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Labor market matching with heterogeneous job seekers in China

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## Abstract

Our study provides empirical evidence for matching functions with three heterogeneous groups of job seekers in China, and bridges the gap of matching function estimation of the Chinese labor market. We find that the effects of non-unemployed job seekers in the empirical matching process for China are rather significant, and an absence of their consideration could lead to biased estimates. Moreover, the result highlights competition among the three groups of job seekers in the matching process, and indicates the potential influences of productivity, job-search services, and economic reform shocks on their matching efficiencies.

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#### 1. Introduction

The matching model has been used widely in labor market issues. It provides a tool for fractional unemployment analysis, and enables the modeling of the contribution of job seekers and vacancies to new hires in an incomplete labor market (See Diamond and Maskin (1979), Blanchard and Diamond (1989), and Pissarides (2000)). Although considerable effort has been made to estimate matching functions for numerous countries, China has been ignored. In order to fill this gap, we specify and estimate matching models for the Chinese labor market and consider heterogeneous job seekers in the matching process.

The conventional aggregate matching function is a regression of new hires on unemployed persons and vacancies<sup>1</sup>. Recently, certain studies have found that biases could arise if employed job seekers and other non-unemployed job seekers are ignored (Broersma and van Ours (1999), Petrongolo and Pissarides (2001), Sunde (2007)). Further, other recent studies have noted that the conventional matching function is influenced by the proportion of heterogeneous job seekers (Hynninen 2009). Thus, in this paper, we introduce heterogeneous factors to the conventional matching function. Further, matching efficiencies are often influenced by exogenous factors; the estimated scales of the matching function enable us to examine the determinants of matching efficiencies.

The segmentation of job seekers is usually based on whether they are employed or unemployed, depending on their employment status (van Ours (1995), Hynninen (2009), etc.). In the urban Chinese labor market, there is another group of job seekers: rural-urban migrants. They are different from employed and unemployed residents because of the strict household registration system. They do not receive unemployment benefits because they are employed for farm work in rural areas, and are not officially recognized as involuntary unemployed persons even if they are unable to find employment. These migrants are more likely to accept a job than permanent residents. Thus, numerous Chinese studies divide job seekers in urban areas into three groups: employed, unemployed, and migrant workers (John Knight and Song (1995), Guihua Xie (2008), etc.) It must be noted that unemployed persons in urban China only include unemployed urban residents. The three above mentioned job-seeker groups seek employment in the same vacancy pool and possibly compete with each other. In our study, we examine the matching processes of each group as well as competition among the three groups.

The data for this study has been sourced from approximately 30,000 public and private labor agencies in China (NBS (1999-2008)). The dataset provides the annual number of job seekers belonging to different groups, flow of new hires from each group, and job vacancies at the provincial level. The period is 1996–2008, and the analysis is conducted for a cross section of

<sup>&</sup>lt;sup>1</sup> In empirical literature, matches are usually assumed to be equal to new hires (Petrongolo and Pissarides (2001)). In our study, we do not consider the job-worker contacts that do not result in employment and assume the reject rate after contact is unrelated to job vacancy and job seekers.

29 Chinese provinces<sup>2</sup>. The data for migrants has not been reported separately for the period 1999-2004; thus, the adjusted periods are 1996-1999 and 2005-2008.

#### 2. Previous Studies

There has been considerable discussion on the heterogeneity of job seekers in previous studies. However, the studies that utilize empirical matching functions for this purpose are not common because of data limitations (Petrongolo and Pissarides (2001)). Burgess (1993) examined the competition provided by employed job seekers for the unemployed, using the replacement ratio, the proportion of employed aged 16-19, and other factors to measure the propensity of the employed to engage in search. Van Ours (1995) developed two types of matching function forms to distinguish the case that employed and unemployed job seekers search in the same pool of vacancies and the case that they search in different pools, using a dataset of pooled 24 observations (8 regions over discrete 3 years) in Netherlands. Further, Broersma and van Ours (1999) used approximations for the non-unemployed job seekers (for instance, it is assumed that 10% of the employed work force searches for another job). A more recent study, Hynninen (2009), although do not have data for new hires of each job-seeker group, they introduce composition of job-seeker groups into the total matching function, and found significant heterogeneity of job seekers in matching process. Using different methods to overcome data limitations, previous studies found that it is important to account for the behavior of non-unemployed job seekers in empirical matching functions. This is the starting point of our study.

