_2 \int_{\underline{z}}^{\bar{z}} \int_{\underline{z}}^{\bar{z}} \max\{J_{j2}^1(z,z'),0\}dG(z)dM_2(z')] - c = 0 \quad \text{for } j = 1,2 \end{aligned} \tag{16}$$

where c denotes the vacancy posting cost. $M_1^1(.)$ and $M_1^0(.)$ are the cumulative distribution functions (cdf) of match productivity for productive and unproductive workers in the state sector, respectively. $M_2(.)$ is the cdf of match productivity for employed workers in the private sector.[26] u is the number of unemployed workers, m_1^1 the number of productive SOE workers, m_1^0 the number of unproductive SOE workers, and m_2 the number of private-sector workers. When a firm posts a vacancy, it meets an unemployed worker with probability $q(\theta_j)u$ and will be matched with the worker if the draw of match productivity z is such that $J_j^0(z) > 0$. Similarly, the firm meets a productive worker from the state sector, an unproductive worker from the state sector, and a worker from the private sector with probabilities $q(\theta_j)m_1^1$, $q(\theta_j)m_1^0$, and $q(\theta_j)m_2$ and will be matched to the employed worker if the value of the match is greater than zero.[27] Under the free-entry condition, the value of posting a vacancy is zero.

5.2 Characterization of the Steady State

We discretize the distribution of the match quality $G(z)$ and assume that there are n grid points $z_1, z_2, ..., z_n$. The probability density of z_i is that $P(z = z_i) = \frac{1}{n}$, for $i = 1, ..., n$. In equilibrium, there are $m_1^1(z_i)$ number of productive workers in the state sector with match quality z_i, and $m_1^0(z_i)$ number of unproductive workers in the state sector who are hit by a bad productivity shock and whose pre-shock match productivity is z_i.[28] The private sector's steady-state employment with match quality z_i is $m_2(z_i)$. The mass of unemployed workers is defined as u.

We first examine the state sector and define z_1^* such that z_1^* is the level of match productivity that gives a firm zero value according to equation (16). If $z < z_1^*$, the value of a state-owned firm will be negative and so the match will not be formed. Therefore, we have $m_1^1(z) = 0$ and $m_1^0(z) = 0$ when $z < z_1^*$.

When $z \geq z_1^*$, the density of workers in the state sector with match productivity z before

[26] In other words, $M_{j'}(z)$ is the probability that a randomly selected worker in sector j' has a match productivity that is less than z.

[27] Note that because the worker and the firm split the surplus through bargaining, the firm's participation condition is the same as the workers; i.e., when the worker has an incentive to form the match, the firm always does as well, and vice versa.

[28] The total number of workers in the state sector is $m_1 = m_1^1 + m_1^0$.

a bad productivity shock satisfies the following.

$$[\delta+\lambda+\sum_{z'=\underline{z}}^{\bar{z}}\frac{f(\theta_1)}{n}\mathbf{1}\{V_1(z')>V_1(z)\}+\sum_{z'=\underline{z}}^{\bar{z}}\frac{f(\theta_2)}{n}\mathbf{1}\{V_2(z')>V_1(z)\}]m_1^1(z)=$$
$$\frac{f(\theta_1)}{n}[u+\sum_{z'=\underline{z}}^{\bar{z}}m_1^1(z')\mathbf{1}\{V_1(z')<V_1(z)\}+\sum_{z'=\underline{z}}^{\bar{z}}m_2(z')\mathbf{1}\{V_2(z')<V_1(z)\}$$
$$+\sum_{z'=\underline{z}}^{\bar{z}}m_1^0(z')\mathbf{1}\{W_1(\phi_{1,0}(z'),z')<V_1(z)\}] \tag{17}$$

where the left-hand side shows the outflows and the right-hand side shows the inflows. There are four possible outflows: receiving an exogenous separation shock at rate δ, receiving a bad productivity shock at rate λ, receiving an offer from the state sector with a higher matching value, and receiving an offer from the private sector with a higher matching value. There are also four types of inflows generated from four types of individuals: an unemployed worker, a productive state-sector worker (before a bad productivity shock) with a lower matching value, a private-sector worker with a lower matching value, and an unproductive state-sector worker hit by a bad productivity shock with value $W_1(\phi_{1,0}(z'),z')$ lower than the matching value $V_1(z)$.

For the group of matches in the state sector after workers receive a bad productivity shock, we have the following equation when $z\geq z_1^*$ where z is the pre-shock match quality.

$$[\delta+\sum_{z'=\underline{z}}^{\bar{z}}\frac{f(\theta_1)}{n}\mathbf{1}\{V_1(z')>W_1(\phi_{1,0}(z),z)\}$$
$$+\sum_{z'=\underline{z}}^{\bar{z}}\frac{f(\theta_2)}{n}\mathbf{1}\{V_2(z')>W_1(\phi_{1,0}(z),z)\}]m_1^0(z)=\lambda m_1^1(z) \tag{18}$$

In this case, three types of outflows exist: receiving an exogenous separation shock, receiving an offer from the state sector with a matching value higher than the current employment value, and receiving an offer from the private sector with a matching value higher than the current employment value. The inflow comes from workers in the state sector with match productivity z who are hit by a bad productivity shock.

We can similarly define z_2^* for the private sector; note that $m_2(z) = 0$ when $z < z_2^*$. When $z \geq z_2^*$, the density of workers in the private sector with match productivity z satisfies the following.

$$
\begin{aligned}
&[\delta + \lambda + \sum_{z'=\underline{z}}^{\bar{z}} \frac{f(\theta_2)}{n} \mathbf{1}\{V_2(z') > V_2(z)\} + \sum_{z'=\underline{z}}^{\bar{z}} \frac{f(\theta_1)}{n} \mathbf{1}\{V_1(z') > V_2(z)\}] m_2(z) = \\
&\qquad \frac{f(\theta_2)}{n}[u + \sum_{z'=\underline{z}}^{\bar{z}} m_2(z') \mathbf{1}\{V_2(z') < V_2(z)\} + \sum_{z'=\underline{z}}^{\bar{z}} m_1^1(z') \mathbf{1}\{V_1(z') < V_2(z)\} \\
&\qquad + \sum_{z'=\underline{z}}^{\bar{z}} m_1^0(z') \mathbf{1}\{W_1(\phi_{1,0}(z'), z') < V_2(z)\}]
\end{aligned}
\tag{19}
$$

Together with the condition that

$$
u + \sum_{\underline{z}}^{\bar{z}} m_1^1(z) + \sum_{\underline{z}}^{\bar{z}} m_2(z) + \sum_{\underline{z}}^{\bar{z}} m_1^0(z) = 1 \tag{20}
$$

we have $3n + 1$ equations and $3n + 1$ unknowns ($m_1^1(z_i)$, $m_1^0(z_i)$, and $m_2(z_i)$ for $i = 1, ..., n$, and u). We can solve for the steady-state unemployment rate u, the size of the state sector as $\sum_{\underline{z}}^{\bar{z}}(m_1^1(z) + m_1^0(z))$, and that of the private sector as $\sum_{\underline{z}}^{\bar{z}} m_2(z)$.

We then calculate the average unemployment duration and long-term unemployment rates. First, the transition rate from unemployment to state- or private-sector employment is the product of the job arrival rate and the job acceptance rate.

$$\psi_j = f(\theta_j)Pr(z \geq z_j^*) \quad j \in \{1, 2\} \tag{21}$$

We define the transition rate from unemployment to employment as ψ, which equals the sum of ψ_1 and ψ_2.

The model setup assumes that the transition rates do not depend on unemployment history. Given that the transition rate from unemployment to employment is not duration-dependent, the probability that an unemployment spell D lasts for k period follows a geometric distribution.

$$Pr(D = k) = (1 - \psi)^{k-1}\psi \tag{22}$$

The average unemployment duration is

$$E[D] = \frac{1}{\psi} \tag{23}$$

The probability that an unemployment spell D is longer than k period is

$$Pr(D > k) = 1 - \sum_{i=1}^{k}(1 - \psi)^{i-1}\psi \tag{24}$$

5.3 Discussion

Our model is closely related to the recent body of work on two-sector search models, which provide several ways of introducing the public sector into the prototype one-sector search and matching framework. The first line of research follows Pissarides (1988) and assumes that unemployed workers make a directed search of private- or public-sector jobs (Quadrini and Trigari, 2007, Hörner et al., 2007, and Gomes, 2014, 2015). The second line of research extends the Burdett-Mortensen model by assuming that firms post wages and workers make random searches (Burdett, 2012 and Bradley et al., 2017).[29] The third line of research extends the Diamond-Mortensen-Pissarides model and allows workers to search randomly across both sectors (Albrecht et al., 2017).[30] Our model falls into the last category.

The most significant difference between our model and the literature is that we assume that state-owned firms are (constrained) profit-maximizers, and employment and wages in the state sector are endogenously determined in the equilibrium. In contrast, all previous studies take public-sector employment and wages as exogenous; they usually assume that the public sector posts an exogenous number of job vacancies and pays a pre-determined wage to its workers. The key difference in our case is that we are modeling China's SOEs, which operate and compete in the same product markets as private firms. As such, (constrained) profit maximization is a more realistic assumption to make. Cooper et al. (2015) and Cooper et al. (2017) also model Chinese SOEs as profit maximizers, and Berkowitz et al. (2017) document the declining role of political influence on SOEs. Nevertheless, we are not assuming that SOEs have the same objectives as non-SOEs or behave similarly to them; we explicitly model institutional differences.

In our model, there are three possible channels that may explain the effect of the state sector on labor market dynamics. The first channel is that state-owned firms may have lower productivity than private firms. This would lead state-owned firms to post fewer vacancies due to the lower value of hiring each worker. Second, state-owned firms cannot fire workers even when they become unproductive; this drives down the profit of state-owned firms and may reduce their incentive to hire. Lastly, state-sector workers may have stronger bargaining

[29] Meghir et al. (2015) also use the wage-posting framework to study the formal and informal sectors.

[30] Bosch and Esteban-Pretel (2012) and Albrecht et al. (2009) also use the Nash-bargaining framework with random search to study the competition between the formal and informal sectors.

power than private-sector workers; this would also reduce state-owned firms' profit from hiring a worker. The relative importance of these channels is an empirical question.

Besides those three, another potential channel that we did not incorporate in our model is the possible difference in growth rates between the two sectors, which in a search model is equivalent to different discount rates (Pissarides, 2000). However, as shown in Hsieh and Song (2015), the relative labor productivity between the two sectors has been quite stable since 2006. In addition, Cooper et al. (2015) find that public manufacturing firms have a larger discount rate (97%) compared to private manufacturing firms (93%). This suggests SOEs may be more willing than private firms to post vacancies because they care more about future profits than present costs. Therefore, we believe differences in growth rates, or discount rates, cannot explain why state-owned firms post much fewer vacancies than private firms.

6 Calibration Strategy

Now we describe the calibration strategy. The parameters listed in Panel A of Table 4 are all calibrated based on findings in the literature or Chinese firm-level data.[31] Because one period is a month in our data, we set the discount rate r at 0.4% to target an annual interest rate of 5%.

