JYVÄSKYLÄ STUDIES IN BUSINESS AND ECONOMICS
56

Sanna-Mari Hynninen

Matching in Local Labour Markets

Empirical Studies from Finland

JYVÄSKYLÄN YLIOPISTO

JYVÄSKYLÄ STUDIES IN BUSINESS AND ECONOMICS 56

Sanna-Mari Hynninen

Matching in Local Labour Markets

Empirical Studies from Finland

Esitetään Jyväskylän yliopiston taloustieteiden tiedekunnan suostumuksella julkisesti tarkastettavaksi yliopiston Historica-rakennuksen salissa H320 kesäkuun 25. päivänä 2007 kello 12.

Academic dissertation to be publicly discussed, by permission of the School of Business and Economics of the University of Jyväskylä, in the Building Historica, H320, on June 25, 2007 at 12 o'clock noon.

UNIVERSITY OF JYVÄSKYLÄ

JYVÄSKYLÄ 2007

Matching in Local Labour Markets

Empirical Studies from Finland

JYVÄSKYLÄ STUDIES IN BUSINESS AND ECONOMICS 56

Sanna-Mari Hynninen

Matching in Local Labour Markets

Empirical Studies from Finland

UNIVERSITY OF JYVÄSKYLÄ

JYVÄSKYLÄ 2007

Editors
Tuomo Takala
School of Business and Economics, University of Jyväskylä
Irene Ylönen, Marja-Leena Tynkkynen
Publishing Unit, University Library of Jyväskylä

URN:ISBN:9789513928681
ISBN 978-951-39-2868-1 (PDF)

ISBN 978-951-39-2842-1 (nid.)
ISSN 1457-1986

Jyväskylä University Printing House, Jyväskylä 2007

ABSTRACT

Hynninen, Sanna-Mari
Matching in local labour markets: Empirical studies from Finland
Jyväskylä: University of Jyväskylä, 2007, 101 p.
(Jyväskylä Studies in Business and Economics
ISSN 1457-1986; 56)
ISBN 978-951-39-2868-1 (PDF), 978-951-39-2842-1 (nid.)
Finnish summary
Diss.

This thesis studies the matching process of job seekers and vacancies in local labour markets in Finland during the period 1991-2004. Four empirical articles are preceded by an introductory theoretical chapter that discusses micro-level factors behind the macro-level matching function.

The first article deals with spatial dependencies in the matching function. According to the results, Finnish local labour markets suffer from a strong congestion effect among job seekers, which is further exacerbated by spatial spillovers from neighbouring areas, particularly in densely populated areas. The results also indicate that the technical efficiency of matching is higher in densely populated areas than elsewhere.

The second article considers the role of the composition of the job-seeker stock in the matching function. The results indicate that the employability of job seekers out of the labour force is notably higher than the employability of other job seekers. Long-term unemployed job seekers in turn contribute negatively to the effective stock of job seekers: they do not provide matches with vacant jobs.

The third article applies a linear mixed model to the estimation of differences in matching efficiency between local labour markets with different population densities. The results indicate that densely populated areas are the most efficient in producing matches. There are, however, problems with the qualitative matching of job seekers and vacancies: despite the fact that the share of job seekers with primary education in the job-seeker stock is lower in densely populated than in other areas, it is nevertheless too high with respect to the educational requirements of vacancies.

The fourth article utilises stochastic frontier analysis in tracing differences in technical efficiency between areas. The results show wide and permanent differences in matching efficiency between local labour markets. If all areas attained the efficiency level of the most efficient area, matches would increase by over 10 per cent. In the job-seeker stock, particularly a relative increase in the groups of job seekers out of the labour force and highly educated job seekers would improve matching efficiency. The results also indicate that the technical efficiency of matching has declined in the period 1995-2004.

Keywords: matching function, local labour markets, technical efficiency, heterogeneity, spatial dependency

Author's address Sanna-Mari Hynninen
University of Jyväskylä
School of Business and Economics
Phone: +358-14-2603334
Email: sanna-mari.hynninen@econ.jyu.fi

Supervisor Professor Jaakko Pehkonen
University of Jyväskylä
School of Business and Economics

Reviewers Professor Monojit Chatterji
University of Dundee
Department of Economic Studies
Scotland, UK

Dr. Petri Böckerman
Labour Institute for Economic Research
Finland

Opponent Professor Monojit Chatterji
University of Dundee
Department of Economic Studies
Scotland, UK

ACKNOWLEDGEMENTS

The studies comprising this thesis were carried out during the years I spent in the School of Business and Economics at the University of Jyväskylä. The project was mainly financed by the Academy of Finland and by the University of Jyväskylä. For further financial support I am grateful to the Yrjö Jahnsson Foundation and the Finnish Cultural Foundation, Regional Fund of Kainuu.

This project has required much patience to sit down and work alone. However, it would have never been realized without lots of people cheering me on. My greatest gratitude I owe to my supervisor Jaakko Pehkonen for his professional effort in supervising my thesis as well as his constant support and faith in me. Jaakko has the exceptional ability of making difficult tasks look possible to do.

Professor Monojit Chatterji and Petri Böckerman PhD had a tough job in reviewing the thesis and suggesting useful corrections and extra implications from the results. I am extremely grateful to them for their contributions. It is a great pleasure to have Professor Chatterji as my opponent.

I thank Hannu Tervo for his valuable comments and advices, particularly at the early stages of the project and Kari Heimonen at the latest stages of the project. To Aki Kangasharju I am grateful for all of his innovative ideas concerning my research topics. I owe special thanks to Jukka Lahtonen for invaluable discussions on models during our journey in the world of the matching function. I am also grateful to him for his collaboration on one of the articles and for help with data aggregations. Tapio Ruokolainen deserves thanks for showing me the door into the academic world and for always being ready to help when needed. I thank Michael Freeman for patiently helping me to render the language of the thesis more fluent.

The atmosphere in our work community has been highly motivating. I would like to thank all my colleagues for creating such positive working conditions. Special thanks go to Kirsi Mukkala with whom I shared a room during the early years of my post-graduate studies.

I thank my parents Marja and Jorma for providing me with a good basis for life. The role of my sister Niina in this project and in my life as a whole is difficult to put in words. I owe my deepest thanks to her for our special, close relationship that began when we were kids in Kuhmo and that continuously gives me the strength to keep going.

Without friends neither an academic life nor life as a whole would be worth living. I thank all of my friends for sharing the adventure of life with me. To my husband Anssi I owe my thanks for standing by me for better or worse. Our daughter Alisa was born just as I was finishing my PhD studies. Her arrival has brought much happiness and showed me the meaning of life in a new way.

CONTENTS

ABSTRACT
ACKNOWLEDGEMENTS

CHAPTER 1 9
INTRODUCTION 9
1.1 Background 9
1.2 Theory behind the matching model of the labour market 11
1.2.1 Urn-ball matching model 11
1.2.2 Telephone-line model 13
1.3 Differences in search efforts on the job-seeker side and ranking in the vacancy side 16
1.3.1 Search effort 16
1.3.2 Ranking 18
1.4 Technical efficiency in the matching function 20
1.5 Earlier Finnish studies 21
1.6 Summary of the empirical articles of the thesis 24
1.6.1 Matching across space: Evidence from Finland 26
1.6.2 Heterogeneity of job seekers in labour market matching 27
1.6.3 Does population density matter in the process of matching heterogeneous job seekers and vacancies? 28
1.6.4 Composition of the job-seeker stock in labour market matching: A stochastic frontier approach 29
1.7 Discussion 31
References 34

CHAPTER 2 41
MATCHING ACROSS SPACE: EVIDENCE FROM FINLAND 41
2.1 Introduction 41
2.2 Spatial aspects in the matching function 43
2.3 The data 45
2.4 The matching process in Finland 47
2.4.1 Basic specification 47
2.4.2 Spatial spill-overs 48
2.4.3 Does population density matter? 49
2.5 Conclusions 52
References 53

CHAPTER 3 55
HETEROGENEITY OF JOB SEEKERS IN LABOUR MARKET MATCHING 55
3.1 Introduction 55
3.2 Data description 57
3.3 Matching models with heterogeneity of job seekers 59
3.4 Results 60

3.5 Conclusions 62
References.. 64

CHAPTER 4 66
DOES POPULATION DENSITY MATTER IN THE PROCESS OF MATCHING HETEROGENEOUS JOB SEEKERS AND VACANCIES? 66
4.1 Introduction.. 66
4.2 Matching efficiency 68
4.3 Data description.. 69
4.4 Matching model 70
4.5 Estimation results 72
4.5.1 Fixed-effects models.. 72
4.5.2 Mixed-effects model.. 74
4.6 Conclusions 77
References.. 80

CHAPTER 5 82
COMPOSITION OF THE JOB-SEEKER STOCK IN LABOUR MARKET MATCHING: A STOCHASTIC FRONTIER APPROACH 82
5.1 Introduction.. 82
5.2 Specification of the stochastic frontier matching model 84
5.3 Data description.. 85
5.4 Results 88
5.4.1 Determinants of the matching efficiency 90
5.4.2 Quantitative effects of inefficiency on matches 92
5.5 Conclusions 93
References.. 98

SUMMARY IN FINNISH (YHTEENVETO) 100

CHAPTER 1

INTRODUCTION

ABSTRACT. This introductory chapter presents micro-level theoretical explanations for the existence of macro-level matching functions, pulls together earlier empirical Finnish studies on labour market matching, and summarizes four empirical papers that estimate the matching function in local labour markets. The urn-ball model assumes that job seekers and vacancies meet randomly and defines the source of matching frictions as coordination failure. The telephone-line model in turn relates matching frictions to relative search costs and search intensities on both sides of the labour market. The implications of the telephone-line model can be applied further to models with heterogeneous job seekers where the ranking behaviour of firms and differences in search intensities between job-seeker groups are included in the empirical model. The empirical studies included in this thesis indicate that these extensions of the basic matching functions have empirical relevance. The heterogeneity of the job-seeker stock and population density as well as spatial dependencies between local labour markets play roles in the matching function.

1.1 Background

Labour markets are commonly characterised by a large number of job seekers searching for new jobs together with a large number of firms searching for new workers. Jobs are created and destructed continuously. Existing plants expand or contract their labour force, new plants start up, and old plants shut down (see e.g. Davis et al. 1996). Job seekers and vacancies in the market do not match without frictions since job seekers differ greatly in the skills and capabilities they have, and vacancies differ greatly in the skill requirements they demand from workers. Information about vacancies and job seekers is imperfect, which also cause delays in the matching process. In addition, both regional and occupational mobility are bounded. If there were no frictions, the number of matches would be determined by the minimum of either the number of job seekers or the number of vacant jobs. Frictions to a certain extent are necessary to guarantee the quality of matches, but at their worst they slow down the matching process leading to higher structural unemployment.

This PhD thesis takes a matching approach to the local labour markets in Finland. A matching function is used as a device to model the complicated trading process in a labour market (Pissarides 2000). The number of matches is taken to be a function of job seekers and vacant jobs: filled vacancies are the output of a production function with job seekers and vacant jobs as inputs. The matching function describes the technology that brings job seekers and vacant jobs together. The process of finding each other is costly and time-consuming for both sides in the labour market. The traditional "black box" view on the matching function assumes it to be an exogenous macro level function that summarises frictions in the labour market (Petrongolo and Pissarides 2001). The "black box" approach is not explicitly interested in the source of these frictions, and thus the policy implications based on this framework are exiguous.

The attention is traditionally paid to the externalities present in the matching function. These externalities are due to the fact that the searchers affect each other, i.e., that the search outcomes are not independent of the behaviour of the other actors in the labour market. An additional job seeker causes congestion to other job seekers by decreasing their matching rates. On the other hand, he has a positive externality to the vacancy side of the market. An additional vacancy in turn congests the vacancy side by decreasing the matching probability of other vacancies while at the same time increasing the matching rates of job seekers. Successful matches are determined by the magnitude of and the relation between these externalities.

This thesis contributes to the newer literature that tries to open the "black box" by modelling the source of frictions in the matching function. I seek explanations for them from heterogeneity among job seekers and heterogeneity among local labour markets. Heterogeneity affects the behaviour of both job seekers and vacancies thereby contributing to the externalities in the matching function. The qualitative matching of job seekers and vacancies determines how many matches are obtained at given amounts of searching workers and firms, i.e. technical efficiency, which is of a considerable concern in the thesis. Opening the aggregate matching function by micro evidence from local labour markets is an important assignment since it gives an opportunity for policy implications; what are the factors that improve the matching process at the local level and further the functioning of the labour market as a whole.

The data consist of several micro-markets and provide comprehensive information about the composition of the job-seeker stocks in the public-sector employment agencies in Finland. I consider matching issues from the viewpoint of local labour markets: since the characteristics of a job seeker affect his employability, the composition of the job-seeker pool in turn affects the ability of a local market to produce matches. I also investigate whether population density plays a role in the matching technology and in the ability of labour markets to produce matches. Population density is a proxy for the tightness of social networks and the proximity of actors in the labour market (Wahba and

Zenou 2003). Social networks have proved to be an important channel for job seekers and vacancies to find each other successfully and to form successful matches (Ioannides and Datcher Loury 2004). In addition, heterogeneity on both sides of the market (the distribution of job seekers' skills and the skill requirements of vacancies) tends to be wider in densely populated areas than elsewhere (Kano and Ohta 2005).

This introductory chapter discusses the theoretical background of the empirical matching function, introduces the empirical contributions of the thesis, and presents the conclusions of the dissertation as a whole. The chapter is organised as follows. Section 1.2 introduces two theoretical models on labour market matching. The static *urn-ball model*, presented in section 1.2.1, assumes the matching process to be random: urns (vacant jobs) passively wait for balls (job seekers) that randomly seek urns, some urns getting more than one ball while some urns receive no balls. A match is created when a vacancy randomly chooses a worker from among the job seekers who have randomly applied for that vacancy. Section 1.2.2 provides a review of an innovation in matching theory: *the telephone-line model* with endogenous search intensities. This model provides a theoretical tool with which to interpret the results of empirical studies on macro-level matching functions with heterogeneous job seekers. The model relates the micro-level events in the local labour markets that lead to the existence of macro-level matching function.

Section 1.3 discusses the search intensities of different kinds of job-seeker groups and the ranking behaviour of firms that post vacancies. Differences in search intensities and in ranking behaviour cause the job-seeker heterogeneity to play a role in the matching function. Section 1.4 discusses the concept of technical efficiency and relates it to the matching function. Technical efficiency determines how many matches will be produced by given numbers of job seekers and vacancies. The fifth section pulls together earlier empirical Finnish literature on the labour market matching. Section 1.6 presents a summary of the empirical sub-studies of the thesis and describes the econometric methods used in them. A discussion on the implications of the dissertation as a whole is presented in section 1.7.

1.2 Theory behind the matching model of the labour market

1.2.1 Urn-ball matching model

The static urn-ball model has underpinned matching function research, providing micro level explanations for the existence of macro level matching function (Petrongolo and Pissarides 2001 and Lahtonen 2006 provide comprehensive reviews of the matching function literature). In the model, vacancies are urns that passively wait for randomly sent job applications (balls) from among which they randomly choose a worker for a vacant job[1]. The frictions in the market are due to coordination failure: some vacancies get many applications while some get no applications. Vacancies with applications choose a worker. The unsuccessful applicants then proceed to a second round of job search. The source of frictions in the urn-ball model is co-ordination failure: even with exactly same number of job seekers and vacancies some vacancies are left without applicants and some of them are overcrowded. In the simplest interpretation, imperfection that leads to unemployment in the model is the lack of information about other job seekers' actions[2].

Stevens (2007) extends the basic framework of the urn-ball model to account for the search intensity of job seekers. Let us suppose that a proportion α of job seekers, s, decide to send a job application to a randomly chosen vacancy. α represents the search intensity of job seekers, which may be low if search is costly, i.e. if the opportunity cost of searching is high. The expected number of matches is equal to the number of vacancies with at least one job application:

$$m = v(1-(1-\frac{1}{v})^{\alpha s}), \tag{1}$$

where each vacancy receives an job application with the probability $\frac{1}{v}$ and $(1-\frac{1}{v})^{\alpha s}$ is the probability that a given vacancy will not receive any applications at all.

Another interpretation for α, as an opportunity to that it denotes the fraction of job seekers that send an application, is that it denotes the fraction of job seekers who would be suitable employees for a randomly selected vacancy (Petrongolo and Pissarides 2001). In this case, not all job seekers are suitable for all the available vacancies, but any given job seeker does not know which vacancies are suitable. According to this interpretation, $(1-\frac{1}{v})^{\alpha s}$ is the probability that a vacancy would not receive applications from *suitable* job seekers.

For large v holding $\frac{v}{s}$ constant the urn-ball matching function can be approximated by

$$m = v(1-e^{-\alpha s/v}), \tag{2}$$

---

1 It is also possible analogously to define job seekers as urns that wait for randomly selected balls i.e. job offers from firms (Kultti et al. 2006).

2 Lagos (2000) criticizes the random matching assumption "nobody knows where anything is" and develops a directed search model where the macro-level frictions are quite similar to the frictions in the urn-ball model but their source is not imperfect information. In the model, the location of agents is determined endogenously. The optimal location of agents leads to a situation where vacant jobs and job seekers exist at the same time at the macro-level, while at the micro-level the short side of the market determines the number of matches.

which is a standard urn-ball functional form (Blanchard and Diamond 1994)

In the continuous-time version we can suppose that each job seeker sends an application at a constant Poisson rate α to a randomly chosen vacancy. The expected number of vacancies receiving at least one application in a time period of length dt is $v(1-e^{-\alpha s dt/v})$, as in the standard urn-ball model (1). If we let dt tend to zero, the Poisson matching rate is linear in the case of job seekers:

$$m = \alpha s . \tag{3}$$

The matching process is assumed to be asymmetric since all search is assumed to occur on the job-seeker side. Firms are passive urns that only wait for balls. If firms are also assumed to make the search effort, the matching technology takes the following symmetric form (Mortensen and Pissarides 1999):

$$m = \alpha s + \gamma v . \tag{4}$$

Stevens (2007) criticises the continuous version of the urn ball model in that it loses its most attractive feature, namely, the implications of congestion externalities: the probability that any vacancy will receive more than one application is of the order dt^2 so that the congestion effect disappears at the limit. She also argues that linear technologies (3) and (4) do not behave well when either s or v is small relative to each other, i.e. they do not behave in very tight or in very thin labour markets. The basic requirement that $m(0,v) = m(u,0) = 0$ is also lost, which leads to unrealistic implications: matches can be produced without job seekers or without vacancies.

1.2.2 Telephone-line model

The mostly used empirical matching function form is Cobb-Douglas (Petrongolo and Pissarides 2001), which has been utilised also in the empirical part of this doctoral thesis. Stevens (2007) develops a theoretical model that relates Cobb-Douglas matching function to the continuous version of the urn-ball model and also provides micro-level interpretation for the behaviour of the matching function. The model is based on the classic "telephone-line" Poisson queuing process first presented by Cox and Miller in 1965. The starting point is that job seekers send out applications (make calls) randomly to firms with vacant jobs at Poisson rate α meaning that they send applications at exponentially-distributed time intervals with expectation $1/\alpha$. Firms respond to applications at Poisson rate γ, i.e. it takes an exponentially-distributed length of time with expectation $1/\gamma$ to give an answer to the application (firms do not man a telephone continuously).

If a firm is not ready to receive an application, there is no answer and the contact fails. If the contact does not lead to a successful match, both parties continue searching. The same kind of congestion problem as in the urn-ball model is present also in the telephone-line model: if other job seekers are sending their applications rapidly, the chance that the firm will be available to respond to the application of an individual job seeker is reduced. The positive externality is also present: an excess job seeker increase the probability that a vacancy get a call from a suitable candidate.

The aggregate matching rate for a telephone-line matching technology with exogenous search intensities in a steady state is

$$m(u,v,\alpha,\gamma) = p\frac{\alpha u \gamma v}{\alpha u + \gamma v}, \tag{5}$$

where all job seekers search at rate α, firms recruit at rate γ, and p denotes the probability that the match is acceptable. The matching function (5) is increasing and concave in u and v, and has constant returns to scale. It is also increasing and concave in the job seekers' search intensity and in the firms' recruitment intensity. The matching rate tends to zero as u or v tends to zero, and as the number of vacancies tends to infinity the contact rate tends to αu which is the rate of applications. Correspondingly, as the number of job seekers tends to infinity, the contact rate tends to γv which is a rate at which firms answer to applications. These features guarantee the empirically relevant feature of the matching process: the short side of the market determines the number of matches[3].

Stevens derives the model where search intensity and recruitment intensity in (5) are endogenised. They are not directly observable but they are functions of search costs and recruitment costs, respectively. This matching function is of a flexible CES form. The parameters of the CES matching function are determined by the workers wage bargaining share β, by the surplus of a successful match and by parameters of the search and recruitment cost functions. In the matching function with endogenous search and recruitment intensity, the elasticity of substitution between job seekers and vacancies is determined by the elasticity of search and recruitment costs. The relation between the elasticity of substitution and the cost elasticity is inverse: if the cost elasticity is very high, searchers cannot easily adjust their intensities in response to changes in u and v. If the marginal cost of searching is almost constant, i.e. the cost elasticity is near unity, the adjustment is easy and the elasticity of substitution tends to unity.

Interestingly, in the telephone-line model the elasticity of matches with respect to job seekers is equal to the proportion of search activity undertaken by firms which in turn is equal to the probability that an individual application makes a successful match. Symmetrically, the elasticity with respect to vacant jobs is equal to the probability that a unit of recruitment effort leads to a successful match which is also the proportion of search effort undertaken by job

[3] The linear urn-ball function (3) is a special case of the telephone-line model. The job-seeker side alone determines the number of matches when the number of vacancies tends to infinity.

seekers. Lower job-seeker elasticity in the matching function indicates stronger congestion problem among job seekers, as is the case also in the urn-ball model.

The source of the congestion is, however, a bit different from that of the urn-ball model. It is not only the coordination problem but the congestion is related to the opportunity costs of searching: the congestion is caused by high search effort of job seekers relative to the recruitment effort of firms. In this kind of conditions, the costs of searching are relatively lower for job seekers than for firms. This is easy to understand if we think of the conditions of high unemployment rate: it is cheap for the unemployed to exert high search effort since the opportunity costs is an unemployment benefit. Recruiting in turn is expensive for firms in the conditions of low aggregate demand. As a consequence, job seekers search more actively than they themselves are searched and congest each other in the labour market.

The Cobb-Douglas matching function is a special case of the CES telephone-line matching function. Namely, the CES form is reduced to the Cobb-Douglas when the cost elasticity of searching is close to one. In the Cobb-Douglas case the elasticities of matches with respect to job seekers and vacancies are constant, independent of the amounts of inputs in the matching production. The elasticity of substitution between job seekers and vacancies is approximately one. The Cobb-Douglas matching function takes the form

$$As^{\alpha}v^{\gamma} \ , \qquad (6)$$

where A denotes the total productivity of the matching production and other parameters are as before. According to the telephone-line model, when there are much more job seekers than vacant jobs the elasticity of matches with respect to job seekers will tend to be low, at given search effort. But both sides of the market respond to that asymmetry: job seekers search less reducing congestion and firms search more effectively raising the matching rate.