It is noteworthy that using registered job seeker and vacancies in local labor offices and other public job exchanges is the most common method to collect data for matching function estimation. Although some studies pointed out that there could be workers and job flows outside the local labor office, a more complete dataset usually does not exist. The results obtained by those dataset highly support the theory and usually consist with each other even in different countries; therefore, they are widely accepted.

## 3. Empirical Matching Functions of the Three Job-seeker Groups

In this section, we estimate matching functions for the three job-seeker groups in China, and further examine competition among these groups.

## 3.1 Model

The conventional aggregate matching function is  $H^u = aU^{\alpha}V^{\beta}$ , where  $H^u$  represents new hires from among the unemployed, U represents unemployed job seekers, and V represents the total notified job vacancies (Pissarides (2001)). It must be noted that the estimates could be biased if there are job seekers other than unemployed persons. Therefore, we not only consider the contributions of job seekers and vacancies to the matching result but also

<sup>&</sup>lt;sup>2</sup> Hong Kong, Macau, Xinjiang, Tibet, and Taiwan are not included.

introduce variables of congestion externalities, which are important factors in the matching process. The terms of congestion externalities are based on Ibourk, etc. (2004).

The general matching functions for each job-seeker group are given below:

$$H^{u} = A_{u} U^{\alpha_{u}} E U V^{\beta_{u}} , \qquad (1)$$

$$H^{e} = A_{e} (S^{e})^{\alpha_{e}} EEV^{\beta_{e}}, \qquad (2)$$

$$H^m = A_m (S^m)^{\alpha_m} EMV^{\beta_m}, \qquad (3)$$

where  $H^u$ ,  $H^e$ , and  $H^m$  represent new hires from unemployed, employed, and urban-rural migrant job seekers, respectively. U,  $S^e$ , and  $S^m$  represent unemployed, employed, and rural-urban migrant job seekers, respectively. Further,  $A_u$ ,  $A_e$ , and  $A_m$  are matching efficiencies of unemployed, employed, and migrant job seekers, respectively.

*EUV*, *EEV*, and *EMV* are efficient job vacancies for unemployed, employed, and migrant job seekers, respectively; they are defined in the following manner:

$$EUV = V - \lambda^{ue}V \frac{S^e}{S} - \lambda^{um}V \frac{S^m}{S}, \quad EEV = V - \lambda^{eu}V \frac{U}{S} - \lambda^{em}V \frac{S^m}{S}, \text{ and}$$

$$EMV = V - \lambda^{eu}V \frac{U}{S} - \lambda^{em}V \frac{S^m}{S}$$
, where  $\lambda$  is significantly positive if the other two groups of

job seekers cause congestion in job vacancies. We take logarithms of the three general matching functions and use the Taylor approximation to assume that

 $\ln(1 - \lambda^{ue} \frac{S^e}{S} - \lambda^{um} \frac{S^m}{S}) \approx -\lambda^{ue} \frac{S^e}{S} - \lambda^{um} \frac{S^m}{S}$  in *EUV*, as well as similar terms in *EEV*, and

*EMV*. Accordingly, the matching functions can be expressed in the following manner<sup>3</sup>.

