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勞動市場分析－電腦數位化下的「求職求才」

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Abstract

Recent rapid advances in information technology have made the job matching process more effective and convenient. However, little empirical evidence has been brought to bear on its magnitude. This paper uses a translog model of the labor market matching technology to evaluate the recent reforms in the matching process on the efficiency of the search equilibrium in terms of the degree of returns to sale and the externality effects. The empirical results suggest that the impacts that frictions and externalities have on the efficiency of the search equilibrium have been enhanced where higher elasticity estimates obtained from the model indicate less congestion and more positive externalities.

Keywords: Job search, Matching function, Matching technology

I. Introduction

Recent rapid advances in information technology have made the job matching process more effective and convenient, such as the computerization of employment offices, job advertising on the internet, and online career networks (e.g., Monster.com, ejob.gov.tw, and 104.com.tw). For example, a hiring firm can post real-time job openings on the "career opportunities" of its website and/or on online career networks, which can be browsed by numerous job seekers. Those searching for jobs post their resumes on the web at a very little cost but attract to a large number of searching employers. Information regarding the characteristics of job seekers, the location of vacancies, as well as the nature of job openings and wages they offer is considered as imperfect. Frictions arise because it takes time to form a productive match between searching parties. At the same time, externalities occur because the probability that a job seeker gets an offer and a hiring firm fills a vacancy depends on the efforts of searching individuals. These recent reforms by technological advances seem to moderate information imperfection and enhance externalities in the matching process between employers and job seekers. Petrongolo and Pissarides (2001) argued that these reforms have been observed recently in most industrial countries and influenced the matching process to the extent that the OECD suggests them to its members as the most cost-effective labor market policies. Therefore, the goal of this study is to empirically evaluate these recent reforms in the matching technology on the efficiency of the search equilibrium in terms of the degree of returns to sale and the externality effects, an area which has not been extensively investigated.

The macrofoundations underlying the modeling of frictions is the aggregate matching function (e.g., Blanchard and Diamond 1989, Warren 1996, and Yashiv 2000). The matching function operates like a production function that takes the stocks of vacancies and unemployment as inputs and produces the flow of new hires as outputs. Unlike most of the studies, I use Employment Placement Service data of Taiwan on effective applicants, effective openings, and placements partly because the monthly vacancy data are only available after August of 1996 and partly because constructing the flow series of new hires is still problematic. Monthly data from employment services include that searching individuals (job seekers and hiring firms) register at the employment agencies, recruitment through screen test conducted by the employment agencies for the public and private sectors, and employment service of graduating students of junior, high and vocational schools. Placements are the number of successful matches via employment agencies within a month. The registration of searching parties on the employment agencies is valid for two months. Therefore, the effective applicants (hereafter, applicants) sum up persons who are newly registered in this month and those who already enrolled last month but have not got jobs yet; similarly, for the effective openings (hereafter, openings).

II. The model

The parties to be matched are applicants, *A*, and openings, *O*. Let *P* denotes the flow of placements at a certain level of matching technology, μ. The matching function, *M*, brings participants on either side of the labor market together by a pair-wise stochastic technology $P = M(\mu, A, O)$. By estimating the matching function, we can give a measure of the degree of returns to scale and of the extent of the externalities. If the elasticity with respect to applicants in the matching function is η_a and the elasticity with respect to openings is η_o, $\eta_a - 1$ measures the negative externality (congestion) caused by the applicant on other applicants, and η_o measures the positive externality (thick-market effect) caused by firms with openings on applicants. Similarly, η_a measures the positive externality from applicants to firms' openings, and $\eta_o - 1$ measures the negative externality by firms' openings on each other. Higher elasticity estimates indicate less congestion and more positive externalities.