The parameters of the matching function (6) are measures of externalities in the matching production directly showing the positive externality that an additional input cause to the other side of the labour market. The negative externality that an additional job seeker or an additional vacancy causes in its own side of the market is $\alpha-1$ and $\gamma-1$, respectively. The share α of job seekers matches successfully with vacancies and the share γ of vacancies matches with job seekers. These externalities indicate search and recruitment intensities in the labour market: higher job-seeker coefficient indicates higher recruitment effort of firms, and higher vacancy coefficient indicates higher search effort of job seekers.

Applying to the social efficiency Hosios (1990) establishes that if the positive and negative externalities cancel each other out the equilibrium is socially efficient. According to the Hosios conditions, the social efficiency is reached if and only if the matching function is homogeneous of degree one and if the worker's share of the firm surplus equals to the elasticity of the matching function with respect to the job seekers. The homogeneity of the matching function has been tested in almost all applied matching function study through the test for the returns to scale (e.g. Kangasharju et al. 2005 in Finland).

In the empirical literature the basic CES and Cobb-Douglas matching functions has been extended in many ways in order to avoid the unrealistic assumption on purely random matching. In applied empirical studies they can be allowed to vary between different groups of job seekers or vacancies, or in different kinds of regional labour markets according to for example population density. Interpretations of α can be derived either from the search intensity literature (Burgess 1993; Blanchard and Diamond 1994; Pissarides 1994; Van Ours 1995; Broersma 1997; Broersma and Van Ours 1999; Mumford and Smith 1999; Anderson and Burgess 2000; Burgess and Turon 2003) or from the ranking literature (Budd et al. 1988; Layard and Bean 1989; Pissarides 1992; Petrongolo and Pissarides 2001). In both cases it implicates the employability of job seekers in the labour market. γ in turn indicates the ability of vacancies to become filled. The abilities to become matched can further deviate in different kinds of labour markets. The next section discusses about ranking and search effort issues in detail.

1.3 Differences in search efforts on the job-seeker side and ranking in the vacancy side

1.3.1 Search effort

The pool of job seekers is a sample of the whole population therefore consisting of a heterogeneous group of people. The sources of observed heterogeneity are for example the position of a job seekers in the labour market (short-term unemployed, long-term unemployed, employed, out of the labour force), education, and age. In addition, there are many personal characteristics affecting the ability to get jobs which cannot be observed. These heterogeneities affect the effort that job seekers are willing to put in the search and the reservation wage that they have. In the firm side, the type of a job seeker affects the attitude of an employer on a job candidate and the wage that a firm is willing to pay for him.

The heterogeneity in vacancies is not less than in the job-seeker side: the requirements of jobs according to education and other characteristics are distributed widely. This connected with job-seeker heterogeneity requires attention when estimating empirical matching functions. Treating the matching function as a black box where players match together randomly does not give empirically most relevant results. In addition, as shown in the telephone-line model above, both sides of the labour market react on the actions of the other side by decreasing or increasing their search efforts according to how congested the market is.

The macroeconomic situation, aggregate demand and supply, forms the environment where the players are operating. It largely determines the fraction of vacancies to job seekers that further determines which side of the labour market is more important in determining the matching rate. By conclusion, job seekers and vacancies act in the interaction with each other and with the environment where they are located. These issues can be included in the macro-level matching function for example by allowing differing reservation wages or search intensities for different groups of job seekers (Burgess 1993; Blanchard and Diamond 1994; Pissarides 1994; Van Ours 1995; Broersma 1997; Broersma and Van Ours 1999; Mumford and Smith 1999; Anderson and Burgess 2000; Burgess and Turon 2003), assuming that firms treat certain groups of candidates in a different way (Budd et al. 1988; Layard and Bean 1989; Pissarides 1992; Petrongolo and Pissarides 2001) or allowing sub-markets to have their own matching processes (Burgess and Profit 2001).

Heterogeneity of job seekers can be included in the macro matching function by assuming different kind of job-seeker groups to have deviating search intensities. Different job seekers choose different amounts of search units that they are willing to allocate to search. The choice is made optimally in order to maximise net returns from search (Pissarides 2000, ch. 5). The net returns are dependent on the search costs, the cost of unemployment, and the expected returns from employment. Assume that the average search intensity in the economy is α. If the average search intensity of group i is α_i, the hazard rate for a group whose individuals supply on average α_i units of search is $\alpha_i m(\alpha S, V)/\alpha S$. This indicates that a probability that a job seeker in group i gets a job is α_i/α times the probability that an average individual gets a job. The similar conditions can be extended also for vacancies of a different type. In empirical matching function specifications, different groups can be included in the model as shares of the total stock of job seekers. These share variables work as shift variables in the matching function.

Rather similar empirical specification can be theoretically explained by differences in reservation wages. Assume that wage offers follow the probability distribution $G(w)$. If the probability distribution is known to a worker, an average worker in a group i chooses a reservation wage R_i such that it accepts wage offers that are as high as or higher than his reservation wage. Average hazard rate for individual in group i is $[1-G(R_i)]m(s,v)/s$, which is decreasing with the reservation wage. Aggregation over all groups yields to a matching function $M=[1-G(R)]m(s,v)$.

If we interpret the importance of the search intensity and reservation wages through the telephone-line model, it is the more important the more there are vacancies in relation to job seekers, i.e. when the search is concentrated on the vacancy side. Then the selectivity of job seekers increases its importance and higher search intensity yields more matches.

1.3.2 Ranking

Blanchard and Diamond (1994) derive a ranking model on the basis of the urn-ball matching function. The number of filled vacancies is a function of vacant jobs and unemployed job seekers with different unemployment-spell duration. All vacancies that get at least one application become filled. If a vacancy gets applications from many unemployed the candidate with shortest unemployment spell is always chosen. Ranking does not affect the total number of matches but determines who will be chosen to a job. Interestingly, Blanchard and Diamond show that the exit rate from unemployment depends on duration, and that the duration itself is a function of the state of the labour market. In a tight labour market long-term unemployed can be the only applicant for a vacancy while in a depressed market most vacancies receive many applications, and the probability to get a job decreases quickly with duration.

In the Blanchard and Diamond model long-term unemployed do not congest short-term unemployed since short-term unemployed always gets the job when. The exit rate from unemployment in the steady state is given by

$$e(\Theta) = \alpha \exp[-\alpha U(\Theta)/V], \tag{7}$$

where $U(\Theta)$ denotes the duration of unemployment. The exist rate is determined by the probability that a job seeker send an application, α, times the probability that the vacancy applied for has no application from an unemployed worker with duration less than Θ.

Blanchard and Diamond solve $U(\Theta)$ for Θ and x, the index of the state of the labour market. Smaller x indicates tighter labour market. The exit rate can therefore be presented as a function of the state of the labour market

$$e(\Theta) = \alpha(1-x)/(1-x\exp[-\alpha(1-x)\Theta]). \tag{8}$$

Hence, the exit rate is an increasing function of duration. When a person has just become unemployed, i.e. $\Theta = 0$, the exit rate is equal to α; an application leads to a successful match for sure. In addition, the exit rate is a decreasing function of x; the tighter labour market the higher exit rate and vice versa.

Blanchard and Diamond (1989) present the ranking model which forms the base for the model above. This earlier model is relevant model applying to my thesis since it is possible to extend it to include also other groups than unemployed job seekers with deviant unemployment spells and to apply it in the matching function with filled vacancies as a dependent variable instead of hires. In Blanchard and Diamond (1989) model, unemployed job seekers are divided in two groups: short-term and long-term unemployed. The job-seeker stock is hence $s = u^s + u^l$. The short-term unemployed job seeker always gets a job when competing with long-term unemployed, and the matching rate for them is therefore $m^s(u^s, v)/u^s$: since long-term unemployed job seekers are able to get only jobs which do not get any applications from short-term seekers, long-term seekers do not cause congestion among short-term seekers

Sort-term unemployed congest the long-term job seekers competing for the same jobs. The matching rate for the long-term unemployed can be presented as $m(u^s + u^l, v)/u^s - m^s(u^s + u^l)/u^l$. If we think the macro-level matching function, following Blanchard and Diamond (1989), we define that the long-term unemployed enter the model with a scale parameter δ . The macro-level matching function is hence the following

$$m(u^s + \delta u^l, v). \qquad (9)$$

When the employability of short-term unemployed is assumed to be the familiar α , i.e. the rate at which they send applications, the employability of long-term unemployed is the scale parameter times α , $\delta\alpha$. Therefore, if the scale parameter deviates from one, the ability of the long-term unemployed to get a job deviates from that of short-term unemployed. Empirical application of this model is presented in detail in Chapter 3 of this thesis.

The implications of Blanchard and Diamond (1989) model can easily be interpreted through the telephone-line model where the coefficient of job seekers in the empirical matching model reflects the return to firm from the search, and the coefficient of vacancies that for job seekers. Following this intuitive, if different job-seeker groups have deviant weights in the matching function it reflects that the assumed return from search for firms is deviant between the job-seeker groups, i.e. it is more profitable for firms to search job seekers from certain groups.

The empirical specification of the model with ranking can be similar to models with differing search intensities among job seekers: groups of job seekers enter into the model with different coefficients. We must keep in mind the interactive nature of the matching process: it is profitable for firms to search certain kinds of job seekers, and for this kind of job seekers it would be profitable to search actively until congestion externalities cancel out the positive externality. If we think this from the point of view of the local labour markets, an increase in the share of the job seekers of a certain type in the whole job-seeker stock accelerates the production of matches if this group is actively recruited by firms. On the other hand, an increase in the search effort in this preferable job-seeker group also accelerates the matching process until congestion externality cancels the positive effect out. The empirical papers of this thesis studying employability differences between job seekers in different labour market position follow this idea. The view of articles is however not at the micro-level but at the level of the local labour markets: what is the role of the composition of the job-seeker stock in regional matching processes, especially in the technical efficiency of matching. The technical efficiency in the matching function is the theme of the next subchapter.

1.4 Technical efficiency in the matching function

The technical efficiency in the regional matching function is determined by the ability of regions to produce matches by the given stocks of job seekers and vacant jobs (Fahr and Sunde 2002; Ilmakunnas and Pesola 2003; Ibourk et al. 2004; Fahr and Sunde 2005). Technical efficiency determines what happens in the matching production at given amounts of job seekers and vacancies: it captures the factors that are independent of the quantitative amounts of inputs. Some regions are able to produce more matches at given levels of inputs. These differences can be derived from the skill mismatch between job seekers and vacant jobs, to regional mismatch problems, to low search effort of job seekers, to ranking behaviour of firms, to blocks in the transmission of information, to wide heterogeneity of job seekers and firms, and to the inefficiency of the functioning of employment agency (e.g. Broersma and Van Ours 1999; Pissarides 1994; Anderson and Burgess 2000; Petrongolo and Pissarides 2001). Since the qualitative matching of inputs in the matching process is a crucial determinant of the formation of successful matches, this doctoral thesis study in detail the efficiency of the matching process in the Finnish local labour markets.

The concept of technical efficiency is derived from the production theory where the efficient production function determines output that a perfectly efficient firm could obtain from any combination of inputs (Farrell 1957). The isoquant in Figure 1 presents all totally efficient vacancy and job-seeker pairs that are needed to produce matches m. It shows minimum amount of vacancies required to obtain the fixed number of matches m at all levels of job seekers. Similarly it shows the number of job seekers required in order to obtain m at given amount of vacancies. Let points C and B be the examples of the local labour offices (LLOs) in Finland where inefficiency is equal to zero. They produce matches at given inputs as much as is possible. LLOs A and B use inputs in the same ratio with each other, v/s is equal in two points. Since m does not change, m/s is lower in point A than in point B. The LLO B produces the same output by using only OB/OA as much of inputs as A. It could also be thought of as producing OA/OB times as much output from the same inputs. Technical efficiency of LLO A is thus determined by OB/OA.

Technical efficiency is only one component of the total efficiency. The other component is cost efficiency (allocative efficiency), which determines whether the amounts of inputs are used in efficient proportions. The overall efficiency is a product of these two components. Since the prices of inputs cannot directly be determined in the matching process and hence the cost function cannot be derived, this thesis concentrates only on the technical efficiency: how efficient local labour markets are in producing matches by given levels of job seekers and vacancies.

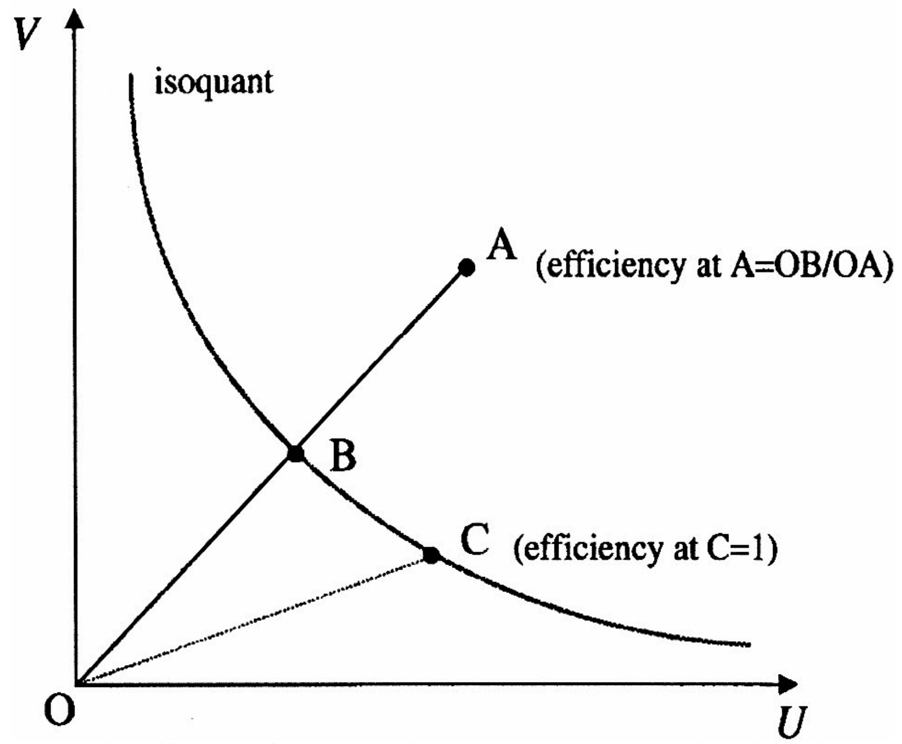

FIGURE 1 The efficiency frontier in the V-U space (Source: Ibourk et al. 2004)

Due to exceptional nature of the matching function compared to the production functions of firms, the interpretations concerning matching efficiency must be done carefully. However, efficiency analysis of the matching function gives a description of factors that affect efficiency and factors that make differences between labour markets in their ability to form matches. From the point of view of this thesis, it gives a tool to analyse the role of the quality of the job-seeker stock in the matching function and the matching differences according to the population density of the labour market. Even Farrell (1957) noted that the technical efficiency of a firm must always, to some extent, reflect the quality of its inputs. Battese and Coelli (1995) developed an econometric method which makes it possible to separate the effects of environmental factors on the technical efficiency from the managerial performance. Chapters 2-5 all deals with the technical efficiency aspects of the matching function taking different econometric perspectives in the measuring of the efficiency differences between local labour markets.

1.5 Earlier Finnish studies

The existing Finnish studies on empirical labour market matching functions deviate in both the type of data and methods they have used, thus providing answers to different research questions. The data sets used are either panel data from different regional aggregation levels (administrative employment regions, local labour offices, travel-to-work areas) or time series data at the aggregate level. The time aggregation differs from monthly to yearly intervals. Cross-sectional disaggregation can, in addition to the regional level, also arise through occupations or, e.g., through the duration of unemployment spells. The estimation methods utilised vary from different kinds of time series analysis to panel-data methods and stochastic frontier analysis. The dependent variable in the matching function can be filled vacancies (i.e. vacancy outflow), vacancies filled by registered job seekers, duration of vacancies or unemployment spells, hires from unemployment or total outflow from unemployment. The choice of the dependent variable is an important stage since it strongly affects the implications of the empirical analysis. Two journal articles, two discussion papers, and two doctoral theses on Finnish labour market matching are summarized in the following paragraphs.

Ilmakunnas and Pesola (2003) [4] focus on changes in the matching technology and matching efficiency by utilising stochastic frontier analysis as an estimation technique. Their data contain annual observations from 14 administrative employment regions for the period 1988-1997. According to the results, returns to scale in the SFA matching function with unemployment outflow as a dependent variable are constant. Ilmakunnas and Pesola also find a downward trend in the matching technology and pro-cyclical variation in matching efficiency. In addition, matching efficiency is positively affected by young job seekers, long-term unemployment, and vacancy spillover from neighbouring regions. Unemployment spillover has a negative effect on matching efficiency.

Bunders (2003) estimates an empirical matching function with the duration of vacant jobs as a dependent variable. The data are yearly panel data from 13 administrative employment regions from 1988 to 2002 on 10 occupational groups. Bunders finds increasing mismatch during the period with substantial differences between regions and occupations. Returns to scale in the matching function are increasing.

Kangasharju et al. (2005) use monthly data from 173 Local Labour Offices from January 1991 to August 2002. The dependent variable is filled vacancies during a month. They estimate both translog and Cobb-Douglas specifications and also compare models where stocks of vacancies match flows of job seekers. According to the results, the translog specifications yield higher estimates for returns to scale than the Cobb-Douglas specifications, by estimating increasing returns for the stock-flow model and constant returns otherwise. Cobb-Douglas also achieves constant returns when flows are included, but with only stocks, returns are clearly decreasing. Kangasharju et al. also tested for the difference between monthly aggregation and quarterly aggregation, concluding that the higher level of time aggregation biases the point estimates downwards.

In his doctoral thesis, which consists of four articles, Lahtonen (2006) uses the monthly data set from Local Labour Offices from January 1991 to September 2004 with aggregation levels from 146 to 173 areas. Lahtonen concentrates on the effects of the educational structure of job seekers on the matching processes

---

[4] Also Pesola (2002).

in local labour markets. He finds that a relative increase in the group of secondary educated job seekers decreases filled vacancies in the market. Lahtonen also tests for the assumption of random search against the stock-flow model where the flow of job seekers matches the stock of vacancies and flows of vacancies in turn the stock of job seekers. He finds that the flows of vacancies match the stocks of job seekers. Searching on the job-seeker side, however, takes time: flows of job seekers do not immediately match the vacancy stock.

Soininen (2006), in her doctoral thesis, takes a time-series approach to the Finnish matching function using quarterly data from 1982/01 to 2005/2. Her study data are regionally aggregated while disaggregation is done according to occupation and duration of unemployment spells. The thesis consists of three articles studying, first, whether the matching process is different before and after the economic crisis and whether this explains the persistence of unemployment. Second, the thesis questions whether stock-flow matching is a micro-level foundation for the aggregate matching function. Third, the thesis questions whether there are differences between occupations in matching and how important empirically corresponding variables are for reliable results.

According to the initial results obtained by applying the cointegrated VAR-method to the analysis of aggregated data, changes in the matching process explain some of the persistence of Finnish unemployment: long-term unemployed due to the recession do not match available vacancies. Second, Soininen finds that the re-employment probability of unemployed job seekers to is clearly dependent on the duration of unemployment: new job seekers match the vacancy stock and the prevailing job-seeker stock match new vacancies. Long-term unemployed, however, do not match either stocks or flows of vacancies. At the aggregate level, Soininen does not find evidence for stock-flow matching. Third, Soininen estimates the matching function separately for nine occupational groups, utilising time series techniques. She finds that for registered job seekers matching is vacancy-driven for most occupations. Otherwise, she finds considerable differences between occupations in the matching process.

Hynninen et al. (2006) apply SFA in order to study the differences between the 19 largest travel-to-work areas in the technical efficiency of hiring processes and the further contribution of these differences to the aggregate unemployment rate. The data are monthly panel data from January 1995 to December 2003. Substantial differences were found in the ability of TTWAs to get unemployed job seekers hired for vacant jobs, and inefficiencies in the hiring process were estimated to have an effect of a 2.5 percentage points on the aggregate unemployment rate. The technical efficiency of the hiring process was positively affected by younger and older job seekers as well as by the volume of ALMPs and the size of the population in the TTWA. Long-term unemployment and other than unemployed job seekers have a negative effect on hiring efficiency.

1.6 Summary of the empirical articles of the thesis

In this thesis, the matching function is based on the idea that the stocks of vacant jobs and job seekers existing at the beginning of a month form matches during that month. A match is a filled vacancy. The thesis consists of four empirical articles that investigate the technical efficiency of the matching function from different perspectives and utilising different modelling and estimation techniques.

The data used in all four articles are monthly panel data from the Local Labour Offices (LLOs) in Finland. The data include information on job seekers, vacant jobs and filled vacancies reported in the public employment agency[5]. The research period spans the period January 1991 to September 2004[6], but a larger part of the research focuses on the period 1995/01-2004/09, i.e., the period after the recession.

The number of LLOs decreased continuously on the research period due to the amalgamation of state-run services for job seekers in larger units. The raw data from the early 1990s consist of over 190 LLOs that are aggregated into 146 units. These units mainly follow the division of LLOs in 2004. However, LLOs inside the same municipality are combained. In addition, LLOs in the capital region Helsinki (Helsinki, Espoo, and Vantaa) are treated as a single unit. Monthly averages of essential variables by LLOs are given in Appendix 1.

The data set is temporally and spatially highly disaggregated. The temporal aspect is extremely important, since the matching function describes a process that takes place continuously. The use of time-wisely more aggregated (yearly or quarterly) data would lead to a matching function where the observed matches are produced by different inputs than those included in the function. In some cases even a month can be too long, since many vacancies are filled within a very short time and hence do not become registered as part of the vacancy stock. The papers in this thesis do not, however, deal with the stock-flow models where the stocks of job seekers are matched only with new flows of vacancies and vice versa (e.g. Coles and Smith 1998; Gregg and Petrongolo 2005; Lahtonen 2006; Soininen 2006). [7]

---

5 The public employment agency plays an important role in the Finnish labour market. The proportion of jobs mediated by LLOs varied between a low of 49 in 1993 and a high of 71 per cent in 1996 over the period 1993-2002 (Hämäläinen 2003). The mean was around 60 per cent.

6 The same data with variations have also been used in Kangasharju et al. (2005), Lahtonen (2006) and in an aggregated form in Hynninen et al. (2006)

7 Spatial aggregation raises a question about the optimal size of the local labour market. The use of aggregated data is based on the assumption that the aggregate economy is a single labour market. Hansen (1970), who was the first to using this kind of modelling, discusses in detail the assumptions on which spatial aggregation is based. Spatial aggregation assumes that submarkets themselves do not suffer from any frictions, but that frictions only exist between submarkets. Markets with unemployment can therefore coexist with markets with vacant jobs, although no market has both, which makes the existence of an aggregate matching function a possibility.