For the matching function, we follow the literature and assume the following functional form

$$f(\theta_j) = \mu\theta_j^{\eta} \quad j \in \{1, 2\}.$$

According to a survey by Petrongolo and Pissarides (2001), most studies that estimate a matching function using U.S. data find that η is in the range of 0.3–0.5. We set $\eta = 0.5$ and $\mu = 0.06$ such that it produces a reasonable value of θ in the calibration. The level of

[31] In the Appendix, we try several alternative calibration parameters and the results are similar.

μ is slightly lower than in the developed-world literature (Petrongolo and Pissarides, 2001) because the average transition rates in China are low. However, our value is closer to that in Meghir et al. (2015), who estimate μ using Brazilian data and find that μ ranges from 0.09 to 0.12.

We normalize the productivity of the private sector to be 1. The bargaining power of private-sector workers is set at 0.5.[32] In addition, we set the value of leisure at 0.3 such that the value of leisure is 40% of the mean labor income of the private sector.[33]

Regarding workers' compensation, we can observe only wages but no other nonwage benefits in the UHS monthly data. Nonwage benefits are important components of workers' total compensation in China, especially in SOEs (Meng, 2012). Therefore, we assume that the total compensation offered by sector j, denoted as $\phi_j(z)$, is composed of both wages $\omega_j(z)$ and nonwage benefits. We assume that wages are a fixed proportion $\tilde{\beta}_j$, which can differ across sectors, of the total compensation; i.e., $\omega_j(z) = \tilde{\beta}_j \phi_j(z)$ for both sectors.

We use firm-level micro data from the 2003-2006 Annual Survey of Industrial Firms (ASIF) conducted by China's NBS to calibrate $\tilde{\beta}_j$. The survey is a census of all state-owned firms and private firms in the industrial sector with more than five million RMB in revenues.[34] Labor compensations include (i) wages; (ii) benefits; and (iii) pensions, health insurance, public housing funds, and unemployment insurance. Wage share $\tilde{\beta}_j$ is defined as the proportion of labor compensation paid as wages. State-owned firms have a smaller wage share, suggesting that a larger proportion of labor compensation in the state sector comes from non-wage benefits. According to the wage share statistics, we set $\tilde{\beta}_1$ to 66.5% and $\tilde{\beta}_2$

[32] In a single-sector model, if $\beta = \eta$, the Hosios condition is satisfied. However, it is not clear whether this still satisfies the Hosios condition in a multi-sector model with different productivities and bargaining powers.

[33] In Shimer (2005), the value of leisure is calibrated at 0.4, and the mean labor income in his model is 0.993.

[34] Following Hsieh and Song (2015), we define a firm as state-owned when the share of registered capital held directly by the state exceeds or equals 50% or when the state is reported as the controlling shareholder.

to 81.7% in our main analysis.[35]

Panel B of Table 4 lists all of the parameter that we calibrate based on observed moments from the UHS: the productivity of the state sector p_1, the bargaining power of state-sector workers β_1, the vacancy posting costs c, the exogenous separation rate δ, the probability of receiving a bad productivity shock λ, and the standard deviation of match quality σ. The first set of moments we target are the labor market transition rates, including the transitions from unemployment to state-sector employment (U-S), from unemployment to private-sector employment (U-P), from state-sector employment to unemployment (S-U), and from private-sector employment to unemployment (P-U). The U-P transition rates, together with the matching function, can be used to identify the costs of posting vacancies c. In addition, the S-U transition rates can identify the exogenous separation rate δ because SOEs cannot lay off workers. The difference between the P-U and S-U transitions identifies the match productivity shock λ that leads to endogenous job destruction in the private sector.

Another set of moments that we target are the accepted wages, which refer to the earnings in the first month when workers move from unemployment to employment. We collect information on the mean and standard deviation of the accepted wages in the state and private sectors. The bargaining power of state-sector workers (β_1) and the productivity of the state sector (p_1) can be jointly identified through the accepted wage of the state sector and the U-S transition rates. When β_1 is high, the accepted wage is higher and the transition rate is lower, whereas when p_1 is high, both the accepted wage and the transition rate become larger. Therefore, β_1 and p_1 have different effects on these two moments. The standard deviation of the match quality distributions (σ) is calibrated using the average

[35] For regional results, which we report in the Appendix, we calculate wage shares by region according to the ASIF. We set $\tilde{\beta}_1$ to be 66.3% and 66.5% for state-owned firms in the inland and coastal areas, respectively, and $\tilde{\beta}_2$ is 79.8% and 82.0% for private firms in the inland and coastal areas, respectively. The statistics show that state-owned firms have similar wage shares in both regions, whereas private firms have slightly higher wage shares in the coastal area.

covariance coefficient (standard deviation divided by the mean) of the accepted wage across the two sectors.

Table 5 shows data moments used in the calibration. The labor market transition rates suggest that the state sector has lower labor market mobility than the private sector, with much fewer inflows and outflows. In addition, accepted wages are higher in the state sector than in the private sector. These patterns hold for most age-education subgroups. There also exist interesting differences across regions. The coastal area has much higher labor market mobility than the inland area in terms of both transitions out of unemployment (U-S and U-P) and transitions into unemployment (S-U and P-U). In addition, the state-sector wage premium is high in the inland area but is close to zero in the coastal area.

7 Main Results

7.1 Calibration Results Based on UHS Sample

Table 6 shows the calibration results based on the UHS data. We find that state-sector workers have much stronger bargaining power than private-sector workers. We normalize the bargaining power of private-sector workers at 0.5, and the calibrated bargaining power of state-sector workers is 0.87. There are many reasons why state sector wages might have larger bargaining powers, including stronger union presence and collective bargaining arrangements. Also, our finding is consistent with the theory proposed in Wang (2017) that state-sector workers have stronger bargaining power because the political elite in China implement a "divide-and-rule" strategy to guarantee political support from a sufficient number of citizens: the elite provide state workers with high wages and earn their support at the cost of private-sector workers.

We also find that the average productivity in the state sector is only 67% of that in the private sector. On the one hand, SOEs have lower total factor productivity and also suffer from inefficiency losses, which may lead to lower labor productivity. On the other hand, SOEs have cheaper access to credit and greater market power and are more likely to concentrate on capital-intensive industries, so their labor productivity may be higher. The calibration result suggests that the former effect dominates the latter. This result is consistent with the empirical macro literature that finds that after the SOE reform, state-owned firms still have lower labor productivity than private firms. For example, Hsieh and Song (2015) find that the average relative labor productivity during 2003-2006 is 0.91 based on data from China Statistical Yearbooks or 0.88 based on the industrial survey data and after adjusting for worker quality.[36]

Table 6 also shows the calibration results for other parameters, including the probability of receiving a destructive productivity shock, λ, the exogenous separation rate, δ, the standard deviation of match quality, σ, and the costs of posting vacancies, c. The average chance of receiving a bad productivity shock that leads to endogenous job destruction is 0.21% per month. The exogenous separation rate is low, at 0.06% per month. Appendix Table C6 shows the model fit, in which transitions and wages fit pretty well.

7.2 Equilibrium Unemployment and Dynamics

In addition, given that the Chinese economy is still in a transitional state, the model can be used to predict the unemployment rate and share of state-sector employment in a stationary state, as shown in Appendix 5.2. Appendix Table C7 suggests that the steady-state unemployment rate is 8.99%, which is higher than what was observed in the data (6.40%). Our model suggests that in the steady state, the share of state-sector employment would be only 9.1%, very low compared to what we observe in the data, which is 53.8%. The reason is that our model predicts there will be many job-to-job transitions from the state sector

[36]They adjust labor productivity by accounting for the differences in worker quality between state-owned firms and private firms using the 2004 Economic Census.

to the private sector, as the value of matches in the state sector on average is lower due to its lower productivity and higher firing costs. Moreover, 23.0% of the matches in the state sector are unproductive (with zero productivity).

Further, using the monthly U-S and U-P transition rates, we predict the unemployment duration and proportion of long-term unemployment by assuming that the unemployment duration follows a geometric distribution. Given the history-independent assumption, we use Equation (23) to calculate the average unemployment duration. The average unemployment duration for the entire sample is 37.8 months, as shown in the first row of Table 7 ("status quo"). Further, we calculate the proportion of long-term unemployment using Equation (24), also shown in the first row of Table 7. The estimated proportion of long-term unemployment with a duration longer than six months is 85.2%, which falls between the upper and lower bounds of the empirical distribution of unemployment spells in Appendix Table C2.[37]

7.3 Counterfactual Experiments

In this model, we incorporate three possible differences between the state sector and the private sector. The state sector cannot lay off workers even when they become unproductive. Based on the calibration results, the state sector also has lower labor productivity, and its workers have higher bargaining power. To examine the relative importance of these differences in explaining the low dynamics of China's urban labor market, we conduct counterfactual experiments by shutting down each channel one by one, and we examine the overall effects of all three channels by eliminating all differences. For each experiment, we examine the impact on the transition from unemployment to employment, average unemployment duration, long-term unemployment rate, steady-state unemployment rate, and state-sector employment share. Table 7 shows the effects on the whole sample. In Appendix B.1, we conduct several robustness checks, such as changing the calibrated parameter values, allowing

[37]For spells longer than six months, the proportion is between 85.1% to 91.0%.

for different search intensities between employed and unemployed workers, using a weighted sample, and combining out-of-labor-force (O) with unemployment (U). The results remain quite robust. In Appendix B.2, we conduct counterfactual analysis for age-education and regional subgroups. The results are similar across different subgroups.

7.3.1 Equalizing the Productivity of the Two Sectors

First, we consider a counterfactual experiment that sets the productivity of the state sector to the level of the private sector. On average, the calibrated productivity of the state sector is 67% of that of the private sector. The direct effect of increasing the productivity of the state sector is an increase in the value of hiring workers for state-owned firms. In addition, the labor compensation of state-sector workers will increase, which makes the state sector more attractive to workers. Therefore, increasing the productivity in the state sector increases the chance that a worker accepts a state-sector offer and rejects a private-sector offer, and it increases the duration that a worker stays in a state-owned firm. This indirect effect further increases the value of hiring a worker for state-owned firms. As a result, state-owned firms post more vacancies.

The second row of Table 7 shows the effect of equalizing productivity on the labor market. The monthly U-S transition rate slightly increases from 0.28% to 0.53%, or by 0.25 ppt. Moreover, we find that increasing the relative productivity of the state sector has a negative impact on the U-P transition rate because of the competition between the two sectors. The monthly U-P transition rate declines from 2.36% to 2.24%. When the relative productivity in the state sector increases, state-sector workers receive higher wages, and state-sector jobs become more attractive. Therefore, the average duration that a worker stays in the private sector declines, and the value of hiring a worker for a private firm declines. As a result, private firms post fewer vacancies. The decline in the U-P transition rate partially offsets the increase in the U-S transition rate. Therefore, the U-E transition rate slightly increases by 0.13 ppt. This finding is consistent with previous studies that indicate that increasing public employment can crowd out private employment (see, e.g., Algan et al., 2002, Quadrini and Trigari, 2007, and Michaillat, 2014).

We also predict the effect on the average unemployment duration and long-term unemployment rates. Given the small effect on the U-E transition, the average unemployment duration declines slightly from 37.8 months to 36.1 months, and the proportion of long-term unemployment with a duration longer than six months declines from 85.2% to 84.5%.