(a) 
$$\ln H_{it}^{u} = \alpha_{u} \ln U_{it} + \beta_{u} \ln V_{it} + \delta^{ue} R_{it}^{e} + \delta^{um} R_{it}^{m} + c_{i}^{u} + c_{t}^{u} + \varepsilon_{it}^{u}$$

(b) 
$$\ln H_{it}^{e} = \alpha_{e} \ln S_{it}^{e} + \beta_{e} \ln V_{it} + \delta^{eu} R_{it}^{u} + \delta^{em} R_{it}^{m} + c_{i}^{e} + c_{t}^{e} + \varepsilon_{it}^{e}$$
, and

(c) 
$$\ln H_{it}^m = \alpha_m \ln S_{it}^m + \beta_m \ln V_{it} + \delta^{mu} R_{it}^u + \delta^{me} R_{it}^e + c_i^m + c_t^m + \varepsilon_{it}^m$$
,

where  $R_{it}^{u} = \frac{U_{it}}{S_{it}}$ ,  $R_{it}^{e} = \frac{S_{it}^{e}}{S_{it}}$ , and  $R_{it}^{m} = \frac{S_{it}^{m}}{S_{it}}$  ( $S_{it}$  is the total number of job seekers). These variables can be explained as indices of the congestion externalities from other groups of job seekers.  $\alpha_{u}, \beta_{u}, \alpha_{e}, \beta_{e}, \alpha_{m}, \beta_{m}, \delta^{ue}, \delta^{um}, \delta^{eu}, \delta^{em}, \delta^{mu}, and \delta^{me}$  are coefficients. If other groups

<sup>3</sup>  $\log EUV = \log V + \log(1 - \lambda^{ue} \frac{S^e}{S} - \lambda^{um} \frac{S^m}{S}) \approx \log V - \lambda^{ue} \frac{S^e}{S} - \lambda^{um} \frac{S^m}{S}$ , and the same as  $\log EEV$  and  $\log EMV$ .

of job seekers cause congestion in seeking jobs, the ratios of other groups will have negative effects on new hires; thus, their coefficients will be significantly negative.

The data for job seekers, job vacancies, and new hires were obtained from public and private labor agencies in China. The proportion of each labor group is shown in Figure 1. Large-scale rural-urban immigration has led to a substantial number of migrants in the urban labor market. The group of employed job seekers is also considerable, and their relatively higher level of education and greater experience may affect other job seekers' opportunities despite the relatively small proportion of the employed job seeker.



Furthermore, Table 1 presents a list of the data collected (the last three columns list the data used in Section 4).

|             | U                 | $S^{e}$         | $S^{m}$         | V               | $H^{u}$         | $H^{e}$         | $H^m$    | PRO     | SEV    | RES   |
|-------------|-------------------|-----------------|-----------------|-----------------|-----------------|-----------------|----------|---------|--------|-------|
|             | 10 <sup>3</sup> * | 10 <sup>3</sup> | $10^{3}$ | yuan    | Number | Rate  |
| Mean        | 433.3             | 191.7           | 494.8           | 1113.1          | 242.1           | 92.1            | 293.7    | 33966.3 | 1115.3 | 0.1   |
| Median      | 289.5             | 52.5            | 265.1           | 526.5           | 180.8           | 34.6            | 193.0    | 29103.3 | 1109.0 | 0.1   |
| Std. Dev.   | 495.6             | 343.6           | 713.5           | 1656.0          | 214.1           | 151.0           | 328.3    | 19280.8 | 716.5  | 0.0   |
| Skewness    | 2.9               | 3.5             | 3.4             | 3.8             | 1.7             | 3.7             | 2.4      | 1.9     | 0.5    | 2.1   |
| Kurtosis    | 14.7              | 17.2            | 15.9            | 20.3            | 6.7             | 19.2            | 9.8      | 7.7     | 3.2    | 9.1   |
|             |                   |                 |                 |                 |                 |                 |          |         |        |       |
| Jarque-Bera | 1280.1            | 1881.6          | 1584.6          | 2666.5          | 192.8           | 2361.1          | 522.0    | 554.2   | 19.3   | 398.5 |
| Pro.        | 0.0               | 0.0             | 0.0             | 0.0             | 0.0             | 0.0             | 0.0      | 0.0     | 0.0    | 0.0   |
|             |                   |                 |                 |                 |                 |                 |          |         |        |       |
| Obser.      | 180               | 180             | 180             | 180             | 180             | 180             | 180      | 375     | 375    | 174   |

Table 1. The Data List

Note: \* All values in the tables except for PRO, SEV, and RES are reported per thousand people.