The spatial aggregation raises a question about the optimal size of the local labour market. Using aggregated data is based on the assumption that the aggregate economy is a single labour market. Hansen (1970), who was the first to using this kind of modelling, discusses in detail the assumptions on which spatial aggregation is based. Spatial aggregation assumes that submarkets themselves do not suffer from any frictions, but that frictions only exist between submarkets. Markets with unemployment can therefore coexist with markets with open vacancies although no market has both, which makes the existence of an aggregate matching function a possibility.

In the country like Finland, distances are so long that the assumption of one micro market cannot be accepted. The thesis operates with different levels of spatial aggregation and tests also whether there is interaction even between travel-to-work areas. Petrongolo and Pissarides (2001) argue that aggregation over micro-markets would bias matching elasticity estimates downwards since due to imperfect mobility of labour, changes in stocks contribute to matches in a local market but these effects are not shown in their whole magnitude in the spatially aggregated data. However, in empirical work using spatially disaggregated data, decreasing returns to scale have often turned out to be the case (Burda 1993; Burda and Profit 1996; Burda and Wyplosz 1994; Burgess and Profit 2001). This is the case also in the articles of this thesis.

The research period covers a deep recession at the beginning of the 1990s, the recovery of it and the normalization of the Finnish labour market at the beginning of the 2000s. These variations are captured in Figure 2 which plots the developments of the average levels of labour market tightness and matching rate from 1991 to 2004. The decline in the tightness and in the matching rate from 1991 to 1992 was huge, from 0.09 to 0.04 and from 0.05 to 0.02, respectively. The recovery started during 1994 but was rather slow. It took 13 years to reach the tightness and the matching rate levels of 1991.

The long-term unemployment was a serious problem since the recession left many people unemployed and new jobs after it were born in different sectors from those where there were left unemployed (e.g. Koskela and Uusitalo 2003). It is described in Chapter 2 how the share of long-term unemployed of all job seekers rose from the level of 1.2 % in 1991 to a high of almost 17 % in 1995 and 1996: during the recovery period long-term unemployment was still rising. The decrease in the long-term unemployment after 1996 started extremely slowly, the share of all job seekers being still 16 % in 1998.

The figure also gives preliminary information about the technical efficiency of the matching process. Both tightness and the matching rate increased continuously after 1993 but the developments of these two labour market indicators separated after 1996. At given fraction of vacant jobs to job seekers, filling vacancies became continuously more difficult after 1996 indicating that the qualitative matching between job seekers and vacancies depressed continuously. The gap between tightness and the matching rate was large also in 1991 indicating growing problems with filling vacancies during upturns, at given ratio v/s (Bowden 1980; Coles and Smith 1996; Wall and

Zoega 2002; Gregg and Petrongolo 2005). The deterioration in matching has not, however, concentrated only on the upturn but has continued almost ten years. The explanation is either the deterioration of the matching technology or the decrease in the technical efficiency, i.e. the shift towards point *A* in Figure 1. The empirical papers of this thesis shed light on both quantitative and qualitative factors behind matching frictions applying different kinds of econometric methods in the analysis.

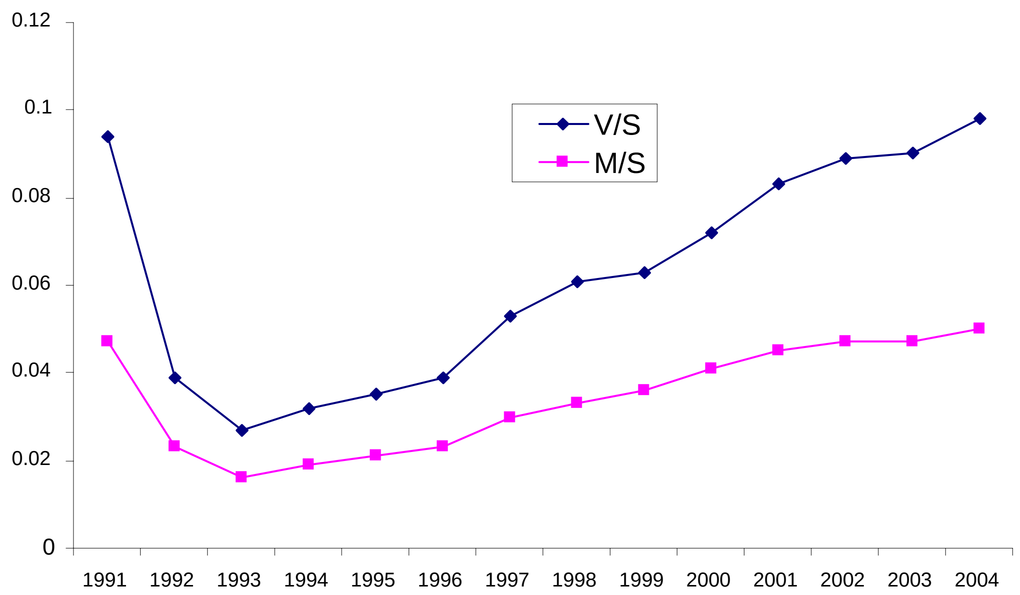

FIGURE 2 Labour market tightness and the matching rate in Finland from 1991-2004

1.6.1 Matching across space: Evidence from Finland

The first article of the thesis deals with the role of spatial spill-overs in the matching function by adding job seekers and vacancies from neighbouring areas into the local matching function. Spatial econometric methods are applied in the analysis. This approach is based on the assumption that the Finnish labour market is a collection of spatially distinct labour markets that are possibly in interaction with each other. The modelling in the paper refers to Burda and Profit (1996) and Burgess and Profit (2001). Spatial spillover variables are weighted averages of the stock of job seekers and that of the stock of vacancies in neighbouring LLOs (Anselin 1988). The neighbourhood is defined so that LLOs are neighbours if the distance between the centres of them is shorter than 100 kilometres. LLOs are aggregated into 120 units in order to follow the borders of the travel-to-work areas. The used travel-to-work division is based on the definition of Statistics Finland prevailing in 2004, in which areas are formed according to the commuting behaviour of workers in 2000. This aggregation makes it possible to concentrate on the congestion externalities that arise due to job seekers and employers in neighbouring economic areas searching in one's local labour market and to leave spillover effects that arise due to normal commuting behaviour out of the analysis. The list of TTWAs and the number of their neighbours are given in Appendix 2.

The role of population density is also considered by grouping the LLOs in two groups according to how densely populated they are and allowing these groups to enter into the model with deviating coefficients. Possible asymmetry of spillovers according to the population density is also taken into account. The results indicate that the Finnish local labour markets suffer from a strong congestion effect among job seekers and that spatial spillovers from neighbouring areas further strengthen the congestion. The results also indicate that the matching efficiency in densely populated areas is higher than elsewhere but that spill-overs from neighbouring areas negatively contribute to it.

1.6.2 Heterogeneity of job seekers in labour market matching

The second paper considers the role of the composition of the job-seeker stock in the matching function. The paper introduces the model where different job-seeker groups enter into the model with their own employability. The model provides estimates both for the employability from the job seeker's point of view and for how a relative increase in a particular group of job seekers affect matches from a LLO's point of view. The estimation technique is a Prais-Winsten regression with temporally autocorrelated errors, panel-corrected standard errors and contemporaneous correlation across panels.

According to the results, from a LLO's point of view, an increase in the share of long-term unemployed job seekers have negative effect and an increase in the share of job seekers out of the labour force a positive effect on matches. The chose of the period, however, affect results. If we consider the whole period from 1991 to 2004, also employed job seekers improve matches, but this effect disappears if we only consider the period from 1995 forwards. The period also affects the interpretation concerning congestion effect among job seekers; the coefficient for job seekers rises from 0.14 in the model with the whole period to 0.35 when the recession is left outside. The recession period had so exceptional implications in the Finnish labour market that it dominates the analysis. The imbalance in the search activity has relieved after the recession due to normalization of the relation of the number vacancies to job seekers. Despite this relief, the imbalance is still present and the returns to scale are still decreasing.

The results indicate that an increase in the share of job seekers out of the labour force improves the matching process in local labour markets. Interpretation through the telephone-line model yields to a result that job seekers out of the labour force provide a strongest positive externality to the vacancy side: therefore the return from the search to firms searching for job seekers out of the labour force is relatively higher than the return from the search to these job seekers out of the labour force. In these conditions, excess job seekers from this group improve matches until the congestion externality cancels this effect out. A difference to a job seeker from the core group is clear:

one job seeker out of the labour force in the matching function corresponds to six unemployed job seekers with an unemployment spell shorter than a year.

Long-term unemployed job seekers in turn contribute negatively on matches. From the LLO's point of view, a percentage point increase in the share of long-term unemployed decrease matches by about 1.4 per cent. The employability of long-term unemployed job seekers is so weak that one job seeker with a long unemployment spell decreases the effective stock of job seekers by 3 persons. Referring to Blanchard and Diamond (1989), it seems that long-term unemployed do not congest other job seekers; their contribution to the effective stock of job seekers is negative.

1.6.3 Does population density matter in the process of matching heterogeneous job seekers and vacancies?

The third paper relates population density to the heterogeneity in the labour market by applying linear mixed-model technique in order to clarify matching efficiency and matching externality differences between LLOs according to the population density. The definition of inefficiency is based on the model of Kim and Schmidt (2000) where the cross-section specific fixed effects are interpreted as efficiency terms. The LLO group with highest intercept is in our case defined to be the most efficient group. Its efficiency is scaled to be equal to 1 and its inefficiency congruently equal to 0. The inefficiency of the other density groups is measured as a difference to the most efficient one. The inefficiency is thus always conditional to the most efficient group.

The view of the previous literature on the role of the population density in the matching process is twofold. The first approach argues that the closer proximity of the parties in the labour market and tighter social networks in densely populated areas makes the matching process working more efficiently there than sparsely populated area (Coles and Smith 1996; Wahba and Zenou 2003). The second approach argues that matches may occur easily if the skill-distribution of workers and the hiring standards of firms are concentrated on the same level (Kano and Ohta 2005). In densely populated areas, where the skill-distribution tends to be wide, the concentration of the job-seeker characteristics may differ from that sought by employers. In addition, due to wider distribution of skills and skill requirements the coordination problems may be more serious. As a result, matching efficiency might be lower in densely populated areas than in sparsely populated areas. We test for the differences in the matching efficiency according to the population density and control for the heterogeneity of job seekers according to the education level.

The LLOs are separated in three groups according to the density and the matching process is modelled by the mixed-effects model. The tradition of the use of mixed-effects model is based on the experiments in the natural sciences (Verbege and Molenberghs 2001). The idea is to study whether wider heterogeneity of job seekers and vacancies in densely populated areas contribute negatively or positively to matches. The proximity of partners and tighter social networks might improve matches there, while wider heterogeneity in both sides of the market might on the other hand slow down the matching process and cause more serious coordination problems than elsewhere.

Table 1 presents the distribution of the shares of education groups of job seekers in different population density groups. The variable measuring the educational distribution of job seekers takes three values in each LLO denoting the average shares of each educational group. The average of this variable is equal to 0.333, a situation where each education group has an equal share in the job-seeker stock. The lower the standard deviation, the more equally each education group is represented in the job-seeker stock, indicating wider heterogeneity. According to the calculations presented in Table 1, the standard deviation is lowest in the high density and highest in the low density LLOs.

TABLE 1 Distribution of shares of different education groups by population density of LLOs

	Observations	**Average**	**Standard deviation**
High density	108	0.333	0.16
Middle	222	0.333	0.182
Low density	108	0.333	0.205

The starting hypothesis before estimations was that high-density areas would otherwise be more efficient than the others but that their efficiency may be negatively affected by the job-seeker heterogeneity. The results are somewhat in line with this hypothesis: the heterogeneity of job seekers contributes more to the labour market matching in high-density areas than elsewhere. In particular, the share of job seekers with low education is higher in high-density areas than would be needed with respect to the education requirements of employers. Yet, the LLOs with highest population density are the most efficient LLOs in producing matches, which indicates that proximity of partners and tighter social networks improve the matching process.

1.6.4 Composition of the job-seeker stock in labour market matching: A stochastic frontier approach

The fourth article takes a stochastic frontier approach on the matching efficiency. In the stochastic frontier analysis (SFA), the matching function determines the upper boundary for matches possible to obtain at given amounts of job seekers and vacant jobs. The SFA matching model is a non-linear model where the error term consists of two parts: random error and inefficiency that always enters to the model with a negative sign. Due to its non-linearity, the model must be estimated by the maximum likelihood. Battese and Coelli (1995) introduced a SFA model where the inefficiency terms are expressed as functions of some explanatory variables that characterize the environment where analysed units are operating.

Inefficiency terms are not hence assumed to be identically distributed but the set of explanatory variables with their estimated coefficient determines the mean of the distribution of the inefficiency terms. The important improvement in the Battese's and Coelli's model in relation to previous ones is that the production function is estimated simultaneously with the effects of the inefficiency regressors on the inefficiency term. The restrictive assumption on the identical distribution of the inefficiency term does not have to be made in any phase of the estimation. Battese's and Coelli's model also enables the inefficiency terms to vary over time, which is a realistic assumption in long time series.

The problem in the efficiency analysis with large panel data sets is the question how to deal with heterogeneity between cross sections that is due other factors but inefficiency. In the Kim and Schmidt (2000) model utilised in the third (and also in the first) article all of the heterogeneity is interpreted as inefficiency. Greene (2005a and b) deals with that problem introducing a "true" fixed-effects model where the cross-sectional specific fixed effects are included into the SFA model in order to capture heterogeneity independent of inefficiency. The model in the fourth article is a combination of Battese's and Coelli's and Greene's models. It is a true fixed-effects model with Battese and Coelli type of errors.

The composition of the job-seeker stock according to the labour market position, education and age is included into the model as inefficiency regressors. They are not thus assumed to directly affect the matching technology but are in turn assumed to affect the distance function that determines the deviation of a LLO from the frontier at given time periods (see Figure 1). According to the results, the composition of the job-seeker stock has a considerable weight in the determination of inefficiency estimates, on average 61 %. Especially job seekers out of the labour force and highly educated job seekers improve matches in LLOs. These results are in line with the second and the third article in this thesis.

According to the telephone-line model, searching is more costly for highly educated job seekers than for secondary or primary educated seekers in relation to the costs that the search causes to the firms searching workers from these particular groups. Therefore, firms search relatively more actively highly educated job seekers than primary or secondary educated job seekers, i.e. the search in the market for highly educated is more concentrated on the firms' side than the search in the market for primary or secondary educated. The same holds also for job seekers out of the labour force: the search activity in this kind of jobs is more concentrated on the firms' side than on the job seekers' side. One explanation could be the flexibility of those who are entering the labour market or fresh skills due to lately finished studies. The interpretation through the telephone-line model does not preclude the possibility that the job seekers out of the labour force also itself search more actively than other groups: they do not, however, search "too" actively in relation to firms searching for them.

The stochastic frontier analysis extends the basic fixed-effects approach on efficiency by making it possible to explicitly calculate the quantitative magnitude of inefficiency in the matching function: how many more matches would be produced without inefficiency? If inefficiency played a zero role, i.e.

all LLOs were located on the frontier matches would increase by almost 24 per cent. If, more realistically, all LLOs attained the efficiency level of the most efficient LLO, matches would increase by over 10 per cent. These calculations indicate that there are notable differences in the matching efficiency between regions and that these differences contribute to the labour market with losses in matches.

The results on the stochastic frontier analysis support the view that the technical efficiency of the matching has declined continuously after 1995: after controlling for the shifts in the matching technology by adding monthly and yearly dummies into the matching function and after controlling for the job-seeker composition, the technical efficiency exhibits a negative trend.

1.7 Discussion

This doctoral thesis studies labour market matching in the Finnish local labour markets utilising the matching function as a modelling device. The data are drawn from the registers of the public employment agencies. The approach in the thesis is empirical: four different methods are used to studying matching externalities and matching efficiency in local labour markets. The roles of spatial dependencies, population density, and job-seeker heterogeneity in the empirical matching process are considered by means of these methods.

The research period spans from 1991/01 to 2004/09, covering the deep recession in Finland at the beginning of 1990s, the recovery after it, and the gradual normalization of the conditions in the labour market. Because the recession period was highly exceptional, the estimations mostly concern the period after it, i.e., from 1995 forwards. The recession left a long-lasting imprint on the Finnish labour market, as can be seen in the results: the search effort is heavily concentrated on the job-seeker side leading to a strong congestion effect among job seekers.

According to the estimations with spatial spillovers, job seekers from neighbouring travel-to-work areas further exacerbate the problem of congestion, particularly in densely populated areas. This indicates that labour market conditions between neighbouring areas are so similar that job search over borders does not lead to better outcomes.

According to the results, densely populated areas are more efficient than other areas in producing matches. Therefore, the tighter social networks and closer proximity approximated by higher population density have an improving effect on the matching process. There are, however, problems in the qualitative matching of job seekers and vacancies in densely populated areas. Namely, despite the fact that the fraction of low-skilled job seekers of the whole job-seeker stock is lower in these areas than elsewhere, it is too high with respect to the educational requirements of vacancies. Active labour market programmes in densely populated areas should focus even more on improving the level of education of unemployed individuals who only have primary education.

The structural change due to the recession was so massive that it has taken the Finnish labour market over ten years to recover from it. In addition, the composition of the job seeker-stock is problematic: on average 14 % of all job seekers and almost 30 % of unemployed job seekers during the study period were of the long-term type. The skills of these long-term unemployed job seekers soon lost their relevance, and under given the imbalance between the relative amounts of job seekers and vacancies, employers were able to apply strict ranking behaviour that put long-term unemployed job seekers at the back of the queue. Long-term unemployed job seekers do not match the vacancies, which is shown in the matching function as a decreasing effect of the long-term unemployed on the effective job-seeker input. Job seekers out of the labour force in turn seem to be sought-after labour force, probably due to their flexibility and fresh skills, at least among those who are finishing their studies. In addition, there is demand for highly educated job seekers, as is shown by their accelerating effect on matching.

The results indicate that a continuous exogenous decline in matching efficiency took place from 1995 to 2004: the ability of the local labour markets to form matches at the given amounts of job seekers and vacancies has declined, and the average time that it takes to fill a vacancy has lengthened. This change is not explained by the position of job seekers in the labour market, or by the education or the age structure of the job-seeker stock. Part of the explanation must, surely, lie in the micro-level characteristics of the job seekers inside these categories but in part the explanation may have to do with the characteristics of vacancies, e.g. the share of vacancies that are unpopular from the point of view of job seekers might have increased.

In addition, in part the problem of decreased efficiency can be traced to the inefficiency of active labour market policies and functioning of the local labour offices. There are notable and permanent differences in matching efficiency between local labour markets which are not completely explained by the structure of the job-seeker stock. If the matching process in all LLOs worked as efficiently as it works in the most efficient one, the number of monthly matches would increase by 10 %. This indicates differences in the functioning of LLOs, e.g., in relation to the local business life. The adoption of good practices identified in efficiently working LLOs could be one step towards a more efficient matching process.

The development in the Finnish labour market is moving towards a labour shortage rather than a shortage of work, which means increasing difficulties in finding workers (aggregate unemployment rate in March 2007 7.7 % according to the Statistics Finland). A labour shortage will, at worst, be an obstacle to economic growth by preventing firms from creating new jobs in the home country. In addition, structural change will continuously shift the demand for labour away from the manufacturing sector to services, which may, together with the problem of the labour shortage, further increase matching problems. (Office of the Council of State 2007)

The recession and its consequences, which are shown in the results of the empirical parts of this thesis, demonstrate the importance of early interventions regarding workers who become unemployed and the importance of those in the labour force continuously updating their skills in time with the changing requirements of working life. If these aspects fail to work, the result is congestion on the job-seeker side of the labour market and a large stock of long-term unemployed job seekers who are effectively positioned outside the labour market. In addition to the responsibility of workers for being alert to changing conditions in an era of global competition, attention should also be directed to the vacancy side. In particular, firms in local areas should be active in posting vacancies that are attractive from the job seeker's point of view, e.g. by providing possibilities for upward mobility and training.

The role of the public employment agency is increasingly becoming one of finding workers for vacant jobs instead of the handling of unemployment. The predicted easing of the congestion on the job-seeker side makes the individual job seeker more important from the point of view of the matching process. In order to avoid congestion on the vacancy side, the public employment agency should take a more intermediary role between firms and job seekers. This requires close interaction with the business life in local labour markets and increased communication about the possibilities and requirements on both sides of the market.

REFERENCES

Anderson, P. and Burgess, S. (2000) Empirical matching functions: Estimation and interpretation using state-level data, The Review of Economics and Statistics 82, 93-102.

Anselin, L. (1988) Spatial Econometrics: Methods and models, Amsterdam, Kluwer.

Battese, G.E. and Coelli, T.J. (1995) A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics 20, 325-332.

Blanchard, O. and Diamond, P. (1989) The Beveridge curve. Brookings Papers on Economic Activity 1, 1-76.

Blanchard, O. and Diamond, P. (1994) Ranking, unemployment duration and wages. Review of Economic Studies 61, 417-434.

Bowden, R. J. (1980) On the existence and secular stability of the u-v loci. Economica 47, 33-50.

Broersma, L. and Van Ours, J. (1999) Job searchers, job matches and the elasticity of matching, Labour Economics 6, 77-93.

Budd A., Levine P., and Smith P. (1988) Unemployment, vacancies, and the long-term unemployed, Economic Journal 98, 1071-1091.

Bunders, M. (2003) Kohtaantofunktio suomalaisilla työmarkkinoilla vuosian 1988-2002 – alue- ja ammattiryhmien väliset erot kohtaannon tehokkuudessa. [in Finnish] Bank of Finland Discussion papers 32.

Burda, M. (1993) Unemployment, labour markets and structural change in Eastern Europe. Economic Policy 16, 101-137.

Burda, M. and Profit, S. (1996) Matching across space: Evidence on mobility in the Czech Republic. Labour Economics 3, 255-278.

Burda, M. and Wyplosz, C. (1994) Gross worker and job flows in Europe. European Economic Review 36, 1287-1315.

Burgess, S. and Profit, S. (2001) Externalities in the matching of workers and firms in Britain. Labour Economics 8, 313-333.

Burgess, S. and Turon, H. (2003) Unemployment equilibrium and on-the-job search. IZA Discussion Paper No. 753.

Coles, M.G. & Smith, E. (1996) Cross-Section Estimation of the Matching Function: Evidence from England and Wales. Economica 63, 589-98

Coles, M.G. & Smith, E. (1998) Marketplaces and matching. International Economic Review 39, 239-254.

Davis, S. J., Haltiwanger, J. C. & Schuh, S. (1996) Job creation and destruction. The MIT Press.

Fahr, R. and Sunde, U. (2002) Estimations of occupational and regional matching efficiencies using stochastic production frontier models. IZA Discussion paper 552.

Fahr, R. and Sunde, U. (2005) Regional dependencies in job creation: an efficiency analysis for western Germany. IZA Discussion paper 1660.