Further, we find that the accepted labor income premium in the state sector increases from 27% to 60%. As shown in Table 5, the average accepted wage premium for the state sector is 3%. However, in the state sector, a larger proportion of the labor income is paid as non-wage benefits. Therefore, after taking into account non-wage benefits, the actual labor income premium is 27%. The increase in state-sector productivity leads to an increase in total output and, therefore, workers' labor income. This suggests that the state sector is more attractive to workers after equalizing productivity because it offers even higher labor compensation.

We also predict the effect of equalizing productivity in the steady state on the unemployment rate and state employment share. In the steady state, the unemployment rate declines from 9.0% to 8.1%, and the share of state-sector employment increases from 9.1% to 20.8%. When we increase the relative productivity of state-owned firms, the U-S transition rate increases and the U-P transition rate declines. In addition, an increasing number of job-to-job transitions occurs from the private sector to the state sector. Therefore, the state-sector employment share increases. Moreover, although the effect on the U-E transition rate is small, a larger fraction of workers are employed in the state sector, which has a low separation rate. As a result, the unemployment rate declines.

7.3.2 Allowing State Sector to Lay off Workers

The second counterfactual analysis allows the state sector to lay off workers who are hit by a bad productivity shock. Allowing the state sector to lay off workers has two effects. First, the average value of hiring a state worker increases because state-owned firms are allowed to freely lay off workers who produce zero output. Second, as the value of a state-sector match increases, state-sector jobs become more attractive to workers, which increases the average duration that a worker stays with a state-owned firm. Therefore, the value of hiring a state worker further increases. These two effects would lead to an increase in the number of vacancies posted by SOEs.

Overall, the effect on the U-S transition rate is positive but moderate. The U-S transition rate slightly increases from 0.28% to 0.31%, as shown in the third row of Table 7. The U-P transition rate does not change, and the total U-E transition rate increases from 2.64% to 2.66%. In addition, the average unemployment duration slightly declines from 37.8 months to 37.6 months, and the proportion of long-term unemployment with a duration longer than six months declines from 85.2% to 85.0%. All of these results suggest that allowing state-owned firms to lay off workers has only a marginal effect on unemployment duration and long-term unemployment rates. The reason the overall effect on U-S and U-E transition rates is small in our analysis is that the bargaining power of workers in the state sector is too large. State-owned firms still do not want to post many vacancies because a large fraction of the surplus is given to workers.

When SOEs are allowed to fire unproductive workers, the SOE labor compensation premium increases from 27% to 45% because the value of matches in the state sector increases. In the steady state, the unemployment rate increases from 9.0% to 9.4% and the state-sector employment share declines from 9.1% to 7.6%. The reason is that allowing state-owned firms to lay off unproductive workers leads to an increase in not only S-U transitions but also U-S transitions. At the same time, job-to-job transitions from the private sector to the state sector increase. Therefore, the effect on the state employment share is ambiguous. The model predicts that the state sector becomes smaller in the new steady state. The unemployment rate is slightly higher because the increase in the E-U transition dominates the increase in the U-E transition.

7.3.3 Equalizing Workers' Bargaining Power in the Two Sectors

The third experiment reduces the bargaining power of state-sector workers to the level of private-sector workers. Our calibration results show that the average bargaining power of state-sector workers is 0.87. In this counterfactual experiment, we set the bargaining power of state-sector workers to 0.5, the same as the bargaining power of private-sector workers.

Reducing the bargaining power of state-sector workers has two effects. First, it increases the proportion of output kept by state-owned firms. Therefore, the value of hiring a worker increases for state-owned firms, making them willing to post more vacancies. Second, it reduces the labor income of state-sector workers, which reduces the attractiveness of state-sector jobs. Workers are more likely to reject a state-sector offer and conduct an on-the-job search to move from the state sector to the private sector. Therefore, the net effects on the U-S transitions can be positive or negative.

According to the fourth row of Table 7, the U-S transition rate increases dramatically from 0.28% to 1.08%, indicating that the first effect dominates the second effect. At the same time, the U-P transition rate declines from 2.36% to 2.27%, which is again the result of the competition between the two sectors. The net effect on the U-E transition is positive and increases from 2.64% to 3.34%. Moreover, the average unemployment duration declines from 37.8 months to 29.9 months, and the proportion of long-term unemployment with a duration longer than six months declines from 85.2% to 81.5%. Overall, we observe a significant effect of a reduction in the bargaining power of state-sector workers on shortening the unemployment duration and lowering long-term unemployment rates.

In addition, as a result of the decline in bargaining power, state-sector workers now receive 35% lower labor income than private-sector workers. The state-sector labor income premium declines from 27% to −35%. This decline occurs because the value of matches in the state sector is lower due to low productivity and high firing costs, leading to lower labor income for state-sector workers after equalizing the bargaining power.

Furthermore, this experiment is quite effective in reducing the unemployment rate and increasing the state-sector employment share. The unemployment rate declines from 9.0% to 6.5% and the share of state-sector employment increases from 9.1% to 26.6% in the new steady state. Because a large increase in U-S transitions dominates the decline in S-P transitions, the state sector expands. At the same time, due to the increase in U-E transitions and increased share of state employment, which has a much lower separation rate, the unemployment rate declines.

7.3.4 Combining All Three Channels

In this counterfactual analysis, we examine the effect of a further SOE reform that eliminates all three differences between the two sectors, turning the state sector into a replica of the private sector. This essentially reduces our model to a one-sector model. Note that ownership per se does not matter; the SOEs could remain in the hands of the state or be privatized.

The last row of Table 7 shows that the monthly U-E transition rate increases from 2.64% to 4.06%, the average unemployment duration declines from 37.8 to 24.7 months, and the proportion of long-term unemployment with a duration longer than six months declines from 85.2% to 78.0%. Combining the three channels has a significant positive effect on labor market mobility. The overall effect of such an SOE reform would also be stronger than any single effect from the above channels in reducing long-term unemployment.

Finally, we examine the effect on the unemployment rate in the steady state. A priori, the effect is ambiguous given that the individual channels either have positive or negative effects. This is similar to Hörner et al. (2007), who also find that the public sector has an ambiguous effect on overall employment. In actuality, we find that the average unemployment rate would decline from 9.0% to 6.4%. Therefore, an overall SOE reform eliminating all differences between the two sectors not only improves labor market dynamics but also reduces the equilibrium level of unemployment.

8 Conclusion

In this study, we first document the labor market mobility patterns in urban China using monthly labor force data. We demonstrate that the Chinese urban labor market is characterized by very low dynamics across different labor force statuses and a very high prevalence of long-term unemployment. In particular, the state sector is much less dynamic than the private sector, with significantly fewer inflows and outflows. We then develop a two-sector search and matching model to examine the potential channels, incorporating three key possible differences between the two sectors: productivity, labor adjustment cost, and workers' bargaining power. We conduct counterfactual experiments to quantify the relative importance of these three channels and find that the strong bargaining power of state-sector workers plays the most important role in explaining the overall low labor market dynamics of China. Our findings suggest that eliminating institutional differences between SOEs and non-SOEs would significantly reduce long-run unemployment and improve labor market efficiency. Specifically, if state-sector wages were brought to market-determined levels, as recently proposed by China's State Council, both the equilibrium levels of unemployment and the proportion of long-run unemployment would decline significantly. Understanding the state sector's labor market impact is thus crucial to properly formulate further SOE reform policies.

One drawback of this paper is that it does not include migrants, who are increasingly part of the urban labor market. This is mainly a limitation of the UHS data that we use.[38] Existing studies suggest that migrants have lower unemployment rates and higher turnover in the labor market (see, e.g., Knight and Yueh 2004 and Feng et al., 2017). Non-*hukou* migrant workers are also disproportionably represented in non-SOEs.[39] Therefore, to some extent the *hukou* and non-*hukou* labor forces are still segmented and can be analyzed separately for the years under study in this paper. Including non-*hukou* migrants would also introduce substantial heterogeneity that we wanted to avoid in the analysis.[40]

Another potential caveat relates to the heterogeneities between SOE and non-SOE workers. Our model cannot handle heterogeneous agents because we do not have firm-worker matched data. However, we believe this is not a major issue for the following reasons. First, because there exist considerable transitions between SOEs and non-SOEs, the two sectors are not segmented. Second, although on average state-sector workers and non-state-sector workers may differ in many aspects, such as innate ability and risk aversion, we believe these differences cannot explain the key regularities we document in this paper, given that our subgroup results—which account for age, education, and regional differences—are similar to the main results.

[38]The migrant sample in the UHS is very similar to the *hukou* population in terms of labor market activities because the UHS may under-sample temporary migrants for various reasons, as discussed in Feng et al. (2017). To gain some understanding of the labor market conditions of migrants without urban-local-*hukou*, one has to look beyond the UHS.

[39]Based on the 2005 Mini-Census data, the percentage of workers without a local *hukou* is only 13.1% for SOEs, but 26.0% for private firms.

[40]The argument is similar to our exclusion of female workers.

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Table 1: Transition probabilities between employment and unemployment (%): China vs. the United States

k	China	U.S.
Panel A: Probabilities of unemployment in month i+k conditional on being employed in month i		
1	0.2	1.1
2	0.3	1.4
3	0.4	1.7
6	0.6	NA
11	0.9	1.9
Panel B: Probabilities of employment in month i+k conditional on being unemployed in month i		
1	2.6	28.8
2	4.6	38.7
3	6.4	45.3
6	10.5	NA
11	16.4	59.4

Note: [China] is based on matched UHS monthly data during the 2003-2006 period. The sample is restricted to males aged 25–54, with local-urban-*hukou*, and not in the government sector. [U.S.] is based on matched Current Population Survey monthly data during the 2003-2006 period, restricted to males aged 25–54. The results are unweighted but the weighted results are similar.

Table 2: Distribution of unemployment spells up to month i, uncensored spells

	25–39 college	25–39 high school	25–39 below HS	40–54 college	40–54 high school	40–54 below HS	Inland	Coastal	Total
Spell $\geq$ 3 months (%)	95.4	97.0	97.3	94.1	95.2	95.2	97.0	94.5	96.0
Number of spells	5307	12861	9267	1842	8835	12369	30320	20161	50481
Spell $\geq$ 6 months (%)	89.5	93.0	93.9	86.8	88.7	88.8	92.9	87.5	90.7
Number of spells	4882	12108	8862	1821	8672	12197	28991	19551	48542

Note: This table pools results from July to December for the years 2003 to 2006 based on matched monthly UHS files from January 2003 to December 2006. The sample is restricted to males aged 25–54, with local-urban-*hukou*, and not in the government sector.

Table 3: Transition probabilities among four labor force statuses (%)

K	U-S	U-P	U-O	S-U	S-P	S-O	P-U	P-S	P-O	O-U	O-S	O-P
1	0.3	2.4	0.1	0.1	0.1	0.0	0.3	0.1	0.1	0.1	0.2	0.6
3	0.7	5.7	0.2	0.2	0.3	0.1	0.6	0.1	0.1	0.3	0.4	1.4
6	1.2	9.3	0.3	0.3	0.5	0.2	1.0	0.2	0.2	0.5	0.7	2.5
12	2.0	14.4	0.6	0.4	1.1	0.3	1.4	0.5	0.4	1.0	1.4	4.6

Note: S, P, U, O stands for state-sector employment, private-sector employment, unemployment and out-of-labor-force, respectively. For example, U-O is the probability of out-of-labor-force in month i+k for those unemployed in month i. The sample is restricted to males aged 25–54, with local-urban-*hukou*, and not in the government sector.