### **3.2 Results**

We use the three-stage least squares (3SLS) analysis for the estimation, with specification for both the cross-section fixed effect and the period fixed effect. We performed a redundant fixed effect test and found that it rejects the null hypotheses that fixed effects are redundant<sup>4</sup>. Furthermore, we examined the endogeneity problem in the Chinese labor market using the Durbin and Wu-Hausman tests. The null hypothesis that the variable under consideration can be treated as an exogenous variable is rejected in eq. (b) but not in eqs. (a) and (c). Therefore, we estimate a 3SLS(1) specification with instruments in all equations and a 3SLS(2) specification with instruments only in eq. (b). Further, the relevance and exogeneity of instruments have been examined.

For the sake of comparison, we also report the results of OLS, TSLS, GMM, as well as a specification where effects of other job-seeker groups are ignored (in the last column of 3SLS\*). The results are reported in Table 2(t-statistic in parentheses).

| Table 2. Results of Matching Function Estimation for the Chinese Labor Market |  |              |              |              |              |         |  |  |
|---|--|--------------|--------------|--------------|--------------|---------|--|--|
| (1) Dependant variable: $\ln H_{it}^{u}$                                      |  |              |              |              |              |         |  |  |
|   | Instruments <sup>(a)</sup> : $(\ln U_{it}, \ln V_{it})$ $\ln S_{it}$ , $\ln S_{it}^{e}$ , $\ln S_{it}^{u}$ |              |              |              |              |         |  |  |
|   | The  | e Model      |              |              | Comparison   |         |  |  |
|   | 3SLS(1)  | 3SLS(2)      | OLS          | TSLS         | GMM          | 3SLS*   |  |  |
| $\ln U_{it}$  | 0.31***  | 0.38***      | 0.38***      | 0.31***      | 0.30***      | 0.54*** |  |  |
|   | (4.7)  | (7.4)        | (7.4)        | (4.2)        | (4.4)        | (5.0)   |  |  |
| $\ln V_{it}$  | 0.42***  | 0.34***      | 0.34***      | 0.43***      | 0.43***      | 0.25**  |  |  |
|   | (4.6)  | (6.5)        | (6.5)        | (4.1)        | (4.3)        | (2.7)   |  |  |
| $S_{it}^{m}$  | $-0.56^{***}$  | $-0.42^{**}$ | $-0.42^{**}$ | $-0.56^{**}$ | $-0.53^{**}$ | —       |  |  |
| $S_{it}$  | (-3.0)   | (-2.8)       | (-2.7)       | (-2.6)       | (-2.7)       |         |  |  |
| $S^{e}_{it}$  | $-0.34^{**}$   | $-0.24^{**}$ | $-0.24^{**}$ | $-0.34^{**}$ | -0.39**      | _       |  |  |
| $\overline{S_{it}}$   | (-2.6)   | (-2.3)       | (-2.3)       | (-2.3)       | (-2.8)       |         |  |  |
| $c_i^{u(b)}$  | Yes  | Yes          | Yes          | Yes          | Yes          | Yes     |  |  |
| $C_t^{u(c)}$  | Yes  | Yes          | Yes          | Yes          | Yes          | Yes     |  |  |
| Adj.R.  | 0.95   | 0.96         | 0.96         | 0.95         | 0.95         | 0.96    |  |  |
| Obser.  | 179  | 183          | 183          | 179          | 179          | 179     |  |  |
| p-value   | 0.00   | 0.00         | 0.00         | 0.00         | 0.00         | 0.00    |  |  |
| $H_0: \alpha + \beta = 1$   |  |              |              |              |              |         |  |  |
|   |  |              |              |              |              |         |  |  |

<sup>&</sup>lt;sup>4</sup> The F-statistics of the cross-section fixed effect tests are 11.7, 2.5, and 4.5 in eqs. (a), (b), and (c), respectively, and that of the period fixed effect tests in eqs. (a), (b), and (c) are 11.3, 3.4, and 2.1, respectively.

