A Two-Sector Equilibrium Search and Matching Model: Interpreting Urban Labour Market Dynamics in China*

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Abstract

This paper employs a direct search and matching two-sector model to analyse urban labour market dynamics in China from 2008 to 2021. A central focus is on the externalities introduced by the public sector, particularly the impact of high wages in state-owned enterprises (SOEs) and their fluctuations due to policy shocks on the labour market outcome. In addition to wage effects, we also examine how other structural factors, mainly matching efficiency and bargaining power, influence the dynamics. Our findings highlight two core results. First, while a restriction on SOE wages has little to no effect on private-sector market tightness or wage determination, it significantly increases SOE market tightness, redirects job seekers toward the private sector, stimulates private-sector vacancy creation, and leads to an overall improvement in unemployment outcomes. Extensions including heterogeneous workers and alternative SOE objectives yield qualitatively similar conclusions. Second, matching efficiency and private-sector bargaining power exhibit substantial time variation, and our estimates indicate that these factors exert a significant influence on historical vacancy-unemployment trends observed in Chinese labour market data.

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1. Introduction

1.1 Background

The Chinese urban labour market has long been studied due to its unique structure, in which state-owned enterprises (SOEs) have continued to play a dominant role since the establishment of the People's Republic of China. A critical turning point for China occurred when it began to embrace the open market in the 1980s. This shift led to the large-scale shutdown and privatisation of SOEs in the 1990s, marking the rise of urban private firms and a massive transition of the labour force into the private sector. As many loss-making SOEs were closed and smaller, competitive ones were let go, substantial resources were redirected towards the private sector. The output growth from the private sector is estimated to have accounted for nearly 70-80% of aggregate growth after 1998 (Hsieh and Song, 2015).

This key transformation, however, exacerbated the significant SOE wage premium over the private sector due to several contributing channels. First, under the principles of communism, government-led unions provided stronger bargaining power to workers in SOEs (Wang, 2017). In contrast, the development of private sector unions during this period had barely begun, resulting in a substantial disparity in bargaining power between the two sectors, as estimated by Sheng and Lu (2017). Furthermore, existing literature shows that workers in privatised SOEs experienced wage declines. For example, Arnold (2022), using a coarsened exact matching algorithm to study SOE privatisation reforms in Brazil, found a 3% decline in wages. Similarly, Sheng and Lu (2017), using Chinese data, demonstrated that bargaining power and the labour income share in privatised SOEs declined significantly, especially among firms in competitive markets.

Second, following the closure of loss-making SOEs and the layoff of redundant workers, labour productivity in SOEs improved and began to converge with that of private firms (Hsieh and Song, 2015). With the improvement in labour productivity, SOE workers began to earn more. Consequently, Sun (2023) identified an average 13% SOE wage premium during this period.

Although the SOE wage premium persists, the widening of the wage gap slowed nationwide between 2008 and 2014. This shift can be attributed to several changes in the labour market environment. First, the *Labour Contract Law of the People's Republic of China* was officially enacted.[1] This legislation guaranteed improved job protection and wage prospects for private-sector workers. It also encouraged greater participation in private-sector collective trade unions, thereby enhancing the bargaining power of employees in

[1]This law was passed by the Standing Committee of the National People's Congress on 19 June 2007 and implemented on 1 January 2008.

private firms. Second, Chinese private firms implemented equity incentive schemes, extending such incentives from senior executives to include core technical and operational staff, mid-level managers, key personnel, and even employees in subsidiary companies (Yang, 2018). These reforms were aimed at boosting post-2008 crisis performance and attracting skilled and highly educated workers by offering more competitive wages.

On the SOE side, although these enterprises continued to benefit from preferential policies and greater economic resources, high wage premiums in public sectors, especially in the monopolistic industry, often failed to reflect individual abilities and contributions (Bao et al., 2022). In response, starting in 2010, the Chinese government introduced the *Interim Administrative Procedures for the Total Wage Budget of Central State-owned Enterprises*. This policy aimed to control wage levels by capping the total wage budget based on SOE performance from the previous year. It authorised central authorities to manage central SOE wages and allowed local governments to oversee local SOE wage growth. Under this framework, each firm's internal redistribution of wages was permitted, but the total wage growth remained constrained. These factors collectively contributed to slower wage growth in SOEs relative to that in the private sector during this period.

However, from 2014 onwards, SOE wage growth began to rebound. Despite this noticeable trend, few studies have thoroughly examined the causes behind the resurgence in SOE wage growth during this period, although some researchers have acknowledged its occurrence. Sun (2023) reports a significantly larger SOE wage premium from 2015 onwards. Using data from A-share listed companies, Gao and Wang (2024) find that state-owned enterprises exhibited higher and faster-growing profitability between 2015 and 2018. Correspondingly, wage levels in SOEs increased with rising profit indicators. This wage growth aligns with the initiation of the mixed-ownership reform, which introduced non-state shareholders and professional managers, and promoted equity incentives such as the employee stock ownership scheme. These reforms aimed to reduce costs by improving managerial efficiency and improve labour productivity by rewarding skilled labour with higher wages. According to human capital resource theory, such financial incentives attract more capable and skilled individuals to public sector positions (Bo et al., 2013), which, in turn, enhances overall SOE performance. Although the *Total Wage Budget* policy remained in place, the continued growth in SOE profits during this period led to a progressively higher ceiling for wage expenditure. However, as Jurzyk and Ruane (2021) find, the relative labour productivity between SOEs and private firms remained largely unchanged after the reform. Therefore, the relatively faster wage growth observed in SOEs during this period is primarily attributable to reductions in managerial inefficiency, resulting in improved profitability, rather than improvements in labour productivity.

Finally, to address the persistently high wage levels and wage growth in the state sector, the State Council in 2018 expanded the *Total Wage Budget* framework by introducing a new principle of *Market orientation.* This reform, as a strong policy intervention directly on wage premiums, called for aligning SOE wages more closely with prevailing market levels. Following this policy shift, a significant decline in wage growth was observed in 2018.

The onset of the COVID-19 pandemic in late 2019 complicates efforts to isolate the effects of this reform. Chinese SOEs assumed an expanded social security role during the pandemic, including the provision of additional job vacancies and the stabilisation of wages. Their relatively strong performance during this period was also supported by direct government intervention (Wu and Xu, 2021). As a result, disentangling the impact of the 2018 wage reform from the broader effects of the pandemic presents a significant empirical challenge.

1.2 Summary

The persistent wage premium in SOEs, along with the fluctuating wage growth driven by policy shocks, motivates this research to examine how externalities introduced by the public sector affect labour market dynamics within an imperfect and frictional search-and-matching framework (Blanchard and Diamond, 1989; Diamond and Maskin, 1979; Pissarides, 2000). This interaction between the SOE and private sectors is particularly significant in China, where these two sectors together account for the majority of employment and job vacancies. Existing studies suggest that the SOE wage premium influences labour allocation by encouraging public sector employment while crowding out private employment through upward pressure on private wages (Algan et al., 2002; Holmlund and Linden, 2006). Horner et al. (2007) show that during periods of economic turbulence, risk-averse unemployed individuals tend to search more intensively for public sector jobs, thereby contributing to higher aggregate unemployment. Using Chinese data, Feng and Guo (2021) find that elevated wages in SOEs negatively affect job creation in the private sector, which in turn weakens labour market transitions and increases unemployment.

Studies on two-sector search and matching models generally follow two main approaches. The first, exemplified by Albrecht et al. (2019), adopts a random search framework, assuming that all unemployed workers search within a unified pool of both private and public vacancies. The second approach, as used by Gomes (2015), employs a direct search setup, where unemployed workers must actively choose the sector, public or private, in which to search for employment. In this paper, I follow the latter approach, applying a direct search framework to examine the Chinese context. In China, it is common to observe significant queuing and overcrowding in the public job market. Public and SOE jobs involve a distinct and often rigorous application process, typically requiring candidates to complete multiple rounds of structured examinations and to acquire political and social knowledge, often unrelated to the actual job content. These requirements are not commonly found in private-sector recruitment and significantly increase both time and search costs for applicants. Therefore, a random search framework, which assumes workers search and receive job offers from either sector at random, may not adequately capture the realities of China's labour market. In particular, it fails to account for the uneven job-opening-to-applicant ratios across ownership types and the sharply different application procedures between public and private firms.

Surprisingly, no existing study appears to apply a direct search model to analyse the Chinese labour market in a two-sector context. For example, Feng and Guo (2021) employ a random search setup and find that high SOE wages negatively impact labour market dynamics. This study, therefore, aims to fill a gap in the literature by using a direct search model to better understand the interaction between public and private sectors in China's labour market.

Unlike studies that concentrate on micro-level unemployment dynamics among heterogeneous individuals, such as by education level, gender or experience, this paper focuses on macro-level labour market movements within a two-sector framework. Specifically, we examine how externalities arising from SOEs, particularly through the channel of the SOE wage premium and its policy-driven fluctuations, shape aggregate unemployment dynamics in China.

In contrast to the prevailing literature, which typically calibrates two-sector search and matching models by taking key parameters (e.g. bargaining power, matching elasticity) as given, this study adopts a more data-driven approach. Leveraging macroeconomic data covering the period from 2008 to 2021, we estimate all key structural parameters directly. This methodology enables a more comprehensive understanding of China's search and matching process and allows us to capture both the direct impact of SOE-related externalities and other structural changes in the labour market, such as variations in private sector bargaining power and matching efficiency over time, which have been noticed by previous studies. To the best of our knowledge, this is the first study since Liu (2013) to estimate the full set of key parameters governing search and matching dynamics in the Chinese labour market at the macro level, while also focusing on a more recent and rarely studied period.

In this paper, we estimate both aggregate and sector-specific matching functions to identify key structural parameters, including matching elasticity and, more importantly, matching efficiency. Our results reveal a decline in matching efficiency for both the SOE and private sectors before 2016, followed by an improvement thereafter. This trend helps explain fluctuations in unemployment that cannot be solely attributed to the SOE wage premium.

Building on the estimated matching functions, we derive several findings using our structural unemployment model and simulations. First, we estimate private-sector bargaining power, job destruction rates, and vacancy posting costs, and find a significant increase in private-sector bargaining power over the study period. Second, we recover market tightness for both sectors and observe that the SOE labour market is substantially more congested than the private sector, empirically validating the widely observed queuing phenomenon in China. Third, we use the estimated model to simulate actual labour market dynamics and conduct counterfactual simulations. In particular, we analyse how SOE wages, in the absence of policy intervention, would affect market tightness and employment outcomes. The results suggest that SOE wage fluctuations have minimal impact on private-sector market tightness or wages. However, imposing restrictions on SOE wages significantly increases SOE market tightness, shifts job seekers to the private sector, stimulates private vacancy creation, and improves aggregate unemployment outcomes.

Furthermore, recognising that wage differences are not the only drivers of labour market dynamics, we conduct additional counterfactual experiments on variables that show substantial time variation in our dataset or parameter estimates. These include the number of SOE vacancies, private-sector bargaining power, and matching efficiency. The results indicate that these factors show a non-negligible influence on labour market outcomes. We derive the Beveridge Curve and Job Creation Curve from our structural model and analyse their evolution over time. The model-generated mechanism is consistent with historical vacancy-unemployment trends observed in Chinese labour market data.

In the extension, we allow for worker heterogeneity in selection and reconstruct a corrected homogeneous representative worker to identify the pure SOE wage premium, which is absorbed through higher bargaining power. When SOEs are allowed to act as profit maximizers, we find that wage limitations in SOEs have a similar effect in reducing aggregate unemployment as in the baseline model. However, unlike in the baseline case where employment gains are driven by private-sector job creation, the improvement here is primarily driven by increased job creation in the SOE sector.

The rest of the paper is structured as follows: Section 2 presents the theoretical derivation of the two-sector search and matching model. Section 3 describes the data sources and construction. Section 4 estimates both aggregate and sector-specific job-worker matching functions. Section 5 estimates the key structural parameters of the model. Section 6 presents simulation results and counterfactual experiments based on the model solution. Section 7 analyses the historical movement of the unemployment-vacancy curve, reflecting the mechanisms explored in earlier sections. Section 8.1 introduces possible extensions to the baseline model, including worker heterogeneity and profit-maximising SOEs. Section 9 concludes the paper.

2. Model

2.1 Matching Process

Inspired by Harris and Todaro (1970), Algan et al. (2002), and Gomes (2015), we extend the Diamond-Mortensen-Pissarides (DMP) search and matching model of equilibrium unemployment into a version assuming direct search of the private or the SOE sector jobs. In this setup, vacancies are posted separately in each market. For simplicity, we assume that only unemployed workers are searching for opportunities in the labor market.[2] All job seekers can search randomly for jobs in either the SOE or the private market according to their unemployment values. Thus, we have the following matching system:

$$M_s = A_s u_s^{\eta_s} v_s^{1-\eta_s}$$

$$M_p = A_p u_p^{\eta_p} v_p^{1-\eta_p}$$

$$\theta_s = \frac{v_s}{u_s} \quad m(\theta_s) = A_s \theta_s^{-\eta_s}$$

$$\theta_p = \frac{v_p}{u_p} \quad m(\theta_p) = A_p \theta_p^{-\eta_p}$$

$$u = u_s + u_p$$

Where A_s and A_p represent matching efficiencies in the state sector and the private sector, respectively. M_s is the number of successful matches in the SOEs, and M_p is the number of successful matches in the private sector. u is the number of unemployed job seekers. u_s and u_v are the number of unemployed job seekers in the SOE and Private sectors, respectively. v_s and v_p are the numbers of vacancies that are posted in the SOE market and private market, respectively. Hence, θ_s and θ_p indicate the separate market tightness. Also, in this model, we assume that the matching functions exhibit the constant returns to scale (CRS) property.

Different assumptions regarding whether state-owned enterprises should be treated as profit-maximizers or whether state-sector employment should be considered exogenous can be found in numerous previous studies. On the one hand, studies such as Cooper et al. (2015) and Feng and Guo (2021) model Chinese SOEs as profit-maximizing entities. On the other hand, studies like Gomes (2015) suggest that the government sets policies governing the sequence of vacancies and wages, and studies such as Albrecht et al. (2019) treat public sector vacancies as an exogenous variable. In this study, we follow the latter approach and treat SOE vacancies as exogenous for two main reasons. First, as noted

[2] This is a very strong assumption. However, in the Appendix, we allow urban employers to search a job and find that employed workers in China exhibit very low job-seeking intensity, consistent with the findings of Feng and Guo (2021), who report a very low frequency of within-job switching in China.

in government reports, the number of vacancies in Chinese SOEs is largely regulated by the SASAC.[3] Second, the primary objective of this research is to investigate how exogenous shocks in the SOE sector influence private-sector behavior and the decisions of unemployed job seekers. In contrast, the number of private-sector vacancies v_p is endogenously determined within the model.

The key distinction between this direct search two-sector matching model and other random search two-sector models lies in the assumption that job seekers cannot simultaneously search in both markets. Instead, they choose to search exclusively in one sector based on their respective unemployment values, U_s and U_p. If $U_s > U_p$, job seekers target the SOE sector; conversely, if $U_p > U_s$, they search in the private sector. In equilibrium, the arbitrage condition implies that $U_s = U_p$. Following this framework, we are able to analyze cross-sector unemployment flows and investigate how labor market congestion in one sector can influence overall unemployment levels.

2.2 The law of Unemployment Motion

$$\dot{u} = -\theta_s m(\theta_s)u_s - \theta_p m(\theta_p)u_p + q(l - u)$$

Here, q denotes the job destruction rate, which is assumed to be exogenous and identical across both sectors. The variable l represents the exogenous total labor force. Notably, in equilibrium, we assume a steady state where $\dot{u} = 0$.

2.3 Private Sector Job Creation

For firms in the private sector, the value of a posted vacancy is given as:

$$(r - g)\Pi_v = -pc + m(\theta_p)(\Pi_e - \Pi_v)$$

The expected profit of a filled job is given as:

$$(r - g)\Pi_e = p - w_p + q(\Pi_v - \Pi_e)$$

Here, r denotes the interest rate, and p represents labor productivity. The variable c refers to the cost of posting a vacancy, which is assumed to be a fixed fraction of labor productivity. The private sector wage, w_p, is endogenously determined within the model. Unlike in developed countries, China has experienced sustained and rapid urban wage growth during the study period, largely driven by robust economic expansion and productivity improvement. To capture this trend, we introduce the term g, which reflects

[3] State-owned Assets Supervision and Administration Commission of the State Council

the balanced growth path of wages related to average production per worker growth in urban China. (see Appendix A for details).

By imposing the free entry condition, $\Pi_v = 0$, we derive the following equation:

$$\frac{pc}{m(\theta_p)} = \frac{p - w_p}{r + q - g}$$

Or equivalently:

$$A_p(p - w_p) = \theta_p^{\eta_p} pc(r + q - g)$$

The condition states that the expected cost of hiring a worker must equal its expected return.

2.4 Private Wage Determination

For an unemployed worker in the SOE sector, his lifetime utility is given by:[4]

$$(r - g)U_s = \theta_s m(\theta_s)(V_s - U_s)$$

The value of an SOE worker is:

$$(r - g)V_s = w_s + q(U_s - V_s)$$

Here, w_s denotes the SOE wage, which is assumed to be exogenous due to institutional characteristics of China's labor market, as discussed in the previous section and supported by existing literature. We define $w_s = \gamma p + \epsilon_s$ where γ denotes the fixed fraction of production[5] that workers can obtain, set directly by SOEs. ϵ_s captures the SOE wage premium draw, and we assume this wage premium also reflects the production growth[6]. Furthermore, we assume that SOEs do not lay off workers in response to endogenous productivity fluctuations. Instead, separations occur only as a result of exogenous shocks. Notable examples include major structural reforms, such as the large-scale layoffs during the late 1990s and the second wave of SOE downsizing in the 2000s.

[4]We exclude unemployment benefits from the value equation not only for simplification purposes, as such an insurance system is still under development in China and not covered by the dataset used in this study. Moreover, analyzing unemployment insurance is beyond the primary scope of this research.

[5]Due to data limitations, we use urban average production per worker and its growth as a proxy for both SOEs and private firms. This represents a strong assumption, as we cannot directly observe average production per worker disaggregated by ownership type. However, this simplification is technically supported by Jurzyk and Ruane (2021), who analyze listed firms on Chinese stock exchanges from 2002 to 2019 and find that the share of value added attributable to SOEs closely matches their share of employment. $\frac{Value_{soe}}{Value} = \frac{Employment_{soe}}{Employment}$

[6]Alternatively, in the extension, we model the SOE wage premium as a markup on bargaining power, expressed as $w_s = (\gamma + \epsilon_s)p$. This formulation reflects the implicit approach taken in much of the existing literature, where higher SOE wages are attributed to greater bargaining power.

For an unemployed worker in the private sector, his lifetime utility is given as:

$$(r-g)U_p = \theta_p m(\theta_p)(V_p - U_p)$$

The value of a private-sector worker is:

$$(r-g)V_p = w_p + q(U_p - V_p)$$

Here, w_p represents the endogenous private sector wage, which will be derived in the subsequent section. For consistency and simplicity, and given the lack of firm-level heterogeneity in the macro-level data, we assume that private firms, like SOEs, do not lay off workers in response to endogenous productivity shocks.