Instead of using a restrictive Cobb-Douglas specification of the form of the matching technology which is widely employed in the previous empirical studies, we use a flexible specification, the transcendental logarithmic (translog) function of the matching technology. As a consequence, we specify a model of the matching technology in which placements are a translog function of the number of applicants and the number of openings:

$$\begin{aligned} \ln P_t = \ln \bar{\mu} + \beta_a \ln A_t + \beta_o \ln O_t + 1/2\, \beta_{aa} (\ln A_t)^2 + 1/2\, \beta_{oo} (\ln O_t)^2 \\ + \beta_{ao} (\ln A_t)(\ln O_t) + \beta_0 T + \varepsilon_t, \qquad t = 1, \Lambda\ N \end{aligned}.$$

Where *T* is a linear trend term (*T* = 1,…*N*) that captures the rate of disembodied technological change; ε_t is an $N(0, \sigma_\varepsilon^2)$ random variable; *t* indexes the *N* observations. The scale elasticity is denoted as $\eta = \eta_a + \eta_o$, where

$\eta_a = \beta_a + \beta_{aa} \ln A + \beta_{ao} \ln O$ is the elasticity of placements with respect to the number of applicants *A*, and $\eta_o = \beta_o + \beta_{oo} \ln O + \beta_{ao} \ln A$ is the elasticity of placements with respect to the number of openings *O*.

III. Empirical results

Monthly data on applicants, openings, and placements are obtained from the Monthly Bulletin of Labor Statistic of Taiwan for the period between January 1991 and June 2003. The time period over which we investigate Taiwan experienced a dramatic change in its industrial structure. This raises the possibility that estimation results based on data collected from this period may not be correct. To mitigate this concern, we add GDP to the model as the explanatory variable to control the macroeconomic environment, thus to have the least biased estimates. Figure 1 displays the natural logarithms of applicants, openings, and placements for 1991:1-2003:6. In order to evaluate the recent reforms in the matching technology on the efficiency of the search equilibrium in terms of the degree of returns to sale and the externality effects, we compare two periods: one is from 1991:01-2001:1, the other is from 2001:2-2003:6. First, estimation is conducted using the whole sample and calculate the elasticity of matching with respect to applicants and openings in the first sub-period and second sub-period respectively. Second, to see if the matching technology has undergone a structural change between two periods, we use a dummy variable, *D*, that takes the value 1 for the second sub-period sample and 0 otherwise.

Table 1 reports the results of estimating the translog model of the matching technology. Column (1) shows the results of estimation from the whole sample, column (2) presents the estimation results with dummy variable added for the structural change. Both columns contain generalized least square estimates of the model obtained by taking Durbin-Watson *d* statistic for correcting serial correlation in the residuals. Standard errors are in parentheses computed using White's heteroskedasticity-consistent covariance matrix. The values for constant return to scale and Cobb-Douglas technology are *F* statistics. All the estimates in column (1) are significantly different from zero at the 0.05 level (except the coefficient on $(\ln A)^2$), providing evidence supporting the use of flexible functional form to represent the matching technology. The null hypothesis of constant return to scale ($\beta_a + \beta_o = 1, \beta_{aa} + \beta_{ao} = 0, \beta_{oo} + \beta_{ao} = 0$) and Cobb-Douglas technology

($\beta_{aa} = 0, \beta_{oo} = 0, \beta_{ao} = 0$) are both rejected. To see if the matching technology has undergone a structural change after 2001:2, we check the estimates with dummy variable terms in column (2). It is found that only the estimates of $D \ln A$ and $D \ln O$ are significantly different from zero at the 0.1 level. Finally, let us look at the elasticity of placements with respect to applicants, η_a, the elasticity of placements with respect to openings, η_o, and the scale elasticity, $\eta = \eta_a + \eta_o$. The results show that these recent reforms in the job matching process have improved the efficiency of the search equilibrium where higher elasticity estimates indicate less congestion and more positive externalities.

IV. Concluding remarks

The empirical results reported above suggest that the impacts that frictions and externalities have on the efficiency of the search equilibrium have been enhanced by technological advances in the matching process. However, stronger evidence still needs to be found to support this argument. One possible problem is that data where the second sub-period covered maybe too short relative to the first sub-period. Another possibility is that the macroeconomic environment experienced great transformation. Controlling GDP is not enough to alleviate the macroeconomic effects on the estimation of the matching technology.