| Instruments: $(\ln V_{it}) \ln S_{it}$ , $\ln S_{it}^m$ , $\ln S_{it}^u$ |          |               |               |               |               |         |  |
|--|----------|---------------|---------------|---------------|---------------|---------|--|
|  | The      | e Model       |               | Comparison    |               |         |  |
|  | 3SLS(1)  | 3SLS(2)       | OLS           | TSLS          | GMM           | 3SLS*   |  |
| $\ln S^e$  | 0.05***  | 0.06***       | 0.05***       | 0.05**        | 0.06***       | 0.11*** |  |
| $\mathrm{III}\mathcal{O}_{it}$   | (3.1)    | (3.1)         | (3.1)         | (2.8)         | (4.7)         | (5.5)   |  |
| $\ln V_{it}$   | 1.17***  | 0.89***       | 0.89***       | 1.18***       | 1.23***       | 1.29*** |  |
|  | (7.4)    | (7.4)         | (7.4)         | (6.6)         | (8.1)         | (7.3)   |  |
| $S_{it}^{m}$   | -5.21*** | $-5.10^{***}$ | $-5.10^{***}$ | $-5.22^{***}$ | -5.30***      | —       |  |
| $\overline{S_{it}}$  | (-10.0)  | (-8.8)        | (-8.8)        | (-8.9)        | (-11.1)       |         |  |
| $\overline{U_{_{it}}}$   | -4.69*** | $-5.02^{***}$ | $-5.01^{***}$ | $-4.72^{***}$ | $-4.95^{***}$ | —       |  |
| $S_{it}$   | (-8.5)   | (-8.4)        | (-8.4)        | (-7.6)        | (-9.3)        |         |  |
| $C_i^{e(b)}$   | Yes      | Yes           | Yes           | Yes           | Yes           | Yes     |  |
| $C_t^{e(c)}$   | Yes      | Yes           | Yes           | Yes           | Yes           | Yes     |  |
| Adj.R.   | 0.86     | 0.87          | 0.87          | 0.86          | 0.86          | 0.78    |  |
| Obser.   | 184      | 184           | 184           | 184           | 184           | 184     |  |
| p-value  | 0.16     | 0.67          | 0.67          | 0.20          | 0.05          | 0.02    |  |
| $H_0: \alpha + \beta = 1$  |          |               |               |               |               |         |  |

## (2) Dependant variable: $\ln H_{it}^e$

(3) Dependent variable:  $\ln H_{it}^m$ ( $\ln S^m \ln V$ )  $\ln S = \ln S^e = \ln S^u$ 

|                           | Instruments: ( | $(\ln S_{it}^m, \ln V_{it})$ | $\ln S_{it}$ , $\ln S_{it}^{e}$ | , $\ln S_{it}^u$ |        |         |
|---------------------------|----------------|------------------------------|---------------------------------|------------------|--------|---------|
|                           | The            | Model                        | Comparison                      |                  |        |         |
|                           | 3SLS(1)        | 3SLS(2)                      | OLS                             | TSLS             | GMM    | 3SLS*   |
| $\ln \mathbf{C}^m$        | 0.40**         | 0.52***                      | 0.52***                         | 0.44**           | 0.38** | 0.52*** |
| $\Pi S_{it}$              | (2.6)          | (7.1)                        | (7.1)                           | (2.5)            | (2.1)  | (3.4)   |
| $\ln V_{it}$              | 0.45***        | 0.40***                      | 0.40***                         | 0.42**           | 0.44** | 0.45**  |
|                           | (2.9)          | (5.2)                        | (5.2)                           | (2.3)            | (2.2)  | (2.3)   |
| $U_{it}$                  | -1.15**        | $-0.74^{**}$                 | $-0.74^{**}$                    | -1.04*           | -1.20* | —       |
| $S_{it}$                  | (-2.1)         | (-1.9)                       | (-1.9)                          | (-1.7)           | (-1.7) |         |
| $S^{e}_{it}$              | -0.59          | -0.26                        | -0.26                           | -0.44            | -0.70  | —       |
| $\overline{S_{it}}$       | (-1.3)         | (-0.7)                       | (-0.7)                          | (-0.9)           | (-1.6) |         |
| $C_i^{m(b)}$              | Yes            | Yes                          | Yes                             | Yes              | Yes    | Yes     |
| $C_t^{m(c)}$              | Yes            | Yes                          | Yes                             | Yes              | Yes    | Yes     |
| Adj.R.                    | 0.93           | 0.93                         | 0.93                            | 0.93             | 0.92   | 0.92    |
| Obser.                    | 181            | 185                          | 185                             | 181              | 181    | 181     |
| p-value                   | 0.08           | 0.31                         | 0.32                            | 0.14             | 0.26   | 0.64    |
| $H_0: \alpha + \beta = 1$ |                |                              |                                 |                  |        |         |