The private sector wage w_p is determined through a Nash bargaining process, in which the firm and the worker negotiate over the division of the total match surplus.

$$S = V_p - U_p + \Pi_e - \Pi_v = \frac{p - (r-g)U_p}{r+q-g}$$

We define β as the bargaining power of a worker and hence have the following:

$$\frac{V_p - U_p}{\Pi_e - \Pi_v} = \frac{\beta}{1-\beta}$$

Together with the equations for Π_e, V_p and the free entry condition, we have:

$$w_p = \beta p + (1-\beta)(r-g)U_p$$

We rewrite the $(r-g)U_p$ equation as follows:

$$\begin{aligned}
(r-g)U_p &= \theta_p m(\theta_p)(V_p - U_p) \\
&= \theta_p m(\theta_p)\beta S \\
&= \theta_p \frac{pc(r+q-g)}{p-w_p}\beta\left(\frac{p-(r-g)U_p}{r+q-g}\right) \\
&= \theta_p pc\beta\left(\frac{p-(r-g)U_p}{p-w_p}\right) \\
&= \theta_p pc\frac{\beta}{1-\beta}
\end{aligned}$$

After plugging this new $(r-g)U_p$ into the w_p equation, we have:

$$\begin{aligned}
w_p &= \beta p + (1-\beta)(r-g)U_p \\
&= \beta p + \beta\theta_p pc
\end{aligned}$$

2.5 No Arbitrage Condition

In equilibrium, we require that $U_p = U_s = U$. Otherwise, all job seekers would choose to search exclusively in the sector offering the higher unemployment value. This condition determines the relationship between private-sector market tightness and SOE-sector market tightness:

$$\theta_p m(\theta_p)(V_p - U) + gU = \theta_s m(\theta_s)(V_s - U) + gU$$

We can then solve this equation for θ_s as a function of θ_p:

$$\begin{aligned}
0 &= \theta_p m(\theta_p)(V_p - U) - \theta_s m(\theta_s)(V_s - U) \\
&= \theta_p m(\theta_p)\frac{\beta p + \theta_p pc\frac{-\beta^2}{1-\beta}}{r+q-g} - \theta_s m(\theta_s)\frac{w_s - \theta_p pc\frac{\beta}{1-\beta}}{r+q-g} \\
&= \theta_p \frac{pc(r+q-g)}{p-w_p}\frac{\beta p + \theta_p pc\frac{-\beta^2}{1-\beta}}{r+q-g} - \theta_s m(\theta_s)\frac{w_s - \theta_p pc\frac{\beta}{1-\beta}}{r+q-g} \\
&= \theta_p \frac{pc(\beta p + \theta_p pc\frac{-\beta^2}{1-\beta})}{(1-\beta)p - \beta\theta_p pc} - \theta_s m(\theta_s)\frac{w_s - \theta_p pc\frac{\beta}{1-\beta}}{r+q-g} \\
&= \theta_p pc\frac{\beta}{1-\beta} - \theta_s m(\theta_s)\frac{w_s - \theta_p pc\frac{\beta}{1-\beta}}{r+q-g}
\end{aligned}$$

We define $\tilde{\beta} = \frac{\beta}{1-\beta}$, hence:

$$0 = \tilde{\beta} - \theta_s m(\theta_s)\frac{\frac{w_s}{\theta_p pc} - \tilde{\beta}}{r+q-g}$$

$$\theta_s m(\theta_s) = \tilde{\beta}\left(\frac{\frac{w_s}{\theta_p pc} - \tilde{\beta}}{r+q-g}\right)^{-1}$$

Finally, we have the equation for market tightness in SOE sector:

$$\theta_s = \left[\frac{1}{A_s}\tilde{\beta}\left(\frac{\frac{w_s}{\theta_p pc} - \tilde{\beta}}{r+q-g}\right)^{-1}\right]^{\frac{1}{1-\eta_s}}$$

Or equivalently:

$$A_s\theta_s^{1-\eta_s}(w_s - \theta_p pc\frac{\beta}{1-\beta}) = (r+q-g)\theta_p pc\frac{\beta}{1-\beta}$$

Hence, we close the model.

2.6 Equation System

Table 2.1: Equation System

	Panel(A) Model Equations
SOE Matching Functions Private Matching Functions	$M_s = A_s u_s^{\eta_s} v_s^{1-\eta_s}; \quad \theta_s = \frac{v_s}{u_s}$ $M_p = A_p u_p^{\eta_p} v_p^{1-\eta_p}; \quad \theta_p = \frac{v_p}{u_p}$
Job Creation	$\frac{pc}{m(\theta_p)} = \frac{p-w_p}{r+q-g}$
Wage Determination	$w_p = \beta p + \beta\theta_p pc$
No Arbitrage Condition	$A_s\theta_s^{1-\eta_s}(w_s - \theta_p pc\frac{\beta}{1-\beta}) = (r+q-g)\theta_p pc\frac{\beta}{1-\beta}$
Unemployment Motion	$\dot{u} = -\theta_s m(\theta_s)u_s - \theta_p m(\theta_p)u_p + q(l-u)$ $u_s + u_p = u$
	Panel(B) Model Variables
Endogenous Variables	$M_s, \quad M_p, \quad u_s, \quad u_p, \quad u, \quad v_p, \quad w_p, \quad \theta_s, \quad \theta_p$
Exogenous Variables	$A_{s/p}, \quad p, \quad r, \quad l, \quad v_s, \quad w_s, \quad g$
Parameters	$\eta_s, \quad \eta_p, \quad \beta, \quad c, \quad q$
	Panel(C) Specification Equations
First Step Key Estimates: $\hat{\eta}$, $\hat{a}$	$lnM_{it} = \eta_1 lnu_{it} + \eta_2 lnv_{it} + a_i + a_t + \epsilon_{it}$ $lnM_{sit} = \eta_1 lnu_{it} + \eta_2 lnv_{sit} + \eta_2\lambda_s(\frac{v_{pit}}{v_{it}}) + a_{si} + a_{st} + \epsilon_{sit}$ $lnM_{pit} = \eta_1 lnu_{it} + \eta_2 lnv_{pit} + \eta_2\lambda_p(\frac{v_{sit}}{v_{it}}) + a_{pi} + a_{pt} + \epsilon_{pit}$
Second Step Key Estimates: $\hat{\beta}$, $\hat{c}$, $\hat{q}$	$e^{\hat{a}_{pit}}(p_{it} - w_{pit}) = \theta_p^{\hat{\eta}} p_{it} c(r_t + q - g_{it})$ $w_{pit} = \beta p_{it} + \beta\theta_p p_{it} c$
Third Step Simulate Variables	$e^{\hat{a}_{pit}}\theta_s^{1-\hat{\eta}}(w_{sit} - \theta_p p_{it}\hat{c}\frac{\hat{\beta}}{1-\hat{\beta}}) = (r_t + \hat{q} - g_{it})(\theta_p p_{it}\hat{c}\frac{\hat{\beta}}{1-\hat{\beta}})$ $\theta_s m(\theta_s)u_{sit} + \theta_p m(\theta_p)u_{pit} = q(l_{it} - u_{it})$ $u_{sit} + u_{pit} = u_{it}$
	Panel(D) Variables Description
M_{it}	Number of annual new hires in both sectors
M_{sit}	Number of annual new hires in SOEs
M_{pit}	Number of annual new hires in private sector
u_{it}	Number of annual unemployed workers
v_{it}	Number of annual vacant jobs in both sectors
v_{sit}	Number of annual vacant jobs in SOEs
v_{pit}	Number of annual vacant jobs in private sector
w_{sit}	Average annual SOE wage
w_{pit}	Average annual private wage
g_{it}	Average annual urban production per worker growth
p_{it}	Average annual private sector labour production
l_{it}	Number of annual labour force
r_t	One-year LPR(Loan Prime Rate) for the year

New hires, vacant jobs, unemployed workers, and job seekers are calculated in units of 10,000 people; Wages and production are calculated in units of 10,000 yuan

3. Data

Our data are primarily sourced from the China Labour Statistics Yearbook. This includes information on the number of labour force, urban unemployed workers, urban employment, job seekers, job vacancies from both public and private labor agencies, as well as flow data on new hires into SOEs and private firms. In addition, province-level data on SOE and private sector wages are well documented.

It is important to note that the urban unemployed job seekers recorded in the dataset include not only registered urban unemployed workers, but also rural migrants and new graduates who have registered with job agencies for employment assistance, even though they are not formally registered as unemployed with the local human resources bureau. Nevertheless, both subgroups are officially classified as part of the unemployed workforce. Furthermore, job seekers may register multiple times when seeking employment through job service agencies, which results in the number of registered urban unemployed job seekers being larger than the number of officially registered urban unemployed workers.

The yearbook covers all official and private job service agencies across Chinese cities. Nevertheless, it should be acknowledged that some individuals search for jobs through informal channels such as personal networks or online platforms. As a result, the job agency data likely underestimates actual job search activity, particularly during the 2008-2021 period when the information technology sector saw rapid development, and internet-based job search became significantly more common. This raises concerns regarding the representativeness of traditional employment agencies in capturing overall matching efficiency and labor market dynamics. However, given the vast size of the Chinese labor market, this dataset remains the most comprehensive macro-level job search data available in China. Using data from local labor offices and job centers is also common in the literature (e.g., Hynninen, 2009; Kano and Ohta, 2005).

For the purposes of our macroeconomic model, we use provincial data from the annual reports on the Chinese labor market covering the period 2008-2021. Our analysis includes a cross-section of 29 Chinese provinces. Additional macroeconomic indicators, such as labor productivity and interest rates, are drawn from the China Statistical Yearbook and Provincial Statistical Yearbooks. All data have been adjusted for inflation using appropriate price indices and are presented in real terms.

The China Labour Statistics Yearbook is available[7] through the official website of the Ministry of Human Resources and Social Security. The China Statistical Yearbook and provincial-level yearbooks can be accessed via the website of the National Bureau of

[7]Unfortunately, online accessibility is limited. Physical copies must be purchased or accessed through libraries, making the data digitisation process for this study both challenging and time-consuming.

Statistics and respective provincial statistical bureaus.

4. Matching Function Estimation

In this section, we estimate the matching functions to obtain the elasticity parameter $\hat{\eta}$, along with the estimated matching efficiencies $\hat{a}_{sit}$ and $\hat{a}_{pit}$, which will serve as inputs for the structural model estimation in the subsequent sections.

4.1 Aggregate Matching

As described in Section 2.1, we adopt a Cobb-Douglas specification for the matching function, which can be conveniently transformed into a log-linear form for estimation. To provide a general overview of the structure of China's urban labor market matching process during the sample period, we first estimate an aggregate matching function, treating SOEs and private firms indistinguishably.

An important assumption in our model is that the matching function is homogeneous of degree one. To empirically assess this, we conduct a Wald test under the null hypothesis $\eta_1 + \eta_2 = 1$ in the unrestricted model and compare it with a constrained specification to evaluate robustness.

The estimation equation is specified as follows:

$$lnM_{it} = \eta_1 lnu_{it} + \eta_2 lnv_{it} + controls + a_i + a_t + \epsilon_{it}$$

Here, we let M_{it} denote the total number of new hires in province i at time t, u_{it} the number of unemployed job seekers, and v_{it} the number of posted vacancies. . The terms a_i and a_t capture province-level and year fixed effects, respectively.

Additionally, we address potential endogeneity concerns, as the numbers of unemployed workers and posted vacancies may be simultaneously determined with the matching process. To mitigate this issue, we estimate the model using both ordinary least squares and an instrumental variables approach, where lagged variables $u_{i,t-1}$, and $v_{i,t-1}$ are used as instruments for their contemporaneous counterparts.

As shown in Table 4.1, all model specifications yield statistically significant estimates for both η_1 and η_2, along with relatively high R-squared values, indicating strong explanatory power. These results suggest that both the number of job seekers and the number of vacancies contribute significantly to successful job matches. Furthermore, the estimated elasticity on the vacancy side is generally larger than that on the seeker side, highlighting a more dominant role for posting vacancies in determining new hires.

Finally, results from the constrained model demonstrate the robustness of the significance and magnitude of both η_1 and η_2, supporting the overall validity and stable performance of the estimated matching process.

Table 4.1: Aggregate Matching Estimation-Unemployed Seeker (2008-2021)

	Unconstrained				Constrained	
	LS(1)	2SLS(2)	LS(3)	2SLS(4)	LS(5)	2SLS(6)
η_1	0.557^{***}	0.558^{***}	0.533^{***}	0.671^{***}	0.450^{***}	0.429^{***}
	(0.107)	(0.170)	(0.111)	(0.180)	(0.008)	(0.013)
η_2	0.641^{***}	0.819^{***}	0.685^{***}	0.877^{***}	0.550^{***}	0.571^{***}
	(0.058)	(0.110)	(0.059)	(0.110)	(0.008)	(0.013)
$Productivity$			0.105^{***}	0.150^{***}		
			(0.031)	(0.037)		
$Urban\ Employment$			-0.000	-0.000		
			(0.000)	(0.000)		
$EU\ Transition$			-0.574	-2.067		
			(1.410)	(2.114)		
$Interest\ Rate$			-0.030	-0.152^{***}		
			(0.027)	(0.043)		
a_i	Yes	Yes	Yes	Yes	Yes	Yes
a_t	Yes	Yes	Yes	Yes	Yes	Yes
$Constraint : \eta_1 + \eta_2 = 1$	No	No	No	No	Yes	Yes
Test $p - value : \eta_1 + \eta_2 = 1$	0.117	0.048	0.090	0.011	—	—
$Num.obs.$	429	377	415	364	429	377
$\bar{R}^2$	0.856	0.755	0.850	0.773	0.731	0.633

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Following Broersma (1997) and Kano and Ohta (2005), we measure matching efficiencies by incorporating year and cross-sectional province fixed effects. The estimated matching efficiency is calculated as:

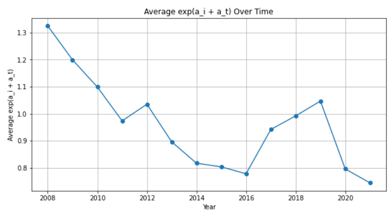
$$\hat{A}_{it} = exp(\hat{a}_i + \hat{a}_t)$$

We compute the annual average matching efficiency across all provinces and visualize both the level and growth rate over time. The results are reported in Figure 4.1 and Figure 4.2.

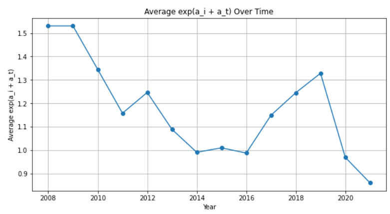
As shown in the figures, aggregate matching efficiency in China experienced a continuous decline during the period from 2008 to 2016. Several factors may help explain this downward trend. First, high levels of job and worker mobility are often associated with increased labor market frictions, which reduce matching efficiency (Cahuc and Zylberberg, 2004). During this period, China saw significant worker reallocation between sectors, as well as rapid urbanization, which led to a large influx of rural labor into urban job markets. As Liu (2013) estimates, the increasing share of rural unemployed job seekers has contributed to lower aggregate matching efficiency. Second, in the aftermath of the 2008 global financial crisis and the second wave of SOE layoffs in the 2000s, the composition of the unemployed in China changed significantly. A higher proportion of the unemployed consisted of long-term unemployed individuals and workers permanently displaced from their jobs. As argued by Hall and Schulhofer-Wohl (2018), these groups typically exhibit lower matching efficiency, further contributing to the aggregate decline.

Since 2016, however, matching efficiency has shown signs of recovery. This improvement coincides with the completion of China's market transition and an increase in employer-led job information-sharing initiatives (Obukhova and Rubineau, 2020). Moreover, improvements in public employment services and the rapid expansion of the information industry have enhanced access to job opportunities. At the same time, as Tudela et al. (2023) suggest, firms in tighter labor markets tend to be more selective, which can reduce matching efficiency. As SOEs became relatively less attractive, more job seekers shifted their search toward the private sector, where market tightness was lower. This reallocation of search effort likely contributed to the recent improvement in overall matching efficiency.

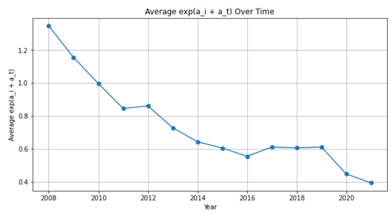
Figure 4.1: Aggregate Average Matching Efficiency-Unemployed Seeker (2008-2021)



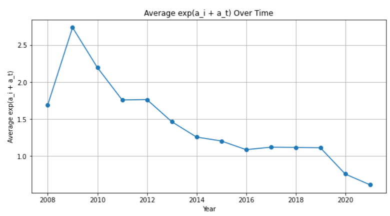
Model 1



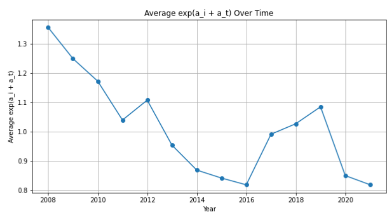
Model 2



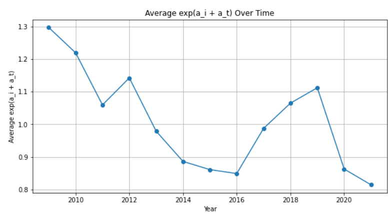
Model 3



Model 4

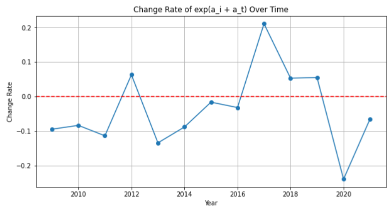


Model 5

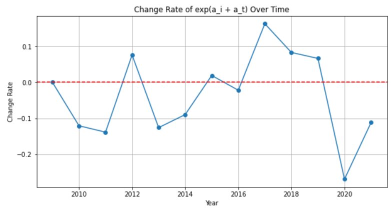


Model 6

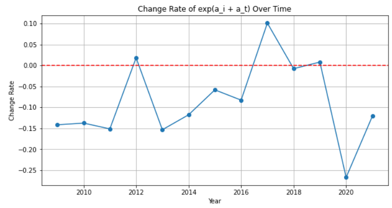
Figure 4.2: Aggregate Matching Efficiency Changing Rate-Unemployed Seeker(2008-2021)



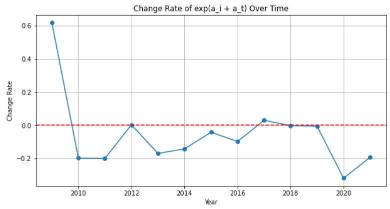
Model 1



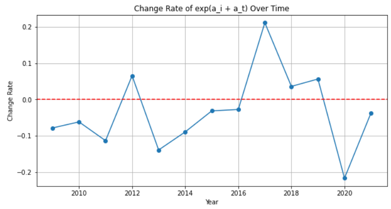
Model 2



Model 3



Model 4



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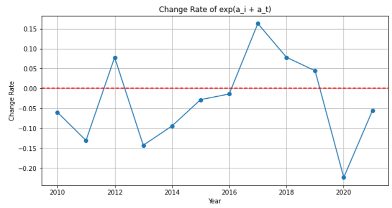


Model 6

4.2 Sector Matching

A major challenge in estimating sector-specific matching functions in accordance with our theoretical model is the lack of disaggregated data on u_{sit} and u_{pit}, the number of unemployed job seekers targeting the SOE and private sectors, respectively. These values are endogenously determined within the structural model and are not directly observable in the data. Instead, we only observe the aggregate number of unemployed workers, u_{it}. As a result, the following sector-level estimations are not fully consistent with the structural model. Nonetheless, they still offer valuable economic intuition and provide plausible estimates of sector-specific matching efficiencies.

Building on previous literature that highlights congestion externalities among different types of job seekers, we extend this concept by incorporating vacancy-side congestion externalities. In our framework, job seekers allocate their search efforts across sectors based on differences in unemployment values. An increase in vacancies in one market raises the probability of successful matching and the unemployment value, potentially attracting job seekers to switch sectors. This reallocation of search effort may reduce matching efficiency in the other market by diverting search intensity away from it. Accordingly, we modify the sectoral matching functions as follows:

$$M_{s/p} = A_{s/p} u^{\eta_{s/p}} Ev_{s/p}^{1-\eta_{s/p}}$$

$$Ev_s = v_s - \lambda_s v_s(\frac{v_p}{v})$$

$$Ev_p = v_p - \lambda_p v_p(\frac{V_s}{v})$$

Here, Ev_s and Ev_p represent the effective number of vacancies in the SOE and private sectors, respectively. The parameters λ_s and λ_p capture the degree of congestion externalities arising from the presence of vacancies in the opposite sector. A higher share of vacancies in one market reduces the effective matching efficiency in the other through intensified competition for job seekers.