Farrell, M.J. (1957) The measurement of productive efficiency. Journal of the Royal Statistical Society Series A 120(3), 253-290.
Greene, W. (2005a) Fixed and random effects in stochastic frontier models. Journal of Productivity Analysis 23, 7-32.
Greene, W. (2005b) Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. Journal of Econometrics 126, 269-303.
Gregg and Petrongolo (2005) Stock-flow matching and the performance of the labor market. European Economic Review 49, 1987-2011.
Hansen B. (1970) Excess demand, unemployment, vacancies and wages. Quarterly Journal of Economics 84, 1-23.
Hosios, A. (1990) On the efficiency of matching and related models of search and unemployment. Review of Economic Studies 57, 279-298.
Hynninen, S., Kangasharju, A., and Pehkonen, J. (2006). Regional Matching Frictions and Aggregate Unemployment. VATT Discussion Paper 383.
Hämäläinen H. (2003) Työvoiman rekrytointi toimipaikoissa vuonna 2002, [in Finnish], Ministry of Labour, Helsinki.
Ibourk, A., Maillard, B., Perelman, S., and Sneessens, H. (2004) Aggregate matching efficiency: A stochastic production frontier approach, France 1990-1994. Empirica 31, 1-25.
Ilmakunnas, P. & Pesola, H. (2003) Regional labour market matching functions and efficiency analysis. Labour 17 (3), 413-437.
Ioannides, Y. M. & Datcher Loyry, L. (2004) Job information networks, neighbourhood effects, and inequality. Journal of Economic Literature XLII, 1056-1093.
Kangasharju, A., Pehkonen, J. and Pekkala, S. (2005) Returns to scale in a matching model: Evidence from disaggregated panel data. Applied Economics 37, 115-118.
Kano, S. & Ohta, M. (2005) Estimating a matching function and regional matching efficiencies. Japan and the World Economy 17, 25-41
Kim, Y. & Schmidt, P. (2000) A review and empirical comparison of Bayesian and classical approaches to inference on efficiency levels in stochastic frontier models with panel data. Journal of productivity Analysis 14, 91-118.
Koskela, E. & Uusitalo, R. (2003) The un-intended convergence: How the Finnish unemployment reached the European level. Labour Institute for Economic Research, Discussion paper 188.
Kultti, K., Miettunen, A., & Virrankoski, J. (2006) Equilibrium unemployment duration in an urn-ball model of the labour market. EALE 2006 Congress paper.
Lagos, R. (2000) An alternative approach to search frictions. Journal of Political Economy 108, 851-873.
Lahtonen, J. (2006) Matching heterogeneous job seekers and vacancies: Empirical studies using Finnish data. Jyväskylä Studies in Business and Economics 50.

Layard R. & Bean C. (1989) Why does unemployment persist? Scandinavian Journal of Economics, 91, 371-396.

Mortensen, D. & Pissarides, C. (1999) New developments in models of search in the labor market in Handbook of Labor Economics. O. Ashenfelter and D. Card eds. Amsterdam, North Holland, 2567-2627.

Mumford, K. & Smith, P. (1999) The hiring function reconsidered: on closing the circle, Oxford Bulletin of Economics and Statistics 61, 343-364.

Office of the Council of State (1997) Rekrytointiongelmat, työvoiman tarjonta ja liikkuvuus [in Finnish]. Valtioneuvoston kanslian julkaisusarja 5/2007.

Petrongolo, B. and Pissarides, C. (2001) Looking into the black box: a survey of the matching function, Journal of Economic Literature 39, 390-431.

Pissarides, C. (1994) Search unemployment with on-the-job search, Review of Economic Studies 61, 457-475.

Pissarides, C. (2000) Equilibrium unemployment theory, MIT Press.

Soininen, H. (2006) Empirical studies on labor market matching. Publications of the Swedish School of Economics and Business Administration Nr. 159.

Stevens, M. (2007) New microfoundations for the aggregate matching function. Forthcoming in International Economic Review.

Van Ours, J. and Ridder, G. (1995) Job matching and job competition: Are lower educated workers at the back of queues? European Economic Review 39, 1717-1731.

Verbege, G. & Molenberghs, G. (2001) Linear mixed models for longitudinal data. Springer Series in Statistics. Springer-Verlag New York, Inc.

Wahba, J. & Zenou, Y (2003) Density, social networks and job search methods: Theory and application to Egypt. CEPR Discussion Paper 3967, London

Wall, H. J. & Zoega, G. (2002) The British Beveridge curve: A tale of ten regions. Oxford Bulletin of Economics and Statistics 64, 21-80

APPENDIX 1 Monthly averages of essential variables by LLOs, 1995/01-2004/09

	Matches	Job seekers	Vacant jobs	Unemployed < 1 year	Unemployed > 1 year	Out of the labour force	Employed	Young	Old	Highly educated	Primary educated	Pop./ km2
Alajärvi	62	1409	76	755	190	83	273	124	257	106	684	11
Alavus	118	2848	65	1332	382	219	701	229	518	211	1332	9
Anjalankoski	94	2143	117	936	253	283	431	192	358	143	1084	24
Eno	26	1251	30	583	219	92	256	79	236	57	733	7
Enontekiö	15	533	4	277	35	49	143	26	92	22	325	0
Eura	94	1508	77	592	164	126	402	88	314	141	793	18
Forssa	161	4292	145	1779	795	306	937	338	839	344	2318	25
Haapajärvi	133	2876	76	1387	340	311	664	290	449	172	1448	11
Haapavesi	87	2000	35	908	166	254	562	175	271	111	926	4
Hämeenkyrö	81	2154	74	923	268	234	558	142	389	172	1028	13
Hämeenlinna	250	8145	164	3284	1569	603	1957	661	1534	901	3637	29
Hamina	96	3341	81	1370	507	305	882	266	597	303	1508	20
Hanko	27	1001	26	431	199	101	205	91	217	59	635	92
Harjavalta	104	3172	97	1312	441	261	862	216	602	278	1577	27
Haukipudas	109	4157	60	2034	684	297	879	407	733	337	1826	11
Heinävesi	26	697	15	307	79	61	198	37	118	44	388	4
Heinola	105	3962	103	1656	715	300	927	269	825	298	2037	13
Helsinki	4322	80736	3665	35702	17867	6588	14397	5826	15180	14658	36726	1180
Huittinen	59	1355	31	623	183	108	306	93	268	116	704	17
Hyrynsalmi	28	612	9	324	39	42	158	30	115	28	337	2
Hyvinkää	154	4755	125	1906	805	619	1003	368	844	432	2407	123
Iisalmi	88	4717	86	2139	661	444	1227	444	677	431	2135	10
Ilomantsi	18	1338	17	675	265	47	249	98	274	53	791	3
Imatra	176	6070	151	2757	1092	293	1150	524	1243	459	3080	24
Ivalo	40	1426	27	736	162	108	366	93	217	94	712	0
Jalasjärvi	55	1006	33	440	112	127	262	74	158	64	468	11
Jämsä	56	3004	42	1293	637	146	601	260	583	268	1358	10
Janakkala	78	1434	82	664	267	94	266	111	331	114	694	26
Järvenpää	104	3537	95	1630	636	384	650	293	609	388	1664	864
Joensuu	364	12245	282	5542	1694	1194	3179	1102	1696	1692	4942	33
Joutsa	20	755	12	333	110	72	193	36	150	39	442	5
Juankoski	47	1390	41	720	236	63	285	103	280	64	732	7
Juva	72	1925	61	855	239	205	472	117	347	142	1001	5
Jyväskylä	441	17771	360	7758	3538	1259	3946	1940	2918	2669	6633	43
Kaarina	80	2985	50	1323	398	271	645	221	596	402	1398	54
Kajaani	139	7100	130	3024	855	759	1996	602	973	832	2836	13
Kangasala	101	2840	76	1408	441	151	539	237	579	308	1301	20
Kangasniemi	23	1038	14	417	166	105	276	63	185	60	579	5
Kankaanpää	167	3151	182	1370	533	369	670	233	582	205	1772	11
Karjaa	31	1828	27	694	324	209	424	114	352	183	983	23
Karkkila	39	1167	58	465	220	109	255	69	236	74	626	19
Karstula	28	901	12	498	168	48	150	87	173	45	482	4
Kauhava	94	1260	39	570	52	231	304	110	164	115	611	17
Kaustinen	47	1400	27	644	114	163	419	121	199	109	625	6
Kemi	107	5914	97	2644	960	540	1312	551	874	527	2492	17
Kemijärvi	85	2211	56	976	255	204	588	125	367	163	1120	2
Kemiö	25	533	21	221	62	57	129	26	116	47	304	12
Kerava	107	2195	111	1028	262	249	450	168	376	238	1071	953

	Matches	Job seekers	Vacant jobs	Unemployed < 1 year	Unemployed > 1 year	Out of the labour force	Employed	Young	Old	Highly educated	Primary educated	Pop./ km2
Kerimäki	35	1157	28	496	104	122	343	57	194	86	603	5
Keski-Karjala	107	3085	60	1380	615	195	668	200	609	185	1656	7
Keuruu	44	1705	26	756	299	100	388	140	318	125	808	7
Kirkkonummi	56	2496	46	1049	640	183	417	182	551	322	1242	51
Kittilä	41	1059	28	541	115	49	258	69	174	53	551	1
Kiuruvesi	34	1400	18	633	132	195	381	119	186	90	722	8
Kokkola	221	7020	168	3205	1204	633	1435	756	1227	695	3070	16
Kolari	35	792	12	426	59	32	220	47	134	50	423	2
Kotka	188	8809	179	3451	1630	1027	2013	713	1574	856	3907	107
Kouvola	231	7541	184	3314	1217	730	1615	623	1406	808	3455	28
Kristiinankaupunki	87	1767	70	808	201	146	452	124	326	163	811	12
Kuhmo	37	2266	24	1025	330	173	555	158	385	125	1165	2
Kuopio	349	12145	241	5318	1632	1231	3219	1175	1648	1659	4591	50
Kurikka	79	1398	22	635	77	211	363	100	207	85	632	24
Kuusamo	174	4246	85	1895	382	600	1178	365	485	285	2007	3
Kuusankoski	75	2935	75	1336	500	198	518	254	595	232	1485	34
Kyrönmaa	85	1619	103	741	204	168	389	144	269	133	735	17
Lahti	603	22545	569	9084	5027	1709	4518	1848	4675	2059	10976	44
Laitila	53	873	43	393	90	88	210	62	172	63	499	17
Lapinlahti	35	1326	35	648	182	107	296	103	233	81	711	9
Lappajärvi	44	837	17	406	95	71	187	61	160	57	374	8
Lappeenranta	245	11422	198	4967	1998	896	2529	1016	2113	1315	5328	19
Lapua	65	1175	22	642	156	88	181	132	211	131	526	19
Laukaa	45	2603	27	1216	528	156	531	213	527	204	1215	15
Lempäälä	39	1936	32	885	325	154	389	129	404	194	903	28
Leppävirta	79	1508	69	627	192	166	409	92	247	140	681	8
Lieksa	51	2740	35	1147	492	268	634	185	452	143	1494	5
Lohja	149	3963	131	1581	695	420	895	274	750	340	2146	61
Loimaa	66	2260	56	1019	337	226	461	177	428	192	1080	18
Loviisa	48	1894	41	803	368	169	366	125	378	142	1038	16
Mäntsälä	47	1480	44	645	243	144	329	108	279	107	766	24
Mänttä	60	1945	35	786	332	100	490	152	390	142	896	20
Mäntyharju	35	1122	29	484	160	87	269	64	219	71	659	6
Mikkeli	166	7785	168	3148	1424	683	1951	612	1387	944	3445	17
Muonio	25	439	14	214	27	35	127	28	70	30	207	1
Naantali	63	1433	63	663	172	124	350	118	255	190	614	62
Nilsiä	48	1290	44	552	143	156	351	72	188	56	734	5
Nokia	61	3216	48	1432	613	166	719	276	625	267	1528	76
Noormarkku	41	1506	38	630	212	177	333	80	307	111	902	10
Nurmijärvi	110	2228	116	915	404	190	516	139	460	218	1241	84
Orivesi	51	1539	23	688	281	77	352	105	319	120	801	9
Oulu	646	19568	481	8888	3307	2547	3693	2309	2679	2562	7904	28
Outokumpu	40	1956	22	916	329	123	475	136	357	116	1008	9
Paimio	73	768	60	316	56	106	224	48	111	90	360	26
Paltamo	33	773	11	372	59	70	226	41	113	55	396	4
Parainen	25	1156	27	512	181	100	250	87	244	161	537	18
Parikkala	10	887	10	344	235	36	193	53	208	57	505	9
Parkano	57	1412	29	614	165	206	299	81	264	78	811	8
Pello	21	904	8	438	72	82	234	47	146	41	519	3
Pieksämäki	70	3505	63	1477	455	448	893	286	530	281	1664	11

	Matches	Job seekers	Vacant jobs	Unemployed < 1 year	Unemployed > 1 year	Out of the labour force	Employed	Young	Old	Highly educated	Primary educated	Pop./ km2
Pielavesi	39	1125	23	529	128	114	259	73	199	47	684	5
Pietarsaari	136	3456	112	1465	566	206	841	298	675	365	1616	23
Pori	335	15282	293	6400	2853	1253	3329	1252	2989	1486	6953	85
Porvoo	104	5136	117	2346	1022	428	943	436	1085	556	2554	44
Posio	23	893	7	406	98	79	251	53	150	36	532	1
Pudasjärvi	80	1747	37	813	256	184	387	138	253	64	975	2
Puolanka	30	620	11	341	52	42	150	44	100	32	346	2
Raahe	315	5970	145	2511	787	862	1476	610	802	393	2770	11
Raisio	104	4392	116	1740	572	428	1240	309	763	460	2059	42
Ranua	20	853	9	414	132	95	171	66	133	36	482	1
Rauma	165	6770	167	2841	1217	480	1542	583	1322	713	3147	56
Riihimäki	114	4500	92	1880	965	316	937	380	864	377	2251	36
Rovaniemi	222	8885	157	4068	1574	633	1968	913	1258	1121	3382	7
Saarijärvi	38	1948	35	776	331	146	521	132	314	121	1004	7
Salla	20	1141	13	565	143	55	294	67	199	57	663	1
Salo	249	5194	216	2266	711	544	1126	330	1089	501	2742	22
Savonlinna	124	6581	112	2799	1038	675	1599	515	1088	620	3038	10
Savukoski	15	362	6	168	30	36	102	17	56	18	189	0
Seinäjoki	244	6721	153	3128	969	598	1646	688	980	903	2461	30
Siilinjärvi	59	2597	38	1237	333	248	649	235	365	268	1067	22
Sisä-Savo	389	2500	399	1235	352	154	610	163	463	167	1265	6
Sodankylä	44	1992	19	958	319	177	461	141	273	125	924	1
Sotkamo	45	1630	31	739	141	166	499	124	236	137	728	4
Suomussalmi	44	2255	25	1159	283	134	506	173	401	103	1136	2
Suupohja	127	3276	54	1627	471	239	703	296	555	201	1585	10
Tammisaari	27	1093	22	499	217	106	171	89	220	120	569	20
Tampere	924	26933	771	11903	5012	1867	5986	2359	4733	4010	10594	248
Tervola	13	595	8	271	95	31	140	39	110	26	322	3
Toijala	43	2591	40	1132	510	144	577	207	512	184	1399	27
Tornio	123	3044	79	1535	456	229	622	335	468	239	1375	19
Turku	1014	22754	755	10228	4508	2204	3976	2308	3941	3381	10177	212
Tuusula	86	1708	72	721	234	200	377	97	348	222	816	132
Utsjoki	20	228	10	106	12	28	71	10	34	18	119	0
Uusikaupunki	68	2738	54	1309	429	190	549	224	600	200	1420	22
Vaala	33	556	9	301	45	24	145	47	93	30	254	2
Vaasa	414	8957	384	3502	1450	809	2365	831	1484	1238	3621	36
Valkeakoski	96	2631	82	1113	459	164	614	209	564	267	1181	57
Vammala	73	2666	68	1092	432	264	676	191	494	223	1236	18
Varkaus	78	3787	74	1459	626	430	952	285	582	359	1606	49
Vihti	67	1846	55	798	238	221	461	133	333	205	859	41
Viitasaari	31	1938	20	933	294	113	466	155	351	94	990	5
Virrat	66	2038	32	885	229	270	518	120	361	142	1076	6
Ylä-Karjala	74	3411	36	1557	512	281	837	226	576	180	1886	5
Ylitornio	51	997	21	392	74	151	289	48	157	43	549	3
Ylivieska	169	4143	93	1916	443	491	1041	415	617	322	1930	13
Ylöjärvi	56	2156	46	906	359	193	486	144	403	229	923	71
Åland Island	214	963	249	380	50	156	328	83	116	109	408	16
Ääneseutu	57	3233	48	1401	702	174	628	302	650	256	1549	13

APPENDIX 2 Number of neighbours by TTWAs

TTWA	Number of neighbours < 100 km	TTWA	Number of neighbours < 100 km
Alajärvi	10	Lohja	6
Alavus	14	Loimaa	11
Enontekiö	1	Loviisa	6
Eura	10	Mänttä	7
Forssa	11	Mäntyharju	9
Haapajärvi	12	Mikkeli	7
Haapavesi	10	Muonio	3
Hämeenlinna	6	Närpiö	6
Hanko	4	Nilsiä	5
Heinävesi	5	Nivala	13
Heinola	7	Nurmes	4
Helsinki	4	Oulainen	11
Huittinen	13	Oulu	6
Hyrynsalmi	4	Parikkala	4
Iisalmi	7	Parkano	11
Iitti	7	Pelkosenniemi	3
Ilomantsi	2	Pello	2
Imatra	2	Pieksämäki	9
Ivalo	0	Pielavesi	7
Jalasjärvi	14	Pietarsaari	7
Jämsä	4	Pori	10
Joensuu	4	Posio	3
Joutsa	7	Pudasjärvi	4
Juankoski	4	Pulkkila	12
Juva	6	Puolanka	5
Jyväskylä	9	Pyhäjärvi	11
Kajaani	3	Raahe	5
Kalajoki	9	Ranua	3
Kangasniemi	9	Rauma	8
Kankaanpää	9	Reisjärvi	13
Kannus	11	Rovaniemi	4
Kärsämäki	10	Saarijärvi	8
Karstula	8	Salla	2
Kauhajoki	12	Salo	7
Kauhava	12	Savonlinna	5
Kaustinen	10	Savukoski	3
Kemi	3	Seinäjoki	13
Kemijärvi	5	Sodankylä	3
Kemiö	4	Suomussalmi	3
Keuruu	8	Suonenjoki	8
Kitee	4	Taivalkoski	4
Kittilä	2	Tammisaari	5
Kiuruvesi	8	Tampere	9
Kokemäki	10	Tervola	4
Kokkola	7	Tornio	3
Kolari	3	Turku	9
Kotka	3	Utajärvi	3
Kouvola	7	Utsjoki	0
Kristiinankaupunki	8	Uusikaupunki	7
Kuhmo	2	Vaala	5
Kuopio	7	Vaasa	10
Kurikka	13	Valkeakoski	6
Kuusamo	2	Vammala	12
Lahti	7	Varkaus	8
Laihia	9	Viitasaari	8
Laitila	9	Virrat	6
Lappajärvi	9	Ylitornio	4
Lappeenranta	4	Ylivieska	13
Lapua	13	Ähtäri	11
Lieksa	2	Äänekoski	7

CHAPTER 2

MATCHING ACROSS SPACE: EVIDENCE FROM FINLAND[8]

ABSTRACT. This paper takes a matching approach to local labour markets in Finland. The monthly data comprise 120 Local Labour Office areas over a 12-year period between January 1991 and August 2002. The basic matching function is extended to account for spatial spill-overs across borders. The role of population density in the matching process is also examined. According to results, there is a congestion effect among job seekers in the local labour markets, which is further strengthened by spatial spill-overs. The results also indicate that job seekers from neighbouring areas cause additional heterogeneity in the matching process in densely populated areas, which decreases the matching efficiency in these areas.

2.1 Introduction

This paper studies the spatial aspects of local labour markets in Finland, taking a matching approach. The complicated process of exchange in labour markets is summarised by a well-behaved function that gives the number of jobs formed at any moment in time as a function of the number of workers looking for jobs, the number of firms looking for workers, and some other variables (Petrongolo and Pissarides 2001). The matching function in this study is extended to account for spatial spill-overs in the Finnish local labour markets, i.e. new employment relationships are expressed as a function of the stock of open vacancies and job seekers in both the local and neighbouring labour markets.

A common approach in using a matching function has been to concentrate on returns to scale, especially on whether the returns to scale are constant or increasing (e.g. Pissarides 1986, Blanchard and Diamond 1989, Warren 1996). If returns to scale are not constant, the mean transition rates for workers and firms

---

8 This paper has been published in Labour (2005), 19(4), 749-765

engaged in search activity are dependent on the number of searchers. In a matching environment, the returns to search for each trader are related to what other traders do (Petrongolo and Pissarides 2001). The average time that it takes a firm to find workers depends crucially on what job searchers have been doing before they encounter the firm, and the probability that a job seeker will find a job depends on what hiring firms have been doing. If the speed of the matching process changes with the amounts of job seekers and vacancies, returns to scale are not constant.

In the case of increasing returns to scale, there is the possibility of more than one equilibrium, i.e. both a high-activity and a low-activity equilibrium, because of positive externalities in the search process (Pissarides 2000). In a high-activity equilibrium firms and workers put more effort into their search and in a low-activity equilibrium they put less effort into their search, as it yields lower returns. According to Blanchard and Diamond (1989), active thick markets may lead to easier matching, independent of the intensity of the search. In a situation of decreasing returns to scale, the matching function is characterised by diseconomies of scale. In that case, negative congestion effects in the labour markets are stronger than positive externalities.

An interesting feature is that estimates on returns to scale also tend to differ between aggregated and disaggregated data. Coles and Smith (1996) argue that spatially disaggregated matching functions may exhibit increasing returns to scale. However, in studies using the data from local labour markets, decreasing returns to scale are often turned out to be the case (Burda 1993; Burda and Wyplosz 1994; Burda and Profit 1996; Burgess and Profit 2001).

Temporal aggregation is another aggregation problem in the matching modelling. Since the matching function describes a process that takes place continually in spatially distinct locations, the use of discrete-time data always introduces temporal aggregation problems. Burdett et al. (1994) argue that the size of the bias in matching elasticity is approximately a linear function of the measurement interval. Thus, it is important to use as highly disaggregated data as possible.

The data in this study are both spatially and temporally highly disaggregated monthly panel data from 120 Local Labour Offices (LLOs) in Finland over 12 years. The Finnish public employment agency is an important actor in the process of connecting worker and employer search [1]. The present focus is mainly on the spatial aspects of the matching process. The key objectives are to look at the spatial externalities in the worker and employer search process between the areas of Local Labour Offices, asymmetries in these effects, and the significance of population density and the size of the labour market in the matching process.

