AGGLOMERATION ECONOMIES IN LOCAL LABOUR MARKETS[1]

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Abstract

This paper studies whether empirical evidence on agglomeration economies can be found in the labour market of city areas. The analysis is based on the assumption that agglomeration economies are driven by worker-firm match quality. Because we assume the random meeting of workers and firms, agents are able to be more selective in choosing matches only if they meet more potential matching partners. Therefore, the search technology becomes crucial in analysing agglomeration economies. We estimate the returns of the search technology for twenty travel-to-work areas which have city area as their central district. On the basis of these on these estimations, the existence of agglomeration economies is inferred. According to the results, the only metropolitan area in our sample shows clear evidence on agglomeration economies. Some growing city areas also show evidence on agglomeration economies.

Keywords: agglomeration economies, local labour markets, matching, search technology

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1. Introduction

Workers in the labour market present a variety of skills and firms a variety of technologies. In cities, especially, the skill-spaces of workers and the technology-spaces of firms tend to expand, as new workers/firms enter the market. It is not clear what kind of effect the growth in the number of workers/firms has on the quality of the worker-firm matches. Quality might be improved because increasing variety in skills will offer a greater choice of matching partners. On the other hand, larger skill-spaces may just create difficulties in screening for the most suitable partners. Therefore, the search technology plays an important role in determining the effect of an increase in the number of workers or firms on match quality. Moreover, because improved match-quality means the existence of agglomeration economies, the analysis of search-technology gives information about agglomeration economies as well.

This paper measures empirically whether agglomeration economies exist in cities. We apply the idea proposed by Sato (2001) that there is a close relationship between the returns of the matching function and the returns of search technology[2]. Namely, if the returns of the homogeneous matching function are increasing, then the search technology will show increasing returns as well. Therefore, agglomeration economies exist. On the other hand, if the returns of the matching function are constant or decreasing, agglomeration economies do not exist. By utilising that theoretical result, we can measure whether agglomeration economies exist through estimation of the labour market matching function.

To obtain reliable estimates for the parameters of the matching function, we make the following decisions. First, as Sato (2001) points out, because city-level matching functions very likely differ from the national aggregate level matching function, we should use more spatially disaggregated data, i.e. city-level data[3]. However, the city labour market consists not only of those living within its administrative area, but also of traders living outside the city and searching for trading partners

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[2] We do not present the details of the equilibrium model of Sato here. It is well-documented in the original paper.

[3] Petrongolo and Pissarides (2001) provide a comprehensive survey of both the theoretical and empirical literature on the matching function. They report that most of the aggregate-level studies imply constant returns to scale, whereas studies using disaggregated data, including Burda (1993), Burda and Wyplotsz (1994) and Burgess and Profit (2001), show decreasing returns to scale.

inside the city. It is for this reason that the neighbouring areas of cities should be included in regression models. In the present study, city areas are identified as travel-to-work areas (TTWAs) which have a city as their central district. Second, as noted for example by Gross (1997), the specification of the empirical matching function may involve simultaneity bias because the current number of matches might also have an effect on the current numbers of vacancies and job seekers. We discuss this problem and possible solution in more detail in Section 2.

The paper is organized as follows. Section 2 presents the empirical matching function and discusses the difficulties related to the estimation of its parameters. Section 3 provides a short data description. Section 4 summarises the estimation results. Section 5 concludes.

2. Empirical matching function

Underlying the matching function is the assumption that market frictions affect market outcomes. Labour market frictions may occur for several reasons including imperfect information on traders' characteristics or actions, heterogeneity in the sense that the skills of workers and skill-requirements of employers do not match, or slow mobility between local markets. Whatever the reason is, the customary empirical observation that unemployed workers and vacant jobs exist in the market at same time might be captured by the matching function $M=f(U,V)$. It states that the number of matches depends on the stocks of jobseekers and vacancies. Empirical studies typically use a log-linearized function of the Cobb-Douglas form:

$$\log M_t = \alpha + \beta_1 \log U_{t-1} + \beta_2 \log V_{t-1} + \varepsilon_t, \qquad (1)$$

where M_t is the number of matches during an observation period. U_{t-1} and V_{t-1} are the lagged stocks of jobseekers and vacant jobs at the end of each observation period. The lag operator is used to avoid the occurrence of simultaneity bias.

The measured flow of matches, however, is not produced only by the initial stocks, but also by the inflows of vacancies and jobseekers over the current time period. We include the flows of new jobseekers and vacancies in the model. A convenient approach is to express the stock of jobseekers and the inflow of new jobseekers in homogeneous search units as $U = U_{t-1} + 0.5u_t$, where u_t refers to the flow of new jobseekers. "Old" and "new" vacancies may be combined equally; a more detailed description of the technique is given in Appendix. The matching function may be written as

$$\log M_t = \alpha + \beta_1 \log(V_{t-1} + 0.5 v_t) + \beta_2 \log(U_{t-1} + 0.5 u_t) + \varepsilon_t . \qquad (2)$$

In (2), M_t is the measure for the flow of matches. V_{t-1} and U_{t-1} refer to the lagged stocks of vacant jobs and jobseekers, and v_t and u_t are flows of new vacancies and jobseekers during each current period.