Using a first-order Taylor expansion,[8] we linearize the effective vacancy term and derive the following estimation equations[9]

$$lnM_{sit} = \eta_1 lnu_{it} + \eta_2 lnv_{sit} + \eta_2\lambda_s(\frac{v_{pit}}{v_{it}}) + a_{si} + a_{st} + \epsilon_{sit}$$

$$lnM_{pit} = \eta_1 lnu_{it} + \eta_2 lnv_{pit} + \eta_2\lambda_p(\frac{v_{sit}}{v_{it}}) + a_{pi} + a_{pt} + \epsilon_{pit}$$

In both equations, a_{si} and a_{pi} represent province fixed effects, while a_{st} and a_{pt} capture year fixed effects for the SOE and private sectors, respectively. To address potential endogeneity and account for the simultaneous equation structure, we employ one-period lagged variables as instruments and estimate the system using not only two-stage least squares (2SLS) but also three-stage least squares (3SLS).

Table 4.2 reports the estimation results for each sector matching function using both 2SLS and 3SLS methods. Columns (1) to (4) present the estimates for the SOE sector, while Columns (5) to (8) correspond to the results of private sector. Across all models, the elasticity of matches with respect to unemployment and vacancies are statistically significant, and their magnitudes remain economically plausible. Notably, in the 3SLS specifications with congestion controls, we observe a decrease in both elasticities, suggesting that congestion may reduce the overall responsiveness of matches to market fundamentals.

The estimated congestion terms provide additional insight. In the SOE sector, the coefficient on v_p/v is negative and significant, indicating that an increase in the share of private-sector vacancies reduces the effective successful matchings in the SOE sector. Similarly, in the private sector, the coefficient on v_s/v is also negative and significant, suggesting a symmetric vacancy-side congestion effect.

[8]Taylor expansion: $\ln\left(1-\lambda_s\left(\frac{v_p}{v}\right)\right) \approx -\lambda_s\left(\frac{v_p}{v}\right)$

[9]Here, we use the specification that considers only unemployed job seekers in the matching process. The alternative specification that includes employed job seekers, along with its corresponding empirical results, is presented in Appendix B.

Table 4.2: Sector Matching Estimation-Unemployed Seeker (2008-2021)

	SOE				Private			
	2SLS(1)	2SLS(2)	3SLS(3)	3SLS(4)	2SLS(5)	2SLS(6)	3SLS(7)	3SLS(8)
η_1	0.664^{***}	0.657^{***}	0.658^{***}	0.509^{***}	0.589^{***}	0.776^{**}	0.653^{***}	0.509^{***}
	(0.179)	(0.179)	(0.168)	(0.150)	(0.179)	(0.236)	(0.168)	(0.149)
η_2	0.770^{***}	0.772^{***}	0.917^{***}	0.434^{***}	0.843^{***}	0.327^{***}	0.917^{***}	0.434^{***}
	(0.105)	(0.105)	(0.017)	(0.083)	(0.101)	(0.055)	(0.017)	(0.083)
v_s/v						0.327^{***}		-0.563^{***}
						(0.055)		(0.082)
v_p/v		-0.162		-0.570^{***}				
		(0.313)		(0.083)				
a_i	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
a_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Num.obs.$	377	377	377	377	377	377	377	377
$\bar{R}^2$	0.752	0.752	—	—	0.808	0.808	—	—

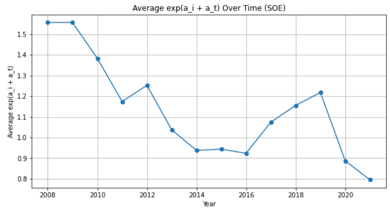
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Also notably, given the remarkable similarity in the estimated elasticities across the SOE and private sector matching functions under 3SLS, we impose a simplifying restriction in the structural model: that both sectors share the same matching elasticity parameters. Formally, we assume $\eta_{1s} = \eta_{1p}$ and $\eta_{2s} = \eta_{2p}$. This assumption is supported by the empirical estimates reported in Table 4.2, and we test its validity using a Wald test, which fails to reject the null of parameter equality (p-value = 0.538).

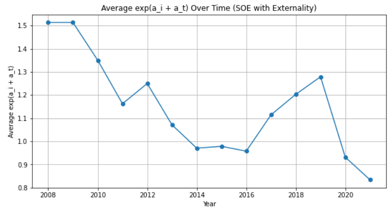
Furthermore, to examine whether the estimated matching functions exhibit constant returns to scale, we conduct a Wald test for the restriction $\eta_1 + \eta_2 = 1$ in both sectors. The null hypothesis is not rejected (p-value = 0.757), providing support for the assumption of constant returns to scale in the matching process.

We construct the estimated matching efficiencies for both the SOE and private sectors in the same manner as the aggregate matching efficiency, in order to examine whether sectoral efficiencies differ over time. As shown in Figure 4.3 and Figure 4.4, the matching efficiencies in both sectors exhibit a similar pattern: a general decline from 2008 to 2016, followed by a noticeable improvement thereafter. This trend closely mirrors the dynamics observed in the aggregate matching efficiency. We further test the hypothesis that $\hat{A}_s = \hat{A}_p$ and fail to reject the null. Thus, in the following sections, we assume identical matching efficiencies between the two sectors.

Figure 4.3: Sector Average Matching Efficiency-Unemployed Seeker (2008-2021)

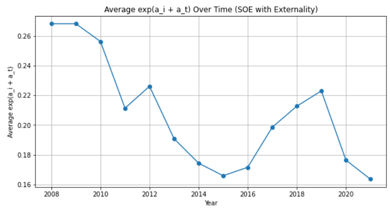


Model 1

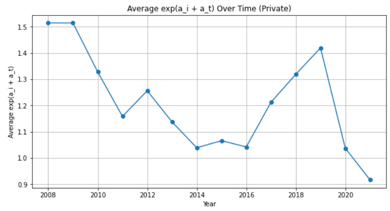


Model 2

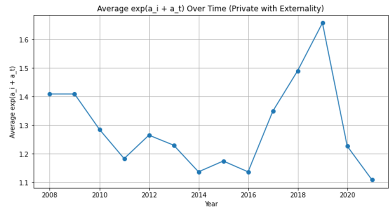
Model 3



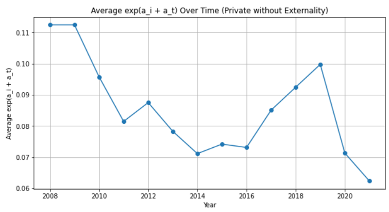
Model 4



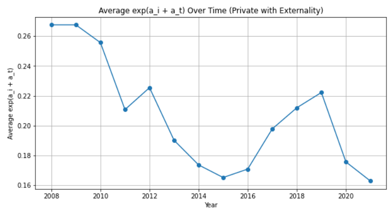
Model 5



Model 6

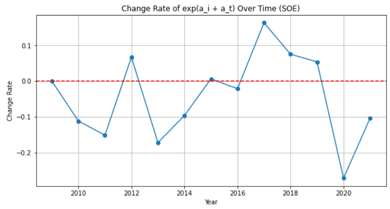


Model 7

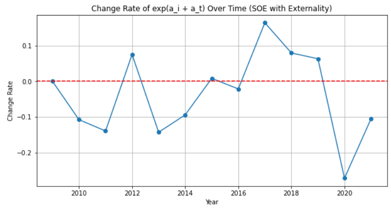


Model 8

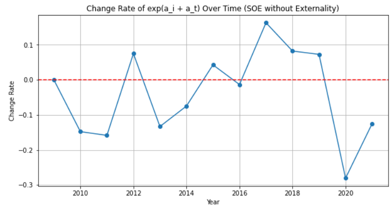
Figure 4.4: Sector Matching Efficiency Changing Rate-Unemployed Seeker (2008-2021)



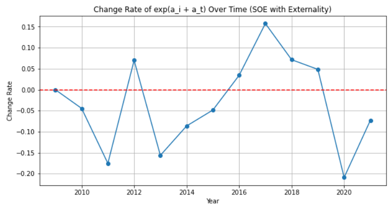
Model 1



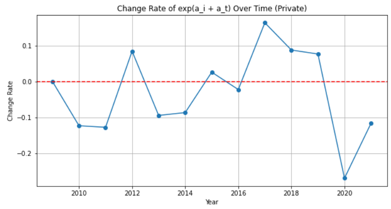
Model 2



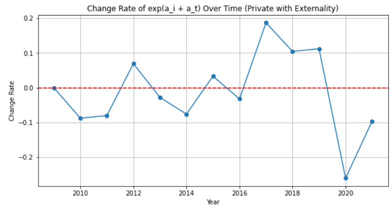
Model 3



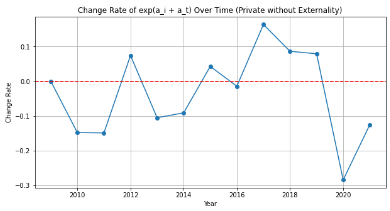
Model 4



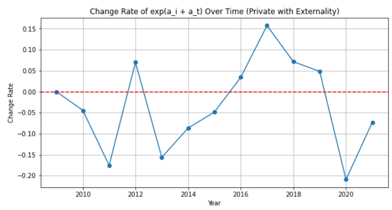
Model 5



Model 6



Model 7



Model 8

5. Structural Model Empirics

In this section, we proceed to estimate the remaining components of the structural search and matching model. First, we use the job creation and wage determination equations to estimate the private-sector bargaining power $\hat{\beta}$, the job destruction rate $\hat{q}$, and the vacancy posting cost $\hat{c}$. Next, we use the estimated parameters to recover the unobserved private-sector market tightness $\hat{\theta}_p$ through the wage equation. Finally, we infer the SOE-sector market tightness $\hat{\theta}_s$ by applying the no-arbitrage condition.

5.1 Estimation Strategy

The equilibrium private-sector market tightness and the private-sector wage are jointly determined by the following system of two equations:

Job Creation:

$$\theta_p = \left[\frac{e^{\hat{a}_{pit}}(p_{it} - w_{pit})}{p_{it}c(r_t + q - g_{it})}\right]^{\frac{1}{\eta}} + \epsilon_{1it}$$

Wage Curve:

$$\theta_p = \frac{w_{pit} - \beta p_{it}}{\beta p_{it} c} + \epsilon_{2it}$$

Where ϵ_1 captures random model deviation on the job creation process that is not a systematic error, such as hiring frictions, shifts in local firms' expectations, or policy shocks on promoting posting. ϵ_2 captures the deviation between observed market tightness and the level implied by the Nash bargaining condition, given observed wages and productivity. This deviation may arise from unobserved heterogeneity in bargaining power or omitted frictions such as labor mobility or institutional effects. We assume $E[\epsilon_{1it}] = 0$ and $E[\epsilon_{2it}] = 0$ respectively[10]. Since θ_p is not observable, we combine the equations of job creation and wage determination to eliminate θ_p, resulting in the following estimation equation:

$$\frac{w_{pit} - \beta p_{it}}{\beta p_{it} c} = \left[\frac{e^{\hat{a}_{pit}}(p_{it} - w_{pit})}{p_{it}c(r_t + q - g_{it})}\right]^{\frac{1}{\eta}} + \epsilon_{1it} - \epsilon_{2it}$$

Thus, we have the following composed error term:

$$\epsilon_{it} = \frac{w_{pit} - \beta p_{it}}{\beta p_{it} c} - \left[\frac{e^{\hat{a}_{pit}}(p_{it} - w_{pit})}{p_{it}c(r_t + q - g_{it})}\right]^{\frac{1}{\eta}} = \epsilon_{1it} - \epsilon_{2it}$$

We estimate the model using the Generalized Method of Moments (GMM). Notably, we use the Loan Prime Rate (LPR) as our exogenous interest rate which is directly supervised by the central bank. The interest rate enters only into the equation determining vacancy posting and is not affected by the joint process of Nash bargaining and job creation. Similarly, the matching efficiency, which has been discussed as exogenous in the previous section, is also not influenced by the bargaining outcome and tightness outcome, but plays a role in job posting, making it a suitable variable for the moment conditions. In addition, we use the one-period lagged urban production growth as an instrument for its current value, as this lagged growth may influence firms' posting decisions but is unlikely to be affected by the contemporaneous bargaining process directly. Accordingly, we define the exogenous vector $Z_{it} = [1, g_{i,t-1}, r_t, \hat{a}_{pit}]$. The moment condition is hence given by:

$$\mathbb{E}\left\{\left[\frac{w_{pit} - \beta p_{it}}{\beta p_{it} c} - \left[\frac{e^{\hat{a}_{pit}}(p_{it} - w_{pit})}{p_{it}c(r_t + q - g_{it})}\right]^{\frac{1}{\eta}}\right] Z_{it}\right\} = 0$$

[10]We allow for a nonlinear error structure in the job creation condition to capture potentially nonlinear deviations in the determination of market tightness. We initially considered a multiplicative error term $e^{\epsilon_{1it}}$, but found that when substituting the job creation condition into the wage determination equation, this specification led to non-identifiability of the structural error, even after applying a first-order Taylor expansion. Therefore, we adopt an additive nonlinear error, provided that it remains mean-zero and independent of the systematic components of the model.

5.2 Global Estimates

In the first step, we estimate a global bargaining power β, job posting cost c and job destruction rate q using GMM, with bootstrapped standard errors. The results are presented in Table 5.1

Table 5.1: GMM Estimates of β, c, and q with Bootstrapped Standard Errors

Parameter	Estimate	Std. Error	t-Statistic	p-Value
β (Bargaining Power)	0.424***	0.082	5.151	0.000
c (Vacancy Cost)	0.579*	0.315	1.838	0.067
q (Job Destruction Rate)	0.375***	0.094	3.980	0.000
Hansen J-statistic	0.024			
p-value (J-test)	0.877			

Notes: Standard errors are computed using 2000 bootstrap replications. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The Hansen J-test evaluates the validity of over-identifying restrictions.

As shown in Table 5.1, all three key structural parameters are estimated with statistical significance. The bargaining power parameter $\hat{\beta}$ is estimated at 0.424. This suggests that private-sector workers capture approximately 42.4% of the total surplus in wage bargaining. The estimate lies below the commonly used calibration benchmark of $\beta = 0.5$ found in the literature, but above the estimate of $\beta = 0.26$ reported by Liu (2013) using Chinese data from 1996 to 2008.

The vacancy posting cost $\hat{c}$ is estimated to be 0.579 times the annual labor productivity. This estimate is slightly lower than that reported by Liu (2013) using Chinese data, but higher than the value found by Albrecht et al. (2019), who used data from Colombia. However, the estimate of the vacancy posting cost remains statistically significant only at the 10% level and is associated with a relatively large bootstrapped standard error, which weakens the credibility of this parameter. To address this concern, we provide an alternative estimation strategy in Appendix C, where we fix the values of c and q on a grid based on commonly used benchmarks in the literature. We then re-estimate the key parameter of interest, β, to examine the robustness of our main findings.

The job destruction rate $\hat{q}$ is estimated to be 0.375, which is notably higher than the values reported by Ma et al. (2015), where SOE job destruction rates ranged from 0.154 to 0.201, and private firms ranged from 0.093 to 0.11. However, it is important to note that the China Labour Statistical Yearbook revised its methodology to include previously omitted micro- and small-sized enterprises and self-employed units. These entities tend to have significantly shorter average survival durations.[11] Given the inclusion of these

[11] According to the 2021 Chinese Government Report, the average lifespans of large, small, and micro

short-lived entities in the post-2013 data, it is reasonable to observe a higher estimated destruction rate compared to earlier studies that excluded them from the sample.

5.3 Rolling Window Estimates

A central objective of this paper is to predict market tightness levels, θ_s and θ_p, which are not directly observable but can be inferred through the structural model given appropriate parameter values. However, these parameters are likely to vary over time during the sample period, and assuming a constant set of parameters may introduce bias into the predicted market tightness.

One important source of such time variation is the change in union membership density, which may lead to greater bargaining power. As documented by Wang and Zhou (2019), the number of private firms with union representation has increased substantially over the past two decades. Yao and Zhong (2008), using city-level data, empirically show that unionization in China positively affects wage bargaining outcomes. Ma (2024) further finds that bargaining power and wage premiums have improved significantly alongside rising union membership. Similarly, Zhang et al. (2022), employing a dynamic general equilibrium framework, illustrate a rising labor income share in China after 2007.

To capture potential time variation in bargaining power, we estimate β, c, and q using a four-year rolling window. Table 5.2 reports the estimation results from GMM method with bootstrapped standard errors. We observe significant variation in the estimates of β across windows. In general, the estimates of bargaining power fall within an economically plausible range, typically between 0.3 and 0.5. Moreover, we observe an increasing trend in bargaining power over time.

However, the validity of the rolling window estimates for c and q may be limited, as their bootstrapped standard errors are relatively large across all windows. In particular, the estimates for q suffer from a lack of statistical significance in six out of nine windows. This raises concerns about the potential identification issues associated with estimating these parameters using the current dataset and model specification.

To check the robustness of the observed changes in bargaining power, and to address concerns regarding the limited precision of vacancy posting cost and job destruction rate estimates, we adopt a specification in which c and q are fixed at their constant global estimates, while allowing only β to vary across time. This specification corresponds to the post-financial crisis period, after the second wave of SOE layoffs and before the COVID-19 outbreak. During this period, China's labor market experienced relatively

firms are approximately 7 to 8 years and 2.5 years, respectively. For small firms, this implies an average annual destruction rate of $E(q) = \frac{1}{2.5} = 0.4$.

stable conditions without major external shocks. Therefore, it is reasonable to assume a constant exogenous job destruction rate and posting cost, while allowing for institutional improvements, such as enhanced unionization and labor protections, that drive changes in workers' bargaining power.

Table 5.3 reports the estimation results under this alternative specification. Figure 5.1 visualizes the estimated β values. Notably, the estimated bargaining power parameter remains within a plausible range of 0.25 to 0.55 across different rolling windows, with strong statistical significance and relatively small bootstrapped standard errors. These results confirm the robustness of the observed dynamics in bargaining power changes in China's urban labor market.