Table 4: Parameters of the model

Panel A: Calibrated based on the literature and firm-level data		
Parameter	Economic meaning	Value
r	discount rate	0.004
η	matching function	0.5
μ	matching function	0.06
p_2	productivity of P	1
β_2	bargaining power of P	0.5
$\tilde{\beta}_1$	wage share of S	66.5% (national), 66.3% (inland), 66.5% (coastal)
$\tilde{\beta}_2$	wage share of P	81.7% (national), 79.8% (inland), 82.0% (coastal)
b	value of leisure	0.3
Panel B: Calibrated based on UHS sample		
Parameter	Economic meaning	Target moments
β_1	bargaining power of S	relative accepted wage (S/P) and U-S
p_1	productivity of S	relative accepted wage (S/P) and U-S
c	costs of posting vacancies	U-P
δ	exogenous separation rate	S-U
λ	probability of bad productivity shock	P-U
σ	std of match quality	std/mean accepted wage

Note: S, P, U stand for state-sector employment, private-sector employment, and unemployment, respectively.

Table 5: UHS moments used in the calibration

Group	Transition rates				Accepted wage	
	U-S (%)	U-P (%)	S-U (%)	P-U (%)	Mean S/P	std/mean
25–39, college	0.32	2.64	0.04	0.26	1.16	0.84
25–39, high school	0.24	1.95	0.06	0.29	0.95	0.89
25–39, below HS	0.18	1.78	0.11	0.27	1.38	0.67
40–54, college	0.44	2.94	0.03	0.16	0.71	0.75
40–54, high school	0.37	2.74	0.08	0.25	0.88	0.78
40–54, below HS	0.29	2.77	0.09	0.34	1.10	0.78
Inland	0.22	1.65	0.05	0.22	1.11	0.85
Coastal	0.36	3.42	0.10	0.34	1.00	0.87
Total	0.28	2.36	0.06	0.28	1.03	0.87

Note: S, P, U stand for state-sector employment, private-sector employment, and unemployment, respectively.

Table 6: Calibration results based on UHS sample

Group	β_1	p_1	λ (%)	δ (%)	σ	c
25–39, college	0.89	0.78	0.23	0.04	1.02	6.57
25–39, high school	0.87	0.66	0.22	0.06	1.05	10.22
25–39, below HS	0.94	0.99	0.16	0.11	0.78	8.68
40–54, college	0.65	0.48	0.12	0.03	0.99	6.47
40–54, high school	0.79	0.56	0.17	0.08	0.97	6.28
40–54, below HS	0.90	0.76	0.25	0.09	0.94	5.35
Inland	0.88	0.76	0.18	0.05	1.00	12.99
Coastal	0.85	0.60	0.24	0.10	1.04	4.53
Total	0.87	0.67	0.21	0.06	1.03	7.74

Table 7: Counterfactual experiments: Main results

	U-S (%)	U-P (%)	U-E (%)	Unemployment duration (months)	% of long-term unemployment ($\geq 6 months$)	Accepted labor income (S/P)	Unemployment rate (%)	State employment share (%)
Status quo	0.28	2.36	2.64	37.8	85.2	1.27	8.99	9.1
Equalizing productivity	0.53	2.24	2.77	36.1	84.5	1.60	8.08	20.8
Allowing SOE layoff	0.31	2.36	2.66	37.6	85.0	1.45	9.39	7.6
Equalizing bargaining power	1.08	2.27	3.34	29.9	81.5	0.65	6.45	26.6
All three channels	n.a.	n.a.	4.06	24.7	78.0	n.a.	6.37	n.a.

Note: S, P, U, E stand for state-sector employment, private-sector employment, unemployment, and employment, respectively.

APPENDIX

Appendix A Data Appendix

A.1 Sample Exclusions

Throughout this paper, we restrict the sample to males in their prime working years between the ages of 25 and 54, a homogeneous group for which the labor force participation choice is not a major concern. We also make two further important restrictions to the sample. First, we exclude those without local-urban-*hukou* or official household registration status. We do so for two reasons. The first reason is that considerable barriers exist for non-local-urban-*hukou* people to be hired by SOEs. The second reason is that the UHS is primarily a sample of local-urban-*hukou* people. Although the data set has included some people without local-urban-*hukou* since 2002, samples are small and not representative of all urban residents without local-urban-*hukou*, as discussed in greater detail in Feng et al. (2017).

Second, we exclude government-sector workers, i.e., those who ever worked in the government sector during the study period (January 2003 to December 2006). The exclusion criterion is based on the 20 industry categories reported in the UHS. More specifically, we define government-sector workers as individuals who work in a state-owned firm that belongs to one of the following industries: scientific research; public facilities; education; health care and social welfare facilities; culture, sports, and arts; public administration and social organizations; and international organizations. According to this classification, 40% of workers in state-owned firms worked in the government sector. We exclude the government sector from our analysis for two reasons. First, government-sector employers are usually not profit maximizers and thus do not fit into the analytical framework of our paper. Second, government-sector jobs are highly stable, and there are very few transitions between the government and non-government sectors. Based on our sample, only approximately 4% of unemployed workers have a previous job in the government sector, indicating that government-sector workers have very low separation rates. In addition, among the government-sector workers who change industry, 98% of them still remain in government. Among non-government-sector workers who change industry, less than 2% of them move to the government sector.

Table A1 reports the sample size by demographic groups. We divide the sample by education groups (college graduate, high school graduate, and below high school) and age categories (25–39 and 40–54). Overall, sample size has been increasing over time. Among the different demographic groups, we see that younger groups have relatively high levels of education.

Table A1: Sample sizes for the 2003-2006 monthly samples

Year	Month	25–39 college	25–39 high school	25–39 below HS	40–54 college	40–54 high school	40–54 below HS	Total
2003	Jan	3433	5379	3164	2640	6328	7136	28080
	Feb	3440	5375	3117	2638	6339	7105	28014
	Mar	3428	5320	3114	2672	6391	7144	28069
	Apr	3396	5313	3042	2708	6416	7138	28013
	May	3393	5281	3001	2717	6435	7133	27960
	Jun	3368	5235	2987	2708	6429	7087	27814
	Jul	3352	5195	2924	2727	6413	7051	27662
	Aug	3358	5237	2924	2747	6494	7113	27873
	Sep	3337	5195	2869	2764	6505	7087	27757
	Oct	3327	5155	2843	2779	6518	7097	27719
	Nov	3308	5093	2803	2791	6526	7049	27570
	Dec	3320	5094	2797	2813	6579	7047	27650
2004	Jan	3953	5311	2990	3269	7052	7343	29918
	Feb	3938	5303	2958	3301	7073	7324	29897
	Mar	3928	5273	2941	3309	7082	7309	29842
	Apr	3897	5235	2901	3325	7110	7288	29756
	May	3878	5191	2878	3321	7059	7234	29561
	Jun	3881	5206	2851	3359	7125	7246	29668
	Jul	3882	5183	2837	3388	7164	7232	29686
	Aug	3862	5159	2811	3406	7169	7194	29601
	Sep	3843	5161	2773	3420	7172	7157	29526
	Oct	3849	5144	2755	3444	7217	7159	29568
	Nov	3838	5136	2726	3455	7230	7143	29528
	Dec	3813	5092	2691	3456	7235	7116	29403
2005	Jan	4531	5664	3354	3536	7138	7447	31670
	Feb	4501	5615	3307	3525	7145	7383	31476
	Mar	4495	5596	3282	3555	7188	7370	31486
	Apr	4498	5565	3243	3583	7221	7341	31451
	May	4487	5537	3203	3579	7240	7306	31352
	Jun	4489	5516	3167	3597	7281	7267	31317
	Jul	4470	5497	3120	3619	7281	7235	31222
	Aug	4446	5466	3074	3615	7292	7167	31060
	Sep	4468	5438	3047	3642	7326	7170	31091
	Oct	4461	5443	3029	3662	7331	7169	31095
	Nov	4479	5422	3010	3678	7349	7156	31094
	Dec	4471	5395	2971	3690	7344	7109	30980
2006	Jan	4741	5573	3001	3854	7650	7328	32147
	Feb	4740	5557	2975	3865	7673	7324	32134
	Mar	4725	5523	2944	3876	7672	7288	32028
	Apr	4713	5510	2916	3910	7694	7252	31995
	May	4727	5510	2881	3919	7723	7226	31986
	Jun	4726	5500	2866	3931	7716	7196	31935
	Jul	4717	5502	2854	3940	7729	7150	31892
	Aug	4733	5502	2836	3966	7760	7108	31905
	Sep	4744	5482	2823	3970	7745	7056	31820
	Oct	4734	5464	2810	3969	7751	7036	31764
	Nov	4731	5455	2782	3985	7752	7009	31714
	Dec	4740	5455	2767	3990	7763	6979	31694

Note: The sample is restricted to males aged 25–54, with local-urban-*hukou*, and not in the government sector.

A.2 Longitudinal Matching of Monthly UHS

To study labor market dynamics, one has to match monthly UHS data. Because sample households are required to stay in the UHS for at least one full calendar year,[41] the longitudinal dimension of the UHS allows us to study labor force dynamics using matched monthly files. We match individuals from January to December for each year from 2003 to 2006 to form 12-month panel data.

To match two sets of monthly data, we use the following identifying variables (ID): (1) geographic code, which identifies a six-digit city, usually a county-level city or a district within a prefecture-level city; (2) household identity, which uniquely identifies a household within a six-digit city; (3) sex; (4) age; and (5) relationship to the household head. We first sort each month's data by the five identifying variables and eliminate individuals with the same set of ID variables for a given month.[42] We then conduct the matching of two adjacent monthly files using the ID variables. Age differences can be 0 or 1, whereas all other ID variables are required to be the same in the two months.[43]

Table A2 reports the results from matching month i with month i+k. We pool all possible combinations of two-month matches for which the difference between the two months is k based on all monthly samples for each year from 2003 to 2006. For example, in the first row of Table A2, in which we match two adjacent months (month i and month $i+1$) with the same calendar year, the results reported include all such matches (for example, we match January 2003 with February 2003, February 2003 with March 2003,...November 2003 with December 2003, and January 2004 with February 2004, ..., but we do not match

[41] A sample individual may stay for more than one year, but we only match sample individuals within a calendar year because sample attrition rates across years are high and some household IDs are reused, causing incorrect matches. However, our main results are unchanged if we include those cross-calendar-year matches.

[42] Duplicate IDs might exist for two reasons: coding mistakes or same-sex twins in the same household.

[43] We do so in two rounds. In the first round, we match individuals using IDs requiring that all variables including age are identical. In the second round, for those unmatched from the first round, we allow the age difference to be 1 and require all other ID variables to be identical.

across different years such as December 2003 with January 2004). Before conducting the matching, note that excluding samples with duplicate IDs only results in negligible sample size reductions of 0.047%. The matching rate, measured as the percentage of month i sample individuals (after those with duplicate IDs are excluded) that can be matched with month $i+1$ is 99.0%. The matching rate declines as k increases. The matching rate of month i with month $i+2$ is 98.4%, whereas samples three months apart have a 97.8% probability of being matched. For two monthly files that are a half-year apart, approximately 95.9% can be matched. When matching two samples for 11 months, such as January 2003 with December 2003, we still get a matching rate as high as 93.0%.