Broersma and Van Ours (1999) have shown that right-side and left-side variables of the equation (2) should closely correspond to each other. Otherwise the estimated parameter values are likely to be biased. In the present study, the variable U consists of the number of jobseekers registered as active jobseekers at their local labour office as measured at the end of each month. Active jobseekers are by definition available for a full-time job but do not have one at the moment, or are waiting for the start of employment already agreed. The variable U does not include workers laid off or receiving unemployment pension. The variable V consists of all vacant jobs at the labour office, also as measured at the end of each month. The left-side variable M is the number of spells of unemployment completed because jobs have been found and or employment started. Unemployed persons moving out of the labour force, or participating in employment training schemes, are excluded from M.

3. Data description

The data are collected by the local labour offices and provided by the Ministry of Labour. It spans the period from January 2000 to December 2003. The total number of local labour offices in Finland exceeds 150, and of all hires about 50 percent are arbitrated by them (Kangasharju et al., 2005). Because unemployed workers use the services of several neighbouring offices in seeking jobs, we have aggregated the data at the level of travel-to-work areas (TTWAs). Moreover, because even TTWAs are in general quite small in Finland we have chosen to use only the twenty biggest TTWAs in the estimations. The sizes of TTWAs are measured by the number of jobseekers. The aggregation is performed according to the classification of Statistics Finland. All TTWAs used in the present study include a city as its central district, but only one of these, namely Helsinki, can be considered a metropolitan area. As Table 1 reveals, there are wide differences in the sizes of TTWAs, and Helsinki is the most important single labour market area in Finland.

Table 1: Descriptive statistics by travel-to-work areas (averages over 2000:01-2003:12).

TTWA	M	V	U	v	u
Kouvola	473	146	4069	180	22
Mikkeli	276	124	3893	158	222
Kotka	541	218	6832	259	300
Rauma	306	144	4176	150	166
Vaasa	491	416	5944	457	339
Kokkola	418	134	3814	165	30
Lappeenra	515	163	6831	227	96
Jyväskylä	939	322	12740	429	666
Turku	2316	887	20979	1233	1248
Rovaniemi	416	135	5558	193	299
Kuopio	846	237	8389	364	477
Seinäjoki	507	131	4133	211	260
Kajaani	646	151	5100	214	218
Joensuu	738	277	7707	356	152
Tampere	2435	939	27524	1190	1538
Lahti	904	64	2124	60	189
Hämeenlin	559	221	5799	300	305
Helsinki	5534	3766	74104	4583	4617
Pori	957	361	11806	422	147
Oulu	1536	79	4032	148	323

Notes: TTWA is an acronym for the travel-to-work area, M refers to the number of monthly matches measured by outflow from unemployment to employment. V and U are stocks of vacant jobs and unemployed jobseekers, respectively. The last two columns, named v and u, refer to the flows of new vacant jobs and jobseekers.

4. Estimation results

We estimate the values for the parameters of equation (2) separately for each travel-to-work areas. All the regressions were estimated by OLS using monthly data from January 2000 to December 2003 for a total of T=48 observations for each 20 TTWAs. Because in time series regressions the error term is likely to be serially correlated, we use the Newey-West HAC estimator with the truncation number 3 to avoid possible biases.

Table 2: Estimated returns to scale of the matching function in twenty TTWAs.

TTWA	Model 1 RTS			Model 2 RTS			Model 3 RTS		
Kouvola	0.69			-0.40			0.75		
Mikkeli	-0.14			-1.50			0.86		
Kotka	0.30			-1.19			1.31	(0.3750)	
Rauma	-1.86			0.49			0.95		
Vaasa	0.59			1.74	(0.0505)		2.56	(0.0055)	**
Kokkola	1.30	(0.2326)		0.53			1.43	(0.2187)	
Lappeenranta	0.87			-0.10			2.04	(0.1023)	
Jyväskylä	0.51			1.77	(0.0644)		2.06	(0.0412)	*
Turku	1.02	(0.4751)		1.12	(0.3675)		2.48	(0.0029)	**
Rovaniemi	0.64			2.36	(0.0416)	*	4.28	(0.0000)	***
Kuopio	1.38	(0.0370)	*	1.25	(0.2078)		1.61	(0.0664)	
Seinäjoki	0.91			0.91			2.18	(0.0078)	**
Kajaani	0.78			0.04			1.08	(0.4322)	
Joensuu	1.00			1.31	(0.1943)		1.67	(0.0697)	
Tampere	1.86	(0.0092)	**	1.95	(0.0285)	*	2.94	(0.0048)	**
Lahti	0.93			1.10	(0.4446)		2.52	(0.0131)	*
Hämeenlinna	1.62	(0.0020)	**	1.56	(0.1709)		2.51	(0.0238)	*
Helsinki	2.35	(0.0001)	***	2.59	(0.0001)	***	3.78	(0.0000)	***
Pori	0.94			0.26			1.59	(0.2389)	
Oulu	0.25			0.54			1.70	(0.0989)	