Table 5.2: Bootstrap Rolling GMM Estimates of β, c, and q by Year Window

Year	Sample Window	Parameter	Estimate	Std. Error	t-stat	p-value
2012	2010–2013	β	0.332**	0.132	2.51	0.014
		c	1.031**	0.498	2.07	0.041
		q	0.346*	0.185	1.87	0.064
2013	2011–2014	β	0.307**	0.129	2.39	0.019
		c	0.796*	0.421	1.89	0.061
		q	0.299***	0.082	3.66	0.000
2014	2012–2015	β	0.480***	0.136	3.52	0.001
		c	1.049***	0.398	2.64	0.010
		q	0.377	0.238	1.58	0.117
2015	2013–2016	β	0.404***	0.152	2.67	0.009
		c	1.313***	0.448	2.93	0.004
		q	0.243	0.199	1.22	0.224
2016	2014–2017	β	0.411***	0.129	3.19	0.002
		c	1.315***	0.421	3.13	0.002
		q	0.255	0.185	1.38	0.172
2017	2015–2018	β	0.427***	0.137	3.11	0.002
		c	1.223**	0.484	2.53	0.013
		q	0.266	0.187	1.42	0.158
2018	2016–2019	β	0.523***	0.116	4.51	0.000
		c	1.167***	0.400	2.92	0.004
		q	0.330*	0.172	1.92	0.058
2019	2017–2020	β	0.512***	0.181	2.83	0.006
		c	1.238**	0.484	2.56	0.012
		q	0.260	0.196	1.32	0.189
2020	2018–2021	β	0.544***	0.196	2.78	0.007
		c	1.213**	0.529	2.29	0.024
		q	0.266	0.174	1.53	0.129

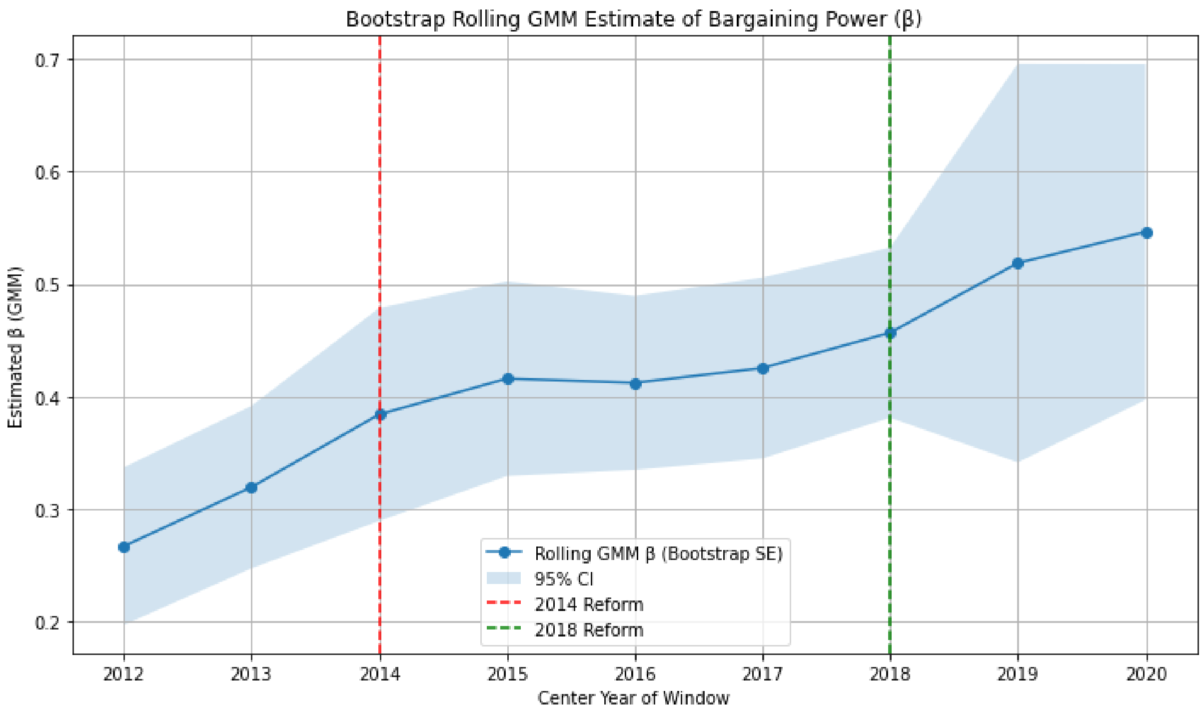
Notes: Standard errors are computed using 2000 bootstrap replications. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Estimates use rolling four-year windows. The center year and its corresponding rolling window are shown together in the first column.

Table 5.3: Bootstrap Rolling GMM Estimates of Bargaining Power (β) Only

Year	Sample Window	$\hat{\beta}$	Std. Error	t-stat	p-value
2012	2010–2013	0.267***	0.036	7.39	0.000
2013	2011–2014	0.320***	0.035	9.11	0.000
2014	2012–2015	0.384***	0.048	7.98	0.000
2015	2013–2016	0.416***	0.045	9.31	0.000
2016	2014–2017	0.412***	0.040	10.36	0.000
2017	2015–2018	0.425***	0.041	10.36	0.000
2018	2016–2019	0.457***	0.039	11.68	0.000
2019	2017–2020	0.519***	0.090	5.78	0.000
2020	2018–2021	0.546***	0.079	6.92	0.000

Notes: Standard errors are computed using 2000 bootstrap replications. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. The sample window corresponds to the rolling four-year period centered around each year.

Figure 5.1: Rolling Estimates of Bargaining Power



5.4 Recovering Market Tightness

Once we have the estimated η, a, and rolling β, along with the global estimated values for c and q, we can recover the trajectories of endogenous market tightness for private and SOE sectors, θ_p and θ_s respectively, using:

$$\theta_{pit} = \frac{w_{pit} - \beta p_{it}}{\beta p_{it} c}$$

$$\theta_{sit}^{1-\eta} = \frac{1}{e^{a_{it}}} \frac{(r_t + q - g_{it})\theta_{pit} p_{it} c \frac{\beta}{1-\beta}}{w_{sit} - \theta_{pit} p_{it} c \frac{\beta}{1-\beta}}$$

As shown in Table 5.4, the estimated θ_p closely aligns with empirical evidence from Chinese labor market data, official reports, and existing literature, which suggest a typical vacancy ratio between 1.2 and 2.0, and above 2.0 for high-skilled vacancies.

The estimated θ_s captures the congestion effects present in the SOE labor market. Within a Harris-Todaro framework, unemployed workers prefer to continue searching for SOE jobs rather than searching for private-sector employment, unless the SOE market becomes extremely congested. This pattern is consistent with observations in China, where many unemployed individuals spend years preparing for and taking SOE or public sector entrance exams, rather than actively seeking opportunities in the private sector. It is common to see over 100 applicants competing for a single SOE or public sector vacancy.

Table 5.4: Summary Statistics of Predicted θ_s and θ_p

	Mean	Std	Min	Median	Max
θ_s	0.776	1.058	0.011	0.313	5.478
θ_p	1.545	0.730	0.229	1.478	3.842

Figure 5.2 shows the predicted dynamics of market tightness. In general, the predicted market tightness values fall within a plausible range. The average market tightness in the SOE sector is consistently lower than that of the private sector across nearly all years, indicating greater congestion in the SOE labor market. Before the 2014 reform, the gap between the two sectors temporarily narrowed, primarily because the private sector became more attractive. This shift led to a sharp reallocation of unemployed workers from the SOE sector to the private sector. Along with the continued improvement in private-sector bargaining power, we observe a decline in θ_p and an increase in θ_s during this period. Following the 2014 reform, however, SOE wage growth experienced a substantial increase. This led to a corresponding decline in SOE market tightness, as more workers were drawn to the sector, resulting in a growing divergence between SOE and private tightness levels. This divergence persisted until around 2018, when new restrictions on SOE wage growth were implemented and the onset of COVID-19 further disrupted labor market dynamics. During this period, the tightness levels in the two sectors appeared to converge once again.

Figure 5.2: Predicted Dynamics of Market Tightness

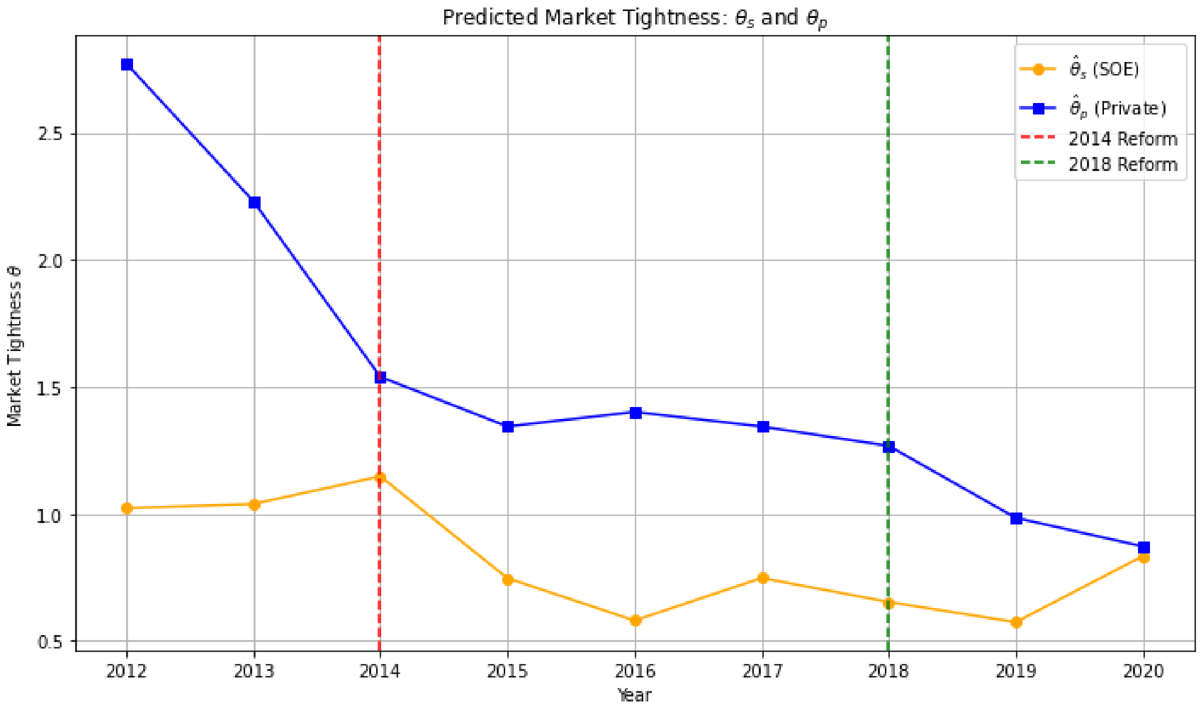


Figure 5.3: Predicted Private-Sector Market Tightness Across Regions

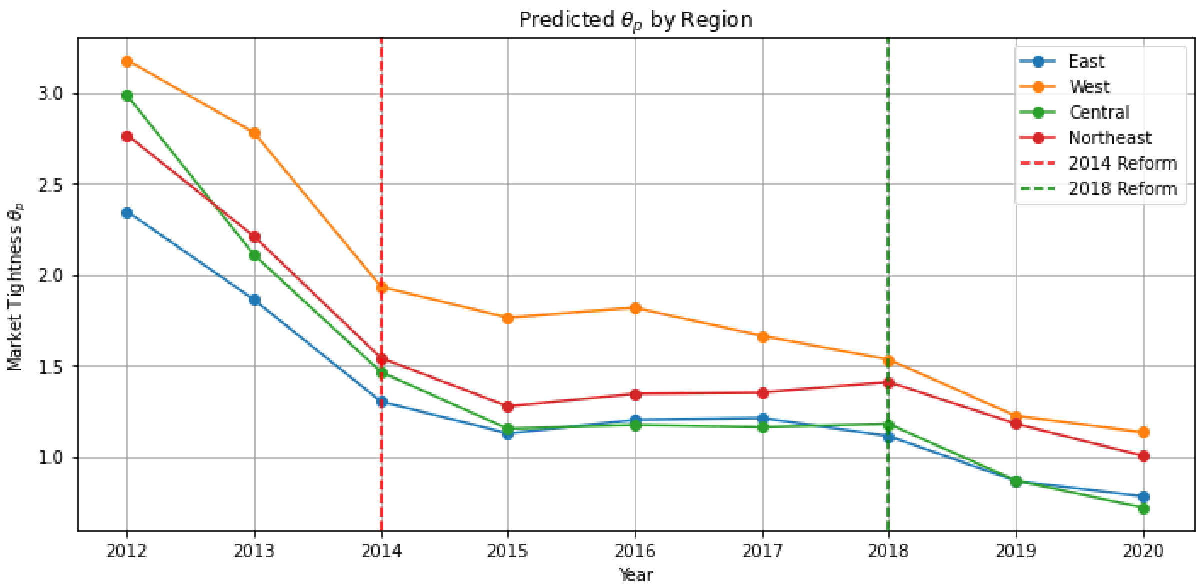
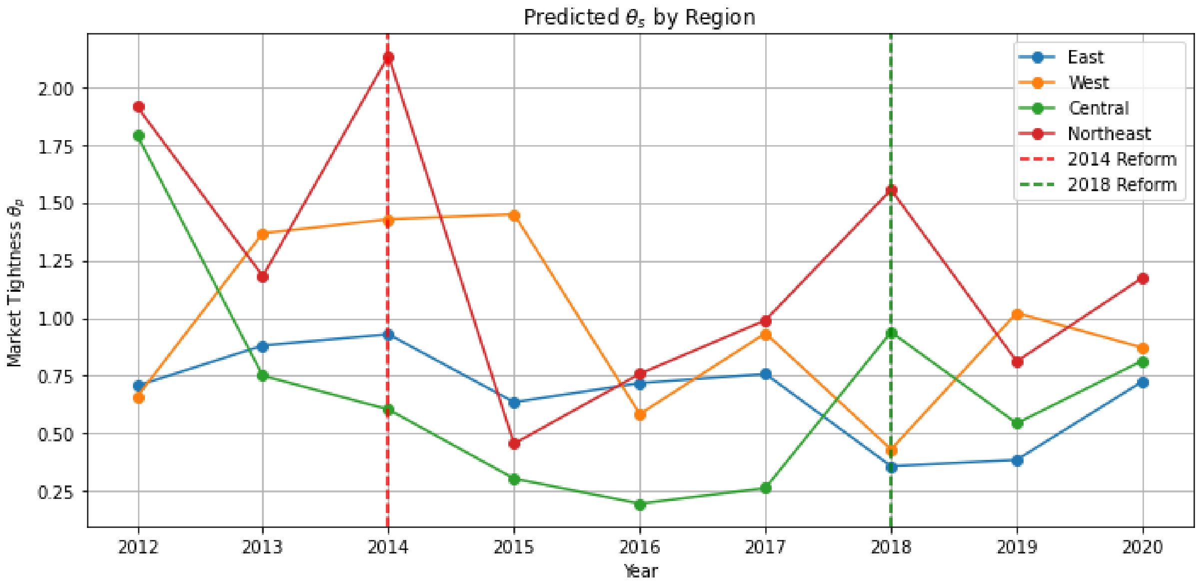


Figure 5.4: Predicted SOE-Sector Market Tightness Across Regions



Notes: Regional classification follows the National Bureau of Statistics standard. The Eastern region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The Central region consists of Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. The Western region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The Northeastern region comprises Liaoning, Jilin, and Heilongjiang.

As shown in Figure 5.3 and Figure 5.4, we observe clear regional differences in market tightness. More developed regions, such as the East and Central, exhibit both the lowest private-sector and SOE-sector tightness during the data period, suggesting a more competitive labor market environment in these areas.

In contrast, less developed regions, namely the West and the Northeast, experience significant labor out-migration to more developed provinces, resulting in less congested local labor markets. Notably, the share of SOE vacancies in the West and Northeast is larger than in developed regions, due to a combination of policy biases, historical legacies, and the relative disadvantages faced by private firms. Along with workers' lower willingness to stay in SOE jobs in these areas, these factors contribute to the relatively higher SOE market tightness observed.

In terms of dynamics, we observe a similar declining trend in private-sector tightness across all regions. Although SOE-sector tightness is more volatile, we still identify an increase before 2014 for most regions except the Central, followed by a general decline across all regions during the period from 2014 to 2018. These patterns are consistent with the aggregate trends discussed earlier.

6. Simulation

Our simulations were conducted as follows. First, we solved the model using the estimated parameters and all observed exogenous variables to obtain baseline solutions for key endogenous variables that determine labor market dynamics. Table 6.1 lists all parameters and exogenous variables in the system.

We then performed two exercises. The first exercise compares the model's baseline solution with the observed data to evaluate the goodness of fit of the model. The second exercise conducts counterfactual simulations to introduce shocks and compares the resulting outcomes with the baseline scenario.

Table 6.1: Parameters and Exogenous Variables

Parameter		**All**	**2015**	**2019**
η	Matching function elasticity (Estimated)	0.509	0.509	0.509
β	Private sector bargaining power (Estimated)	0.424	0.416	0.519
q	Job destruction rate (Estimated)	0.375	0.375	0.375
c	Vacancy posting cost (Estimated)	0.579	0.579	0.579
Exo. Var.		**All**	**2015**	**2019**
A	Average matching efficiency (Estimated)	0.974	0.897	1.131
v_s	Number of average vacant jobs in SOEs	74.878	55.922	53.850
w_s	Average annual SOE wage	7.264	6.741	10.090
r	One-year LPR(Loan Prime Rate)	0.052	0.0600	0.044
g	Urban average production per worker growth	0.106	0.118	0.103
p	Average annual production per worker	8.902	8.620	11.073
l	Average total labour force	589.566	615.501	638.065

Table 6.2: Data vs Baseline Solution

	Description	**Data**	**Model**
θ_p	Private sector tightness	****	1.639
θ_s	SOE sector tightness	****	1.015
w_p	Private sector wage	6.120	6.867
v_p	Private sector vacancy	134.183	133.790
u_p	Unemployed job seeker in privte sector	****	81.642
u_s	Unemployed job seeker in SOE sector	****	73.782
u	Unemployed job seeker	156.923	155.424

Table 6.2 shows the results of the first exercise. As can be seen in the tables, the calibrated model using estimated parameters works well for matching the aggregate average data. While the model slightly overestimates the average private-sector wage relative to the observed data, it closely matches the number of unemployed workers and the number of

private-sector vacancies, with almost no significant gap between the model and the data at the aggregate level.

6.1 Wage Reform Shocks

After the 2014 Mixed Ownership Reform of SOEs, substantial growth in profits and productivity led to significant public-sector wage increases, creating a considerable gap between SOE wages and private-sector wages.

To simulate a counterfactual scenario in which no substantial jump in public-sector wages occurred in 2015, we adjust the 2015 SOE wage. Specifically, we set the counterfactual SOE wage as the 2014 level multiplied by the private-sector wage growth rate in 2015, instead of applying the actual high public-sector wage growth observed that year. This adjustment allows us to construct a hypothetical situation in which SOE wages evolve more moderately. Results are reported in the Table 6.3.

Table 6.3: 2015 Baseline Solution vs Counterfactual Simulations

	Description	**Baseline**	$w_s = 6.367$
θ_p	Private sector tightness	1.479	1.479
θ_s	SOE sector tightness	1.039	1.701
w_p	Private sector wage	6.464	6.464
v_p	Private sector vacancy	163.393	182.404
u_p	Unemployed job seeker in private sector	110.472	123.325
u_s	Unemployed job seeker in SOE sector	53.835	32.867
u	Unemployed job seeker	164.307	156.193

The main purpose of the 2018 SOE wage reform was to establish a market-oriented public-sector wage system that aims to address the problem of downward wage rigidity among SOE employees, where real wages would increase but never decrease and to control the excessive public-sector wage growth that had occurred since the 2014 reform. This reform, in turn, led to a convergence in wage growth rates between the public and private sectors.

To simulate a counterfactual scenario in which no exogenous control over public-sector wage growth occurred in 2019, we adjust the 2019 SOE wage. Specifically, we set the counterfactual SOE wage as the level of 2018 multiplied by the average SOE sector wage growth rate observed from 2015 to 2018, instead of applying the actual observed wage for 2019. This adjustment allows us to construct a hypothetical scenario where SOE wages evolve without control. The results are reported in Table 6.4.

Table 6.4: 2019 Baseline Solution vs Counterfactual Simulations

	Description	**Baseline**	$w_s = 10.177$
θ_p	Private sector tightness	1.050	1.050
θ_s	SOE sector tightness	0.507	0.477
w_p	Private sector wage	9.241	9.241
v_p	Private sector vacancy	77.667	74.051
u_p	Unemployed job seeker in private sector	73.961	70.518
u_s	Unemployed job seeker in SOE sector	106.197	112.956
u	Unemployed job seeker	180.158	183.473

Interesting findings emerge from the model: the SOE wage policy appears to have little to no impact on private market tightness or private sector wages. However, it significantly influences SOE market tightness, the number of unemployed job seekers in each sector, private sector vacancy postings, and overall unemployment.