Table A3 shows the matching results when all of the monthly files are matched into a long panel. Among all individuals that appear at least once, only a small fraction of them can be matched for less than 12 months, and 86.2% stay for exactly 12 months. Overall, the matched results are consistent with the UHS design patterns.

Table A2: Matching month i with month $i+k$ based on all 2003-2006 monthly samples

k	Duplicate ID (%)	Matching rate (%)	Matched sample size
1	0.047	99.0	1315962
2	0.047	98.4	1189637
3	0.046	97.8	1064520
6	0.048	95.9	697963
11	0.055	93.0	113243

Note: This table is based on pooled results for matching month i with $i+k$ months using all monthly samples during the 2003-2006 period. The sample is restricted to males aged 25–54, with local-urban-*hukou*, and not in the government sector.

A.3 Classification of Labor Force Statuses

In the UHS, there are 15 categories for "employment status" that are consistently reported for all sampled individuals, including (1) staff and workers in state-owned economic units; (2) staff and workers in urban collectively owned economic units; (3) staff and workers in

Table A3: Distribution of all matched individuals based on number of months matched (%)

Months matched	25–39 college	25–39 high school	25–39 below HS	40–54 college	40–54 high school	40–54 below HS	Total
1	1.59	1.38	0.96	1.25	1.22	1.54	1.35
2	1.43	1.25	0.98	0.88	0.79	1.06	1.06
3	1.12	1.05	1.06	1.07	0.91	1.38	1.11
4	1.28	1.07	0.92	0.96	0.79	1.13	1.02
5	1.28	1.19	1.10	1.07	0.90	1.21	1.12
6	1.47	1.13	0.97	1.10	0.91	1.20	1.12
7	1.36	1.00	0.82	0.99	0.73	1.32	1.05
8	1.29	1.05	0.88	0.80	0.94	1.15	1.04
9	1.33	1.31	1.13	1.01	0.94	1.10	1.13
10	1.60	1.54	1.12	1.36	1.27	1.62	1.44
11	2.57	2.44	2.33	2.25	2.10	2.49	2.36
12	83.71	85.57	87.73	87.25	88.51	84.81	86.19
sample size	18480	23893	13259	13822	29231	30207	128892

Note: This table shows percentage of individuals in the matched file with a certain number of months that can be matched. The results are based on matched sample using monthly UHS files from January 2003 to December 2006. The sample is restricted to males aged 25–54, with local-urban-*hukou*, and not in the government sector.

other types of economic units, such as foreign-owned enterprises; (4) self-employed workers or owners of enterprises; (5) persons employed by private firms; (6) retired staff and veteran cadre who are re-employed; (7) other employees; (8) retired people; (9) people who are unable to work because of disabilities and illnesses; (10) housewives; (11) people waiting to be employed; (12) people waiting for assignment; (13) students at school; (14) people waiting to enter higher levels of school; and (15) other non-working-age non-employed people.

Following Feng et al. (2017), we assign categories (1) to (7) as employed (E), categories (11) and (12) as unemployed (U), and categories (8), (9), (10), (13), (14), and (15) as out-of-labor-force (O). A careful perusal of the explanations of the 15 labor force categories suggests that our classification of employment, unemployment, and out-of-labor-force are largely consistent with the International Labour Organization definitions. For example, to be qualified as "unemployed" (category 11), one has to be "capable of working, has performed paid work before, but does not have a job at the time of the survey, and is actively looking for job, and is currently available for work." The UHS is also careful to assign people as "mainly responsible for housekeeping" (category 10) only if they "have no intention to seek paid employment outside home." Further, we assign people in category (1) into state-sector employment (S) and other employed workers, including those in categories (2) to (7), into private-sector employment (P).[44] Table A4 shows the fractions of state-sector employment, private-sector employment, unemployment, and out-of-labor-force in our monthly UHS sample.

The UHS-based labor force statuses are not exactly the same as in other countries, such as the U.S. Feng et al. (2017) discuss a number of discrepancies between the UHS-based and CPS-based definitions of labor force statuses. First, unlike the CPS, there is no clear reference week for the labor force status in the UHS in a given month. Second, the exact definitions of employment are slightly different. If a full-time student is paid for even one hour of work during summer break in the reference week, he or she would be defined as "employed" according to the CPS but as "out-of-labor-force" in the UHS. Third, in terms of job searches—important criteria for unemployment—the CPS has a four-week reference period and lists specific activities that qualify as active searching, whereas no such details are given in the UHS. Feng et al. (2017) carefully examine such differences and attempt various robustness checks, including the misclassification method proposed by Feng and Hu (2013).

[44]It is possible that some re-employed retired people might be working in SOEs (category 6), but this should not matter because we focus on individuals aged 25–54. We also follow the literature and do not include collectively owned firms in the state sector (see, e.g., Ge and Yang, 2014 and Hsieh and Song, 2015) because they receive little support from the state and have difficulties obtaining bank credit and entering protected industries (Zhu, 2012).

Table A4: Labor force statuses for the 2003-2006 monthly samples (in %)

Year	Month	State-sector employment	Private-sector employment	Unemployment	Out-of-labor-force
2003	Jan	53.7	35.3	6.4	4.6
	Feb	53.7	35.5	6.4	4.5
	Mar	53.6	35.5	6.6	4.4
	Apr	53.5	35.7	6.5	4.3
	May	53.5	35.7	6.5	4.2
	Jun	53.3	35.8	6.6	4.3
	Jul	53.3	35.9	6.6	4.2
	Aug	53.2	36.0	6.6	4.2
	Sep	53.2	36.1	6.6	4.2
	Oct	53.1	36.1	6.6	4.1
	Nov	52.9	36.3	6.7	4.1
	Dec	53.0	36.3	6.6	4.1
2004	Jan	51.8	37.6	6.2	4.4
	Feb	51.7	37.8	6.1	4.4
	Mar	51.6	37.9	6.2	4.3
	Apr	51.5	38.0	6.2	4.3
	May	51.5	38.1	6.2	4.2
	Jun	51.5	38.2	6.2	4.2
	Jul	51.4	38.2	6.2	4.2
	Aug	51.3	38.3	6.3	4.2
	Sep	51.1	38.4	6.4	4.2
	Oct	51.2	38.4	6.3	4.1
	Nov	51.1	38.4	6.4	4.1
	Dec	51.0	38.5	6.4	4.1
2005	Jan	44.3	44.3	6.5	4.9
	Feb	44.3	44.5	6.4	4.8
	Mar	44.4	44.4	6.4	4.8
	Apr	44.4	44.6	6.3	4.7
	May	44.4	44.7	6.2	4.7
	Jun	44.3	44.9	6.1	4.7
	Jul	44.4	44.8	6.1	4.6
	Aug	44.4	44.9	6.1	4.5
	Sep	44.4	44.9	6.1	4.5
	Oct	44.4	45.0	6.1	4.5
	Nov	44.3	45.0	6.1	4.6
	Dec	44.2	45.1	6.1	4.6
2006	Jan	44.3	45.6	5.5	4.6
	Feb	44.2	45.6	5.5	4.6
	Mar	44.2	45.7	5.6	4.6
	Apr	44.1	45.8	5.5	4.6
	May	44.0	45.9	5.6	4.5
	Jun	44.0	46.0	5.6	4.5
	Jul	43.9	46.0	5.6	4.5
	Aug	43.9	45.9	5.6	4.5
	Sep	43.8	46.1	5.6	4.5
	Oct	43.8	46.2	5.6	4.4
	Nov	43.8	46.2	5.7	4.4
	Dec	43.7	46.3	5.6	4.4

Note: The sample is restricted to males aged 25–54, with local-urban-*hukou*, and not in the government sector.

Appendix B Additional empirical results

B.1 Robustness Checks

This section shows four robustness checks. We first consider different parameter values in the calibration exercise. We then allow for different search intensity between employed and unemployed workers. We also recalculate data moments using weights. Lastly, we treat out-of-labor-force (O) as unemployment (U).

For each robustness check, we re-calibrate the model and re-simulate the counterfactual experiments. Table B1 shows the moments used in the calibration. Table B2 presents the calibrated bargaining power of state-sector workers and the productivity of the state sector, as well as the predicted unemployment rate and state employment share in the steady state. Table B3 shows the results of the counterfactual experiments, including the average unemployment duration, the proportion of long-term unemployment with a duration longer than six months, and the unemployment rate, for each of the counterfactual experiments.

B.1.1 Different parameter values in the calibration exercise

In this section, we conduct robustness checks to examine whether our calibration and counterfactual results are sensitive to the parameters that we select. We first consider different values on the bargaining power of the private sector (baseline is 0.5). We use 0.4 as the alternative bargaining power of the private sector in our robustness checks. In addition, we consider a different value of leisure. Compared with 0.3 in the baseline, we use 0.4 in our robustness checks. Lastly, we select different parameters in the matching function and consider a different value of the elasticity parameter, η, using 0.4 instead of 0.5 in the baseline model.

B.1.2 Allowing search intensity to be different for employed and unemployed workers

Here we consider an alternative model that allows for different search intensities across unemployed workers, state-sector workers, and private-sector workers and use transition rates between the two sectors to calibrate the search intensity of state-sector and private-sector workers.

Our baseline model assumes equal search intensity across employed and unemployed workers. One concern may be that this assumption causes the large difference in firing costs to play a small role in the different level of dynamics between the two sectors. Firing costs lead the firm to hold on to unproductive workers until the match exogenously separates or the worker gets an outside offer; thus, the cost is a function of the expected duration of the unproductive match. As it is assumed that job offers come to the employed at the same rate as the unemployed, this means the expected duration of a match is much shorter, and the cost associated with a firm holding on to unproductive workers will decrease substantially.

We redefine market tightness as

$$\begin{aligned} \theta_1 &= \frac{v_1}{u + \zeta_1 m_1 + \zeta_2 m_2} \\ \theta_2 &= \frac{v_2}{u + \zeta_1 m_1 + \zeta_2 m_2} \end{aligned} \tag{25}$$

where ζ_1 and ζ_2 are the search intensities of employed workers in state-owned firms and private firms. Unemployed workers' search intensity is assumed to be 1 and we allow employed workers in the two sectors to have different search intensities.