The results show that the congestion effect among job seekers in local labour markets is both considerable and also spreads across the boundaries of neighbouring LLOs. An open vacancy is filled more easily than a job seeker is employed. The efficiency of the matching process is lower in LLOs with high population density than elsewhere but it increases to higher level than elsewhere when spatial spill-overs are controlled for. This indicates that the congestion effect among job seekers is stronger in densely populated areas than elsewhere. Returns to scale in the matching function are decreasing.

The remainder of this paper is organised as follows. Section 2.2 justifies the perspective of this study on the basis of the literature. Section 2.3 describes the data. Section 2.4 deals with the matching process in Finland, and Section 2.5 concludes.

2.2 Spatial aspects in the matching function

A common practice in earlier matching function research has been to use aggregate time series data for the whole economy or for a particular sector, usually manufacturing. A spatially aggregated matching function in turn is based on the assumptions of disequilibrium in homogeneous micro markets and the limited mobility of labour (Petrongolo and Pissarides 2001). It has also been assumed that submarkets themselves do not suffer from any frictions, but that frictions only exist between submarkets. Markets with unemployment can therefore coexist with markets with open vacancies although no market has both, which makes the existence of an aggregate matching function a possibility. If job matching took place instantaneously, there would be no matching function. Hansen (1970), who was the first to using this kind of modelling, discusses in detail the assumptions on which spatial aggregation is based. In fact, it was on the basis of those assumptions that he derived the Beveridge curve.

In many recent studies spatial aggregation has been rejected and the data collected from local labour markets (Burda and Profit 1996; Coles and Smith 1996; Burgess & Profit 2001; Ilmakunnas and Pesola 2003; Kangasharju et al. 2004 a and b). This practice takes into account the possibility that the aggregate economy is actually a collection of spatially distinct and heterogeneous labour markets that can themselves suffer from many frictions. Blanchard and Diamond (1989) emphasise in their study that large labour market flows in relation to stocks generate delays in the finding of both jobs and workers even though the process was extremely efficient. This practice also enables a closer examination of spatial aspects in the matching function and the magnitude of interactions between the submarkets in the economy.

Thus, it has been found empirically useful to consider the national labour market as a collection of spatially distinct labour markets that interact with each other. Job seekers and firms are located somewhere, and their location is one of the key factors in the matching process. Burda and Profit (1996) extended the basic spatially and temporally disaggregated matching function $M_{i,t} = m_{i,t}(U_{i,t-1},V_{i,t-1})$ to account for spill-overs, $U_{i,t-1}^*$ and $V_{i,t-1}^*$, from neighbouring areas to a local outflow from unemployment. They found that "foreign" unemployment has significant effects on local matching and that the sign and strength of the effect depend on distance.

Burgess and Profit (2001) extended this approach further to account for both an unemployment and a vacancy outflow as dependent variables, and by analysing cyclical variations of spatial dependence in matching. They found cyclical variations in the strength of the spatial spill-overs in the matching process: when agents are in a strong position in the business cycle, they can afford to only search locally. When their position weakens, agents widen their search radius and make a more intense search effort in neighbouring markets. Ilmakunnas and Pesola (2003) found neighbouring unemployment rates to have a negative effect and vacancy rates a positive effect on the local outflow from unemployment in Finland. Their study uses yearly data from 1988 to 1997 from 14 (13 in the models with spill-over variables) labour market districts in Finland. This study, in turn, utilises both spatially and temporally more disaggregated data from the Finnish local labour markets and different modelling techniques.

Burgess and Profit (2001) detected some signs of asymmetry in spatial spill-overs in the matching process, that is, the ratio of an area's own unemployment to unemployment in neighbouring areas affects the magnitude of spill-overs. They found that unemployed workers widen their search radius and search more intensively in neighbouring areas if the unemployment rate is much higher in their home area than in neighbouring areas. Firms may also tend to recruit workers more intensively from areas with very high unemployment.

One central objective of this study is to examine the effects of population density on the matching process at the spatial level. According to Coles and Smith (1996) the search process would be faster and matching rates higher in areas with a dense pool of workers and firms. According to them, the numbers of job seekers and vacancies do not matter; it is the population density of the "market place" that matters. At a given level of job seekers and vacancies both parties would be in close proximity and able to communicate with each other with less effort and at lower cost. In their study, however, wages correlated positively with city size, suggesting better matches in larger cities, since unemployed agents search more effectively when wages are high. According to them, the explanation could be that the benefit from searching in a thicker market might come in the form of higher-quality matches rather than a faster matching rate.

Petrongolo (2001) found in her micro-level study in Britain that thicker and more active markets do not necessarily lead to easier trading. Like Coles and Smith (1996), she suggests that the matching process may display increasing returns where the quality, as opposed to the number, of matches is concerned. Accordingly, thick markets provide better matching opportunities for highly specialised labour and therefore tend to enhance average productivity and wages.

Kano and Ohta (2005) represent an opposing view. They argue that matching efficiency can be negatively correlated with population density. Their explanation is that skill endowments and the reservation wages of workers are distributed more widely in urbanised areas with high population density. On the other side of the market, hiring standards and wage structures are also distributed over a wide range. Thus, higher population density can make it harder to form a successful match.

2.3 The data

Finland's 120 Local Labour Offices are the point of departure in this study. LLOs are administrational units whose geographical borders do not follow Travel-to-Work areas (TTWAs). Therefore, the data on LLOs are aggregated to follow the TTWAs as precisely as possible. The aggregation according to the borders of TTWAs minimises the effects of commuting and mobility of labour that belong to daily life in areas. This kind of aggregation also makes it possible to concentrate on congestion externalities that arise due to job seekers and employers in neighbouring economic areas searching in one's local labour market and to leave spill-over effects that arise due to normal commuting behaviour out of the analysis.

The data are from the registers at the Ministry of Labour that record monthly outflow of vacancies and the end-of-month stocks of registered vacancies and job seekers [2]. The time span of the data is from January 1991 to August 2002. The basic descriptive statistics are given in Table 1. Corresponding facts about the high population-density group of LLOs are given in the same table. This group consists of 42 LLOs with population density as high as or higher than a mean value for the LLOs that is 16 persons per a square kilometre. The descriptive statistics are measured as monthly averages measured over the whole period over LLOs.

The Finnish local labour markets are quite exceptional in the international context. There is a numerically low labour force living dispersed across a very large area. During the 1990s, however, large migration outflows took place from rural areas to urban centres, and the labour force became more concentrated in just a few centres than it had been during previous decades. Highly educated workers, in particular, have been willing to move into urban centres (e.g. Ritsilä and Haapanen 2003). The role of population density in the matching process is thus of considerable interest.

TABLE 1 Basic descriptive statistics

	All Local Labour Offices			**42 LLOs with highest population density**		
	Mean	**Min/Max**	**Std.dev.**	**Mean**	**Min/Max**	**Std.dev.**
Number of all job seekers	4 973	153/153 337	12 091	10 665	366/153 337	19 010
Number of unemployed job seekers	3 152	48/114 832	8 250	6 837	217/114 832	13 081
Number of open vacancies	106	0/8 292	393	231	0/8 292	608
Number of filled vacancies	136	0/9 373	442	286	1/9 373	705
Population density (population/ km^2)	16	0.25/175	21	34	16/175	28
Size of labour force	20 331	494/743 017	64 918	46 791	3 759/743 017	104 438
Unemployment rate (%)	18.5	2.1/40.3	6.3	15.4	2.8/30.5	4.7

Figure 1 shows how the job seeker/vacancy ratio and vacancy outflow behave in the business cycle. During a recession finding a job is harder since many people are searching and few open vacancies are being posted. On the employer side, filling an extra vacancy is more costly when the economy is booming and fewer workers are searching. Thus, the job seeker/vacancy ratio is countercyclical. That ratio increased dramatically during the severe recession in Finland at the beginning of the 1990s. In 1993 there were on average 285 job applicants per vacancy, whereas during 2001 this figure was 95. The vacancy outflow in turn varies cyclically, and was lowest at the deepest point of the recession. The turning point was reached during 1994. Thereafter the job seeker/vacancy ratio decreased while the number of filled vacancies increased. The existence of a negative relationship between the job seeker/vacancy ratio and vacancy outflow is thus very clear.

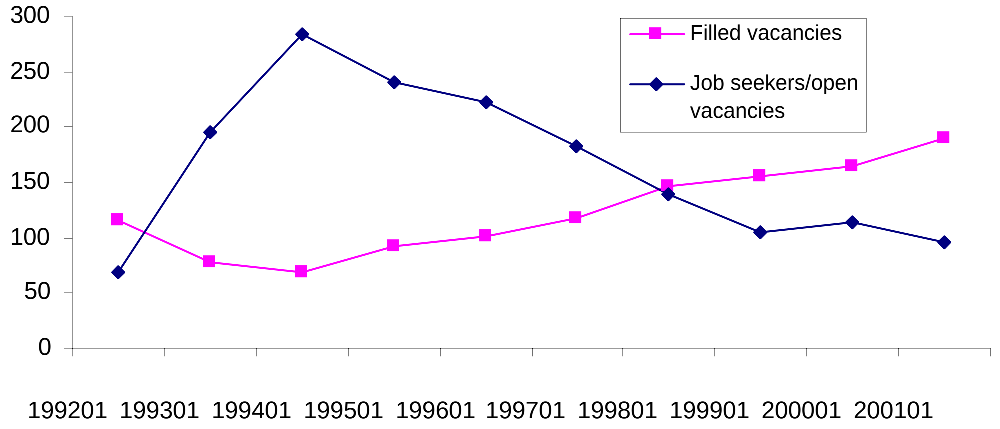

FIGURE 1 Vacancy outflow and job seeker/vacant job ratio, 12-month moving averages

The job seeker variable in this study consists of unemployed job seekers (either unemployed or temporarily laid off), employed job seekers who have registered at their own LLO, and registered job seekers who are currently out of the labour force. Persons working a short week or on a disability pension are also included in the total number of job seekers. Eligibility for unemployment benefits requires active job search: an unemployed person has to report regularly to the Local Labour Office. Employed job seekers are those who are working but are threatened by unemployment, hope to switch jobs, or are in a subsidised job and looking for other type of employment. It has been well documented in previous studies that accounting for the role of non-unemployed job seekers in the matching process is important (e.g. Blanchard and Diamond 1994; Lindeboom et al. 1994; Van Ours 1995; Broersma 1997; Broersma and Van Ours 1999; Hämäläinen 2003; Kangasharju et al. 2004b).

2.4 The matching process in Finland

The main focus of this study are the spatial externalities between the Local Labour Offices in the search process carried out by workers and firms, possible asymmetries in these effects, and the significance of population density and the size of the labour market in the matching process. Estimated matching functions can give a measure of the extent of the externalities in the matching process, which can appear both locally and between bordering areas. The congestion effect measures the negative externality caused by job seekers to other job seekers or by firms to other firms. The thick-market effect measures the positive externality from firms to job seekers or vice-versa.

If the elasticity with respect to job seekers in the matching function is α and the elasticity with respect to vacancies β, α-1 measures the congestion caused by job seekers to other job seekers and β the thick-market effect from firms to job seekers. α measures the positive externality from workers to firms, and β-1 measures the negative externality caused by firms to each other. Thus, higher elasticity estimates indicate less congestion and more positive externalities. (Petrongolo & Pissarides 2001).

The modelling starts with the basic log-linear Cobb-Douglas specification. In subsequent models spatial spill-over variables, the stocks of vacancies and job seekers in neighbouring areas are included in the model. Finally, dummy variables on high population density are included in the model and the effects of population density on matching efficiency, matching elasticities, and the possibility of asymmetry of spatial spill-overs are explored.

2.4.1 Basic specification

The basic model is a Cobb-Douglas specification of the matching function in log-linear form with fixed effects for months and years, and also for districts:

$$\ln M_{i,t} = \mu_i + \alpha \ln S_{i,t-1} + \beta \ln V_{i,t-1} + \eta_y + \gamma_s + u_{i,t}, \qquad (1)$$

where $M_{i,t}$ is the number of filled vacancies in LLO i during month t, $S_{i,t-1}$ and $V_{i,t-1}$ are stocks of registered job seekers and open vacancies in LLO i at the beginning of period t, μ_i is a LLO fixed effect controlling for regional characteristics, η_y is a time fixed effect controlling for aggregate shocks, γ_s a time fixed effect controlling for seasonal fluctuations in the matching process, and $u_{i,t}$ is the error term.

The results of the OLS regressions are summarised in Table 2. In the random-effects specification the constant-returns-to-scale assumption is rejected, and the results indicate diminishing returns to scale (Table 2: specification 1). As is typical of matching models where the dependent variable is a vacancy outflow, the coefficient for vacancies is higher than that for job seekers. The problem in the random-effects specification is that random effects tend to correlate between explanatory variables, and therefore the Hausman test recommends the model with LLO-specific fixed effects.

The coefficients for job seekers and vacancies become lower when LLO-specific fixed effects are included into the model, and the effect for the coefficient of job seekers is stronger (Table 2: specification 2). One explanation could be that appropriate technology in the matching process is needed to support job searching, and the fixed effects capture this technology. Another explanation is that there are so many time-invariant differences between LLOs that district-specific fixed effects have an important role in the model.

TABLE 2 Summary table for the matching models

	Specification			
Dependent variable: ln (filled vacancies)	(1)	(2)	(3)	(4)
ln(stock of job seekers)$_{t-1}$	0.412***	0.236***	0.427***	0.43***
	(0.008)	(0.046)	(0.008)	(0.053)
ln(stock of vacancies)$_{t-1}$	0.437***	0.385***	0.437***	0.377***
	(0.006)	(0.006)	(0.006)	(0.006)
Neighbouring LLO variables				
ln (W x stock of job seekers)$_{t-1}$			-0.065***	-0.496***
			(0.007)	(0.069)
ln (W x stock of vacancies)$_{t-1}$			0.004	0.076***
			(0.007)	(0.009)
Constant	-0.925***		-0.559***	
	(0.049)		(0.054)	
Returns to scale	0.85***	0.62***	0.80***	0.39***
R^2	0.80	0.84	0.80	0.84
		16 680	16 680	16 680

Note: All models include yearly and monthly dummies. Specifications 2 and 4 include LLO- specific fixed effects. Panel-corrected standard errors are in parentheses. *** denote statistical significance at the 0.1% level, ** at the 1% level, and * at the 5% level. In tests for returns to scale, *** denote deviation from unity at the 0.1% level. W denotes a row-standardised binary contiguity matrix based on road distances between LLOs. LLOs with the road distance shorter than 100 km are defined as neighbours

2.4.2 Spatial spill-overs

Adding the stocks of job seekers and vacancies in neighbouring LLOs into the model yields

$$\ln M_{i,t} = \mu_i + \alpha \ln S_{i,t-1} + \alpha^* \ln S^*_{i,t-1} + \beta \ln V_{i,t-1} + \beta^* \ln V^*_{i,t-1} + \eta_y + \gamma_s + u_{i,t}, \quad (2)$$

where $\alpha^*\ln S^*_{i,t-1}$ and $\beta^*\ln V^*_{i,t-1}$ measure the external effects of job seekers and vacancies on neighbouring areas. The neighbourhood matrix W is a binary matrix, whose element takes a value 1 if the centres of two LLO areas locate closer than 100 km from each other by road and 0 otherwise. The neighbourhood matrix is row-standardised so that the neighbouring variables are weighted averages of the values in the neighbouring locations (Anselin 1988).

The results are interesting. In contrast to Burgess and Profit (2001), an increase in job seekers in the neighbouring locations decreases matches in the local area, and an increase in open vacancies in the neighbouring offices somewhat increases local matches (Table 2: specifications 3 and 4). Adding the spill-over variables also has an increasing effect on the coefficient for local job seekers.

Ilmakunnas and Pesola (2003) analyse spatial spill-overs in the matching process in Finland using yearly data from 14 labour market districts with unemployment outflow as a dependent variable. Unlike the modelling used in this study, they posit unemployment and vacancy rates as spill-over variables. According to their results on the fixed-effects model, an increase in unemployment rates in neighbouring regions considerably decreases local outflow from unemployment, and an increase in neighbouring vacancy rates increases local outflow from unemployment.

In the fixed effects model the coefficient for neighbouring job seekers is highly negative (Table 2: specification 4). The congestion caused by neighbouring job seekers seems to be strong. Thus, it seems that job seekers have a negative spill-over effect on the neighbouring labour market – they strengthen the congestion among job seekers in the area. Neighbouring vacancies have a positive externality on local job seekers but this externality is weak. As a consequence, the returns to scale are remarkably lower in the models with spill-over variables than in the basic model.

Interpretations based on dependencies between local filled vacancies and foreign vacancy stocks are not unambiguous. According to the results of Burgess and Profit (2001) on Britain, an increase in the neighbouring vacancy stock decreases the local vacancy outflow but increases the local unemployment outflow. Local unemployed workers are matched with neighbouring vacancies, which decreases the local vacancy outflow. In the present results, however, neighbouring vacancies have a positive externality on local job seekers, resulting in a positive effect on the local vacancy outflow. An explanation could be that the vacancy outflow itself is spatially autocorrelated. However, the results on the spatial lag model with a spatially lagged dependent variable are not statistically significant and thus not reported here.

2.4.3 Does population density matter?

Open vacancies in Finland are filled most quickly in the eastern and northern part of the country (Bunders 2003) where population density is usually low, and most slowly in the southern part of the country, where the Finnish population is highly concentrated. In their efficiency analysis Ilmakunnas and Pesola (2003) found high estimates on matching efficiency in regions with relatively high unemployment rates. This might be caused by quick filling process of relatively few vacancies due to relatively large pool of job seekers

An interesting question is the role of population density in the matching process. According to Coles and Smith (1996), the search process would be faster and matching rates higher in areas with a dense pool of workers and firms. According to them, it is not the numbers of job seekers and vacancies that matter but the population density of the “market place”. At a given level of job seekers and vacancies both parties would be in close proximity and able to communicate with less effort and at lower costs. According to Coles and Smith (1996), higher wages also increase the matching rate, presumably by motivating unemployed to greater search effort.

Kano and Ohta (2005), in turn, investigated regional variation in matching efficiencies due to differences in the distribution of a heterogeneous labour pool and firms. They found that matching efficiency was negatively correlated with population density. Firms have different hiring standards and wage structures because their production technologies are different. Job seekers have different skill levels and different reservation wages. The distribution of hiring standards and skill levels and of wage structures and reservation wages are decisive to the achievement of the successful match.

If the distribution of firms in an area is characterised by lower hiring standards and worker distribution in turn is characterised by a lower skill level, successful matching occurs relatively easily. If, instead, the firms in the area are distributed over a wide range of hiring standards and workers over a wide range of skill levels, successful matching does not happen so easily and quickly. Skill requirements and endowments are distributed more widely in urbanised areas with high population density and, therefore, according to Kano and Ohta (2005), population density would lower matching efficiency.

To determine the effects of population density in the matching process in Finland, population density (population/km^2) is added as an interaction dummy variable into to the model. This dummy variable takes the value 1 if population density in the area is higher than the average value, which is the case in 42 LLOs, and 0 otherwise. The population density dummy shows if the level of matching technology is higher or lower in the LLOs with high population density. The coefficients of the new interaction variables, in turn, show if an area’s own stocks of job seekers and vacancies have stronger or weaker effects on matches in areas with high population density. They also show if the magnitude of spill-over effects is dependent on population density in the local area.

$$\ln M_{i,t} = \mu + \alpha_1 \ln S_{i,t-1} + \alpha_1^* \ln S^*_{i,t-1} + \alpha_2 Pop \times \ln S_{i,t-1} + \alpha_2^* Pop \times \ln S^*_{i,t-1} + \beta_1 \ln V_{i,t-1} + \beta_1^* \ln V^*_{i,t-1} + \beta_2 Pop \times \ln V_{i,t-1} + \beta_2^* Pop \times \ln V^*_{i,t-1} + Pop + \eta_y + \gamma_s + u_{i,t}, \quad (3)$$

where POP denotes the population density dummy and * denotes spatial spill-over variables and their coefficients.

In the specification without spatial spill-over variables (Table 3: specification 5), the effect of job seekers on matches in the LLOs with high population density do not differ from the situation of the other LLOs. The effect of vacancies, in turn, differs: the coefficient is notably higher. Interestingly, the constant term for the high population density areas is very low. Matching rates at the given pools of job seekers and vacancies are thereby much lower than elsewhere, but an increase in vacancies, however, increases matches more than elsewhere. This might be caused by wider qualitative choice in the pool of job seekers in densely populated areas.

TABLE 3 Summary table for the matching models, population density included

Variables	**Specification**	
Dependent variable: ln (filled vacancies)	(5)	(6)
Population density dummy	-0.412***	1.255***
	(0.084)	(0.12)
ln(stock of job seekers) $_{t-1}$	0.365***	0.376***
	(0.01)	0.011)
ln(stock of vacancies) $_{t-1}$	0.409***	0.413***
	(0.007)	(0.007)
population density x ln(stock of vacancies) $_{t-1}$	0.01	0.008
	(0.013)	(0.014)
population density x ln(stock of vacancies) $_{t-1}$	0.111***	0.069***
	(0.009)	(0.01)
Neighbouring LLO variables		
ln (W x stock of job seekers) $_{t-1}$		-0.046***
		(0.007)
ln (W x stock of vacancies) $_{t-1}$		0.008
		(0.008)
population density dummy x ln (W x stock of job seekers) $_{t-1}$		-0.201***
		(0.015)
population density dummy x ln (W x stock of vacancies) $_{t-1}$		0.052***
		(0.013)
Constant	-0.531***	-0.34***
	(0.067)	(0.067)
Returns to scale, LLOs with high population density	0.89***	0.66***
Returns to scale, other LLOs	0.77***	0.74***
R^2	0.80	0.81
Number of observations	16 680	16 680

Note: All models include yearly and monthly dummies. Panel-corrected standard errors are in parentheses. *** denote statistical significance at the 0.1% level, ** at the 1% level, and * at the 5% level. In tests for returns to scale, *** denote deviation from unity at the 0.1% level. W denotes a row-standardised binary matrix based on road distances between LLOs. LLOs with the road distance shorter than 100 km are defined as neighbours.

But what is the situation with regard to spatial spill-overs? The negative effect of neighbouring job seekers on local matches is notably higher in the high-density areas than elsewhere (Table 3: specification 6). The positive effect of neighbouring vacancies, in turn, is higher than elsewhere. These results together indicate that job seekers from other areas cause strong congestion problems among registered job seekers in densely populated areas. New vacancies in neighbouring areas, in turn, make the situation easier.

The results on the efficiency of the matching process are interesting. When the spatial spill-overs are not controlled for, the efficiency of the matching process seems to be much lower in the densely populated areas than elsewhere. This indicates that wider heterogeneity of both job seekers and vacancies cause frictions in the matching process in densely populated areas. When the spill-overs are included into the model, the efficiency term becomes higher than elsewhere. This suggests that job seekers from neighbouring areas cause additional heterogeneity into the matching process in densely populated areas and this heterogeneity is captured by the spill-over variables.