An increase in the SOE wage induces a reallocation of unemployed job seekers, shifting their search efforts from the private sector to the SOE sector. Given fixed exogenous SOE vacancies, this shift leads to a decline in SOE market tightness. Surprisingly, this reallocation does not translate into higher tightness in the private market. Instead, the model predicts that private firms will precisely destroy an equivalently reasonable number of vacancies, thereby maintaining a stable level of market tightness and keeping private wages unchanged.

Furthermore, the simulations suggest that a reduction in the SOE wage (i.e., a control for a smaller gap between w_s and w_p) leads to lower overall unemployment, while an increase in the SOE wage (i.e., a larger wage gap) results in higher unemployment. These dynamics are economically plausible: as the private sector becomes relatively more attractive, job seekers shift their search accordingly, prompting private firms to post more vacancies and improving labor market conditions, particularly when a large pool of workers competes for a fixed number of SOE positions.

Finally, we consider a strong policy intervention in which SOE wages are strictly aligned with market principles. Specifically, we set $w_s = w_p$ in 2019, following the policy statement that wages for all positions should be market-oriented. In this scenario, we continue to treat the decisions regarding job creation and wage determination in SOEs as exogenous; that is, SOEs do not behave as profit-maximizing private firms. Instead, we simply anchor the SOE wage level to the prevailing private-sector wage, in order to simplify the interpretation of the results.The simulation outcomes under this assumption are reported in Table 6.5.

Table 6.5: 2019 Baseline Solution vs Counterfactual Simulations

	Description	Baseline	$w_s = w_p$
θ_p	Private sector tightness	1.050	1.050
θ_s	SOE sector tightness	0.507	1.050
w_p	Private sector wage	9.241	9.241
v_p	Private sector vacancy	77.667	110.016
u_p	Unemployed job seeker in private sector	73.961	104.767
u_s	Unemployed job seeker in SOE sector	106.197	51.280
u	Unemployed job seeker	180.158	156.047

In this scenario, the SOE wage premium over the private-sector wage is fully eliminated. As a result, we observe exactly identical market tightness levels in both sectors. The number of unemployed individuals searching in each sector becomes exactly proportional to the number of vacancies available, respectively. Furthermore, we observe an overall reduction in total unemployment, as the previously more attractive yet highly congested SOE market no longer exists.

6.2 SOE Vacancy Change

Table 6.6: Baseline Solution vs Counterfactual Simulations

	Description	Baseline	$v_s = 56.444$	$v_s = 105.927$
θ_p	Private sector tightness	1.639	1.639	1.639
θ_s	SOE sector tightness	1.015	1.015	1.015
w_p	Private sector wage	6.867	6.867	6.867
v_p	Private sector vacancy	133.790	158.837	91.602
u_p	Unemployed job seeker in priavte sector	81.642	96.926	55.898
u_s	Unemployed job seeker in SOE sector	73.782	55.618	104.376
u	Unemployed job seeker	155.424	152.544	160.274

When there is a positive policy shock to SOE vacancy posting, as shown in Table 6.6, we observe no changes in either model-implied private market tightness or SOE market tightness. Unemployed individuals shift toward the SOE market and are proportionally absorbed by the newly created vacancies, which helps maintain stable SOE tightness. At the same time, the private sector reduces vacancy postings in response to the outflow of job seekers, which similarly helps preserve private market tightness.

Private sector wages remain unchanged. Despite the increase in SOE vacancies, we observe a slight rise in total unemployment. This occurs because private vacancies are destroyed while individuals move from the relatively less congested private market to the more congested SOE market.

However, when we simulate the opposite scenario, a negative policy shock reducing SOE vacancy posting, we observe a decline in total unemployment. The same channel operates in reverse: fewer SOE vacancies induce a shift of job seekers toward the private market, leading to more private vacancies and a movement from a more congested to a less congested market, which improves overall job market performance.

6.3 Bargaining Power Change

Table 6.7: Baseline Solution vs Counterfactual Simulations

	Description	**Baseline**	$\beta = 0.416$	$\beta = 0.519$
θ_p	Private sector tightness	1.639	1.691	1.126
θ_s	SOE sector tightness	1.015	1.004	1.073
w_p	Private sector wage	6.867	6.834	7.22
v_p	Private sector vacancy	133.790	135.692	108.17
u_p	Unemployed job seeker in private sector	81.642	80.243	96.075
u_s	Unemployed job seeker in SOE sector	73.782	74.615	69.790
u	Unemployed job seeker	155.424	154.859	165.865

In this section, we conduct a counterfactual experiment that allows for variation in bargaining power, as identified in the Section 5.3. We set the baseline value of β at its global estimate and consider two scenarios. Specifically, in the first scenario, we decrease the bargaining power to the level estimated for 2015; in the second scenario, we increase the bargaining power to the level estimated for 2019. We then compare the resulting differences in labor market outcomes relative to the baseline. Table 6.7 presents the results.

Interestingly, all endogenous outcomes change with shifts in bargaining power. When we use the estimated bargaining power from 2019, which is higher than the global estimate, we observe a smaller model-implied private market tightness. This occurs because more individuals switch to searching in the private market, anticipating potentially higher wages. However, unlike in the previous simulation, where private firms created exactly enough vacancies to absorb the increased flow of unemployed job seekers, the number of vacancies now declines in the model's solution. This is because firms must pay higher wages when a vacancy is filled, increasing their costs. As a result, the negative effect of higher bargaining power on vacancy creation outweighs the positive effect of increased unemployment inflow into the private sector on vacancy creation. This leads to an overall decline in private market tightness. Moreover, we also observe a rise in total unemployment in this scenario.

When we impose a lower bargaining power (based on 2015 estimates), we observe a higher model-implied private market tightness. On the one hand, individuals shift away from the private market due to the prospect of lower wages. On the other hand, private firms still create more vacancies, but now the underlying mechanism differs. Specifically, the positive effect of lower wage costs outweighs the negative effect of increased unemployment outflow from the private sector on vacancy creation, resulting in a net increase in the number of vacancies. However, since the drop in job seekers entering the private market is less substantial than the increase in vacancies, overall private market tightness increases. This also leads to congestion in the SOE market, as more job seekers turn there instead. Additionally, we observe a decline in total unemployment in this scenario.

In general, the predicted declining trajectory of private market tightness appears plausible. This aligns with the observed increase in bargaining power (estimated through the rolling window approach) and the data-implied decline in SOE vacancies from 2012 to 2020, which forces more labour to search in the private market.

6.4 Matching Efficiency Change

Table 6.8: Baseline Solution vs Counterfactual Simulations

	Description	**Baseline**	$A = 0.897$	$A = 1.131$
θ_p	Private sector tightness	1.639	1.571	1.756
θ_s	SOE sector tightness	1.015	0.880	1.363
w_p	Private sector wage	6.867	6.740	7.088
v_p	Private sector vacancy	133.790	134.501	131.393
u_p	Unemployed job seeker in private sector	81.642	85.593	74.840
u_s	Unemployed job seeker in SOE sector	73.782	85.112	54.929
u	Unemployed job seeker	155.424	170.705	129.769

In this section, we conduct a counterfactual experiment to examine how changes in matching efficiencies affect the model's outcomes. As estimated in Section 4.2, matching efficiencies exhibit substantial variation over the sample period. It is therefore reasonable to argue that such changes would be expected to significantly influence the dynamics of key endogenous variables. We set the baseline value of A at its global average and consider two scenarios. Specifically, in the first scenario, we decrease the matching efficiency to its average level estimated for 2015; in the second scenario, we increase the matching efficiency to its average level estimated for 2019. We then compare the resulting labor market outcomes relative to the baseline. The results are presented in Table 6.8.

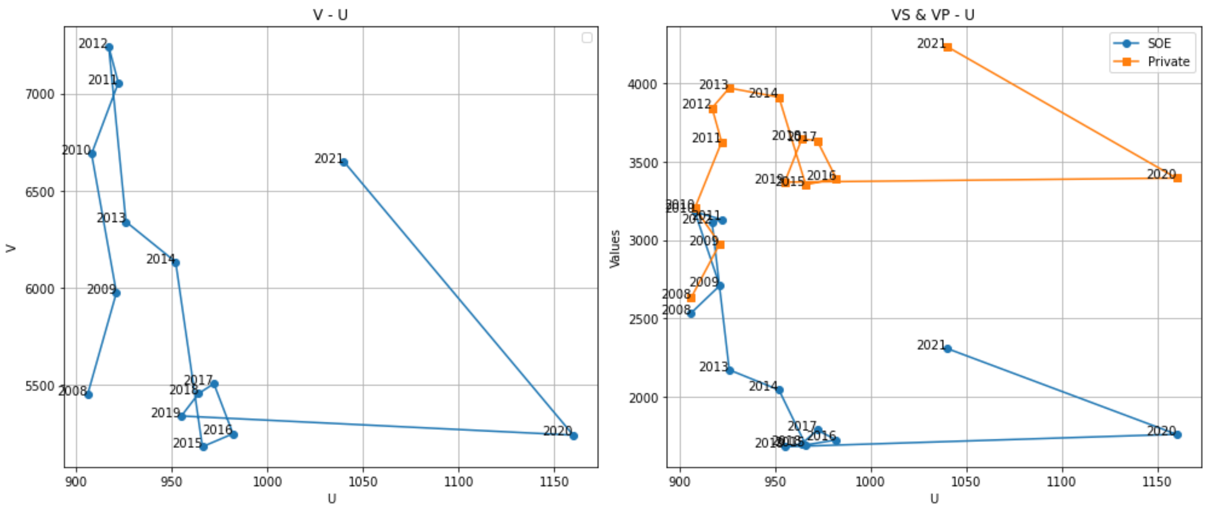
As shown in the table, we observe a decrease in the total unemployment rate as matching efficiency improves, which induces more new hires. We also observe an increase in market tightness in both sectors as a result of the improvement.

Interestingly, although the number of unemployed workers decreases in both markets, the magnitudes of the declines differ. Specifically, the reduction in unemployment is larger in the SOE sector compared to the private sector. This can be explained by two channels. First, as matching efficiency improves in both sectors, the number of unemployed workers naturally falls. Second, higher market tightness increases workers' situation, leading to higher wages in the private sector. This, in turn, encourages more unemployed workers from the SOE market to switch to the private market. As a result, we observe a relatively larger decline in unemployment within the SOE sector.

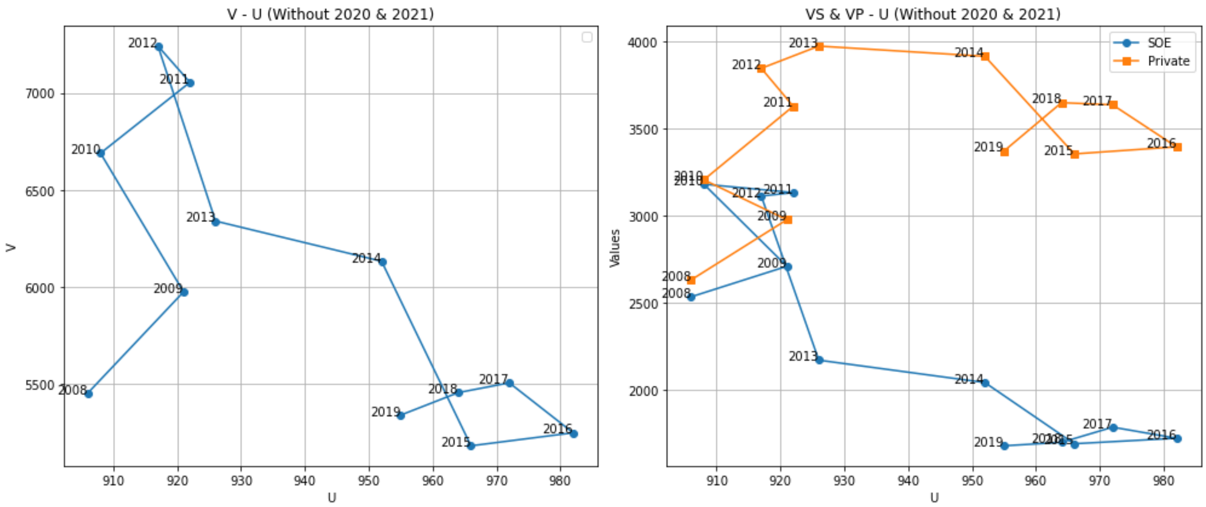
Meanwhile, private-sector job vacancies appear less sensitive to changes in matching efficiency. This is because two opposing mechanisms offset each other: on the one hand, rising private-sector wages should discourage job creation by increasing the costs of firms; on the other hand, the inflow of job seekers from the SOE sector incentivizes private firms to create more vacancies. Overall, these two effects largely cancel out, resulting in only a minor change in private-sector job vacancies.

7. U-V Curve

Figure 7.1: U-V Curve



Full period

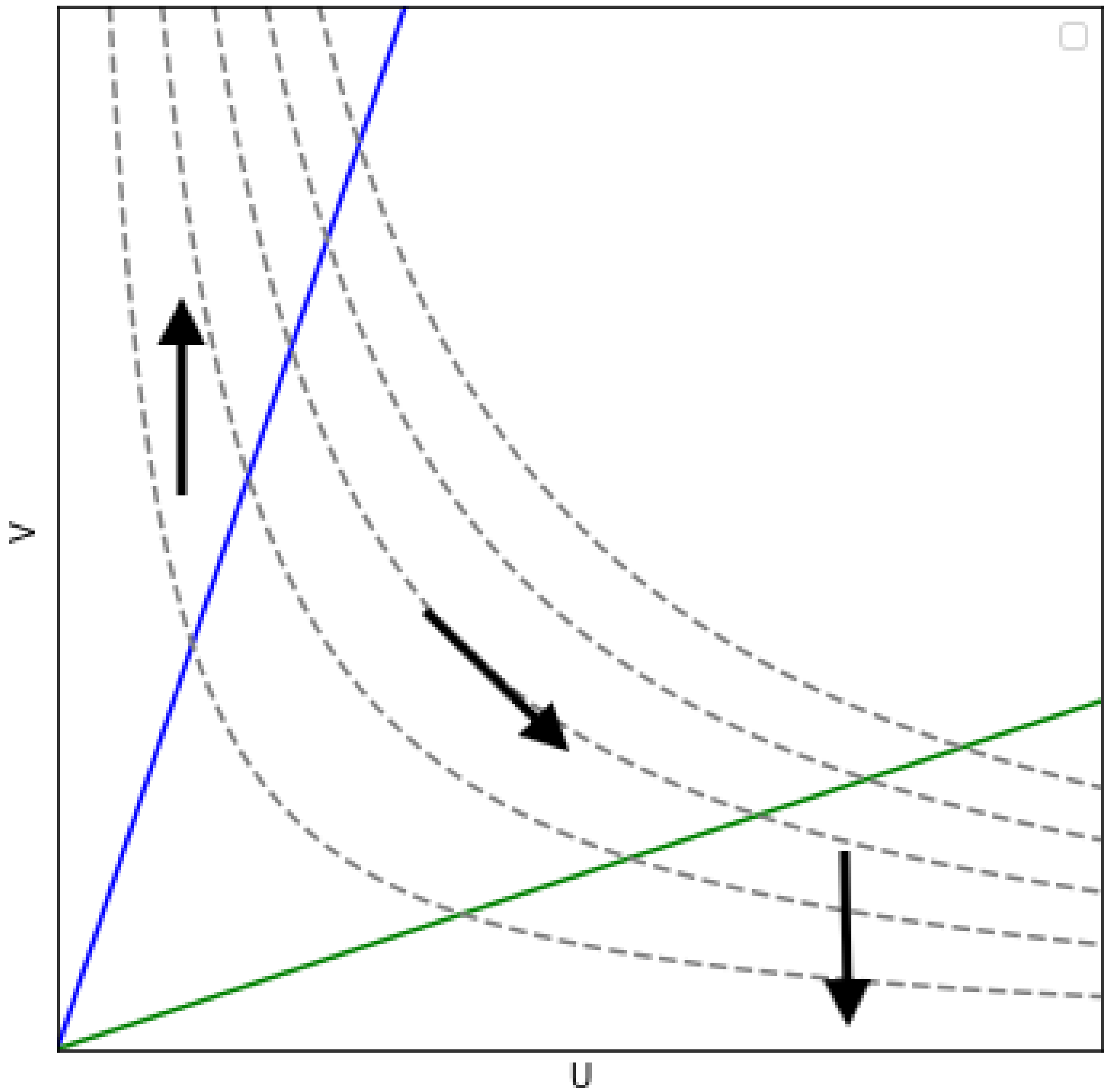


Pre-Covid

We can now use the model's mechanisms to study and explain the dynamics of the data-constructed U-V curve in China. The U-V curve is jointly determined by the following system[12]:

[12]See detailed derivations in Appendix E. Let α denote the fration of unemployed workers who search in the SOE market. And Thus $1-\alpha$ denotes the fration of unemployed workers who search in the private market.

Figure 7.2: Shifts in BC and JC



Job Creation Market Tightness:

$$v = \Big[\alpha\theta_s + (1-\alpha)\theta_p\Big]u$$

Beveridge Curve:

$$(v - v_s)^\eta = \frac{1}{A(1-\alpha)^\eta} qlu^{-\eta} - \frac{1}{A(1-\alpha)^\eta} qu^{1-\eta} - \frac{\alpha^\eta}{(1-\alpha)^\eta} v_s^{1-\eta}$$

Figure 7.1 is obtained using real data to reconstruct the historical U-V pairs in China. Figure 7.2 further simplifies these data points and illustrates the shifts in the Beveridge Curve and Job Creation curve that determine the points.

Before 2013, the actual U-V pairs moved majorly upward with relatively stable unemployment rate. In this period, wage growth in the SOE sector was relatively less attractive, while bargaining power in the private sector was increasing. As a result, more individuals shifted their job search toward the private sector. This inflow mechanism created more vacancies in the private sector, as discussed in the previous section, which had a positive effect on reducing unemployment.

At the same time, the number of SOE vacancies was gradually increasing. This slightly reduced the incentive for job seekers to move from the more congested SOE market to the less congested private market. While this effect was limited, it became more noticeable as private sector bargaining power continued to rise. Therefore, the negative effect on unemployment reduction, though modest, cannot be ignored. In sum, these opposing forces resulted in a slight increase, but overall a relatively stable unemployment rate during this period. However, as the estimates suggest, matching efficiency in China continued to decline during this period, leading to a relatively poor matching situation. The outward shift of the Beveridge Curve is the primary factor explaining the upward movement in the U-V pairs.

We observe a modest increase in unemployment in 2013 with the decrease in SOE vacancies, but a larger increase is observed from 2014 to 2016. After the 2014 SOE reform, wage growth in the SOE sector became significantly more attractive than in private firms. On the one hand, although SOE job vacancies were declining, they remained relatively stable. The outflow of job seekers from the SOE market due to lower vacancy availability was not sufficient to offset the inflow driven by rising SOE wages. As a result, more people shifted their search toward the SOE sector, resulting in a more congested market than before. This shift led to an outflow of job seekers from the private market, and combined with increasing bargaining power, prompted private firms to reduce their vacancy postings. The earlier trend of rising private vacancies came to a halt and even reversed to some extent. With more job seekers now targeting the relatively more congested SOE market and fewer opportunities available in the private sector, a sharp increase in unemployment was observed during this period. Correspondingly, we observe a downward rotation of the JC curve. Combined with the declining matching efficiency, this results in a movement of the U-V pairs toward the lower-right corner of the diagram.