The value of the match between a worker–private firm pair becomes

$$
\begin{aligned}
rV_2(z) = {} & p_2 z + (\delta + \lambda)(U - V_2(z)) \\
& + \zeta_2 f(\theta_1) \int_{\underline{z}}^{\bar{z}} 1\{V_2(z) > V_1(z')\}\beta_1(V_1(z') - V_2(z))dG(z') \\
& + \zeta_2 f(\theta_2) \int_{\underline{z}}^{\bar{z}} 1\{V_2(z) > V_2(z')\}\beta_2(V_2(z') - V_2(z))dG(z') \qquad (26)
\end{aligned}
$$

The value of the match between a worker–state-owned firm pair becomes

$$
\begin{aligned}
rV_1(z) = {} & p_1 z + \delta(U - V_1(z)) + \lambda(V_1^0(z) - V_1(z)) \\
& + \zeta_1 f(\theta_1) \int_{\underline{z}}^{\bar{z}} 1\{V_1(z') > V_1(z)\}\beta_1(V_1(z') - V_1(z))dG(z') \\
& + \zeta_1 f(\theta_2) \int_{\underline{z}}^{\bar{z}} 1\{V_2(z') > V_1(z)\}\beta_2(V_2(z') - V_1(z))dG(z') \qquad (27)
\end{aligned}
$$

The value of a match in the state sector that receives a bad productivity shock becomes

$$
\begin{aligned}
rV_1^0(z) = {} & 0 + \delta(U - V_1^0(z)) \\
& + \zeta_1 f(\theta_1) \int_{\underline{z}}^{\bar{z}} 1\{V_1(z') > W_1(\phi_{1,0}(z), z)\}\beta_1(V_1(z') - W_1(\phi_{1,0}(z), z))dG(z') \\
& + \zeta_1 f(\theta_2) \int_{\underline{z}}^{\bar{z}} 1\{V_2(z') > W_1(\phi_{1,0}(z), z)\}\beta_2(V_2(z') - W_1(\phi_{1,0}(z), z))dG(z') \qquad (28)
\end{aligned}
$$

Although our data do not provide job-to-job transition information, we can observe transitions between the two sectors. When we assume equal search intensity for all states, the model predicts that the transition rate from the state sector to the private sector (S-P) is 0.094%, and the transition rate from the private sector to the state sector (P-S) is 0.056%. In our data, the S-P transition rate is 0.14%, and the P-S transition rate is 0.064%.

Given that the baseline model already predicts a P-S that is smaller than the P-S in the data, the search intensity of private-sector workers is set to be the same as that of unemployed workers (normalized to 1). We calibrate the search intensity of state-sector workers by matching S-P transition rates. The calibrated search intensity is 0.81. Other calibrated parameters are shown in Appendix Table B2.

B.1.3 Results using weighted sample

We also re-calibrate the model using weighted moments from the UHS sample. Similar to Feng et al. (2017), we first divide the UHS sample into age (six five-year categories)/region (six regions) /education (three education levels) cells. We then calculate population sizes for each corresponding cell, using Census 2000 and Census 2010 data.[45] The weights are then calculated as the ratio of population size and sample size for each cell. We recalculate the transition rates, distribution of accepted wage, unemployment rate, and state employment share by weight.

Table B1 presents the weighted moments targeted in the calibration. U-S and U-P transition rates are lower in the weighted sample than in the unweighted sample, while P-U transition rates are higher. The state-sector wage premium is higher in the weighted sample. Given that younger individuals who have relatively high unemployment rates are slightly underrepresented in the UHS (Feng et al., 2017), the unemployment rate using weighted data is 7.6%, 1.2 ppt higher than that using unweighted data. The state employment share is 52.1%, 1.7 ppt lower than in the unweighted sample.

B.1.4 Results treating out-of-labor-force as unemployment

Because the UHS does not report detailed information on individual search behavior, it is possible that the distinction between unemployment and out-of-labor-force can be murky in the data. Therefore, we report robustness check results that treat out-of-labor-force as

[45] We first estimate population sizes for each year between the two census years 2000 and 2010 using the linear interpolation method. We then choose the year 2005 as the basis for our weight calculation, as our sample covers the 2003–2006 period. To match our sample, only males aged 25 and 54 with local urban *hukou* are included.

unemployment. Table B1 presents the moments targeted in the calibration. We get lower U-S and U-P transition rates and higher S-U and P-U transition rates. The unemployment rate is now a measure of the non-employment rate, which is 10.5%.

B.1.5 Robustness check results

Table B2 shows the calibration results for alternative models. Among different specifications, the bargaining power of state-sector workers ranges from 0.72 (when we allow for on-the-job search) to 0.90 (when we use the weighted sample). The productivity of state-owned firms ranges from 0.46 (when $\beta_2 = 0.4$) to 0.78 (when we combine out-of-labor-force with unemployment). Nevertheless, the models with different parameters are still able to predict similar unemployment rates (ranging from 9.5% to 11.0%)[46] and state employment share (ranging from 2.9% to 10.0%) in the steady state.

Moreover, the general findings from the counterfactual experiments remain unchanged, as shown in Table B3. Equalizing productivity between the two sectors results in a decline of 0.2–6.0 months in the unemployment duration. Allowing SOEs to lay off workers has small effects on the unemployment duration, ranging from 0.2 to 0.6 month. Reducing the bargaining power of state-sector workers significantly reduces the unemployment duration by 4.4–18.3 months. Reducing the bargaining power of state-sector workers has the strongest effect on reducing the unemployment duration and long-term unemployment rates relative to the other two channels among most specifications. The only two exceptions are when $\beta_2 = 0.4$ and when we allow for on-the-job search. In these two cases, both equalizing the productivity and equalizing the bargaining power have big impacts on the unemployment duration and long-term unemployment rates. However, our finding that the firing cost plays a small roll in labor market dynamics is not driven by our specification.

[46] In a robustness check where we combine out-of-labor-force with unemployment, the unemployment rate is actually non-employment rate, so we do not consider this as an upper bound for the estimate of the unemployment rate.

Across different specifications, a further SOE reform that combines the three channels always has a significant effect on labor market mobility by reducing the unemployment duration (by 13.9 to 18.6 months) and the proportion of long-term unemployment with a duration longer than six months (by 5.4 to 9.3 ppt). We also obtain consistent results for unemployment level: SOE reform leads to a decline in the unemployment rate, and the decline ranges from 0.78 ppt to 2.99 ppt.

Table B1: Moments used in the robustness checks

	Transition rates				Accepted wage		Unemployment	State
	U-S (%)	U-P (%)	S-U (%)	P-U (%)	Mean S/P	std/mean	rate (%)	employment share (%)
Baseline	0.28	2.36	0.06	0.28	1.03	0.87	6.40	53.8
Weighted sample	0.24	2.16	0.06	0.29	1.11	0.86	7.59	52.1
Combine O with U	0.23	1.61	0.10	0.33	1.03	0.87	10.49	53.8

Note: S, P, U stand for state-sector employment, private-sector employment, and unemployment (non-employment in the case when we combine O with U), respectively.

Table B2: Robustness check on parameter and model equilibrium

	Parameter		Model equilibrium	
	β_1	p_1	Unemployment rate (%)	State employment share (%)
Baseline model	0.87	0.67	8.99	9.1
$\beta_2 = 0.4$	0.68	0.46	10.07	2.9
$b = 0.4$	0.86	0.68	9.74	6.5
$\eta = 0.4$	0.93	0.60	10.16	4.7
on-the-job search	0.72	0.55	9.49	8.4
weighted sample	0.90	0.76	11.03	7.3
combine O with U	0.87	0.78	15.69	10.0

Note: The robustness check is for the whole sample.

Table B3: Counterfactual experiments: Robustness check

	Status quo			Equalizing productivity			Allowing SOE layoff			Equalizing bargaining power			All three channels		
	unemp. duration	long-term unemp.	unemp. rate	unemp. duration	long-term unemp.	unemp. rate	unemp. duration	long-term unemp.	unemp. rate	unemp. duration	long-term unemp.	unemp. rate	unemp. duration	long-term unemp.	unemp. rate
Baseline model	37.8	85.2	8.99	36.1	84.5	8.08	37.6	85.0	9.39	29.9	81.5	6.45	24.7	78.0	6.37
$\beta_2 = 0.4$	37.8	85.2	10.07	31.9	82.6	8.40	37.6	85.1	10.23	33.4	83.3	9.62	22.2	75.9	8.65
$b = 0.4$	37.8	85.1	9.74	35.9	84.4	9.10	37.5	85.0	10.09	28.4	80.7	8.26	22.9	76.5	8.79
$\eta = 0.4$	37.5	85.0	10.16	36.5	84.6	9.21	38.5	85.4	10.41	29.4	81.2	8.92	23.6	77.1	8.90
on-the-job search	40.0	85.9	9.49	35.0	84.1	7.21	39.6	85.8	9.84	35.0	84.0	7.92	25.2	78.4	6.49
weighted sample	41.4	86.4	11.03	41.6	86.4	10.88	41.1	86.3	11.44	31.2	82.2	9.34	26.7	79.5	10.25
combine O with U	53.1	89.2	15.69	51.1	88.8	14.73	52.5	89.1	16.20	40.3	86.0	12.64	34.5	83.8	13.26

Note: The robustness check is for the whole sample.

B.2 Subgroup Results

We divide workers into six subgroups according to their age and education. There are two age groups—25–39 and 40–54—and three education groups—college, high school, and below high school. We calibrate our model for the whole sample and separately for each of the six age-education subgroups. The advantage of calibrating the model for each subgroup is that we are able to control for differences in worker productivity that arise from their differences in experience and education.[47] However, calibrating the model by groups assumes that each group is a closed labor market and no competition exists across groups. In addition, we calibrate our model separately for the coastal and inland areas. As shown in Section 4, the two regions have very different labor market mobility patterns. Our calibration and counterfactual results also shed light on these regional differences.

B.2.1 Results by Age-education Group

Table 6 shows calibrated parameters for each age-education group. Workers younger than 40 years without a high school degree in the state sector have the highest bargaining power (0.94) compared to those in the private sector, whereas workers older than 40 years with a college degree have the lowest bargaining power (0.65). The highest relative productivity (state/private) goes to young workers without a high school degree (0.99) and the lowest goes to older workers with a college degree (0.48). These results are consistent with the facts that we observed in the data, as shown in Table 5. The state-sector wage premium is highest among high-school dropouts younger than 40 years (38%), and lowest among workers older than 40 years with a college degree (-29%). At the same time, the U-S transition rates of both groups are low relative to their U-P transition rates. The reason is that although high-school dropouts younger than 40 years have high productivity, their bargaining power

[47] We cannot allow for unobserved heterogeneity of workers within an age-education group because we do not have firm-worker matched data.

is too strong, and state-owned firms do not want to hire them. In contrast, although college graduates older than 40 years have relatively low bargaining power, state-owned firms still do not want to hire them because their productivity is low.

Using our calibrated parameters, the model predicts that the longest unemployment duration goes to high school dropouts younger than 40 years (51 months), and the shortest is for college graduates older than 40 years (30 months), as shown in the first panel of Table B4. Our model also predicts that less-educated workers and young workers have higher unemployment rates, as shown in Table C7.

Table B4 shows the counterfactual results for each age-education group. In general, equalizing productivity across the two sectors and reducing the firing costs of SOEs do not have significant effects on long-term unemployment, while reducing the bargaining power of state-sector workers and comprehensive SOE reform are much more effective in reducing long-term unemployment for all age-education groups. In particular, when equalizing productivity between the two sectors, groups with lower relative productivity (older and highly educated workers) experience a larger decline in unemployment duration and long-term unemployment rates. For example, the increases in the U-S and U-E transition rates are largest for college graduates older than 40 years (1.24 ppt and 0.80 ppt, respectively). However, these workers also have lower bargaining power. Therefore, the effect of reducing bargaining power on reducing long-term unemployment for them is smaller.

In a further SOE reform that combines the above three channels, the effects on the average unemployment duration and long-term unemployment rates are stronger for young workers and less-educated workers. The largest decline in the unemployment duration is for high-school dropouts younger than 40 years, from 51 months to 32 months. The smallest decline is for college graduates older than 40 years, from 30 months to 20 months. SOE reform also has a heterogeneous effect on the unemployment rate for different age-education groups.