The problem in the analysis on the different groups of areas is that LLO-specific fixed effects are replaced by group-specific ones. Therefore, the analysis reported here would be useful to broaden in the future to utilise linear mixed models that allow the model with dummies for groups to also include LLO-specific variation in the intercept term (Verbeke and Molenberghs 2001).

2.5 Conclusions

According to this study, the Finnish local labour markets suffer from a congestion effect among job seekers and spatial spill-overs from neighbouring areas further strengthen the congestion. As a consequence, returns to scale in the empirical matching function are decreasing.

The results indicate that the population density matters in the matching process. The level of matching efficiency is lower in areas with high population density but after controlling for the negative effect of job seekers from neighbouring areas it becomes higher than elsewhere. Thus, the results suggests that firms in the areas of high population density are distributed over a wide range of hiring standards and the workers over a wide range of skill levels and that this heterogeneity is largely caused by job seekers from neighbouring areas. The spatial spill-over variables capture this effect.

Endnotes

1 The proportion of jobs mediated by LLOs in Finland is quite high. It varied between 1993 and 2002 from 49 per cent to 71 per cent, and was lowest in 1993 and highest in 1996 (Hämäläinen 2003). On average, the share is 60 per cent. Public employers have a statutory duty to report an open vacancy, whereas for private firms this is optional. Despite this, the largest reported share of open vacancies is in the private sector (Räisänen 2004).

2 Unemployment statistics are also compiled by Statistics Finland using a questionnaire. Statistics Finland publishes the official unemployment rate in Finland, which is comparable to that of other EU countries. Regional information in that survey is, however, available on a more aggregated level than that used here. Moreover, the unemployment register includes much more detailed information on job applicants and filled vacancies.

Acknowledgements

This research was funded by the Academy of Finland (project number 53374). I am grateful to Jaakko Pehkonen, Hannu Tervo, Aki Kangasharju, ERSA 2004 Congress participants, and anonymous referees for helpful comments and suggestions.

REFERENCES

Anselin L. (1988) Spatial Econometrics: methods and models. Kluwer Academic Publishers.

Blanchard O. and Diamond P. (1989) The Beveridge curve. Brookings Papers on Economic Activity, 1, 1-76.

Blanchard O. and Diamond P. (1994) Ranking, unemployment duration, and wages. Review of Economic Studies, 61, 417-434.

Broersma L. (1997) Competition between employed and unemployed job searchers: is there a difference between the UK and The Netherlands. Applied Economics Letters 4, 199-203.

Broersma L. and Van Ours J. (1999) Job searchers, job matches and the elasticity of matching. Labor Economics 6, 77-93.

Bunders M. (2003) Kohtaantofunktio suomalaisilla työmarkkinoilla vuosina 1988-2002 – alue- ja ammattiryhmien väliset erot kohtaannon tehokkuudessa. [in Finnish]. Bank of Finland, Discussion Papers No. 32.

Burda M. (1993) Unemployment, labour markets and structural change in Eastern Europe. Economic Policy, 16, 101-137.

Burda M. and Profit S. (1996) Matching across space: evidence on mobility in the Czech Rebublic. Labour Economics, 3, 255-278.

Burda M. and Wyplosz C. (1994) Gross worker and job flows in Europe. European Economic Review, 36, 1287-1315.

Burdett K., Coles M., and Van Ours J. (1994) Temporal aggregation bias in stock-flow models. CEPR Discussion Paper No. 967.

Burgess S. and Profit S. (2001) Externalities in the matching of workers and firms in Britain. Labour Economics, 8, 313-333.

Coles M. and Smith E. (1996) Cross-section estimation of the matching function: evidence from England and Wales. Economica, 63, 589-597.

Hansen B. (1970) Excess demand, unemployment, vacancies and wages. Quarterly Journal of Economics, 84, 1-23.

Hämäläinen H. (2003) Työvoiman rekrytointi toimipaikoissa vuonna 2002. [in Finnish]. Ministry of Labour, Helsinki.

Ilmakunnas P. and Pesola H. (2003) Regional labour market matching functions and efficiency analysis. Labour: Review of Labour Economics and Industrial Relations, 17, 3, 413-437.

Kangasharju A., Pehkonen J., and Pekkala S. (2004a) Returns to scale in a matching model: evidence from disaggregated data. University of Jyväskylä, School of Business and Economics, Working Paper No. 275.

Kangasharju A., Pehkonen J., and Pekkala S. (2004b) Matching, on-the-job search and temporal aggregation: panel data evidence from Finland. University of Jyväskylä, School of Business and Economics, Working Paper No. 276.

Kano S. and Ohta M. (2005) Estimating a matching function and regional matching efficiencies: Japanese panel data for 1973-1999. Japan and the World Economy, 17, 25-41.

Lindeboom M., Van Ours J., and Renes G. (1994) Matching employers and workers: an empirical analysis on the effectiveness of search. Oxford Economic Papers, 46, 45-67.

Petrongolo P. (2001) Reemployment probabilities and returns to matching. Journal of Labor Economics, 19, 3, 716-741.

Petrongolo P. and Pissarides C. (2001) Looking into the black box: a survey of the matching function. Journal of Economic Literature, 39, 390-431.

Pissarides C. (1986) Unemployment and vacancies in Britain. Economic Policy, 3, 676-690.

Pissarides C. (2000) Equilibrium unemployment theory. 2nd ed. Cambridge: MIT Press.

Ritsilä J. and Haapanen M. (2003) Where do the highly educated migrate? Micro-level evidence from Finland. In Haapanen, M.: Studies on the determinants of migration and the spatial concentration of labour. University of Jyväskylä.

Räisänen H. (2004) Työvoiman hankinta julkisessa työnvälityksessä. [in Finnish]. Government Institute for Economic Research, Research Reports No. 107.

Van Ours J. (1995) An empirical note on employed and unemployed job search. Economics Letters, 49, 447-452.

Verbeke G. and Molenberghs G., 2001. Linear mixed models for longitudinal data. Springer Series in Statistics.

Warren R. (1996) Returns to scale in a matching function. Economic Letters, 50, 135-142.

CHAPTER 3

HETEROGENEITY OF JOB SEEKERS IN LABOUR MARKET MATCHING[9]

ABSTRACT. This study examines the matching of heterogeneous job seekers and vacant jobs. Job seekers are divided into four employability groups according to their labour market status: employed job seekers, job seekers out of the labour force, unemployed job seekers with a spell of unemployment shorter than a year, and long-term unemployed job seekers. The data set is temporally, spatially, as well as with respect to job seekers' labour market status highly disaggregated monthly data from 146 Local Labour Offices (LLOs) in Finland over 14 years. According to the results, the employability of job seekers differs, and therefore the composition of the pool of job seekers in a local labour market affects the ability of that market to form successful matches. The long-term unemployed appear to have negative effect on matches while job-seekers out of the labour force notably improve the matching production.

3.1 Introduction

This study examines job matching in local labour markets focusing on the status of job seekers in the matching process, and on spatial autocorrelation in local labour market conditions. The matching function, which summarises the complicated trading process in the labour market by expressing the outcome of the investment of resources by firms and workers in the trading process as a function of the inputs (Pissarides 2000), is utilised as a modelling device.

There has been considerable debate about ranking in the labour market between different kinds of job seekers, and it has been shown that all job seekers are not all equally ranked in firms' recruitment processes. For their part

---

9 The paper was presented in ERSA 2005 Congress in Amsterdam in the session for refereed papers. The study was funded by the Academy of Finland (project number 53374). I am grateful to Jaakko Pehkonen, Hannu Tervo, and ERSA Congress 2005 participants for helpful comments. Special thanks to Jukka Lahtonen for cooperation with the model formulation.

job seekers are heterogeneous, which in turn leads to large variation in the search intensity and reservation wages of individuals. Search intensity is determined by search costs, the cost of unemployment, and the expected returns from employment (Petrongolo and Pissarides 2001). Higher expected returns from employment increase the opportunity cost of being unemployed and therefore also increase search intensity.

Burgess (1993) found that the competition for jobs between employed and unemployed job seekers is an important determinant of the outflow rate from unemployment. He also found that the more vacancies there were in the job market, the greater was the share of employed job seekers of all job seekers. Therefore, the crowding out effect of employed job seekers is connected with the number of open vacancies and cyclical variations. Anderson and Burgess (2000) utilised the same model, assuming the search process of employed workers to be endogenous. According to the results, when the economy is booming and the number of job offers increases, employed workers find it more profitable to spend time searching for new vacancies if they are not satisfied with their current ones.

According to Burgess and Turon (2003), more on-the-job search leads to a more stagnant pool of unemployed workers since on-the-job search lowers both the inflow to unemployment and outflow from it. In addition, the stock of vacancies is more, the unemployment outflow less, and the unemployment inflow more cyclically sensitive in markets with on-the-job search than in those without it. On the level of unemployment Burgess and Turon (2003) did not, however, find on the-job-search to have any notable effect.

Pissarides (1994) found on-the-job search more likely to occur with short as opposed to long job tenure, owing to the accumulation of job-specific human capital in the case of the latter. Van Ours (1995) adds that there are differences between vacancies in how competition for jobs occurs. Vacancies for which many different recruitment channels are used tend to be those for which competition exists between employed and unemployed job seekers. Broersma and Van Ours (1998) also argue that it is very important to account for the effect of non-unemployed job seekers in the matching process. Mumford and Smith (1999) divided job seekers into three groups – employed job seekers, unemployed job seekers, and job seekers out of the labour force – and found evidence that employers rank job seekers according to their labour market status.

In the case of long-term unemployment it is clear, from many previous studies, that long-term unemployment cause shifts in the aggregate matching function (e.g. Budd et al. 1988; Layard and Bean 1989; Pissarides 1992). This is associated on the unemployed side of the labour market with both a reduction in the search intensity of the long-term unemployed and a deterioration in human capital and on the firms' side with the reluctance of employers to hire them (Layard and Bean 1989). Pissarides (1992) argues that the question is one of thin market externality. After a negative shock many people lose their jobs. If their unemployment spells lengthen, they become less attractive to the employers. Fewer jobs come on the market in the next period, and even more unemployed persons become long-term unemployed. Because job seekers as a whole have less human capital, the job market becomes thin.

In his further study, Pissarides (1994) included employed job seekers in the model and found that the existence of on-the-job search influences the composition of jobs and creates congestion for unemployed workers. In practice, firms advertise relatively more jobs that are targeted at employed job seekers, which makes it more difficult for unemployed persons to find a suitable job. This leads to an outward shift in the Beveridge curve, since unemployment remains high despite the increase in vacancies.

Thus, job competition and ranking both between employed and unemployed job seekers and between short-term and long-term unemployed job seekers takes place. Long-term unemployed job seekers are in the least competitive position and their search intensity is also lower than that of other job search groups. Blanchard and Diamond (1994) note, however, a difference between a tight and a depressed labour market. In a tight labour market, a long-term unemployed job seeker may be the only applicant for a given vacancy, whereas in a depressed labour market most vacancies attract many applicants.

In this paper, the data are temporally, spatially, and with respect to the labour market status of job seekers highly disaggregated. The data consist of monthly panel data from 146 Local Labour Offices (LLOs) in Finland over a period of 14 years. In addition to unemployed job seekers with an unemployment spell shorter than a year, three groups of job seekers with special labour market status are distinguished. These groups are long-term unemployed job seekers, employed job seekers, and job seekers out of the labour force. The data set is drawn from the registers of the Ministry of Labour. Therefore, it includes job seekers and vacancies registered at the public employment agency, which plays an important role in the labour market in Finland.[1]

The paper is organised as follows. Section 3.2 describes the data, and Section 3.3 derives the matching models with the four categories of heterogeneous job seekers. Section 3.4 reports the results, which show that long-term unemployed job seekers have a negative effect and job seekers out of the labour force a positive effect on matches. Section 3.5 concludes.

3.2 Data description

The data set consists of monthly panel data from 146 Local Labour Offices (LLOs) in Finland over 14 years (1991:01-2004:09). It is temporally, spatially, as well as by the labour market status of job seekers highly disaggregate data drawn from the registers of the Ministry of Labour. Table 1 gives the descriptive statistics of the data set. The period from 1991 to 2004 in the Finnish labour market covers the serious recession at the beginning of the 1990s, the recovery after it and the boom of information technology at the end of 1990s. The development of the tightness of the labour market (vacant jobs / all job seekers) during the period is presented in Figure 1.

TABLE 1 Descriptive statistics

	Average	Min / Max	Std. Dev.
Filled vacancies	122	0 / 7 717	371
Vacant jobs	98	0 / 7 566	331
Job seekers	4 017	153 / 109 477	7 770
Share all unemployed	0.61	0.24 / 0.86	0.09
< 1 year	0.49	0.2 / 0.8	0.09
> 1 year	0.12	0 / 0.33	0.09
Share out of the labour force	0.08	0.002 / 0.44	0.05
Share employed	0.23	0.06 / 0.56	0.05
Vacant jobs / all job seekers	0.03	0 / 3.24	0.06

Note: In addition to unemployed, employed and job seekers out of the labour force, job seekers include job seekers who are not positioned in these categories. This group consists of e.g. those registered job seekers who are working a short week.

On average, about 12 per cent of all job seekers are long-term unemployed. Figure 1 shows the dramatic increase in the long-term unemployment at the beginning of 1990s from about zero level to almost 17 per cent at worst. The share of employed job seekers was about 23 per cent in 1991, decreasing during the following two years of serious recession, and increasing thereafter. The share of job seekers out of the labour force decreased slightly during the recession but showed a notable increase after the recession. Therefore, the importance of both groups of non-unemployed job seekers, employed job seekers and job seekers out of the labour force increased in the pool of all job seekers during the research period. Figure 1 is in line with the previous literature on the behaviour of heterogeneity variables in different economic conditions and therefore gives a starting point for the more profound analysis.

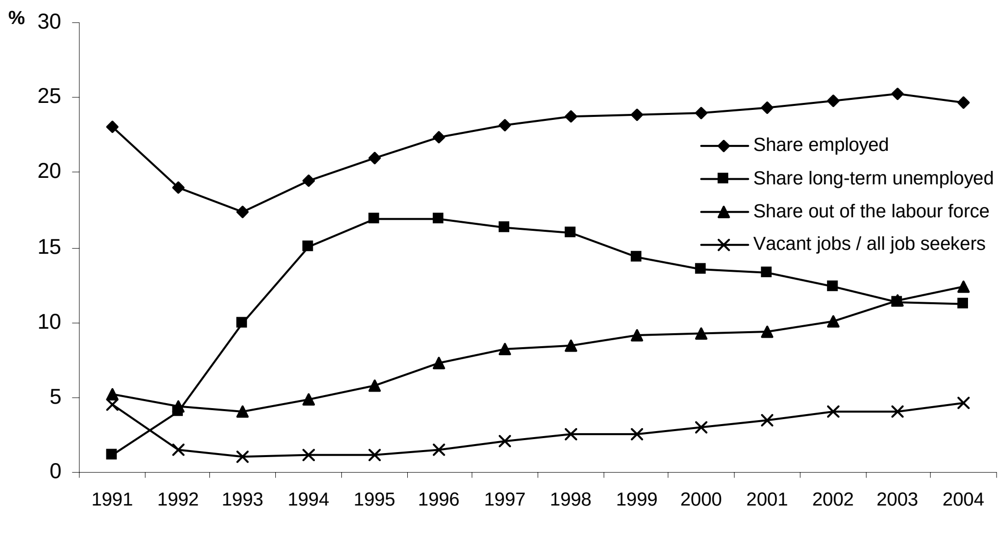

FIGURE 1. The composition of the job-seeker stock and the tightness of the labour market, averages by years across all LLOs

3.3 Matching models with heterogeneity of job seekers

Unemployed job seekers with a spell of unemployment shorter than a year form the main group of job seekers (49 per cent on average), and therefore they are assumed to form a "core" group of job seekers. Ranking issues are included in the model by adding long-term unemployed job seekers (the continuous spell of unemployment longer than a year), employed job seekers, and job seekers out of the labour force into the model, and allowing each of these three groups the possibility of getting jobs different from those of the "core" group of job seekers. Since the labour market status of job seekers affects their employability in the labour market, changes in the shares of different kinds of job seekers in the whole pool affects the rate at which successful matches are formed in the labour market.

The model is a Cobb-Douglas matching function with some transformations. The basic version is

$$M_{i,t} = A(S_{i,t-1})^{\alpha}(V_{i,t-1})^{\beta}, \tag{1}$$

where $M_{i,t}$ denotes filled vacancies during a month t in LLO i, $S_{i,t-1}$ all job seekers in a LLO at the end of the previous month, and $V_{i,t-1}$ vacant jobs in a LLO at the end of the previous month.

Heterogeneity of job seekers is added into the model assuming differently positioned job seekers to have different employability. An efficient stock of job seekers, ESS, is derived by following Ibourk et al. (2004) and Kangasharju et al. (2005) with some variations.

$$ESS = (U + E_{LTU}LTU + E_{OUT}OUT + E_{EMP}EMP), \tag{2}$$

where U denotes the core group of job seekers, i.e., unemployed job seekers with unemployment spell less than a year. LTU denotes long-term unemployed job seekers, OUT job seekers out of the labour force, and EMP employed job seekers. The employability of the group U is set equal to 1. The coefficients E with varying subscripts denote the employability of other job-seeker groups with respect to U. It also holds that

$$ESS = (U + LTU + OUT + EMP + E_{LTU}LTU + E_{OUT}OUT + E_{EMP}EMP - LTU - OUT - EMP) \tag{3}$$

which is equal to

$$ESS = S + (E_{LTU} - 1)LTU + (E_{OUT} - 1)OUT + (E_{EMP} - 1)EMP, \tag{4}$$

where S denotes the whole stock of job seekers. $S_{i,t-1}$ in (1) is now replaced by the effective stock of job seekers $ESS_{i,t-1} = S_{i,t-1} + \delta LTU_{i,t-1} + \lambda OUT_{i,t-1} + \gamma EMP_{i,t-1}$, where for example δ denotes $(E_{LTU} / E_{CORE} - 1)$ and other coefficients respectively. E_{CORE} denotes the employability of unemployed job seekers with the unemployment spell less than a year and it is set to equal to 1. If the employability of the special groups differs from that of the core group, their coefficients δ, λ and γ and will differ from zero. The matching function with the effective stock of job seekers takes the form

$$M = A(S + \delta LTU + \lambda OUT + \gamma EMP)^{\alpha} V^{\beta}, \tag{5}$$

Multiplying and dividing ESS by S before adding up into to the matching function yields

$$M_{i,t} = A[S_{i,t-1}(1 + \delta(LTU / S)_{i,t-1} + \lambda(OUT / S)_{i,t-1} + \gamma(EMP / S)_{i,t-1}]^{\alpha} V^{\beta}{}_{i,t-1} \tag{6}$$

By taking logarithms, and utilising Taylor approximation to assume that $\ln[1 + \delta(LTU / S) + \lambda(OUT / S) + \gamma(EMP / S)] \approx \delta(LTU / S) + \lambda(OUT / S) + \gamma(EMP / S)$ we obtain the following empirical fixed-effects model:

$$\ln M_{i,t} = \mu_i + \alpha \ln S_{i,t-1} + \beta \ln V_{i,t-1} + \alpha\delta(LTU / S)_{i,t-1} + \alpha\lambda(OUT / S)_{i,t-1} + \alpha\gamma(EMP / S)_{i,t-1} + \varepsilon_{i,t} \tag{7}$$

3.4 Results

The method of estimation is the Prais-Winsten regression with panel-corrected standard errors and an assumption of contemporaneous correlation across panels (see StataCorp. 2005). Temporal correlation AR(1) is also allowed with panel-specific autocorrelation coefficients. This method takes into account the possibility of differently behaving matching in LLO-areas in the turbulent research period, and allows for cross-sectional dependence in the matching as well.

The results show that variation in the vacancy stock contributes to filled vacancies much more than variation in the job-seeker stock. The coefficient for vacancies is rather robust across specifications and during the research period. The job-seeker side in turn suffers from strength congestion, and the matching function exhibits decreasing returns to scale (Table 2). Cutting the recession period out from the analysis, however, notably increases the importance of job seekers: the coefficient increases from 0.14 to 0.35. Therefore, the matching has improved together with improving labour market conditions, and it has approached the matching function reported by Petrongolo and Pissarides (2001).

TABLE 2 Results

Variables	Specifications			1995/01-2004/09
Dependent variable: ln M_t	(1)	(2)	(3)	(4)
ln S_{t-1}	0.06* (0.03)	0.13***(0.03)	0.14* (0.05)	0.35***(0.07)
n V_{t-1}	0.44***(0.004)	0.42***(0.004)	0.41***(0.01)	0.41***(0.01)
Heterogeneity variables				
$(LTU/S)_{t-1}$		-0.79***(0.14)	-0.96***(0.23)	-1.4***(0.27)
$(OUT/S)_{t-1}$		2.04***(0.12)	2.11***(0.18)	1.77***(0.22)
$EMP/S)_{t-1}$		0.72***(0.11)	0.48**(0.18)	-0.11 (0.23)
Returns to scale	0.5***	0.55***	0.55***	0.76***
R_2	0.74	0.75	0.98	0.98
Number of observations	23 944	23 944	23 944	17 082
Modified Wald test for groupwise heteroskedasticity	7 090***	6 999***		
Employability coefficients				
Long-term unemployed		-5.08	-5.86	-3.00
Job seekers out of the labour force		16.69	16.07	6.06
Employed job seekers		6.54	4.43	1.00

Notes: All models include yearly and monthly dummies and LLO-specific fixed effects. Standard errors (in specifications 3-4 panel-corrected) are in parentheses. In specifications 3-4 error terms are assumed to be autocorrelated AR(1) with autocorrelation coefficient specific to all panel. *** denote statistical significance at the 0.1% level, ** at the 1% level, and * at the 5% level. In tests for returns to scale, *** denote deviation from unity at the 0.1% level. Specification 4 includes only the period 1995:01-2004:09.

In addition to the core group, long-term unemployed, employed and job seekers out of the labour force, variable S_{t-1} includes job seekers who does not belong to any of these groups. They are those who are e.g. working a short week. In order to guarantee the reference group being exactly unemployed job seekers with the spell of unemployment shorter than a year, the group of uncategorised job seekers has been controlled for in estimations analogously with other groups. They do not, however, enter the model with a significant coefficient, i.e., the employability of them does not differ from that of the core group.

The heterogeneity of job-seekers plays an important role in the matching, and the coefficients of the heterogeneity variables take the expected signs. A percentage point increase in the share of long-term unemployed decreases matches by 0.96 per cent (Specification 3), while a corresponding increase in job seekers out of the labour force increases matches by about 2 percent and in employed job seekers by about 0.48 per cent. If we only consider the period 1995-2004 (leaving the recession out) the negative effect of long-term unemployment strengthens, and the special effect of employed job seekers disappears. Lindeboom et al. (1994) found employment offices in the Netherlands to be the least efficient recruitment channel for employed workers compared to other channels, since it is not designed for mediating jobs for already employed persons. They also argue that the sample of employed job seekers using employment offices may be a negative selection of the total sample of employed job seekers. These findings may hold in Finland as well when usual economic conditions are prevailing.