After 2016, as matching efficiency started to improve, we observe an inward shift of the BC, but the slope of the aggregate market tightness remained relatively flat. Finally, after the 2018 reform, wage patterns in both the SOE and private sectors became much more aligned. Alongside the stabilization of SOE vacancies, private sector vacancies also stabilized. This stability was the result of two opposing forces the continued inflow of job seekers and the rising bargaining power balancing each other out. As a result, the reallocation of unemployed workers across sectors became more efficient, and market tightness in the two sectors converged, combined with improving matching efficiency, contributing to an overall improvement in the labour market. However this improvement was limited as the private sector tightness had already reached a low level, resulting in a persistent flat JC slope.

8. Extension

8.1 Worker Heterogeneity

Notably, our baseline model assumes homogeneous workers. Due to the unavailability of micro-level firm-worker matched data, we were unable to fully estimate the model at the individual level and instead conducted our analysis using provincial-level data. To extend the framework and align it with potential future datasets, it is essential to incorporate worker heterogeneity. Introducing worker heterogeneity allows us to examine potential self-selection across sectors. Specifically, high-skilled or highly educated workers may preferentially search for jobs in the SOE sector. This tendency could stem from political rent-seeking opportunities, similar wage levels with less competition, or public-spirited motivations. As a result, the observed SOE wage premium may reflect more than institutional differences or bargaining advantages due to political connections; it may also capture underlying self-selection effects. Therefore, wage variation across sectors partly reflects the sorting of workers. Although this self-selection mechanism does not fundamentally alter the structure of our baseline model, in which individuals make sectoral choices and search accordingly, it complicates the analysis of wage determination. Relying on macro-level provincial average data introduces potential biases and limits the interpretability of our estimation results, especially in identifying pure wage-setting mechanisms.

As proposed by Beaudry et al. (2014), when selection occurs along observable characteristics such as gender, race, education, and experience - and the analysis is conducted at the aggregate rather than individual level - a two-step adjustment is required to control for these observed factors and correct the wage measures used in subsequent regressions. Following their recommendation, we estimate separate regressions for each year and province, regressing log wages on a vector of individual characteristics and ownership-type dummy variables. We then use the estimated coefficients on the ownership dummies as our measure of mean average wages in SOEs and private firms across different provinces. In detail, we use $w_{is} = e^{\alpha+\beta\bar{X}+\gamma_s}$ to represent the corrected mean SOE wage and $w_{ip} = e^{\alpha+\beta\bar{X}}$ to represent the corrected mean private wage for province i, where α is the estimated constant term, β are the coefficients on the characteristic terms, $\bar{X}$ are the province sample mean characteristics, and γ_s is the coefficient on the SOE dummy variable. This approach enables us to construct an adjusted representative 'homogeneous' worker for each province in each year.

In this section, we introduce the China Family Panel Studies (CFPS) dataset. The CFPS is a nationally representative longitudinal survey covering seven waves every two years from 2010 to 2022. It provides rich individual-level data, including personal demographics, wage levels, educational attainment, Hukou status,[13] and other labor market characteristics.

Unfortunately, the dataset does not include firm identifiers or vacancy-level information, which prevents us from analyzing heterogeneity in the matching function. We restrict our empirical analysis to the wage determination aspect. It is worth noting that in each new survey wave, approximately one-third of the original households are replaced by new ones. While this enhances the representativeness of the sample, it raises concerns about the dataset's suitability for constructing a consistent panel for individual-level analysis. After trimming extreme wage values at the 5% level for full-year workers and dropping observations with missing key variables, we are left with a limited panel in which only about 50% of individuals appear in more than two waves. Additionally, given the consistently low observed job mobility between SOEs and private firms in the dataset, we are unable to implement panel fixed-effects models to account for unobserved individual heterogeneity driving sectoral self-selection. As a result, we restrict our analysis to observed heterogeneity and follow the methodology of Beaudry et al. (2014), assuming that selection occurs only based on observable characteristics. Table 8.1 presents summary statistics from the CFPS dataset.

Table 8.1: CFPS Summary

	2010	**2012**	**2014**	**2016**	**2018**	**2020**	**2022**
Observations	4942	4879	4888	2632	5734	4647	5140
Male	58.05	57.84	56.91	53.99	56.64	55.73	55.25
Female	41.95	42.16	43.09	46.01	43.36	44.27	44.75
Rural Migrant	65.60	38.45	42.68	56.31	48.90	50.72	50.58
Urban Resident	34.40	61.55	57.32	43.69	51.10	49.28	49.42
SOE	37.39	33.24	35.58	26.06	34.58	35.98	34.07
Private	62.61	66.76	64.42	73.94	65.42	64.02	65.93
Illiteracy	4.55	6.76	5.77	5.36	4.60	3.14	2.55
Lower Secondary or Below	40.57	42.63	42.64	42.67	37.53	32.92	33.15
Upper Secondary	26.51	24.70	24.00	21.62	22.93	21.76	19.38
Tertiary	28.37	25.91	27.60	30.36	34.93	42.18	44.92

[13] Hukou is China's household registration system, which identifies an individual's place of origin. In this study, we focus solely on the urban labor market, defining a rural migrant as an individual with a rural Hukou who is working in an urban area.

First, we examine the presence of self-selection into SOE employment and the associated wage premium by estimating a probit model and conducting propensity score matching (PSM). The probit model estimates the probability that a worker is employed in an SOE as a function of observed characteristics such as age, education, gender, and migrant status. As shown on the left side of Table 8.2, the results suggest that workers in SOEs tend to be older, male, more educated, and less likely to be rural migrants. These patterns indicate a process of positive selection into SOEs based on observable traits. This finding highlights the necessity of correcting the province-level representative worker's wage in the estimation.

We then use the estimated propensity scores to match SOE workers with observationally similar individuals in the private sector. This matching procedure controls for observable heterogeneity and isolates the wage difference attributable to SOE employment itself. The average treatment effect on the treated (ATT), reported in the right side of Table 8.2, shows that SOE workers earn approximately $e^{0.083}$ ≈8.68% more in yearly wages compared to their matched private-sector counterparts. To assess the robustness of this estimate, we compute bootstrap standard errors based on 1,000 replications.

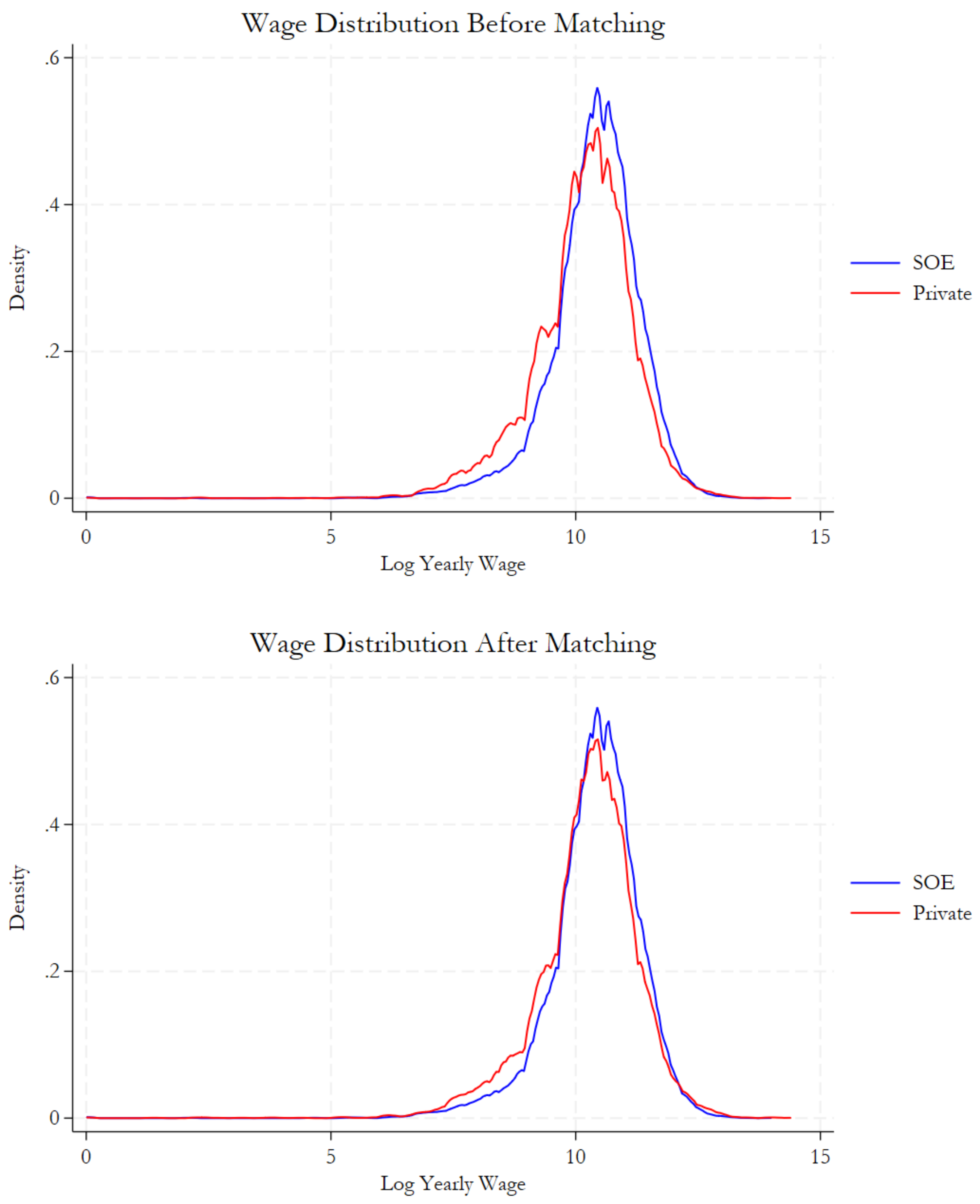
These findings suggest that, even after accounting for observable characteristics, a significant wage premium persists for SOE employment. This residual gap may reflect compensating differentials for job stability or benefits, or other institutional features unique to SOEs. As illustrated in Figure 8.1, the distribution of log yearly wages for SOE workers is more left-skewed compared to that of private-sector workers, reinforcing the idea that wage-setting mechanisms may differ across sectors.

Table 8.2: Probit Regression and Matching Diagnostics

Variable	**Probit Coefficient (SE)**	**Matching Statistics**
Age	0.047*** (0.004)	ATT Estimate: 0.083***
Age^2	-0.000*** (0.000)	Bootstrap SE: 0.022
Gender (Male)	0.093*** (0.016)	Bootstrap z: 3.73
Migrant Status	-0.291*** (0.017)	Mean Bias: 2.3%
Education	0.547*** (0.010)	Max Bias: 3.5%
Constant	-2.857*** (0.111)	
Sample Size: 32,834		Common Support: Yes
Matching Method: Nearest Neighbor		

Note: Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure 8.1: Wage Distribution



Second, we document the existence of a wage premium for SOEs after controlling for observed heterogeneity in a linear specification, as reported in Table 8.3. This specification is also used to obtain the corrected wages (Beaudry et al. 2014). In this setup, the first specification includes controls for age, gender, education, migrant status, and ownership. In the second specification, we add a quadratic term for age to capture potential non-linearities in the wage-age profile. The third specification incorporates interaction terms between education and all individual characteristics to test the robustness of the estimates.

Across all models, we find consistent patterns: individuals who are male, better educated, and employed in SOEs tend to earn higher wages. The magnitude of these effects remains stable across specifications. Notably, employment in an SOE is associated with a $e^{0.065}$ = 6.72% higher yearly wage compared to employment in a private firm, after controlling for observed characteristics and interaction terms. This wage premium is statistically significant at the 1% level.

Table 8.3: Estimates of Wage on Characteristics

	(1)	(2)	(3)
	lnw	lnw	lnw
Age	0.000	0.102***	0.099***
	(0.000)	(0.003)	(0.004)
$Gender$	0.408***	0.432***	0.584***
	(0.010)	(0.010)	(0.044)
$Migrant\ Status$	-0.019*	0.004	-0.008
	(0.011)	(0.010)	(0.046)
$Education$	0.288***	0.276***	0.180***
	(0.006)	(0.006)	(0.038)
$Ownership$	0.097***	0.085***	0.065***
	(0.011)	(0.011)	(0.011)
$Age2$		-0.001***	-0.001***
		(0.000)	(0.000)
Age & $Educ$	No	No	Yes
Gen & $Educ$	No	No	Yes
Mig & $Educ$	No	No	Yes
$Year$	Yes	Yes	Yes
$Province$	Yes	Yes	Yes
$Constant$	9.370***	7.452***	7.463***
	(0.0455)	(0.0654)	(0.133)
$R - squared$	0.259	0.293	0.308
$Observations$	32834	32834	32834

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Finally, we run by year and province regressions to obtain corrected mean wages that control for observed heterogeneity. In the baseline model, we relied on the assumption of homogeneous workers and used aggregate mean wage data. In this subsection, we relax this assumption and explicitly allow for worker heterogeneity. By controlling for observable heterogeneity and employing corrected individual-level wage data, we aim to improve the robustness of the empirical analysis. In particular, this approach addresses the identification issue present in the original wage equation specification: $w_{pit} = \beta p_{it} + \beta\theta_p p_{it} c + \epsilon_{it}$ where ϵ_{it} may capture worker heterogeneity and self-selection bias. If left uncorrected, this can bias the estimation of parameters. Unfortunately, due to the lack of micro-level production data, we are unable to re-estimate the structural model for the private-sector wage and market tightness determination system at the provincial level, as done in Section 5. A potential problem arises if we attempt to use yearbook-level production data to estimate the wage equation: wages reported in the CFPS are systematically underestimated and do not represent a consistent share of true productivity. However, in the following extension, by correcting the mean wage for SOEs and assuming that SOEs behave as profit maximizers, we are able to jointly identify the bargaining powers in both the SOE and private sectors without relying on production data.

8.2 Profit Maximizer SOE

In our baseline model, we treat SOEs not pursuing profit maximisation in their vacancy posting behaviour, assuming they are directly supervised by the government. This simplification introduces key limitations, as recent reforms have pushed SOEs towards more market-oriented and profit-driven operations. Many recent studies now model SOEs as profit-maximising agents, requiring vacancy posting decisions to be endogenised within the search and matching framework.

By using the corrected mean wages derived in the previous subsection, we are able to identify the pure SOE wage premium that is not attributable to self-selection or observed worker heterogeneity. Specifically, we can model the SOE wage premium in two different ways. First, we can model the premium as a structural average markup that enters the wage bargaining process additively. The wage equation for the SOE sector is thus specified as: $w_{sit} = \gamma p_{it} + \gamma\theta_s p_{it} c + premium_{it} + \epsilon_{it}$. This constant represents the structural wage markup attributed to SOE employment, net of bargaining process on production and market tightness effects. Second, we can model this premium as an advantage in bargaining, specifically, as a component of bargaining power, to be consistent with the studies suggesting higher bargaining power in SOEs. In the following estimation, we adopt the latter model specification, assuming that the SOE wage premium is absorbed into higher bargaining power within profit-maximizing SOEs. This specification reflects a relative advantage for workers in SOEs, rather than a pure premium transfer that is unrelated to market performance.

We calibrate the bargaining powers in the joint wage determination system for both the private and SOE sectors using targeted moments. In this specification, we impose a common vacancy posting cost and production technology across sectors, while allowing for sector-specific bargaining powers. By reconstructing the wage of a representative worker at the provincial level, we address the self-selection bias in wage determination. This allows us to use the observed SOE to private wage ratio as a valid moment to identify the difference in bargaining power between the two sectors. And c is jointly identified together with the sector-specific bargaining powers through the structural wage ratio function. The details of derivation can be found in Appendix F.

Table 8.4: Estimates of γ, β and c, and with Bootstrapped Standard Errors

Parameter	Estimate	Std. Dev.
γ (SOE Bargaining Power)	0.471	0.066
β (Private Bargaining Power)	0.631	0.091
c (Vacancy Cost)	0.835	0.178

Notes: Standard errors are computed using 1000 bootstrap replications.

As shown in Table 8.4, the estimated bargaining power in the private sector is 0.471, which is lower than the 0.631 estimated for the SOE sector. Even after controlling for observed worker heterogeneity and allowing the bargaining parameter to absorb the SOE wage premium, a gap in bargaining power remains. However, this gap is smaller than the 0.45 estimated by Feng and Guo (2021), who did not account for potential self-selection in the wage data.

Table 8.5 reports the simulation results under the assumption that the labor market dynamics converge to a steady-state equilibrium. We simulate a counterfactual SOE wage policy shock that directly restricts the SOE wage premium, which, in our specification, operates through a change in bargaining power.

Table 8.5: 2019 Baseline Solution vs Counterfactual Simulations

	Description	$\gamma = 0.631$	$\gamma = 0.551$	$\gamma = 0.471$
θ_p	Private sector tightness	0.695	0.695	0.695
θ_s	SOE sector tightness	0.356	0.505	0.695
w_p	Private sector wage	6.536	6.536	6.536
w_s	SOE sector wage	7.182	6.873	6.536
v_p	Private sector vacancy	92.0315	82.335	73.010
v_s	Private sector vacancy	33.862	51.102	73.010
u_p	Unemployed job seeker in private sector	132.359	118.355	104.945
u_s	Unemployed job seeker in SOE sector	95.151	101.288	104.948
u	Unemployed job seeker	227.510	219.644	209.893

When the SOE wage policy targets reducing the SOE wage premium by limiting workers' bargaining power, while also shifting vacancy posting to a market-determined process, the dynamics of the labor market become more complex than in the baseline model, where both SOE wage setting and vacancy posting are exogenous. Notably, a reduction in SOE workers' bargaining power leads to three distinct and interacting effects. First, lower worker bargaining power allows SOEs to capture a larger share of the match surplus, increasing the value of hiring and incentivizing firms to post more vacancies. Second, the reduced bargaining power makes employment in the SOE sector less attractive to job seekers, prompting a shift in search behavior toward the private sector. Third, the increased willingness of SOEs to post vacancies improves the availability of jobs in the SOE sector, partially offsetting the outflow of job seekers by providing more outside options within the sector.

This increase in job opportunities has two further implications: on one hand, it raises the probability of a successful match for job seekers in the SOE market and helps prevent a sharp decline in wages by strengthening workers' fallback options in bargaining. On the other hand, as workers gain better outside options, SOEs may not experience the expected increase in match frequency, and wages may not fall as much as anticipated. As a result, SOE firms may become less enthusiastic about expanding vacancies than initially expected. Overall, the net effect on SOE market labour dynamics can be either positive or negative.

In the private sector, there is no direct intervention altering its characteristics; thus, private firms respond passively to shifts in worker flows. If more workers shift toward the private market, private firms respond by creating more vacancies until the equilibrium wage and market tightness return to their previous levels. Conversely, if fewer workers enter, job creation contracts accordingly.

As shown in the table, we observe a clear pattern. Wages in the SOE sector decline, but not in direct proportion to the reduction in bargaining power, as the outside option continues to play a role in wage negotiation. SOE firms are willing to create more jobs due to the now lower wage level. Most notably, we observe an increase in the number of unemployed job seekers in the SOE market. Given that the matching probability for job seekers in the SOE market has improved, it is unlikely that this increase stems from new unemployment. Instead, it suggests that there is no significant outflow of job seekers from SOEs, but rather an increased inflow from the private sector, even though SOE wages have become less attractive. This implies that workers value the increased job opportunities more than the wage level itself.

Correspondingly, we observe a decline in vacancies posted in the private sector, reflecting the outflow of job seekers. Overall, we see an improvement in aggregate unemployment, primarily because the state sector expands and absorbs more labor.

Finally, when we completely eliminate the SOE wage premium and allow SOEs to operate fully as private firms, we observe a more symmetric market composition: equal wage levels, equal number of vacancies, and lower aggregate unemployment. This simulation highlights the potential of policies that reduce the SOE-specific premium and promote market-oriented reforms.