The reform leads to a larger decline in the unemployment rate of young workers and less-educated workers. Therefore, the inequality in unemployment duration and unemployment rate shrinks after the SOE reform.

B.2.2 Results by Region

We now compare the calibration and counterfactual results between the inland and coastal areas. Table 6 shows that SOE workers in the coastal area have slightly lower bargaining power than those in the inland area (0.85 versus 0.88). In addition, state-owned firms in the coastal area have lower productivity than those in the inland area (0.60 versus 0.76). There could be several reasons for this finding. First, a larger gap can exist in the total factor productivity between SOEs and private firms in the coastal area. Second, state-owned firms in the inland area may have easier or cheaper access to credit than those in the coastal area. Lastly, industry distributions may be different such that inland SOEs are more likely to concentrate on capital-intensive industries than coastal SOEs. We also find that both the exogenous separation rate (δ) and the endogenous separation rate (λ) are higher in the coastal area. In addition, coastal firms have a much lower vacancy posting cost than inland firms (4.5 versus 13.0). These parameters explain the much higher transition rates between unemployment and employment in the coastal area.

Our model predicts a huge regional difference in labor market dynamics. The average unemployment duration for workers in the inland area is 53 months, but it is only 26 months for workers in the coastal area, as shown in the first panel of Table B5. Moreover, Table C7 shows that the inland area has a higher unemployment rate (9.9%) compared to the coastal area (8.0%) in the steady state. The steady-state unemployment rates in both areas are higher than the unemployment rates observed during 2003–2006. In addition, although the shares of state-sector employment in both areas are lower than those observed during 2003–2006, the share of state-sector employment is still higher in the inland area (12.1%)

than the coastal area (5.9%) in the steady state.

Table B5 shows the counterfactual results for the coastal and inland areas. When equalizing productivity across the two sectors, the effect on unemployment duration and long-term unemployment rates is small for both areas. When SOEs are able to lay off unproductive workers, both regions experience a minor decline in the U-E transition rates. Therefore, increasing the productivity of SOEs or reducing their firing costs cannot solve the problem of long-term unemployment in both regions. In contrast, reducing the bargaining power of state-sector workers is quite effective in increasing the U-E transitions, shortening the unemployment duration, and lowering long-term unemployment rates in both areas. In addition, relative to the coastal area, the inland area experiences a larger decline in unemployment duration and unemployment rate.

Lastly, a comprehensive SOE reform has a strong effect on improving labor market mobility in both areas. At the same time, the reform also reduces the steady-state unemployment rate for both. The effects on labor market mobility and unemployment level are stronger in the inland area. The average unemployment duration in the inland area declines from 53 to 35 months, and that in the coastal area declines from 26 to 17 months. The unemployment rate in the inland area declines from 9.9% to 5.6%, and that in the coastal area declines from 8.0% to 6.4%. In the new equilibrium, the inland area would have a lower unemployment rate than the coastal area.

Table B4: Counterfactual experiments: Results by age-education group

	U-S (%)	U-P (%)	U-E (%)	Unemployment duration (months)	% of long-term unemployment ($\geq$ 6 months)	Accepted labor income (S/P)	Unemployment rate (%)	State employment share (%)
Status quo								
25–39, college	0.33	2.64	2.97	33.7	83.5	1.44	7.62	10.4
25–39, high school	0.24	1.95	2.19	45.6	87.5	1.17	10.93	9.9
25–39, below HS	0.18	1.78	1.97	50.9	88.8	1.70	11.64	10.5
40–54, college	0.44	2.94	3.39	29.5	81.3	0.87	4.26	3.9
40–54, high school	0.37	2.74	3.10	32.2	82.8	1.08	7.07	6.2
40–54, below HS	0.30	2.77	3.07	32.6	82.9	1.38	9.56	9.1
Equalizing productivity								
25–39, college	0.51	2.64	3.15	31.8	82.5	1.71	6.89	17.9
25–39, high school	0.47	1.85	2.32	43.1	86.9	1.51	9.70	22.8
25–39, below HS	0.19	1.78	1.97	50.8	88.8	1.72	11.63	10.7
40–54, college	1.68	2.51	4.19	23.9	77.4	1.31	2.82	34.3
40–54, high school	1.00	2.47	3.46	28.9	80.9	1.51	5.66	28.5
40–54, below HS	0.48	2.68	3.16	31.7	82.5	1.64	8.95	16.8
Allowing SOE layoff								
25–39, college	0.37	2.73	3.09	32.3	82.8	1.71	7.81	9.1
25–39, high school	0.26	1.94	2.20	45.5	87.5	1.41	11.51	8.2
25–39, below HS	0.19	1.78	1.97	50.7	88.7	1.98	12.13	8.8
40–54, college	0.48	2.94	3.41	29.3	81.2	0.92	4.34	3.6
40–54, high school	0.38	2.73	3.11	32.1	82.7	1.21	7.30	5.7
40–54, below HS	0.32	2.77	3.09	32.4	82.8	1.66	9.96	7.5
Equalizing bargaining power								
25–39, college	1.51	2.57	4.08	24.5	77.9	0.72	4.78	32.6
25–39, high school	0.88	1.88	2.76	36.2	84.5	0.63	7.88	27.7
25–39, below HS	1.49	1.56	3.04	32.9	83.1	0.87	6.41	47.9
40–54, college	0.64	2.93	3.57	28.0	80.4	0.62	4.00	5.3
40–54, high school	0.85	2.69	3.54	28.3	80.6	0.64	6.02	12.4
40–54, below HS	1.51	2.61	4.12	24.3	77.7	0.70	6.29	31.4
All three channels								
25–39, college	n.a.	n.a.	4.70	21.3	74.9	n.a.	5.28	n.a.
25–39, high school	n.a.	n.a.	3.39	29.5	81.3	n.a.	7.79	n.a.
25–39, below HS	n.a.	n.a.	3.08	32.4	82.9	n.a.	8.10	n.a.
40–54, college	n.a.	n.a.	4.90	20.4	74.0	n.a.	3.06	n.a.
40–54, high school	n.a.	n.a.	4.63	21.6	75.3	n.a.	5.03	n.a.
40–54, below HS	n.a.	n.a.	4.74	21.1	74.7	n.a.	6.73	n.a.

Note: S, P, U, E stand for state-sector employment, private-sector employment, unemployment, and employment, respectively.

Table B5: Counterfactual experiments: Results by region

	U-S (%)	U-P (%)	U-E (%)	Unemployment duration (months)	% of long-term unemployment ($\geq$ 6 months)	Accepted labor income (S/P)	Unemployment rate (%)	State employment share (%)
Status quo								
Inland	0.23	1.65	1.88	53.1	89.2	1.33	9.88	12.1
Coastal	0.37	3.42	3.79	26.4	79.3	1.23	8.00	5.9
Equalizing productivity								
Inland	0.36	1.59	1.95	51.3	88.9	1.56	9.09	21.3
Coastal	0.87	3.17	4.04	24.7	78.1	1.65	6.93	22.0
Allowing SOE layoff								
Inland	0.25	1.65	1.90	52.6	89.1	1.51	10.46	10.0
Coastal	0.40	3.41	3.82	26.2	79.2	1.38	8.20	5.1
Equalizing bargaining power								
Inland	0.91	1.57	2.48	40.3	86.0	0.70	6.58	33.3
Coastal	1.24	3.32	4.56	21.9	75.6	0.63	6.33	16.1
All three channels								
Inland	n.a.	n.a.	2.90	34.5	83.8	n.a.	5.58	n.a.
Coastal	n.a.	n.a.	5.77	17.3	70.0	n.a.	6.37	n.a.

Note: S, P, U, E stand for state-sector employment, private-sector employment, unemployment, and employment, respectively.

Appendix C Supplementary Tables

Table C1: International comparison

	Unemployment rate (2006, %)	Long-term unemployment (2006, %)
Transitional Countries		
Czech Republic	7.1	75
Estonia	5.9	62
Poland	13.8	69
Slovak Republic	13.4	84
Slovenia	6.0	68
Developed Countries		
Australia	5.2	31
Austria	4.8	44
Belgium	8.2	65
Canada	6.3	16
France	8.4	60
Germany	10.3	71
Greece	9.0	72
Italy	6.8	64
Japan	4.1	48
United Kingdom	5.3	40
United States	4.6	18

Note: Long-term unemployment refers to unemployment spells with a duration greater than six months. Data sources: OECD website.

Table C2: Distribution of unemployment spells up to month i, including left-censored spells

	25–39 college	25–39 high school	25–39 below HS	40–54 college	40–54 high school	40–54 below HS	Inland	Coastal	Total
Spell $\geq$ 3 months (%)									
LB (%)	90.0	93.7	94.7	93.4	94.3	94.3	94.5	92.6	93.7
UB (%)	95.6	97.1	97.4	94.2	95.2	95.2	97.1	94.6	96.1
Spell $\geq$ 6 months (%)									
LB (%)	77.7	84.6	87.3	85.1	86.2	86.8	86.5	83.1	85.2
UB (%)	89.8	93.3	94.0	87.1	88.6	88.8	93.1	87.8	91.0
Number of spells	5626	13316	9524	1857	8917	12480	31137	20583	51720

Note: This table pools results from July to December for the years 2003 to 2006 based on matched monthly UHS files from January 2003 to December 2006. The sample is restricted to males aged 25–54, with local-urban-*hukou*, and not in the government sector. All unemployed spells are included, including those left-censored.

Table C3: Distribution of unemployment spells up to month i (including the government sector)

	25–39 college	25–39 high school	25–39 below HS	40–54 college	40–54 high school	40–54 below HS	Inland	Coastal	Total
Panel A: Uncensored spells only									
Spell $\geq$ 3 months (%)	95.2	97.0	97.3	93.9	95.1	95.0	96.9	94.4	95.9
Number of spells	5393	12906	9280	1872	8905	12451	30514	20293	50807
Spell $\geq$ 6 months (%)	89.1	92.8	93.8	86.3	88.4	88.5	92.7	87.2	90.5
Number of spells	4956	12153	8869	1851	8741	12279	29178	19671	48849
Panel B: All spells									
Spell $\geq$ 3 months (%)									
LB (%)	89.8	93.7	94.7	93.1	94.2	94.2	94.4	92.5	93.6
UB (%)	95.4	97.0	97.4	93.9	95.1	95.0	97.0	94.5	96.0
Spell $\geq$ 6 months (%)									
LB (%)	77.3	84.4	87.2	84.7	86.0	86.5	86.3	82.8	84.9
UB (%)	89.5	93.2	94.0	86.6	88.4	88.5	92.9	87.5	90.7
Number of spells	5717	13361	9537	1887	8987	12562	31334	20717	52051

Note: This table pools results from July to December for year 2003-2006 based on matched monthly UHS files from January 2003 to December 2006. The sample is restricted to males aged 25–54, with local-urban-*hukou*.