Notes: TTWA refers to travel-to-work area, RTS refers to returns to scale, with in parentheses the p-values from the F-test H_0: RTS=1, against the alternative H_1: RTS>1 given for those regions where estimated RTS>1. The asterisks *, ** and *** stand for statistical significance at the levels of 5%, 1% and 0.1%, respectively. Models 1 and 2 are estimated in levels (2 includes a quadratic time trend), whereas model 3 is estimated in differences.

We exploit the result provided by Sato (2001) that agglomeration economies exist, if returns of the homogeneous matching function are increasing. We test for constant returns to scale as a linear hypothesis H_0: $\beta_1 + \beta_2 = 1$, against the alternative H_1: $\beta_1 + \beta_2 > 1$ where returns to scale in the area are estimated as increasing. Table 2 summarises the results. Model 1 refers to the base specification. Model 2 includes a quadratic time trend, and model 3 is estimated using differences instead of level variables to ensure the stationarity of all the variables.

According to model 1, the hypothesis of constant returns to scale can be rejected at the 0.1 percent level of significance only in Helsinki area, which is the only metropolitan area in our data sample. The tests for Hämeenlinna and Tampere also show rejection at the 1 percent level of significance. Tampere, Hämeenlinna and Helsinki are located in Southern Finland. Hämeenlinna is about 75 kilometres from Helsinki to the north-west and Tampere about 150 kilometres in the same direction. These cities are well-connected by road and rail. Therefore, the result for Hämeenlinna is very likely affected by its proximity to Helsinki. Tampere is likely also to benefit from Helsinki, and may be classified as a growing city area. Measured by the number of jobseekers, it is the second largest TTWA in our sample of twenty TTWAs.

Models 2 and 3 show how robust the result of the base model is. Only the strong evidence shown by Helsinki, and evidence shown by Tampere, are persistent over all three models. The estimated values for RTS are all positive in model 3. This is not true in models 1 and 2. Because negative values contradict the usual assumption of the matching function, model 3 is the most reliable model. According to model 3, in addition to Helsinki and Tampere, seven other areas show some evidence on agglomeration economies. These seven areas are growing centres; however, further analysis is required to more clearly explain why agglomeration economies exist in those areas in particular.

5. Conclusion

The aim of this paper was to measure the existence of agglomeration economies in labour markets by using the city-level data. The measurement technique was based on the theoretical result proposed by Sato which posits a close relationship between returns of the matching function and agglomeration economies.

The results show that it is possible to detect agglomeration economies empirically in labour markets. We find evidence for increasing returns in the search technology in several areas, but only the evidence from the biggest labour market area, Helsinki, is stable across the different models. This is a reasonable result because Helsinki is the only metropolitan area in Finland. Nevertheless, the variation across the models indicate that further analysis on the factors behind agglomeration economies is required.

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Appendix

In Equation (2), stocks and flows are expressed in homogeneous search units. We assume an exponential probability distribution of duration with a constant hazard rate λ. During a period of unit length, the flow out of unemployment can be expressed as:

$$M = (1 - e^{-\lambda})U + \int_0^1 \left[1 - e^{-\lambda(1-t)}\right] u_t \, dt \,, \qquad \text{(A.1)}$$

where U is the initial stock, and u_t the inflow within the period. Therefore, the first term expresses the outflow from the initial stock and the second term the outflow from the inflow.

Given the assumption of uniform inflow u, the equation A.1 can be written in simpler form

$$M = (1 - e^{-\lambda})U + \left[1 - \frac{1}{\lambda}(1 - e^{-\lambda})\right] u \,. \qquad \text{(A.2)}$$

Each agent belonging in u has the matching probability which is $\left[(1 - e^{-\lambda})^{-1} - \frac{1}{\lambda}\right]$ times the matching probability of each agent in U. Search units of all jobseekers can be expressed as:

$$U + \left[(1 - e^{-\lambda})^{-1} - \frac{1}{\lambda}\right] u \,. \qquad \text{(A.3)}$$

For small λ, by using a second order Taylor expansion of *exp(-λ)* around $\lambda = 0$, the term in square brackets has an approximation of 1/2, which gives Equation (2).