9. Conclusion

In this paper, we primarily examine the dynamics of China's labour market between 2008 and 2021 using a two-sector search and matching model. We simulate the effects of SOE wage shocks and changes in other structural characteristics of the market to understand their impact on labour market outcomes. To achieve this, we first estimate all key structural parameters using macro-level data, and then conduct counterfactual simulations. Our estimation results reveal substantial variation in matching efficiency and private-sector bargaining power over time. These two factors significantly influence labour market transitions. When SOEs' vacancies are supervised by the planner, the simulation results suggest that controlling SOE wage growth induces a reallocation of unemployed workers toward the private sector, lowers the aggregate unemployment rate, and stimulates private-sector job creation. While in a profit-maximising SOE setup, this improvement in employment is mainly due to SOE job creation. However, in both cases, we find that SOE wage controls have only a limited effect on private-sector wage determination.

Despite these contributions, several limitations of this study must be acknowledged: First, although our baseline analysis is based on macro-level data, and we later extend the model to incorporate micro-level data to account for observed individual heterogeneity, such as age, education, gender, and experience, we are unable to address unobserved heterogeneity, including worker abilities and skills, due to low data variations. This restricts our ability to analyze sorting mechanisms and differential responses among heterogeneous workers. Moreover, in the absence of firm-worker matched data, we cannot observe match-specific productivity and instead rely on macro-level labor productivity measures. This may obscure transitions driven by idiosyncratic productivity shocks or unobserved characteristics. Prior studies, such as Albrecht et al. (2019), emphasize the importance of heterogeneity in both productivity and preferences in explaining sectoral sorting and wage dispersion.

Second, while we simulate policy shocks (e.g., SOE wage restrictions), we do not implement a formal causal identification strategy to estimate their effects. This is due to two main challenges. First, although the SOE wage reform had a pilot phase, the identities of treated firms remain confidential, preventing us from constructing a treatment and control group for a difference-in-differences analysis. Second, the outbreak of COVID-19 in late 2019 distorted the evaluation of this policy, as SOEs assumed greater social responsibilities, including employment guarantees and wage stability, making it difficult to isolate the effect of wage reform from pandemic interventions.

Finally, in our baseline model, we treat SOEs not pursuing profit maximisation and the public wages and vacancies are directly supervised by the government. However, this setup calls for a more explicit modeling of government behavior. In particular, the structure now becomes a three-player game, requiring the incorporation of a government budget constraint or a tax-financing mechanism for public vacancy creation. Such financing considerations may influence both worker utility, as taxpayers, and firm behavior. Moreover, it is necessary to clarify the government's objective in participating in the labor market: whether it aims to reduce unemployment, improve public-sector productivity, or balance fiscal revenue with social policy goals. Understanding this incentive structure is essential for future studies.

Addressing these limitations presents a promising direction for future research, which would help build a more comprehensive understanding of China's labour market dynamics.

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A. Appendix: Bellman with Trends

Poisson Process

$$F(\tau - t) = 1 - e^{-\lambda(\tau - t)}$$

$$f(\tau - t) = \lambda e^{-\lambda(\tau - t)}$$

Value of Employment

The continuous time value of employment is given as follows:

$$\begin{aligned}
V_e(w(t), t) &= \int_t^{\infty} \Big(w(\tau)(1 - F(\tau - t)) + V_u(\tau) f(\tau - t) \Big) e^{-r(\tau - t)} \, d\tau \\
&= \int_t^{\infty} \Big(w(\tau) e^{-(\lambda + r)(\tau - t)} + V_u(\tau) \lambda e^{-(\lambda + r)(\tau - t)} \Big) \, d\tau \\
&= \int_t^{\infty} \Big(w e^{\int_t^{\tau} g(u)\, du} e^{-(\lambda + r)(\tau - t)} + V_u(\tau) \lambda e^{-(\lambda + r)(\tau - t)} \Big) \, d\tau
\end{aligned}$$

Where we define $w(\tau) = we^{\int_t^{\tau} g(u)\, du}$. g(u) is the wage change rate which could be either exogenous or endogenous. In a steady state, we have a constant growth path g such that $g < r + \lambda$, with time-invariant values V_e^* and V_u^*, which then give:

$$V_e(w, t) = V_e^* e^{gt}$$

$$V_u(t) = V_u^* e^{gt}$$

Thus:

$$\frac{d}{dt} V_e(w, t) = g V_e^* e^{gt} = g V_e(w, t)$$

The steady-state value of employment is given as follows:

$$\begin{aligned}
V_e(w, t) &= \int_t^{\infty} \Big(w e^{g(\tau - t)} e^{-(\lambda + r)(\tau - t)} + V_u^* e^{g\tau} \lambda e^{-(\lambda + r)(\tau - t)} \Big) \, d\tau \\
&= \Big[w e^{(\lambda + r - g)t} + V_u^* \lambda e^{(\lambda + r)t} \Big] \int_t^{\infty} e^{-(\lambda + r - g)\tau} \, d\tau \\
&= \Big[w e^{(\lambda + r - g)t} + V_u^* \lambda e^{(\lambda + r)t} \Big] \frac{1}{\lambda + r - g} e^{-(\lambda + r - g)t} \\
&= \frac{w}{\lambda + r - g} + \frac{V_u^* e^{gt} \lambda}{\lambda + r - g} \\
&= \frac{w}{\lambda + r - g} + \frac{V_u(t) \lambda}{\lambda + r - g}
\end{aligned}$$

Thus

$$(r + \lambda - g)V_e = w + \lambda V_u$$

$$rV_e = w + \lambda(V_u - V_e) + gV_e$$

Which is exactly:

$$rV_e = w + \lambda(V_u - V_e) + \frac{d}{dt}V_e(w,t)$$

Value of Filled Vacancy

The firms have to pay the wage as a proportion of the labour production and its potential growth, which, in return, brings a higher present value of a filled job vacancy. The value is given as:

$$\begin{aligned}
J_e(p,w,t) &= \int_t^\infty \left((p-w)e^{g(\tau-t)}e^{-(\lambda+r)(\tau-t)} + J_u^* e^{g\tau}\lambda e^{-(\lambda+r)(\tau-t)} \right) d\tau \\
&= \left[(p-w)e^{(\lambda+r-g)t} + J_u^*\lambda e^{(\lambda+r)t} \right] \int_t^\infty e^{-(\lambda+r-g)\tau}\, d\tau \\
&= \left[(p-w)e^{(\lambda+r-g)t} + J_u^*\lambda e^{(\lambda+r)t} \right] \frac{1}{\lambda+r-g} e^{-(\lambda+r-g)t} \\
&= \frac{p-w}{\lambda+r-g} + \frac{J_u^* e^{gt}\lambda}{\lambda+r-g} \\
&= \frac{p-w}{\lambda+r-g} + \frac{J_u(t)\lambda}{\lambda+r-g}
\end{aligned}$$

Which is exactly:

$$rJ_e = p - w + \lambda(J_u - J_e) + gJ_e$$

B. Appendix: Matching with Employed Job Seekers

In this appendix, we estimate an extended specification of the matching functions that incorporates employed job seekers. This allows us to provide a more comprehensive view of the matching process, beyond the baseline specification that considers only unemployed job seekers. The estimated equations are as follows:

$$lnM_{it} = \eta_1 ln(u_{it} + \phi s_{it}) + \eta_2 lnv_{sit} + a_i + a_t + \epsilon_{it}$$

$$lnM_{sit} = \eta_1 ln(u_{it} + \phi s_{it}) + \eta_2 lnv_{sit} + \eta_2 \lambda_s (\frac{v_{pit}}{v_{it}}) + a_{si} + a_{st} + \epsilon_{sit}$$

$$lnM_{pit} = \eta_1 ln(u_{it} + \phi s_{it}) + \eta_2 lnv_{pit} + \eta_2 \lambda_p (\frac{v_{sit}}{v_{it}}) + a_{pi} + a_{pt} + \epsilon_{pit}$$

A notable finding is the consistently low estimates of ϕ, which reflect the limited impact of employed job seekers on overall labor market matching. This result aligns with the findings of Feng and Guo (2021), who document extremely low mobility among on-the-job job seekers in China. As shown in the tables, our key parameters of interest, η_1 and η_2, remain highly statistically significant, and their magnitudes are economically plausible.

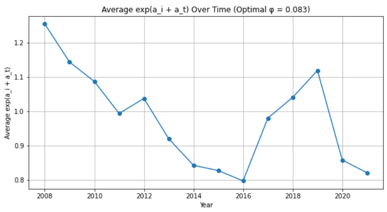
Figures illustrate the dynamics of estimated matching efficiencies over time. The overall pattern closely mirrors that observed in the previous estimation framework where on-the-job search was included, indicating the robustness of our findings with respect to model specification in both aggregate matching and sectoral matching estimations.

Table B.1: Aggregate Matching Estimation (2008-2021)

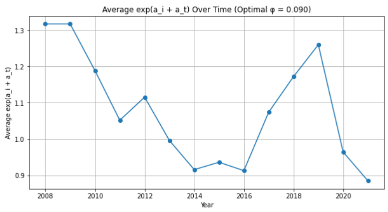
	Unconstrained Nonlinear				Constrained Nonlinear	
	LS(1)	2SLS(2)	LS(3)	2SLS(4)	LS(5)	2SLS(6)
η_1	0.739***	0.568**	0.748***	0.775***	0.679***	0.687***
	(0.111)	(0.229)	(0.018)	(0.019)	(0.042)	(0.054)
η_2	0.457***	0.670***	0.474***	0.667***	0.321***	0.313***
	(0.062)	(0.121)	(0.064)	(0.126)	(0.042)	(0.054)
Productivity			0.125***	0.165***		
			(0.030)	(0.037)		
Urban Employment			−0.000	−0.001		
			(0.002)	(0.002)		
EU Transition			0.190	−0.544		
			(1.333)	(2.00)		
Interest Rate			−0.038	−0.141***		
			(0.024)	(0.044)		
ϕ^*	0.083	0.090	0.112	0.110	0.080	0.090
a_i	Yes	Yes	Yes	Yes	Yes	Yes
a_t	Yes	Yes	Yes	Yes	Yes	Yes
$Constraint : \eta_1 + \eta_2 = 1$	No	No	No	No	Yes	Yes
Test $p - value : \eta_1 + \eta_2 = 1$	0.060	0.259	0.025	0.033	—	—
$Num.obs.$	429	377	415	364	429	377
$\bar{R}^2$	0.845	0.751	0.858	0.771	0.845	0.784

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

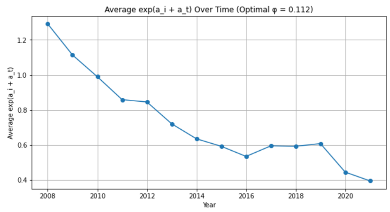
Figure B.1: Aggregate Average Matching Efficiency (2008-2021)



Model 1



Model 2



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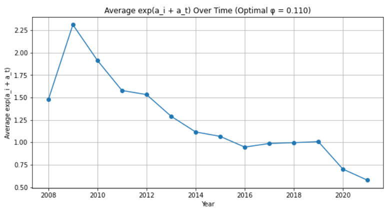

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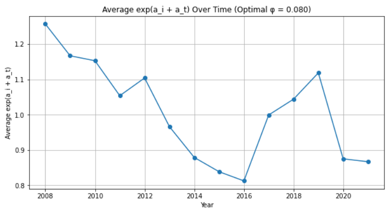
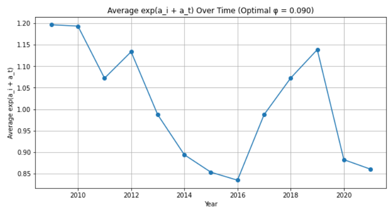
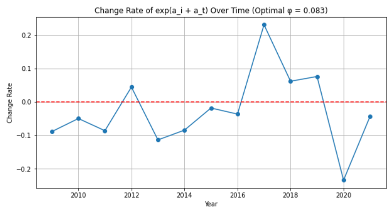


Model 5

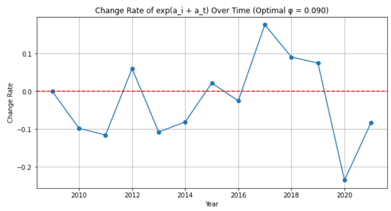


Model 6

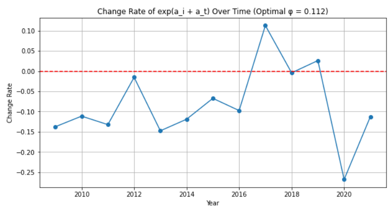
Figure B.2: Aggregate Matching Efficiency Changing Rate (2008-2021)



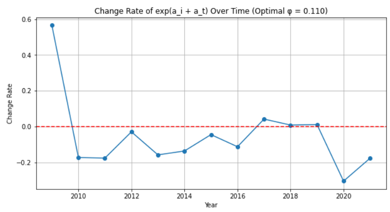
Model 1



Model 2



Model 3



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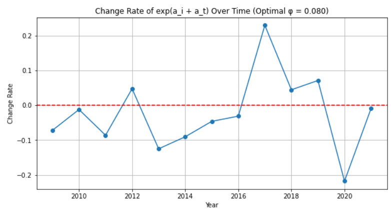
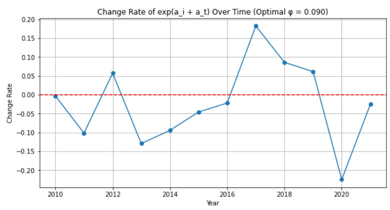


Model 5



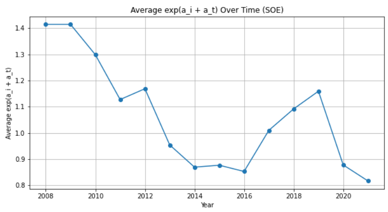
Model 6

Table B.2: Sector Matching Estimation (2008-2021)

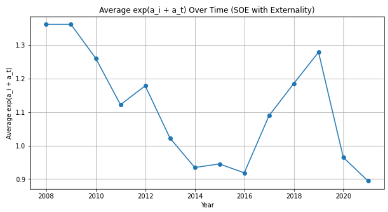
	SOE				Private			
	2SLS(1)	2SLS(2)	3SLS(3)	3SLS(4)	2SLS(5)	2SLS(6)	3SLS(7)	3SLS(8)
η_1	0.751***	0.759***	0.508***	0.873***	0.505**	0.485**	0.495***	0.873***
	(0.179)	(0.241)	(0.178)	(0.156)	(0.223)	(0.225)	(0.180)	(0.156)
η_2	0.569***	0.569***	0.795***	0.199**	0.713***	0.354***	0.800***	0.199**
	(0.105)	(0.122)	(0.032)	(0.079)	(0.108)	(0.055)	(0.033)	(0.079)
V_S/V						0.354***		−0.798***
						(0.055)		(0.079)
V_P/V		−0.284		−0.804***				
		(0.314)		(0.080)				
ϕ^*	0.100	0.100	0.100	0.100	0.090	0.100	0.100	0.100
a_i	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
a_t	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$Num.obs.$	377	377	377	377	377	377	377	377
$\bar{R}^2$	0.752	0.750	—	—	0.805	0.805	—	—

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

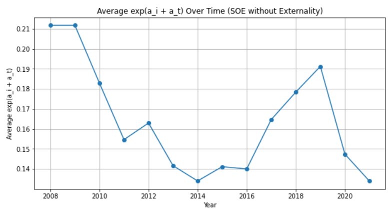
Figure B.3: Sector Average Matching Efficiency (2008-2021)



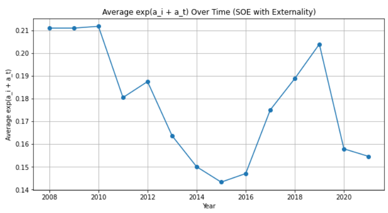
Model 1



Model 2



Model 3



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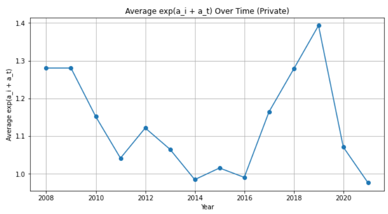
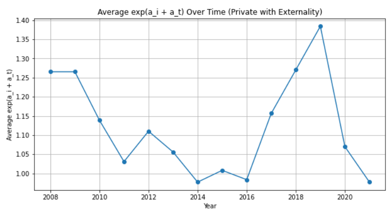
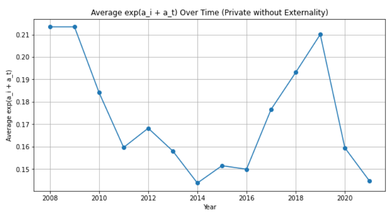


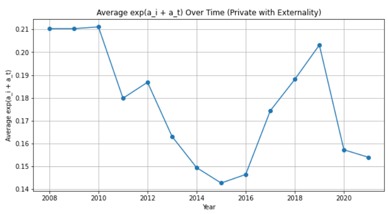
Model 5



Model 6

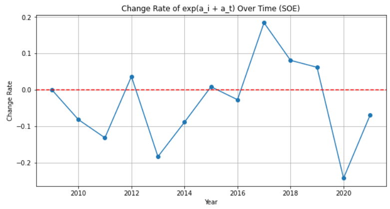


Model 7

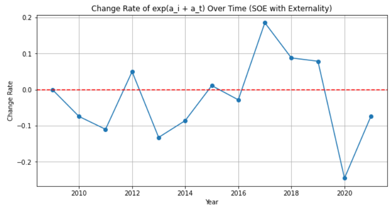


Model 8

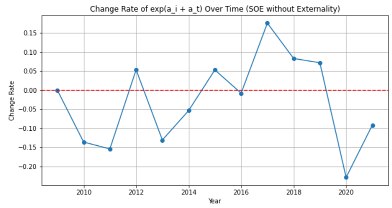
Figure B.4: Sector Matching Efficiency Changing Rate (2008-2021)



Model 1



Model 2



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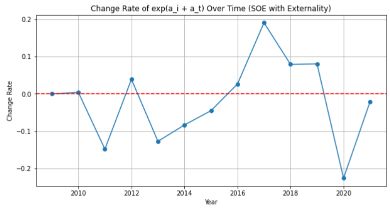
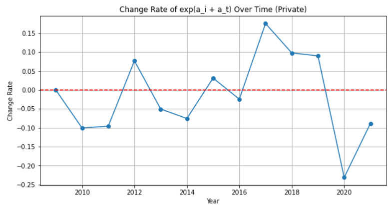
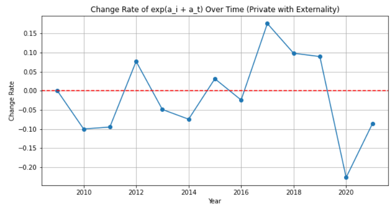


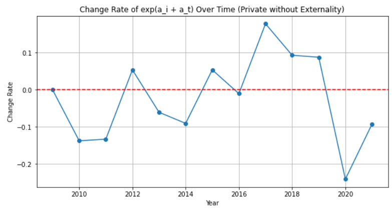
Model 4



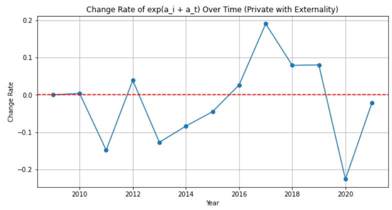
Model 5



Model 6



Model 7



Model 8

C. Appendix: Estimates of Structural Equations with Fixed Parameters

Here, we fix c and q to values commonly used in the literature and focus on estimating the key global parameter β. We further conduct sensitivity checks across alternative values of c, q, and η.

Across all combinations of fixed values for the vacancy cost parameter, the separation rate, and the matching elasticity parameter, our GMM estimates of β remain statistically significant at the 1% level and exhibit consistent patterns. In particular, while the magnitude of β varies with the assumed values, the overall structure of the estimates remains robust. The range of estimated bargaining power coefficients (approximately 0.2 to 0.6) aligns well with findings in the existing literature.