Owing to the specification of the model, both matching elasticity and the employability of different groups together determine the effect of the composition of the job seeker stock on the amount of successful matches. Table 2 shows the employability of the three special groups of job seekers with respect to the core group. For example, the employability coefficient E_{LTU} for long-term unemployed job seekers is obtained by $\alpha\delta/\alpha + 1$, where αδ is the estimated coefficient for the share of that group in the regression model, α is the coefficient for all job seekers in the model, and $\delta = E_{LTU}-1$. The coefficients are derived in section 3.3.

The employability coefficients for the long-term unemployed calculated from specifications 2-4 varies between -5.9 and -3, and for the job seekers out of the labour force from 6.1 to 16.7. The corresponding variation for employed job seekers lies between 1 and 6.5. If we consider the effective stock of job seekers, which includes all groups of job seekers weighted by their employability coefficients, an increase in long-term unemployed job seekers by one person decreases the relevant stock of job seekers by 3 persons (according to the specification 4). On the other hand, we need only one job seeker out of the labour force to compensate for 6 job seekers from the core group.

There are many alternative explanations for the positive effect of job seekers out of the labour force on successful matches in LLOs. Firstly, they may be preferable to other job seekers from the recruitment perspective. Their skills may be the most suitable for the vacancies in question or the signal they send to employers may make them preferable to other categories of job seekers. Secondly, their search effort may be greater than that of others, especially if they are recent school-leavers. Thirdly, job seekers out of the labour force are probably the most flexible job seeker group and the most willing to accept e.g. part time jobs. This group includes students and parents caring for their children at home, for whom a part-time job would be the most attractive way to earn money.

3.5 Conclusions

The results of this study indicate that the employability of job seekers with differing labour market status also differs, and therefore the composition of the pool of job seekers in a local labour market affects the ability of that market to form successful matches. According to the results, an increase in the share of job seekers out of the labour force increases successful matches, while an increase in the share of long-term unemployed job seekers weakens the ability of a labour market to form successful matches. There are reasons for this on both sides of the labour market. Employers rank job seekers in the recruitment process according to their labour market status, and search intensity differs between different kinds of job seekers. Job seekers out of the labour force are probably the most flexible group of job seekers in the Finnish local labour markets.

Endnotes

1 The proportion of jobs mediated by LLOs in Finland is high. It varied between 49 and 71 per cent on the period 1993-2002, being lowest in 1993 and highest in 1996 (Hämäläinen 2003). The mean is around 60 per cent.

REFERENCES

Anderson P. and Burgess S. (2000) Empirical matching functions: estimation and interpretation using state-level data, The Review of Economics and Statistics, vol. 82, pp. 93-102.

Anselin L. (1988) Spatial Econometrics: methods and models, Kluwer Academic Publishers.

Blanchard O. and Diamond P. (1994) Ranking, unemployment duration, and wages, Review of Economic Studies, vol. 61, pp. 417-434.

Broersma L. (1997) Competition between employed and unemployed job searchers: is there a difference between the UK and The Netherlands?, Applied Economics Letters, vol. 4, pp. 199-203.

Broersma L. and Van Ours J. (1999) Job searchers, job matches and the elasticity of matching, Labour Economics, vol. 6, pp. 77-93.

Budd A., Levine P., and Smith P. (1988) Unemployment, vacancies, and the long-term unemployed, Economic Journal, vol. 98, pp. 1071-1091.

Burgess S. (1993) A model of competition between unemployed and employed job searchers: an application to the unemployment outflow rate in Britain, Economic Journal, vol. 103, pp. 1190-1204.

Burgess S. and Turon H. (2003) Unemployment equilibrium and on-the-job search, IZA Discussion Paper No. 753.

Hämäläinen H. (2003) Työvoiman rekrytointi toimipaikoissa vuonna 2002, [in Finnish], Ministry of Labour, Helsinki.

Ibourk, A., Maillard, B., Perelman, S., and Sneesens, H. (2004) Aggregate matching efficiency: a stochastic production frontier approach, France 1990-1994, Empirica, vol. 31, pp. 1-25.

Kangasharju A., Pehkonen J., and Pekkala S. (2005) Temporal and Spatial Aggregation in the Matching Function, University of Jyväskylä. Unpublished manuscript.

Layard R. and Bean C. (1989) Why does unemployment persist?, Scandinavian Journal of Economics, vol. 91, pp. 371-396.

Lindeboom M., Van Ours J., and Renes G. (1994) Matching employers and workers: an empirical analysis on the effectiveness of search, Oxford Economic Papers, vol. 46, pp. 45-67.

Mumford K. And Smith P. (1999) The hiring function reconsidered: on closing the circle, Oxford Bulletin of Economics and Statistics, vol. 61, pp. 343-364.

Petrongolo B. and Pissarides C. (2001) Looking into the black box: a survey of the matching function, Journal of Economic Literature, vol. 39, pp. 390-431.

Pissarides C. (1992) Loss of skill during unemployment and the persistence of employment shocks, Quarterly Journal of Economics, vol. 107, pp. 1371-1391.

Pissarides C. (1994) Search unemployment with on-the-job search, Review of Economic Studies, vol. 61, pp. 457-475.

Pissarides C. (2000) Equilibrium unemployment theory, MIT Press.

StataCorp. (2005): Stata Statistical Software: release 7.0. College Station, TX: StataCorp LP.

Van Ours J. (1995) An empirical note on employed and unemployed job search, Economics Letters, vol. 49, pp. 447-452.

CHAPTER 4

DOES POPULATION DENSITY MATTER IN THE PROCESS OF MATCHING HETEROGENEOUS JOB SEEKERS AND VACANCIES? [10]

ABSTRACT. This paper studies the matching of job seekers and vacant jobs using data on local labour markets. We estimate differences in the ability of the local markets to form new matches and trace whether these differences can be explained by the differing population densities across markets or by the heterogeneity of job seekers measured by the distribution of their education level. We find that high-density areas are more efficient in forming matches than other areas despite frictions caused by the wider heterogeneity of job seekers in those areas than elsewhere.

4.1 Introduction

The recent literature on labour market matching has placed increased emphasis on the heterogeneity of job seekers and vacant jobs (Burgess 1993; Pissarides 1994; Van Ours 1995; Broersma and Van Ours 1998; Mumford and Smith 1999; Anderson and Burgess 2000; Fahr and Sunde 2001; Burgess and Turon 2003). According to the findings of these studies, heterogeneity is the main source of frictions and therefore a crucial issue when investigating labour market matching. In addition, most of the recent studies take the labour market not as homogeneous entity but as a collection of several heterogeneous micro-markets.

---

10 This paper was written together with Jukka Lahtonen. We both are equally responsible for all sections. The article is forthcoming in *Empirica*. The study was funded by the Academy of Finland (project number 7210269) and Yrjö Jahnsson Foundation. We are grateful to anonymous referees in Empirica, Jaakko Pehkonen, Aki Kangasharju, Pekka Ilmakunnas, and ERSA 2005 Congress participants for useful comments and suggestions.

This paper analyses the matching of vacant jobs and job seekers differing by education in local labour markets of varying population densities. The motivation for the study comes from three sources. Firstly, Coles and Smith (1996) argue that the density of population, not the amounts of vacant jobs and job seekers, determines the matching rates in the labour market. In particular, they claim that the matching process is more efficient the more concentrated the market is, because the communication of parties close to each other requires lower effort and imposes lower costs.

Kano and Ohta (2005) in turn take another view on the role of density. They argue that successful matches may occur easily if the skill-distribution of workers and the hiring standards of firms are concentrated on the same level. However, in urbanised areas, where the skill-distribution tends to be wide, the concentration of the job-seeker characteristics may differ from that sought by employers. It implies obstacles to the matching process despite the fact that the actors are in close geographical proximity.

Thirdly, Wahba and Zenou (2003) consider population density as a proxy for the size of social networks and therefore also for the speed of information transmission. They conclude that as long as the size of the network remains reasonable, size will have a positive effect on matching efficiency. However, the effect may become negative in very densely populated areas owing to the dominance of the congestion effect.

In this paper, we estimate how Local Labour Offices (LLOs) in Finland form successful matches at given levels of inputs in the matching process. In addition, we investigate whether the efficiency of the matching process deviates in areas with a deviant population density. By controlling for heterogeneity in the labour market, thus allowing different employability for job seekers with different levels of education, we can estimate differences in matching inefficiency that do not result from the educational distribution of job seekers and the education requirements of employers.

Our data are informative and highly disaggregated. The data set consists of monthly panel from 146 LLOs in Finland over 10 years. Job seekers are divided into three groups according to their level of education. These groups are primary, secondary, and highly education. The data set is drawn from the registers of the Ministry of Labour, and it contains job seekers and vacancies registered at local public employment agencies which have an important role in the labour market in Finland.[1]

The paper is organised as follows: Section 4.2 defines the concept of matching efficiency. Section 4.3 describes the data, Section 4.4 introduces the model, and Section 4.5 presents the results. Section 4.6 concludes.

4.2 Matching efficiency

The technical matching efficiency in the labour market captures the ability of the labour market to form successful matches between job seekers and vacancies. It is determined by the product of the rate at which job seekers and employers meet and the probability that a contact will lead to a successful match (Anderson and Burgess 2000). Inefficiency in a technical sense measures how far the observed output lies from the output that could be achieved at given inputs. In the stochastic frontier literature the production function defines the upper boundary for output (see e.g. Kumbhakar and Lovell 2000; and for the matching function context see e.g. Ibourk et al. 2004).

We assume that labour market matching follows the production process determined by the familiar Cobb-Douglas production function. Bleakley and Fuhrer (1997) as well as Wall and Zoega (2002) estimate shifts in the matching function interpreting region-specific fixed-effects as inefficiency terms. The standard panel data model with time-invariant individual effects in a common logarithmic form is

$$\ln y_{i,t} = \alpha_i + \beta' \ln x_{i,t} + v_{i,t}, \qquad (1)$$

where i refers to a regional unit and t to a time period. Without a distributional assumption but allowing for a correlation between α_i and $\ln x_{i,t}$ this model can be estimated consistently by 'within- groups' ordinary least squares. In the context of the efficiency analysis, the fixed effects model is interpreted as

$$\ln y_{i,t} = \alpha + \beta' \ln x_{i,t} + v_{i,t} - u_i, \qquad (2)$$

where u_i satisfies $u_i \geq 0$, and $u_i > 0$ is an indication of technical inefficiency, which in the fixed-effects framework is assumed to be time-invariant (Kim and Schmidt 2000). For this logarithmic specification the technical efficiency of the region i is $TE_i = \exp(-u_i)$.

If we follow Kim and Schmidt and define $\alpha_i = \alpha - u_i$, the model collapses to a standard panel data model (1). We have $\alpha_i < \alpha$ and $u_i = \alpha - \alpha_i$. Then the region with the highest intercept α_i is that with the lowest inefficiency u_i. Since unit-specific constants are estimated by the mean within-unit deviation of $\ln y_{i,t}$ from $\beta' \ln x_{i,t}$, observations are not compared to the zero inefficiency level but to each other (Greene 2005a). Therefore, we obtain the relative inefficiency and equivalently relative technical efficiency estimators instead of absolute measures (Kim and Schmidt 2000; Greene 2005a and 2005b). Hence the most efficient region is scaled to have an inefficiency level of 0 and a technical efficiency level of 1. These relative estimators for inefficiency and technical efficiency are

$$u_i^* = \max(\alpha_i) - \alpha_i \,,\ TE_i^* = \exp(-u_i^*)\,. \qquad (3)$$

The problem in this fixed effects framework is that all time-invariant heterogeneity is interpreted as inefficiency (Greene 2005a). In order to catch the source of the heterogeneity, we separate our LLOs into different groups according population density and estimate the average efficiencies in areas with differing population density. We control for the educational structure of job seekers to find out whether it explains part of the efficiency differences. After controlling for the educational structure, estimated fixed effects indicate inefficiency that does not owe to the educational structure[2].

4.3 Data description

We have time series for 146 Local Labour Offices, LLOs, in Finland. The source of the data is the unemployment register of the Ministry of Labour. Each series contain observations from the period 1995:1 - 2004:9 (117 months). The variables in the matching function are filled vacancies within a month and the stocks of vacant jobs and job seekers at the end of each previous month. Job seekers are furthermore differentiated between three levels of education, namely primary, secondary and high level of education[3]. Table 1 provides descriptive statistics for the variables at the LLO level, and Table 2 describes the connection between our educational classification and the ISDEC 1997 classification.

TABLE 1 Descriptive statistics

	Filled Vacancies	Vacant Jobs	All Job Seekers	Primary Educated	Secondary Educated	Highly Educated
Min	0	0	183	83	65	6
1st Q	25	14	1225	630	484	75
Median	54	36	2082	1025	887	158
Mean	142	114	4045	1862	1725	457
3rd Q	120	91	3723	1830	1604	335
Max.	7717	7566	106329	49937	41946	20731

Note: Statistics are calculated from monthly observations across all LLOs.

TABLE 2 Relation between 3-group classification and ISDEC 1997.

ISDEC 1997	Name	3-group classification
Level 0	Pre-primary education	-
Level 1	Primary education	1 Primary
Level 2	Lower secondary education	1 Primary
Level 3	Upper secondary education	2 Secondary
Level 4	Post secondary non-tertiary ed.	2 Secondary
Level 5	1st. stage of tertiary education:	
	5B-programmes	3 Highly
	5A-programmes	3 Highly
Level 6	2nd stage of tertiary education	3 Highly

To study the effect of population density on matching efficiency we rank LLOs on the basis of their average population densities (population/km^2) during the period. The rank order of the LLOs according to population density remained stable during the research period despite some minor changes within offices. Three groups of LLOs are formed: group 1 contains the 36 LLOs with highest population density, and group 3 the 36 LLOs with lowest population density. Thus, the groups consist of LLOs belonging to the first and fourth quartiles of the population density distribution. The remaining 74 offices belong to group 2.

Table 3 describes the composition of the job-seeker stock according to the level of education in the three density groups. We see that the distribution of the educational structure is widest in the group of high population density. On average, 46 per cent of job seekers in group 1 have primary education and almost 12 per cent are highly educated, while in the group 3 the corresponding proportions are about 53 per cent and 6 per cent. This gives a starting point for our econometric analysis of the role of heterogeneity in matching efficiency in areas with differing population densities.

TABLE 3 The composition of job-seeker stocks according to education level in density groups

Proportions (in % of the whole stock)	**Group 1**	**Group 2**	**Group 3**
Averages			
Primary	46	48.9	53.2
Secondary	42.3	42.5	41.1
Highly	11.7	8.6	5.7
Minimums			
Primary	31.5	33.2	39.3
Secondary	25.5	26.5	28.1
Highly	3.5	2.1	1.2
Maximums			
Primary	67.6	69.8	69
Secondary	55.8	57.5	53.9
Highly	26.8	24.5	17.4

Note: If all education groups were equally represented in the job seeker stock, their shares would be 33.3 %.

4.4 Matching model

In a basic matching function the inputs are the number of job seekers U and the number of vacant jobs V. The output is produced matches, i.e. filled vacancies M formed within a given time period. If job seekers or firms search more intensely for a match, we observe an increase in the number of matches, indicating an improvement in the matching technology or efficiency. Thus, from now on, we denote the average employability of job seekers by s and the corresponding ability of vacancies to become filled by a. The aggregate matching function is now (Pissarides 2000)

$$M = m(sU, aV) \tag{4}$$

where the first term, *sU*, is the number of the efficiency units of job seekers and the latter term is the number of the efficiency units of vacancies. Furthermore, the pools of job seekers and vacancies can be distinguished into three groups according to their education level and education requirement level, respectively. Note that now *s* is the average of the group-specific employability of job seekers and *a* the average ability of vacancies to become filled.

$$M = m\left(\sum_{i=1}^{3} s_i U_i, \sum_{j=1}^{3} a_i V_i\right) = m(sU, aV) \tag{5}$$

For estimation purposes, we measure the employability of the different groups with respect to the employability of one particular group, let it be s_2 (secondary educated job seekers)[4]. In the model, the employability of these groups is set to equal to 1[5]. By adding and subtracting terms the function comes into the following Cobb-Douglas form (See Appendix for details):

$$M_{i,t} = A\left((U + (s_1 - 1)U_1 + (s_3 - 1)U_3)_{i,t-1}{}^{\alpha} V_{i,t-1}{}^{\beta}\right) \tag{6}$$

Dividing the job seeker input by *U* and taking logs yields

$$\ln M_{i,t} = c_i + \alpha \ln(U)_{i,t-1} + \alpha \ln(1 + \gamma(\frac{U_1}{U})_{i,t-1} + \eta(\frac{U_3}{U})_{i,t-1}) + \beta \ln(V)_{i,t-1}, \tag{7}$$

where γ denotes ($s_1 - 1$) and $\eta = (s_3 - 1)$ respectively. Taylor-expansion provides linear approximation for the second term of the expression.

$$\ln M_{i,t} = c_i + \alpha \ln(U)_{i,t-1} + \alpha\gamma(\frac{U_1}{U})_{i,t-1} + \alpha\eta(\frac{U_3}{U})_{i,t-1} + \beta \ln(V)_{i,t-1} \tag{8}$$

The parameters of the expression have clear interpretations: α captures the overall elasticity of matches with respect to job seekers and β that for vacancies. The coefficients for the share variables give the average percentage change in matches given a change of one percentage point in the relative share of that job-seeker group. As seen in equation (8), both the overall elasticity of matches with respect to inputs and differences in employability affect the significance of the composition of the job-seeker stock in the matching process. On the other hand, the composition of stocks partly determines the elasticity of matches with respect to stocks.

4.5 Estimation results

4.5.1 Fixed-effects models

The estimation method in our fixed-effects specifications is the Prais-Winsten regression with panel corrected standard errors. Disturbances are assumed to be heteroscedastic, i.e. each panel is allowed to have its own variance. In order to allow for possible dependencies in matching processes across panels, disturbances are assumed to be contemporaneously correlated, i.e. each pair of panels is allowed to have its own covariance. It is also assumed that there is first-order autocorrelation within panels and that the coefficient of AR(1) process is common to all the panels. The results from the basic fixed-effects model without these assumptions are also reported (Table 4; Specification 1).

The importance of vacancies in matching production is higher than that of job seekers, which is usual in the matching model with the flow of filled vacancies as a dependent variable (see Petrongolo and Pissarides 2001). This difference however decreases as the model specifications improve. Positive externalities due to increases in inputs are not large enough in either side to cancel out negative congestion effects owing to a rise in inputs (especially on the job-seeker side), and the matching process exhibits decreasing returns.

Both highly and primary educated job seekers improve the production of successful matches in LLOs in comparison to the secondary educated. A percentage point increase in the share of highly educated job seekers increases matches by 2.1 per cent and a corresponding rise in the share of primary educated by 1.7 per cent (Table 4; Specification 3). These coefficients indicate that there is relatively higher demand for primary and highly educated than secondary educated workers. Fahr and Sunde (2001) find that an additional job seeker in the group of lowest education level creates relatively higher probability of a new match than is the case in other groups. This indicates a congestion effect among the secondary educated in the public employment agency suggesting that it is not an efficient job-finding channel for them.

TABLE 3 Results of estimations for fixed-effects models

Variables	**Specification**		
Dependent variable: ln Mt	(1)	(2)	(3)
ln U_{t-1}	0.25***(0.05)	0.32***(0.08)	0.37***(0.08)
ln V_{t-1}	0.43***(0.01)	0.42***(0.01)	0.41***(0.01)
Education variables			
$(HIGH/U)_{t-1}$			2.12***(0.57)
$(LOW/U)_{t-1}$			1.67***(0.3)
Other controls			
$(LTU/U)_{t-1}$			-2.11***(0.26)
$(Share < 25)_{t-1}$			-0.43 (0.49)
$(Share > 50)_{t-1}$			-0.71 (0.41)
Autocorrelation coefficient		0.2	0.18
Returns to scale	0.68***	0.74***	0.78***
R^2	0.78	0.98	0.98
Number of observations	17 082	17 082	17 082
Modified Wald test for groupwise heteroskedasticity	7962***		
Average value of fixed effects			
All		-0.32	-1.17
Group 1		-0.18	-1.02
Group 2		-0.34	-1.18
Group 3		-0.40	-1.30
Relative efficiency			
Group 1		0	0
Group 2		0.163	0.156
Group 3		0.220	0.273
Relative efficiency			
Group 1		1	1
Group 2		0.85	0.86
Group 3		0.80	0.76

Notes: All models include yearly and monthly dummies. Standard errors (in Specifications (2) and (3) panel-corrected) are in parentheses. In Specifications (2) and (3) the error terms are assumed to be contemporaneously correlated and autocorrelated AR(1) with an autocorrelation coefficient common to all panels. *** denote statistical significance at the 0.1% level, ** at the 1% level, and * at the 5% level. In tests for returns to scale, *** denote deviation from unity at the 0.1% level. Relative efficiency and inefficiency are calculated according to formula (3) presented in Section 4.2. LTU stands for long-term unemployed persons.

In order to take into account the sources of heterogeneity not related to the job seekers educational distribution we control for the composition of the stock of job seekers according to the persistence of unemployment and the age structure. The shares of job seekers below age of 25 years or over 50 years do not have a significant effect on matches, while the increase in long-term unemployment has an negative effect with a coefficient -2.1. Similar results have been reported e.g. Budd et al. (1988), Layard and Bean (1989), as well as Pissarides (1992).

Figure 1 plots the fixed effects against population density. The positive dependence between them is clear: fixed effects increase with population density with a correlation of 0.33. Comparison of the estimated fixed effects from the model with the heterogeneity variables and the model without them is reported in Table 4. We follow the method introduced in Section II and scale the level of technical efficiency of the most efficient group to be equal to 1 and that of the inefficiency correspondingly equal to 0. In Specification (2) without controls for heterogeneity the relative efficiency estimates are 0.85 for the middle group and 0.80 for the low-density group. Interestingly, incorporating heterogeneity controls into the model widens the efficiency gap between the most densely and the least densely populated areas. This indicates that a narrower distribution of the education level of job seekers and the requirements of vacant jobs brings some efficiency gains in the matching production in sparsely populated areas. This somewhat supports Kano's and Ohta's (2005) view on the role of heterogeneity and population density in the matching process.