- Notes: <sup>(a)</sup> Endogenous variables are in parentheses.
  - <sup>(b)</sup> Regional dummies (the cross-section fixed effect)
  - (c) Year dummies (the period fixed effect)

The results reveal that all the job-seeker groups and vacancies have statistically significant positive coefficients, and most of the congestion externality terms have significant negative coefficients. Further, it is indicated that a greater number of job seekers or vacancies lead to a greater number of new hires, which supports the matching theory. Moreover, the matching processes are often affected by the congestion externalities of other groups of job seekers, which is consistent with our expectation. Furthermore, it is evident that the comparative estimates in the last column of 3SLS\* (effects of other groups of job seekers are ignored) are biased, particularly in the unemployed and employed job-seeker groups. Therefore, we can conclude that in the case that congestion externalities are significant, the conventional matching function form could lead to misspecification.

In this study, we also examined returns to scale since it is often of interest in studies of matching functions. We found that the null hypothesis of constant returns to scale is rejected decisively in the matching function of unemployed job seekers; however, it cannot be rejected in the matching functions of employed job seekers and migrants. The estimates and test results indicate that there could be decreasing returns to scale for unemployed job seekers (the sum of coefficients of  $\ln U_{it}$  and  $\ln V_{it}$  is less than one) and constant returns to scale for employed job seekers and migrants.

Further, the results of our model (Specifications (1) and (2)) offer the following indications as empirical evidence of China's labor market. First, among the three groups, the group of rural-urban migrants have the largest impact on the other two groups ( $-0.56^{***}$  and  $-0.42^{**}$ 

in eq. (1) of  $\ln H_{it}^{u}$ , and  $-5.21^{***}$  and  $-5.10^{***}$  in eq. (2) of  $\ln H_{it}^{e}$ , Specs. (1) and (2),

respectively). Second, the group of employed job-seekers is most greatly influenced by congestion externalities  $(-5.21^{***} \text{ and } -4.69^{***} \text{ in Spec. (1) and } -5.10^{***} \text{ and } -5.02^{***}$  in Spec. (2)). Third, externalities of employed job seekers reduces new hires from among the unemployed job-seekers, while there is no significant effect on rural-urban migrants (-

 $0.34^{**}$  and  $-0.24^{**}$  in eq. (1) of  $\ln H_{it}^{u}$  and -0.59 and -0.26 in eq. (3) of  $\ln H_{it}^{m}$ ).

It is not surprising that rural-urban migrants in China greatly influence other job-seeker groups and receive few congestion externalities from employed job seekers. Firms prefer migrants because of their lower labor and monitor costs. Further, congestion externalities to migrants particularly from unemployed urban residents also exist. The reason for this could be that city policies protect their residents and occasionally make it compulsory for enterprises to employ a certain proportion of unemployed residents (Knight and Song (2005)).

In this section we estimated the empirical matching functions of China, and confirmed the

competitions among job-seeker groups. It must be noted that the matching process is not only influenced by congestion externalities of other job seekers, but also determined by the efficiency of job-worker matching within the group. In the next section, we examine the matching efficiencies of the three job seeker groups.

#### 4. Determinants of Matching Efficiencies of Each Job-Seeker Group

Matching efficiency is defined as the technology variable in matching functions (variables  $A_u$ ,  $A_e$ , and  $A_m$  in our model). There is no existing theoretical framework for determining matching efficiency, and previous studies often examined potential determinants on the basis of the actual situation (Destefanis, S. and R. Fonseca (2007)). In China's case, the potential determinants could be labor productivity growth— $\Delta PRO$ —(Cahun and Zylberberg 2004), job search services provided by government and private agencies—SEV—(Petrongolo and Pissarides 2001), and economic reform shocks—RES.