Reference

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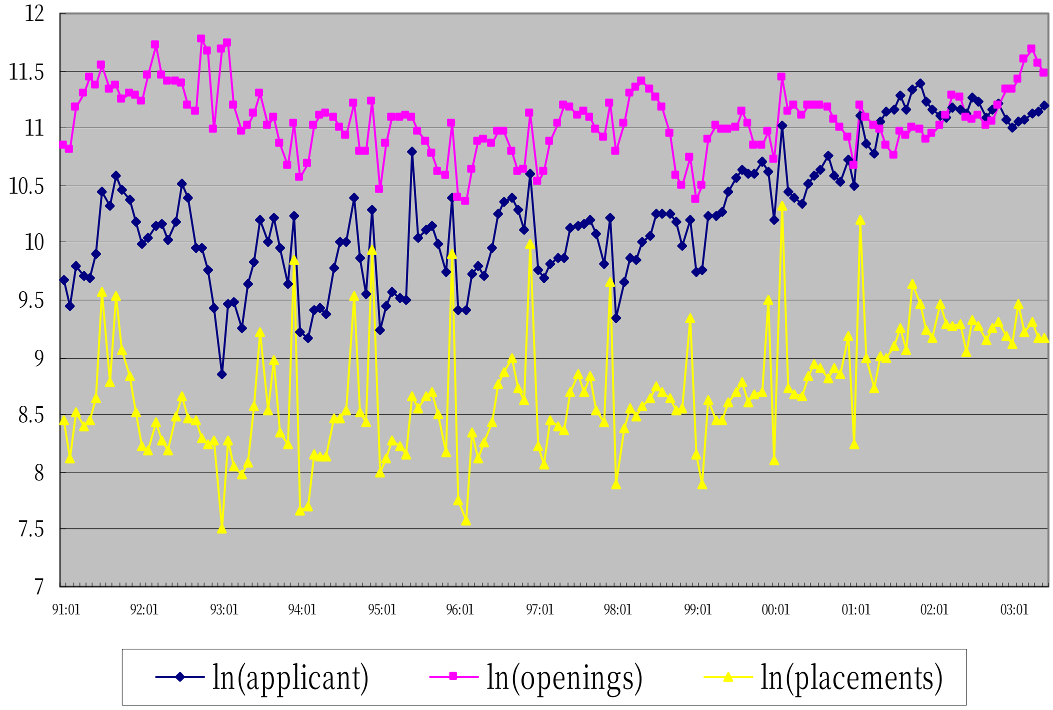
Figure 1



12
11.5
11
10.5
10
9.5
9
8.5
8
7.5
7
91:01
92:01
93:01
94:01
95:01
96:01
97:01
98:01
99:01
00:01
01:01
02:01
03:01
ln(applicant)
ln(openings)
ln(placements)

Table 1 *Empirical result*

		(1)			(2)
β_a		-6.759			-6.680
		(-2.505)			(3.480)
β_o		6.206			6.130
		(2.177)			(3.123)
β_{aa}		0.227			0.194
		(0.144)			(0.297)
β_{oo}		-0.100			-0.978
		(0.296)			(0.373)
β_{ao}		0.484			0.504
		(0.122)			(0.154)
T		-0.020			-0.022
		(0.004)			(0.007)
$D\ln A$					18.657
					(11.196)
$D\ln O$					-18.525
					(11.135)
$D(\ln A)^2/2$					-3.174
					(2.204)
$D(\ln O)^2/2$					0.157
					(0.989)
$D(\ln A)(\ln O)$					1.497
					(1.391)
R^2		0.707			0.706
D.W.		1.865			1.845
Constant Return to Scale		6.040			
Cobb-Douglas Technology		5.785			
			η_a	η_o	η
(1) Whole sample	1st sub-period		0.873	0.409	1.282
	2nd sub-period		1.185	0.811	1.996
(2) Whole sample	1st sub-period		0.699	0.259	0.958
with dummy variable	2nd sub-period		1.022	0.672	1.694