Figure C.1: GMM Sensitivity of $\hat{\beta}$

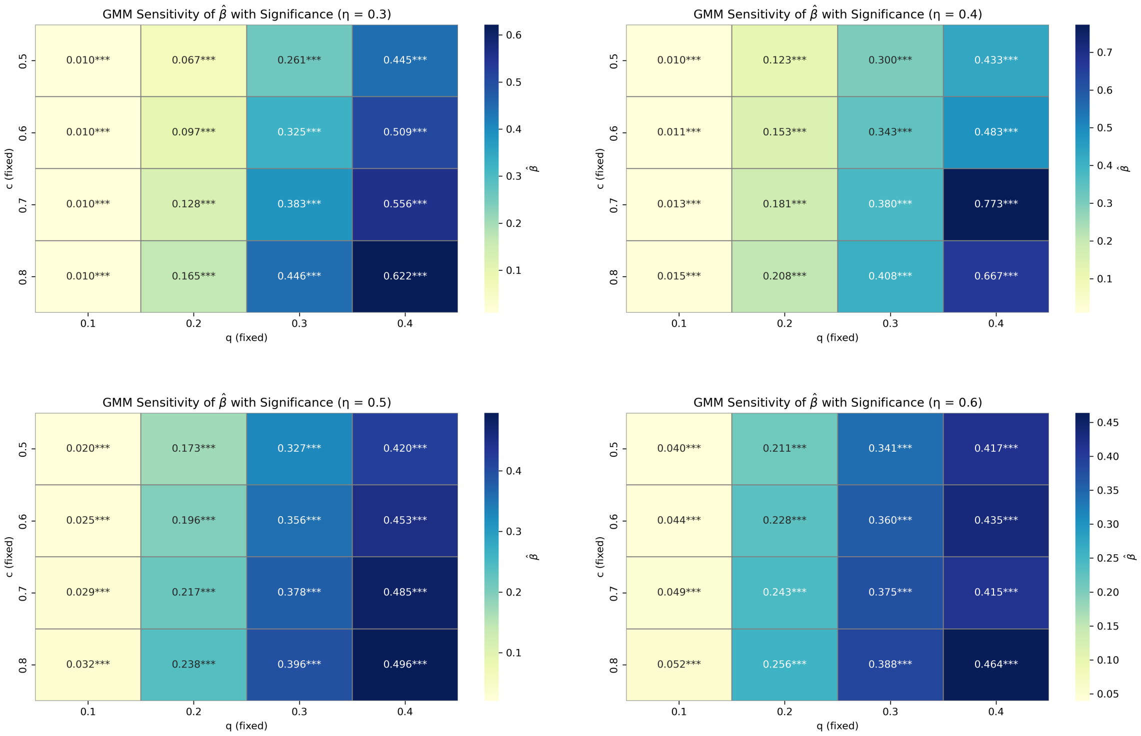
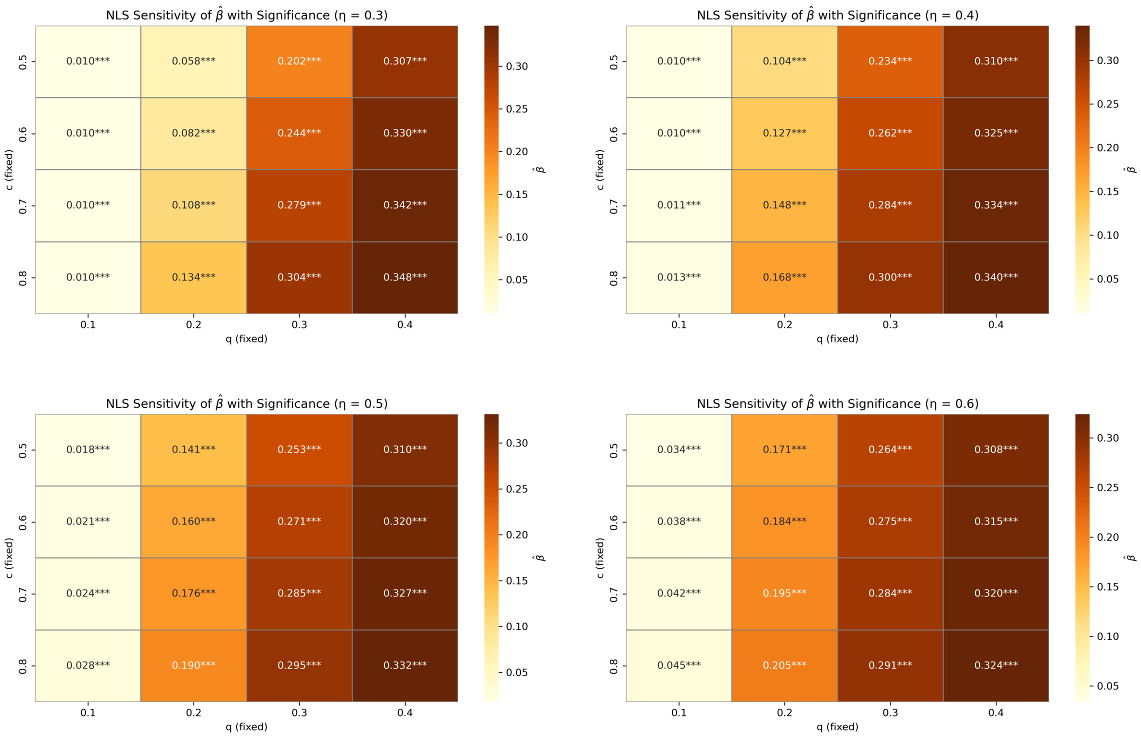


Figure C.2: NLS Sensitivity of $\hat{\beta}$



D. Appendix: Further Counterfactual Experiments

Table D.1: Baseline Solution vs Counterfactual Simulations

	Description	**Baseline**	$q = 0.325$	$q = 0.425$
θ_p	Private sector tightness	1.639	1.825	1.582
θ_s	SOE sector tightness	1.015	1.694	0.898
w_p	Private sector wage	6.867	7.218	6.759
v_p	Private sector vacancy	133.790	135.760	132.858
u_p	Unemployed job seeker in private sector	81.642	74.396	84.004
u_s	Unemployed job seeker in SOE sector	73.782	44.204	83.374
u	Unemployed job seeker	155.424	118.600	167.378

Table D.2: Baseline Solution vs Counterfactual Simulations

	Description	**Baseline**	$c = 0.400$	$c = 0.600$
θ_p	Private sector tightness	1.639	2.156	1.304
θ_s	SOE sector tightness	1.015	1.566	0.724
w_p	Private sector wage	6.867	7.030	6.728
v_p	Private sector vacancy	133.790	188.016	93.777
u_p	Unemployed job seeker in private sector	81.642	87.193	71.903
u_s	Unemployed job seeker in SOE sector	73.782	47.820	103.441
u	Unemployed job seeker	155.424	135.013	175.344

Table D.3: Baseline Solution vs Counterfactual Simulations

	Description	**Baseline**	$p = 8.245$	$p = 10.550$
θ_p	Private sector tightness	1.639	1.639	1.639
θ_s	SOE sector tightness	1.015	0.590	6.521
w_p	Private sector wage	6.867	6.360	8.138
v_p	Private sector vacancy	133.790	89.563	202.909
u_p	Unemployed job seeker in private sector	81.642	54.654	123.820
u_s	Unemployed job seeker in SOE sector	73.782	126.945	11.482
u	Unemployed job seeker	155.424	181.598	135.302

E. Appendix: U-V Curve Derivations

Market Tightness:

$$\begin{aligned} v &= v_s + v_p \\ &= \theta_s u_s + \theta_p u_p \\ &= \theta_s \alpha u + \theta_p (1-\alpha) u \\ &= \Big[\alpha\theta_s + (1-\alpha)\theta_p\Big] u \end{aligned}$$

Beveridge Curve:

$$\begin{aligned} \theta_s m(\theta_s) u_s + \theta_p m(\theta_p) u_p &= q(l-u) \\ A u_s^{\eta} v_s^{1-\eta} + A u_p^{\eta} v_p^{1-\eta} &= q(l-u) \\ A u^{\eta}\Big[\alpha^{\eta} v_s^{1-\eta} + (1-\alpha)^{\eta} v_p^{\eta}\Big] &= q(l-u) \\ \alpha^{\eta} v_s^{1-\eta} + (1-\alpha)^{\eta}(v-v_s)^{\eta} &= \frac{1}{A} q l u^{-\eta} - \frac{1}{A} q u^{1-\eta} \\ (v-v_s)^{\eta} &= \frac{1}{A(1-\alpha)^{\eta}} q l u^{-\eta} - \frac{1}{A(1-\alpha)^{\eta}} q u^{1-\eta} - \frac{\alpha^{\eta}}{(1-\alpha)^{\eta}} v_s^{1-\eta} \end{aligned}$$

F. Appendix: SOE Profit Maximizer

The SOE sector wage w_s is determined through a Nash bargaining process, in which the firm and the worker negotiate over the division of the total match surplus.

$$S = V_s - U_s + \Pi_s - \Pi_v = \frac{p - (r-g)U_s}{r+q-g}$$

We define β as the bargaining power of a worker and hence have the following:

$$\frac{V_s - U_s}{\Pi_s - \Pi_v} = \frac{\gamma}{1-\gamma}$$

Together with the equations for Π_s, V_s and the free entry condition, we have:

$$w_s = \gamma p + (1-\gamma)(r-g)U_s$$

We rewrite the $(r-g)U_p$ equation as follows:

$$\begin{aligned}(r-g)U_s &= \theta_s m(\theta_s)(V_s - U_s)\\ &= \theta_s m(\theta_s)\gamma S\\ &= \theta_s \frac{pc(r+q-g)}{p-w_s}\gamma\left(\frac{p-(r-g)U_s}{r+q-g}\right)\\ &= \theta_s pc\gamma\left(\frac{p-(r-g)U_s}{p-w_s}\right)\\ &= \theta_s pc\frac{\gamma}{1-\gamma}\end{aligned}$$

After plugging this new $(r-g)U_p$ into the w_p equation, we have:

$$\begin{aligned}w_s &= \gamma p + (1-\gamma)(r-g)U_s\\ &= \gamma p + \gamma\theta_s pc\end{aligned}$$

No Arbitrage Condition is given as:

$$\begin{aligned}(r-g)U_s &= (r-g)U_p\\ \theta_s pc\frac{\gamma}{1-\gamma} &= \theta_p pc\frac{\beta}{1-\beta}\\ \theta_s\frac{\gamma}{1-\gamma} &= \theta_p\frac{\beta}{1-\beta}\end{aligned}$$

The wage ratio is given as:

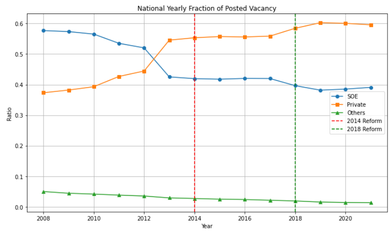
$$\frac{w_s}{w_p} = \frac{\gamma+\gamma\theta_s c}{\beta+\beta\theta_p c}$$

Additionally, with Job creation functions, we have:

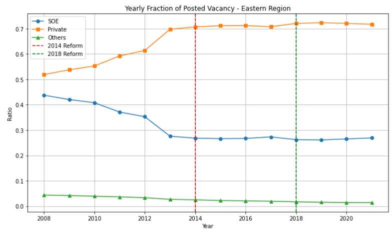
$$\begin{aligned}\frac{\theta_p}{\theta_s} &= \left[\frac{A(p-w_p)}{pc(r+q-g)}\right]^{\frac{1}{\hat{\eta}}} \Big/ \left[\frac{A(p-w_s)}{pc(r+q-g)}\right]^{\frac{1}{\hat{\eta}}}\\ \frac{\theta_p}{\theta_s} &= \left[\frac{p-w_p}{p-w_s}\right]^{\frac{1}{\hat{\eta}}}\\ \frac{\theta_p}{\theta_s} &= \left[\frac{p(1-\beta-\beta\theta_p c)}{p(1-\gamma-\gamma\theta_s c)}\right]^{\frac{1}{\hat{\eta}}}\\ \frac{\theta_p}{\theta_s} &= \left[\frac{1-\beta-\beta\theta_p c}{1-\gamma-\gamma\theta_s c}\right]^{\frac{1}{\hat{\eta}}}\end{aligned}$$

G. Appendix: Wage and Vacancy

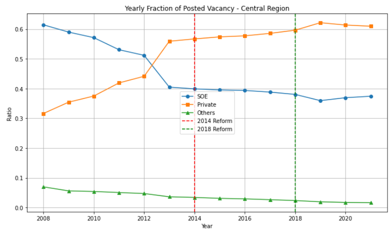
Figure G.1: Yearly Fraction of Posted vacancy (2008-2021)



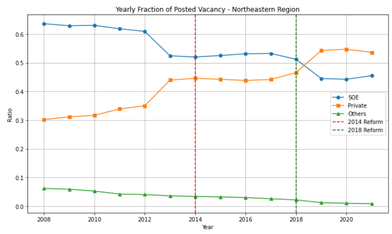
Nation



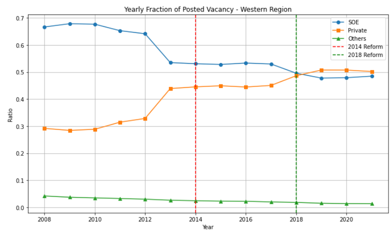
Eastern Region



Central Region

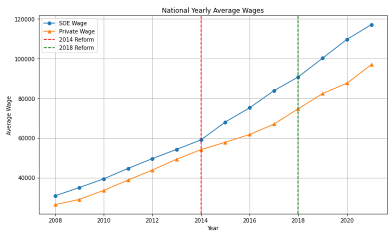


Northeastern Region

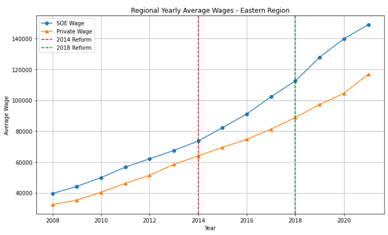


Western Region

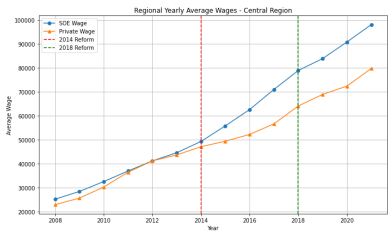
Figure G.2: Yearly Average Nominal Wage (2008-2021)



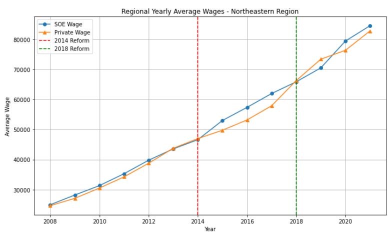
Nation



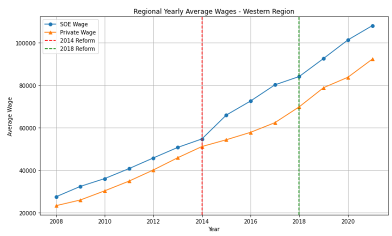
Eastern Region



Central Region

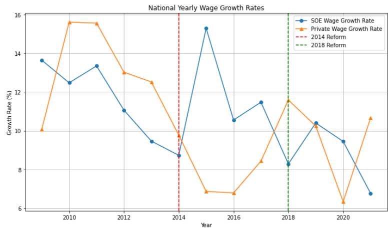


Northeastern Region

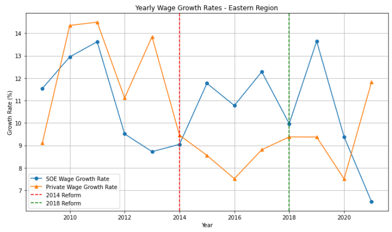


Western Region

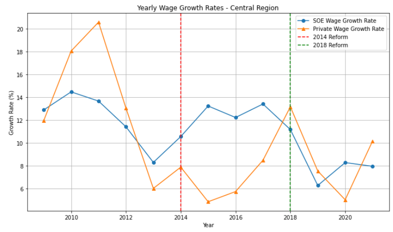
Figure G.3: Yearly Average Nominal Wage Growth (2009-2021)



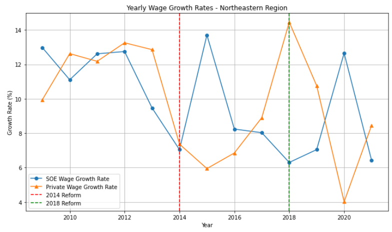
Nation



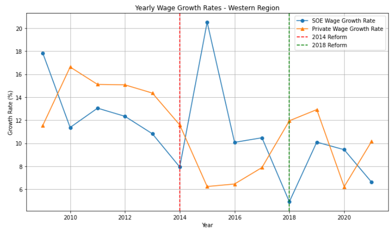
Eastern Region



Central Region



Northeastern Region



Western Region

Notes: Regional classification follows the National Bureau of Statistics standard. The Eastern region includes Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The Central region consists of Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. The Western region includes Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. The Northeastern region comprises Liaoning, Jilin, and Heilongjiang.

Figure G.4: Sector Mean Wage (2008-2021)

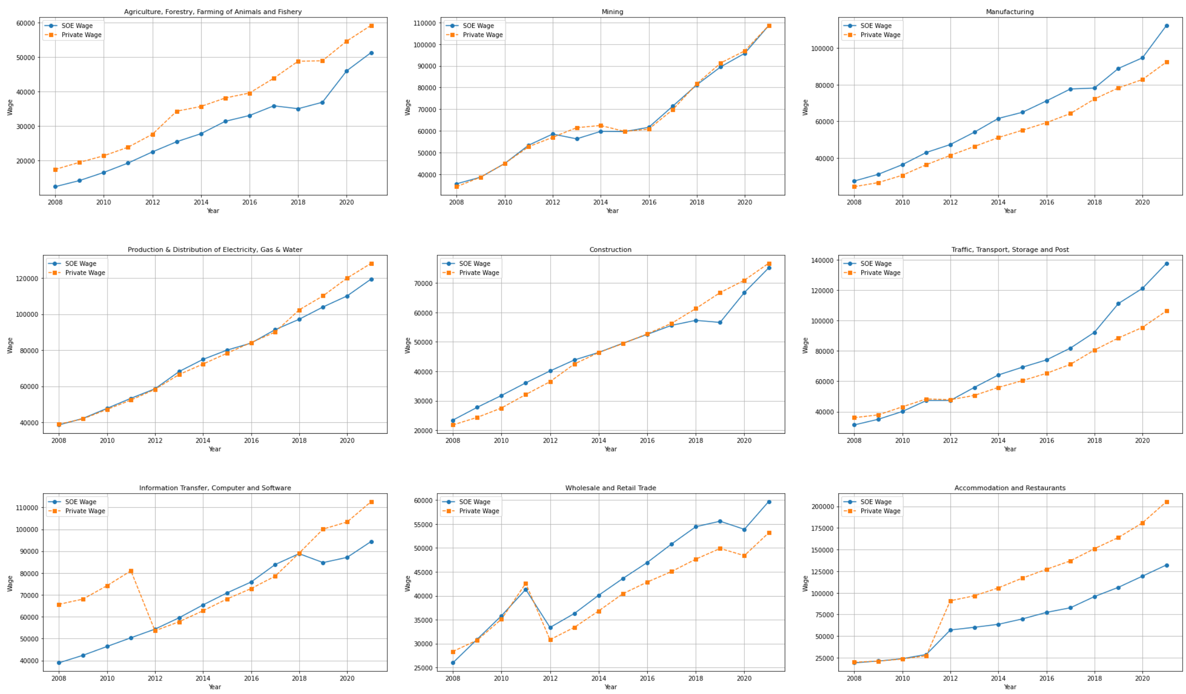


Figure G.5: Sector Mean Wage Continue (2008-2021)