Further, the determinants of matching efficiency may also differ among the three job-seeker groups. Productivity growth could lead to difficulties in finding appropriate jobs if the group of workers undergoes little training; on the other hand, it could benefit the group that undergoes special training that is demanded by new jobs. In China, an important employment policy is to provide job training to unemployed residents. However, on the other hand, the economic reform in late 1990s destroyed millions of inefficient jobs of urban residents, and created new jobs. This threatened the original resident workers, while providing opportunities to migrant workers. We use regression to examine the possible determinants of matching efficiency for each job-seeker group.

In empirical literature, matching efficiency is usually estimated through dummy variables of period, regions, or both (Blanchard and Diamond 1989, etc.). Accordingly, we obtain the

matching efficiency of each job-seeker group as  $A_u = e^{c_i^u + c_i^u}$ ,  $A_e = e^{c_i^e + c_i^e}$ , and  $A_m = e^{c_i^m + c_i^m}$  for

employed, unemployed and migrant job seekers, respectively. We chose specification (1) for our empirical matching functions.

The data pertaining to job search services is obtained from regional job agencies, and we use annual layoff and unemployment inflow during the economic reform period as the proxy variable of economic reform shocks. Note that economic reform came to an end in the early 2000s; thus, the reform shocks do not influence matching efficiency after 2004. Therefore, we divide our work into two periods: 1997–1998, which is the peak period of economic reform with reform shocks, and 2005–2008 when the period of reform was over and there were no economic reform shocks. The estimation method is ordinary least squares. The observations have been recorded for a cross section of 29 Chinese province and the results are reported in Table 3(t-statistic in parentheses).

| Period: 1997–1998 |                                  |                                 |                                    |  |  |  |  |  |
|-------------------|----------------------------------|---------------------------------|------------------------------------|--|--|--|--|--|
| Dependent         | $\mathbf{\Lambda}^{U}$           | <b>A</b> <sup>E</sup>           | $A^M_{it}$                         |  |  |  |  |  |
| Variables         | $\Lambda_{it}$                   | $\Lambda_{it}$                  |                                    |  |  |  |  |  |
| Indep. Varia.     |                                  |                                 |                                    |  |  |  |  |  |
| $\Delta PRO_{it}$ | $5.4 \times 10^{-5} * (1.8)$     | $7.9 \times 10^{-5}$ (0.6)      | $-6.4 \times 10^{-5}$ *** (-2.9)   |  |  |  |  |  |
| $SEV_{it}$        | $4.0 \times 10^{-4} * * * (4.4)$ | $-5.0 \times 10^{-4}$ (-1.2)    | 2.0×10 <sup>-4</sup> *** (5.7)     |  |  |  |  |  |
| $RES_{it}$        | -3.8* (-1.9)                     | 18.1 ** (2.0)                   | 2.4 (1.6)                          |  |  |  |  |  |
| $RES_{i,t-1}$     | 4.4** (2.8)                      | -18.1 ** (-2.6)                 | -4.0** (-3.6)                      |  |  |  |  |  |
| Constant          | 1.1*** (5.7)                     | 2.4*** (3.0)                    | 1.4*** (10.5)                      |  |  |  |  |  |
| Adj.R.            | 0.26                             | 0.11                            | 0.37                               |  |  |  |  |  |
| Period: 2006–2008 |                                  |                                 |                                    |  |  |  |  |  |
| Dependent         | $\Lambda^U$                      | A E                             | A M                                |  |  |  |  |  |
| Variables         | $A_{it}$                         | $A_{it}$                        | $A_{it}$                           |  |  |  |  |  |
| Indep. Varia.     |                                  |                                 |                                    |  |  |  |  |  |
| $\Delta PRO_{it}$ | $3.1 \times 10^{-5} **(2.6)$     | $-6.1 \times 10^{-5} ** (-2.1)$ | $-2.6 \times 10^{-5} * * * (-2.4)$ |  |  |  |  |  |
| $SEV_{it}$        | 2.1×10 <sup>-4</sup> *** (5.3)   | $-2.0 \times 10^{-4} ** (-2.8)$ | 1.3×10 <sup>-4</sup> *** (3.7)     |  |  |  |  |  |
| Constant          | 0.9** (11.3)                     | 2.2*** (11.2)                   | 1.2*** (16.3)                      |  |  |  |  |  |
| Adj.R.            | 0.27                             | 0.10                            | 0.17                               |  |  |  |  |  |