Table C4: Transition probabilities among four labor force statuses (%): Subgroup results

K	U-S	U-P	U-O	S-U	S-P	S-O	P-U	P-S	P-O	O-U	O-S	O-P
25–39, college												
1	0.3	2.6	0.1	0.0	0.1	0.0	0.3	0.1	0.0	0.5	0.3	0.6
3	0.8	6.3	0.1	0.1	0.2	0.0	0.6	0.1	0.0	1.2	1.0	1.6
6	1.3	10.2	0.2	0.2	0.4	0.0	1.0	0.2	0.1	2.3	2.2	2.8
12	2.7	17.8	0.4	0.2	0.8	0.0	1.3	0.6	0.1	3.7	2.9	5.5
25–39, high school												
1	0.2	2.0	0.0	0.1	0.1	0.0	0.3	0.0	0.0	0.4	0.1	1.0
3	0.6	5.0	0.1	0.2	0.2	0.0	0.7	0.1	0.0	0.7	0.3	2.8
6	1.0	8.4	0.1	0.3	0.4	0.0	1.0	0.2	0.0	1.2	0.5	5.3
12	1.7	12.9	0.1	0.4	0.9	0.1	1.5	0.4	0.1	3.2	1.2	8.9
25–39, below HS												
1	0.2	1.8	0.0	0.1	0.1	0.0	0.3	0.0	0.0	0.1	0.0	0.4
3	0.5	4.4	0.0	0.3	0.4	0.0	0.6	0.1	0.0	0.3	0.2	1.1
6	0.7	6.9	0.1	0.5	0.8	0.0	1.0	0.2	0.1	0.5	0.5	2.4
12	1.3	10.8	0.2	0.8	1.6	0.1	1.3	0.3	0.1	0.6	0.8	3.6
40–54, college												
1	0.4	2.9	0.1	0.0	0.1	0.0	0.2	0.1	0.1	0.0	0.1	0.5
3	1.0	6.7	0.3	0.1	0.2	0.1	0.4	0.2	0.2	0.1	0.2	1.2
6	1.5	11.1	0.7	0.1	0.4	0.1	0.6	0.3	0.3	0.3	0.3	2.4
12	3.2	20.2	0.8	0.2	0.8	0.2	0.9	0.7	0.6	0.2	0.8	4.7
40–54, high school												
1	0.4	2.7	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.6
3	0.9	6.4	0.2	0.2	0.3	0.1	0.5	0.2	0.2	0.2	0.3	1.5
6	1.6	10.5	0.5	0.3	0.5	0.3	0.9	0.3	0.3	0.2	0.4	2.7
12	2.6	15.6	0.9	0.6	1.2	0.5	1.2	0.6	0.4	0.5	0.8	4.9
40–54/Below HS												
1	0.3	2.8	0.2	0.1	0.1	0.1	0.3	0.1	0.1	0.1	0.2	0.6
3	0.7	6.4	0.4	0.2	0.3	0.2	0.8	0.2	0.3	0.2	0.5	1.2
6	1.2	10.6	0.7	0.4	0.7	0.4	1.2	0.3	0.5	0.3	0.7	2.0
12	2.0	16.0	1.2	0.6	1.3	0.8	1.9	0.6	0.7	0.7	1.7	3.9
Inland												
1	0.2	1.6	0.1	0.0	0.1	0.0	0.2	0.1	0.1	0.1	0.2	0.4
3	0.6	3.9	0.1	0.1	0.2	0.1	0.5	0.1	0.1	0.2	0.4	1.1
6	1.0	6.4	0.3	0.2	0.4	0.2	0.9	0.3	0.2	0.3	0.7	2.0
12	1.8	10.5	0.4	0.3	0.9	0.3	1.3	0.5	0.4	0.5	1.3	3.8
Coastal												
1	0.4	3.4	0.1	0.1	0.1	0.0	0.3	0.1	0.1	0.2	0.2	0.8
3	0.9	8.3	0.2	0.3	0.3	0.1	0.8	0.1	0.1	0.6	0.5	2.0
6	1.4	13.5	0.4	0.5	0.7	0.2	1.2	0.2	0.2	1.0	0.8	3.5
12	2.3	20.1	0.9	0.7	1.5	0.3	1.7	0.5	0.4	2.0	1.4	6.4

Note: Same as Table 3.

Table C5: Transition probabilities among four labor force statuses (%, including the government sector)

K	U-S	U-P	U-O	S-U	S-P	S-O	P-U	P-S	P-O	O-U	O-S	O-P
						25–39, college						
1	0.6	2.6	0.1	0.0	0.0	0.0	0.3	0.1	0.0	0.4	0.6	0.6
3	1.5	6.3	0.1	0.0	0.1	0.0	0.6	0.3	0.0	1.3	1.9	1.6
6	2.6	10.0	0.2	0.1	0.2	0.0	1.0	0.6	0.1	2.4	3.9	2.8
11	5.1	17.3	0.4	0.1	0.5	0.0	1.3	1.1	0.1	3.6	4.7	5.4
						25–39, high school						
1	0.3	2.0	0.0	0.1	0.1	0.0	0.3	0.1	0.0	0.4	0.1	1.0
3	0.8	5.0	0.1	0.2	0.2	0.0	0.7	0.1	0.0	0.8	0.5	2.7
6	1.2	8.4	0.1	0.2	0.4	0.0	1.0	0.3	0.0	1.2	0.8	5.3
11	2.2	12.8	0.1	0.3	0.8	0.1	1.5	0.5	0.1	3.2	2.0	8.8
						25–39, below HS						
1	0.2	1.8	0.0	0.1	0.1	0.0	0.3	0.0	0.0	0.1	0.1	0.4
3	0.5	4.4	0.0	0.3	0.4	0.0	0.6	0.1	0.0	0.3	0.2	1.1
6	0.8	7.0	0.1	0.4	0.8	0.0	1.0	0.2	0.1	0.5	0.5	2.4
11	1.3	11.0	0.2	0.7	1.5	0.1	1.3	0.4	0.1	0.6	1.1	3.6
						40–54, college						
1	0.6	3.0	0.2	0.0	0.0	0.0	0.2	0.1	0.1	0.0	0.3	0.5
3	1.4	6.8	0.3	0.0	0.1	0.1	0.4	0.3	0.2	0.1	0.6	1.4
6	2.3	11.1	0.6	0.1	0.2	0.1	0.6	0.5	0.3	0.3	0.9	2.6
11	4.3	19.8	0.8	0.1	0.5	0.2	0.9	1.2	0.6	0.2	2.8	4.6
						40–54, high school						
1	0.5	2.7	0.1	0.1	0.1	0.0	0.2	0.1	0.1	0.1	0.2	0.6
3	1.1	6.4	0.2	0.1	0.2	0.1	0.6	0.2	0.2	0.2	0.4	1.5
6	2.0	10.4	0.5	0.3	0.4	0.2	0.9	0.4	0.3	0.2	0.6	2.6
11	3.0	15.5	0.8	0.4	1.0	0.4	1.2	0.8	0.4	0.5	1.2	5.0
						40–54/Below HS						
1	0.4	2.8	0.2	0.1	0.1	0.1	0.3	0.1	0.1	0.1	0.2	0.6
3	1.0	6.4	0.4	0.2	0.3	0.2	0.8	0.2	0.3	0.2	0.5	1.2
6	1.7	10.6	0.7	0.4	0.6	0.4	1.2	0.4	0.5	0.3	0.8	2.0
11	2.9	15.8	1.2	0.6	1.2	0.8	1.9	0.8	0.7	0.7	1.8	3.8
						Inland						
1	0.3	1.6	0.1	0.0	0.1	0.0	0.2	0.1	0.1	0.1	0.2	0.5
3	0.8	3.9	0.1	0.1	0.2	0.1	0.5	0.2	0.1	0.2	0.6	1.1
6	1.4	6.4	0.3	0.1	0.3	0.2	0.9	0.4	0.2	0.3	1.0	2.0
11	2.6	10.4	0.4	0.2	0.6	0.3	1.3	0.7	0.4	0.5	1.9	3.8
						Coastal						
1	0.5	3.4	0.1	0.1	0.1	0.0	0.3	0.1	0.1	0.2	0.3	0.8
3	1.1	8.3	0.2	0.2	0.3	0.1	0.8	0.2	0.1	0.6	0.7	2.0
6	1.8	13.5	0.4	0.3	0.5	0.1	1.2	0.4	0.2	1.0	1.2	3.5
11	2.9	20.1	0.9	0.5	1.1	0.3	1.7	0.8	0.4	2.0	2.2	6.4
						Total						
1	0.4	2.4	0.1	0.0	0.1	0.0	0.3	0.1	0.1	0.1	0.2	0.6
3	0.9	5.7	0.2	0.1	0.2	0.1	0.6	0.2	0.1	0.3	0.6	1.4
6	1.6	9.3	0.3	0.2	0.4	0.1	1.0	0.4	0.2	0.5	1.1	2.5
11	2.7	14.4	0.6	0.3	0.8	0.3	1.4	0.8	0.4	1.0	2.0	4.6

Note: S, P, U, O stands for state-sector employment, private-sector employment, unemployment and out-of-labor-force, respectively. For example, U-O is the probability of out-of-labor-force in month i+k for those unemployed in month i. The sample is restricted to males aged 25–54, with local-urban-*hukou*.

Table C6: Model fit

	U-S (%)		U-P (%)		S-U (%)		P-U (%)		accepted wage mean S/P		accepted wage std/mean	
	data	model	data	model	data	model	data	model	data	model	data	model
25–39, college	0.324	0.331	2.641	2.638	0.036	0.036	0.262	0.262	1.158	1.170	0.839	0.857
25–39, high school	0.243	0.243	1.950	1.950	0.062	0.062	0.286	0.286	0.953	0.953	0.890	0.890
25–39, below HS	0.179	0.184	1.781	1.782	0.113	0.113	0.272	0.272	1.385	1.384	0.673	0.673
40–54, college	0.445	0.445	2.941	2.941	0.031	0.031	0.155	0.155	0.708	0.708	0.750	0.750
40–54, high school	0.366	0.366	2.738	2.738	0.076	0.076	0.245	0.245	0.880	0.880	0.784	0.784
40–54, below HS	0.295	0.300	2.766	2.770	0.087	0.087	0.342	0.342	1.104	1.124	0.784	0.779
Inland	0.224	0.231	1.648	1.652	0.045	0.045	0.222	0.222	1.106	1.105	0.852	0.848
Coastal	0.364	0.368	3.421	3.421	0.103	0.103	0.341	0.341	1.000	0.996	0.867	0.867
Total	0.281	0.281	2.362	2.362	0.065	0.065	0.276	0.276	1.033	1.033	0.870	0.870

Table C7: Unemployment rate and state employment share: Data vs. model equilibrium

	Data		Model Equilibrium		
	Unemployment rate (%)	State employment share (%)	Unemployment rate (%)	State employment share (%)	Fraction of SOE unproductive matches (%)
25–39, college	4.78	61.9	7.62	10.4	27.2
25–39, high school	8.88	50.7	10.93	9.9	24.7
25–39, below HS	12.02	34.5	11.64	10.5	23.0
40–54, college	2.06	69.4	4.26	3.9	11.4
40–54, high school	4.69	56.8	7.07	6.2	16.3
40–54, below HS	6.85	47.8	9.56	9.1	25.4
Inland	6.33	58.5	9.88	12.1	27.0
Coastal	6.52	46.5	8.00	5.9	18.9
Total	6.40	53.8	8.99	9.1	23.0