Table 3. Determinants of Matching Efficiency in the Chinese Labor Market

Coefficients of  $\Delta PRO_{it}$  in the equations of  $A_{it}^{M}$  are significantly negative, which indicates

that the productivity growth has a rather significant negative effect on the matching efficiency of migrants in both the periods. The reason for this could be that the education level of rural migrants is rather low, and most of them do not receive sufficient job-training; thus, they suffer from the productivity growth. However,  $\Delta PRO_{it}$  has significant positive coefficients

in the equations of  $A_{it}^U$ . It is indicated that higher productivity growth leads to a higher level

of matching efficiency of urban residents, which could be a result of the job-training subsidy provided to residents. For the employed job-seeker group, although the productivity growth does not have a significant effect on matching efficiency in the period 1997–1998, it causes a significant reduction in the matching efficiency after the economic reform. This is because when there is a growth in productivity, employed workers may find it difficult to adapt to skills demanded by new jobs.

Further, job search services— $SEV_{it}$ —has rather significant positive coefficients in the unemployed and migrant job-seeker groups, which indicates that job search services in China contribute to an increase in matching efficiency in these groups. However, it appears that job

search services do not increase matching efficiency of employed job-seekers and have even led to a decrease in matching efficiency for this group in the period 2006–2008. One possible reason for this is that more job-searching services encourage more on-the-job searches, which leads to congestion within the group of employed job seekers.

Finally, the result indicates that economic reform shocks also influence matching efficiencies. The direct impact is a significant negative effect on the matching efficiencies of unemployed residents ( $-3.8^*$ ). The reason for this could be that residents are not able to adapt to new jobs immediately. However, the effect of reform shocks becomes positive (4.4\*\*) over a period of time. The most important reason for this could be the re-employment promotion policy for unemployed urban residents during the economic reform process. On the other hand, reform shocks have an immediate positive effect on employed and rural-urban migrant job-seekers (18.1\*\* and 2.4) as they are not threatened by job destruction and could benefit from newly created jobs. However, this effect becomes negative over a period of time (-18.1\*\* and -4.0\*\*) for the possible reason that the job-seekers in these groups do not receive job-training subsidies and new jobs are given to trained unemployed residents through government policies.

### 5. Conclusion

We estimated matching functions of unemployed, employed, and migrant job seekers in urban China. We find that the number of new hires is not only determined by the contribution of job seekers and vacancies, but also by congestion externalities from other groups of job seekers. The estimates of congestion externalities are rather significant, and not considering these externalities could lead to misspecification.

Further, we observed heterogeneities of the three job-seeker groups in the matching process. First, the degrees of congestion externalities differ among the three groups: rural-urban migrants cause the greatest congestion externalities in other groups, and employed job seekers receive larger congestion externalities than the other two groups. Second, the influences of matching efficiencies also vary greatly. Although unemployed job seekers underwent job relocation during the economic restructuring in the 1990s, they received most government support for skill training and re-employment. Both productivity growth and job-search services improve their matching efficiency. Moreover, migrant job seekers also benefit from job-search services; however, their matching efficiencies decline as productivity growth had a negative effect on employed job seekers in the 2000s, and the reason for this could be the lack of further job training to adapt to new jobs.

Overall, we conclude that it is important to incorporate non-unemployed job seekers into the matching process and consider the heterogeneities of job-seeker groups. Future research could include a more detailed segmentation of job seekers, effect of endogenous job creation, and determinants of equilibrium unemployment.

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