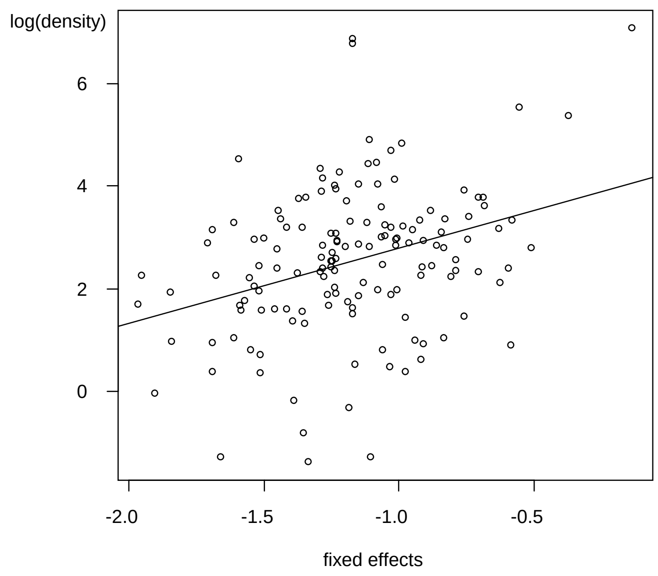

FIGURE 1 Estimated fixed effect against population density (logarithmic transformation)

Note: Correlation coefficient is 0.33 at 1 % level of significance.

4.5.2 Mixed-effects model

Next we test for the significance of the grouping of LLOs according to population density by utilising the linear mixed model technique (Verbege and Molenberghs 2001). The linear mixed model provides additional information in connection with two aspects. First, we are able to organize the research units by groups, which allows for statistical testing of possible differences. Second, we can relax the assumption that the coefficients for variables across groups are equal.

The model to be estimated is expressed in a hierarchical, two-stage analytical form, or equivalently in the Laird-Ware form (Laird and Ware, 1982). Following this view the model, which includes fixed effects for intercepts, vacant jobs, all job seekers, the relative shares of the education groups and some other control variables, can be expressed as

$$\ln M_{i,t} = c + c_1 D_1 + c_2 D_2 + \alpha \ln(U_{i,t-1}) + \alpha D_1 \ln(U_{i,t-1}) + \alpha D_2 \ln(U_{i,t-1}) +$$
$$\alpha\gamma\left(\frac{U_1}{U}\right)_{i,t-1} + \alpha\gamma D_1\left(\frac{U_1}{U}\right)_{i,t-1} + \alpha\gamma D_2\left(\frac{U_1}{U}\right)_{i,t-1} + \alpha\eta\left(\frac{U_3}{U}\right)_{i,t-1} + \alpha\eta D_1\left(\frac{U_3}{U}\right)_{i,t-1} + \alpha\eta D_2\left(\frac{U_3}{U}\right)_{i,t-1}$$
$$+ \beta\ln(V_{i,t-1}) + \beta D_1 \ln(V_{i,t-1}) + \beta D_2 \ln(V_{i,t-1}) + \rho X_{t-1} +$$
$$b_i + \varepsilon_{it};$$
$$b_i \sim N(0, \psi^2);$$
$$\varepsilon_{it} \sim N(0, \sigma^2 \lambda_{itt}), Cov(\varepsilon_{it}, \varepsilon_{it'}) = \sigma^2 \lambda_{itt'}$$
(9)

In the above formulation, α, β, c, c_1, c_2, γ, η and ρ are fixed effects. $U_{i,t-1}$ denotes the number of job seekers in LLO i at period $t-1$, and correspondingly $V_{i,t-1}$ is the number of vacant jobs. X_{t-1} refers to other control variables including the relative shares of long-term unemployed job seekers, job seekers aged above 25 and those aged over 50. The second line of the equation includes the proportion of primary/highly educated job seekers of the total number of job seekers. The index 1 indicates primary education and 3 high level of education.

We add random intercept b_i , which is assumed to be normally distributed with variance ψ^2, and a constant across LLOs. Random effects are considered as random variables, not as parameters, so only their standard errors are estimated. ε_{it} is a normally distributed error term with specified covariance between LLOs. The differences between the density groups are estimated using dummy-variables D_1 and D_2 representing LLOs belonging to density groups 1 and 2, respectively. We expect random effects to be possibly correlated with explanatory variables, which is a common feature in econometric models. Therefore we do not attempt to infer causal statements from the results; instead, we only estimate the effects that the explanatory variables have on the response variables according to the data.

The results obtained from the restricted maximum likelihood estimation are reported in Table 5. Specification (4) does not include the education share variables. Both intercepts and slopes are allowed to vary across LLOs. Among low-density LLOs the average intercept value is -4.3, the coefficient for job seekers 0.9 and that for vacancies 0.4. There appears to be increasing returns to scale in that group. The interactions between the explanatory variables and group-dummies indicate that the intercept is 6.0 higher in the high-density group and 3.9 higher in the middle group than in the low-density group. The result indicates that factors not related to changes in the numbers of job seekers and vacancies contribute most strongly to efficiency in the high-density group and most weakly in the low-density group. Comparison of the coefficients for job seekers reveals that congestion effect among job seekers is stronger in the middle and high-density groups than among low density LLOs.

TABLE 5 Results of estimations for mixed-effects models

Variables Dep. variable: ln M	Specification (4)	 (5)
Intercept	-4.29***(0.39)	-3.74***(0.44)
ln U_{t-1}	0.90***(0.05)	0.72***(0.06)
ln V_{t-1}	0.36***(0.01)	0.36***(0.01)
Education variables		
$(HIGH/U)_{t-1}$		1.14*(0.49)
$(LOW/U)_{t-1}$		2.16***(0.31)
Interactions with d1:		
d1*Intercept	5.97***(0.52)	3.97***(0.59)
d1*ln U_{t-1}	-0.84***(0.06)	-0.38***(0.07)
d1*ln V_{t-1}	0.14***(0.01)	0.12***(0.01)
Education variables		
d1*$(HIGH/U)_{t-1}$		1.22 (0.42)
d1*$(LOW/U)_{t-1}$		-2.95***(0.47)
Interactions with d2:		
d2*Intercept	3.94***(0.44)	3.09***(0.51)
d2*ln U_{t-1}	-0.59***(0.06)	-0.38***(0.07)
d2*ln V_{t-1}	0.10***(0.01)	0.10***(0.01)
Education variables		
d2*$(HIGH/U)_{t-1}$		-0.35 (0.39)
d2*$(LOW/U)_{t-1}$		-1.08 **(0.37)
Other control variables:		
$(LTU/U)_{t-1}$		-2.01***(0.18)
$(Share < 25)_{t-1}$		-0.92*(0.36)
$(Share > 50)_{t-1}$		-0.67*(0.27)
Random effects:		
Intercept	0.42	0.38
residual	0.48	0.48

Notes: Monthly and yearly dummies are included in both specifications to capture time effects. Significance levels: *** significant at level 0.1 %, ** at level 1%, * at level 5 %. Dummy variable d1 refers to the group of high-density LLOs, d2 to the middle group and low-density LLOs are the reference group. LTU stands for long-term unemployed persons.

In Specification (5) the effect the distribution of education across job seekers is controlled for by including education share variables to the model. Among low-density LLOs an increase in the relative share of primary educated job seekers has a positive effect on matches whereas in the high-density group the corresponding share of lower educated seekers displays a negative impact. The coefficients for the share of highly educated job seekers do not seem to differ statistically significantly across density-groups. We also include three other control variables, namely relative shares of long-term unemployed job seekers, unemployed seekers aged below 25 and unemployed seekers aged over 50. All these control variables negatively affect the number of monthly matches. The order of the intercepts does not change after inclusion of the additional variables: the intercept is on average highest among high-density LLOs, and lowest in the low-density group.

The results are in line with the starting hypothesis: high-density LLOs are more efficient in matching job seekers and jobs but the wider distribution of job seekers' education level and employers' education requirements in those LLOs cause some inefficiency. In particular, an increase in the share of lower educated job seekers is likely to decrease the matching performance of high-density LLOs.

4.6 Conclusions

This paper studied the matching of job seekers and vacant jobs in local labour markets. We estimated the ability of the local markets to form new matches and traced whether the differences in it could be explained by the differing population density across markets and by the distribution of the education level of job seekers. The starting hypothesis was that high-density areas would be otherwise more productive than the others but that their efficiency might be negatively affected by the job-seeker heterogeneity. Our results are in line with this hypothesis. In particular, the share of job seekers with low education is higher in high-density areas than is needed with respect to the education requirements of employers. We conclude that the high-density areas are the most efficient at producing matches despite frictions caused by the wider heterogeneity of job seekers in those areas than elsewhere.

APPENDIX

An efficient stock of job seekers takes the following form:

$$ESS = (U_2 + s_1U_1 + s_3U_3) \quad \text{(A.1)}$$

The employability of group 2, secondary educated job seekers, is set equal to 1. The coefficient s_1 denotes the employability of primary educated with respect to secondary educated and s_3 the employability of highly educated with respect to secondary educated job seekers. It also holds that

$$ESS = (U_1 + U_2 + U_3 + s_1U_1 + s_3U_3 - U_1 - U_3) \quad \text{(A.2)}$$

which is equal to

$$ESS = (U_2 + (s_1 - 1)U_1 + (s_3 - 1)U_3, \quad \text{(A.3)}$$

where U denotes the whole stock of job seekers. Thus, the matching function with an efficient stock of job seekers takes the form

$$M = A(U + \gamma U_1 + \eta U_3)^{\alpha} V^{\beta}, \quad \text{(A.4)}$$

where γ denotes $(s_1\text{-}1)$ and η $(s_3\text{-}1)$. Dividing the job-seeker input by U yields

$$M = A[U(1 + \gamma(\frac{U_1}{U}) + \eta(\frac{U_3}{U})]^{\alpha} V^{\beta} \quad \text{(A.5)}$$

Endnotes

1. The proportion of jobs mediated by LLOs in Finland is high. Between 1993 and 2002 it varied from 49 to 71 per cent, being lowest in 1993 and highest in 1996 (Hämäläinen 2003). On average, the share is about 60 per cent. Public employers have a statutory duty to report an open vacancy, whereas for private firms this is optional. Despite this, the largest reported share of vacancies is in the private sector (Räisänen 2004).
2. It is worth noting that the educational structure of job seekers, per se, does not affect matching efficiency. It calls for successful matching between the education level of job seekers and the education requirements of employers that the matching works more efficiently. Therefore, employability differences cannot directly be derived from search intensity or the ranking behaviour of firms but rather from matching between the supply of and demand for education.
3. In the original data set nine levels of education were distinguished. This system of classification has been used by Statistics Finland since 1971, and was revised in 1997 to correspond to the international standard ISDEC 1997. For the estimations we aggregate the job seekers into three groups of education levels. Table 2 presents the relation between the three-group classification and ISDEC 1997.
4. Due lack of data, we are not able to allow for the different ability to become filled for vacancies with different education requirements. We assume that owing to the

interactive nature of the production of matches, controlling for the heterogeneity of job seekers also controls for the requirements on the vacancy side. There are no positive effects due to the particular education level of a job seeker on the employability if there is no demand for that level of education.

5. Our modelling follows the Appendix in Ibourk et al. (2004) with some exceptions.

REFERENCES

Anderson, P.M. & Burgess, S.M. (2000) Empirical Matching Functions: Estimation and Interpretation Using Disaggregate Data. Review of Economics and Statistics 82: 93-102

Bleakley H. & Fuhrer, J.C. (1997) Shifts in the Beveridge Curve, Job Matching and Labour Market Dynamics. New England Economists Review 0:9: 3-19

Broersma L. & Van Ours, J. (1998) Job Searchers, Job Matches and the Elasticity of Matching. Labour Economics 6: 77-93

Budd, A, Levine, P. & Smith, P. (1988) Unemployment, Vacancies, and the Long-term Unemployment. Economic Journal 98: 1071-1091

Burgess, S.M. (1993) A Model of Competition between Unemployed and Employed Job Searchers: An Application to the Unemployment Outflow Rate in Britain. Economic Journal 103: 1190-204

Burgess, S.M. & Turon H. (2003) Unemployment Equilibrium and On-the-job Search. IZA Discussion Paper No. 753

Coles, M.G. & Smith, E. (1996) Cross-Section Estimation of the Matching Function: Evidence from England and Wales. Economica 63: 589-98

Fahr, R. & Sunde, U. (2001) Disaggregate Matching Functions. IZA Discussion Paper No. 335

Greene, W. (2005a) Fixed and Random Effects in Stochastic Frontier Models. Journal of Productivity Analysis 23: 7-32

Greene, W. (2005b) Reconsidering Heterogeneity in Panel Data Estimators of the Stochastic Frontier Model. Journal of Econometrics 126: 269-303

Hämäläinen H. (2003) Työvoiman rekrytointi toimipaikoissa vuonna (2002) [in Finnish], Ministry of Labour, Helsinki

Ibourk A.; Maillard, B.; Perelman, S.; Sneessens H.R. (2004) Aggregate Matching Efficiency: A Stochastic Production Frontier, France 1990-1994. Empirica 31: 1-25

Kano, S. & Ohta, M. (2005) Estimating a Matching Function and Regional Matching Efficiencies. Japan and the World Economy 17: 25-41

Kim, Y. & Schmidt, P. (2000) A Review and Empirical Comparison of Bayesian and Classical Approaches to Inference on Efficiency Levels in Stochastic Frontier Models with Panel Data. Journal of Productivity Analysis 14: 91-118

Kumbhakar, S. and Lovell, C.A. (2000) Stochastic Frontier Analysis. Cambridge University Press

Laird, N.M. & Ware, J.H. (1982) Random-effects Models for Longitudinal Data. Biometrics, 38: 963-974

Layard, R & Bean, C. (1989) Why Does Unemployment Persist? Scandinavian Journal of Economics 91: 371-396

Mumford, K. & Smith, P.N. (1999) The Hiring Function Reconsidered: on Closing the Circle. Oxford Bulletin of Economics and Statistics 61: 343-364

Petrongolo, B, & Pissarides, C. (2001) Looking into the Black Box: A Survey of the Matching Function. Journal of Economic Literature 39: 390-431

Pissarides, C. (1992) Loss of Skill during Unemployment and the Persistence of Employment Shocks. Quarterly Journal of Economics 107: 1371-1391

Pissarides, C. (1994) Search Unemployment with On-the-job Search. Review of Economic Studies 61: 457-475

Pissarides, C.A. (2000) Equilibrium unemployment theory. MIT Press

Räisänen H. (2004) Työvoiman hankinta julkisessa työnvälityksessä. [in Finnish], Government Institute for Economic Research Reports No. 107

Van Ours, J. (1995) An Empirical Note on Employed and Unemployed Job Search. Economic Letters 49: 447 – 472

Verbege G. & Molenberghs G. (2001) Linear Mixed Models for Longitudinal Data. Springer Series in Statistics. Springer-Verlag New York, Inc.

Wahba, J. & Zenou, Y (2003) Density, Social Networks and Job Search Methods: Theory and Application to Egypt. CEPR Discussion Paper 3967, London

Wall, H. J. & Zoega, G. (2002) The British Beveridge Curve: A Tale of Ten Regions. Oxford Bulletin of Economics and Statistics 64: 261-80

CHAPTER 5

COMPOSITION OF THE JOB-SEEKER STOCK IN LABOUR MARKET MATCHING: A STOCHASTIC FRONTIER APPROACH[11]

ABSTRACT. This paper investigates the technical efficiency of labour market matching taking a stochastic frontier approach. The data set consists of monthly data from 145 Local Labour Offices (LLOs) in Finland over the period 1995/01-2004/09. The true fixed-effects model is utilised in order to separate cross-sectional heterogeneity from inefficiency. According to the results, there are notable differences in matching efficiency between regions, and these differences contribute significantly to the number of filled vacancies. If all regions were as efficient as the most efficient one, the number of total matches per month would increase by over 10 %. If inefficiency had no role in the matching function, the number of matches would increase by almost 24 %. The weight of the composition of the job-seeker stock and other environmental variables in the determination of matching inefficiency is on average 61 %. In particular, job seekers out of the labour force and highly educated job seekers improve technical efficiency in the matching function.

5.1 Introduction

Labour markets are commonly characterised by a large number of individuals searching for new jobs simultaneously with a large number of firms searching for new workers. This phenomenon is due to frictions in the matching process: job seekers and vacant jobs do not match immediately. To a certain extent, frictions are necessary to guarantee the quality of matches, but at worst they

11 This paper was funded by the Academy of Finland and Yrjö Jahnsson Foundation. I am grateful to Aki Kangasharju, Jaakko Pehkonen, Ari Hyytinen and Mika Kortelainen for helpful comments and suggestions.

slow down the matching process yielding higher structural unemployment: job seekers do not match the available vacancies. Reasons behind the inefficiency of matching can be related to skill mismatch between job seekers and vacant jobs, to regional mismatch problems, to low search effort by job seekers, to ranking behaviour by firms, to impediments in the transmission of information, to wide heterogeneity of job seekers and firms in the labour market, and to inefficiency in the functioning of employment agency (e.g. Broersma and Van Ours 1999; Pissarides 1994; Anderson and Burgess 2000; Petrongolo and Pissarides 2001; Hynninen and Lahtonen 2007).

The qualitative matching of inputs is a crucial determinant of matching efficiency, as it determines whether or not a contact between a job seeker and a vacancy leads to a match. Therefore, in this study we focus on the role of the composition of the job-seeker stock in matching efficiency. We take a stochastic frontier approach to labour market matching in Finland (Coelli et al 1999; Kumbhakar and Lovell 2000). The concept of technical efficiency in the production function, presented in detail in Farrell (1957), is in the matching function determined by the ability of regions to produce matches by the stocks of job seekers and vacant jobs (Fahr and Sunde 2002; Ilmakunnas and Pesola 2003; Ibourk et al. 2004; Fahr and Sunde 2005). The matching function is interpreted as a frontier that determines the upper boundary for successful matches that could be produced by the given stocks of job seekers and vacant jobs.

The traditional fixed-effects model provides time-invariant estimates for efficiency relative to the best in the sample (Kim and Schmidt 2000). The problem in this approach is that all time-invariant heterogeneity across cross-sections is included in the efficiency term. Stochastic frontier analysis (SFA) avoids this problem of misspecification by providing a tool for the separation of efficiency from heterogeneity (Greene 2005a and b). Efficiency is also allowed to vary over time, which is a realistic assumption in long time series. In addition, a model specification of the Battese and Coelli (1995) type allows efficiency terms to be functions of variables that cause frictions in the matching process.

Ilmakunnas and Pesola (2003) and Hynninen et al. (2006)[12] have previously applied stochastic frontier analysis to the production of hires from unemployment in Finland. In this study, we investigate the efficiency of the production of filled vacancies. We apply Greene's (2005a and b) true fixed-effects stochastic frontier model with the inefficiency terms of the Battese and Coelli (1995) type. We utilise estimated efficiencies in order to calculate the quantitative effects of total inefficiency on matches. The matching function represents the production of filled vacancies during a month with job seekers and vacant jobs as inputs. The data are monthly panel data from 145 Local

12 Hynninen et al. (2006) studies the technical efficiency of hiring processes and the contribution of inefficiencies to the aggregate unemployment rate in 19 largest travel-to-work areas (TTWAs) in Finland. The study finds substantial efficiency differences between TTWAs, which further contribute significantly to the aggregate unemployment rate, i.e. 2.5 percentage points.

Labour Offices (LLOs) in Finland from the period 1995/01 – 2004/09[13]. The data consist of registered job seekers, vacant jobs and filled vacancies reported in state-run LLOs[14]. The data provide information on the composition of the job-seeker stock according to labour market status, age, and education.

The paper is organised as follows: Section 5.2 introduces the stochastic frontier approach to the matching function and specifies the models, Section 5.3 describes the data set, Section 5.4 discusses the results of the efficiency analysis and Section 5.5 concludes. Notable regional differences in efficiency were found. According to the results, aggregate level matches would increase by over 10 % if all regions were as efficient as the most efficient one. If there were no inefficiency at all in the matching, the number of filled vacancies would increase by almost 24 %. In the job-seeker stock, job seekers out of the labour force and highly educated job seekers make the most important contribution to matching efficiency by notably increasing it.

5.2 Specification of the stochastic frontier matching model

We assume that labour market matching follows the production process determined by the familiar Cobb-Douglas production function (Pissarides 2000):

$$M_{i,t} = AS^{\alpha}{}_{i,t-1}V^{\beta}{}_{i,t-1}, \tag{1}$$

where $M_{i,t}$ denoted filled vacancies (vacancy outflow) during a month t in LLO i, $S_{i,t-1}$ the job-seeker stock and $V_{i,t-1}$ the stock of vacancies at the end of the previous month.

The stochastic logarithmic production frontier model takes the following form, defined by Battese and Coelli (1995) and Greene (2005a and b):

$$\ln M_{i,t} = [\mu_i + \alpha \ln S_{i,t-1} + \beta \ln V_{i,t-1}] + v_{i,t} - u_{i,t} \tag{2}$$

The expression in square brackets states the matching frontier that gives the maximum output, matches, which can be achieved at given amounts of production inputs, job seekers and vacancies. According to Greene (2005a and b) the model can be called the true fixed-effects model since it separates the true fixed effect μ_i from inefficiency $u_{i,t}$. In other words, time-invariant cross-sectional heterogeneity in the production of matches is separated from the

---

13 Åland Island is excluded from the analysis due to its exceptional labour market conditions.

14 The state-run employment agencies play an important role in the Finnish labour market. The proportion of jobs mediated by LLOs varied between a low of 49 in 1993 and a high of 71 per cent in 1996 over the period 1993-2002 (Hämäläinen 2003). The mean was around 60 per cent.

inefficiency that causes deviations from the frontier. This decomposition is not possible in the basic fixed-effects models.

The observable error term $\varepsilon_{i,t} = v_{i,t} - u_{i,t}$ consists of two components that we do not directly observe. The "normal" error terms $v_{i,t}$ are iid and follow the $N(0,\sigma_v{}^2)$ distribution. $u_{i,t}$ are non-negative random variables accounting for technical inefficiency in the production of matches. They are assumed to be distributed independently of $v_{i,t}$, following the $N(Z_{j,it}\delta_j,\sigma_u{}^2)$ distribution truncated at zero (Coelli 1997). The $Z_{j,it}$ vector denotes inefficiency regressors and δ_j s are coefficients to be estimated. The variance of the composed error term is expressed as $\sigma^2 = \sigma^2{}_v + \sigma^2{}_u$. The relative importance of the residual associated to the inefficiency term is $\gamma = \sigma^2{}_u / \sigma^2$. σ^2 and γ are parameters to be estimated instead of $\sigma^2{}_v$ and $\sigma^2{}_u$.

The distribution of the inefficiency terms is effected by "environmental factors" that vary between cross-sectional units and over time. The inefficiency term is a function of these environmental factors, $u_{i,t} = Z_{j,it}\delta_j + w_{i,t}$, where the random variable $w_{i,t}$ is defined by the truncation of the normal distribution with zero mean and variance σ_u^2 such that the point of truncation is $-Z_{j,it}\delta_j$, i.e. $w_{i,t} \geq -Z_{j,it}\delta_j$. These assumptions are consistent with $v_{i,t}$ being non-negative truncations of the $N(Z_{j,it}\delta_j,\sigma_u{}^2)$ distribution (Battese and Coelli 1995). This specification assumes that all environmental factors that might increase or decrease inefficiency in the production influence directly the degree of technical efficiency, not the shape of the production technology as in the conventional fixed effects framework (Coelli et al. 1999).

The parameters of the stochastic frontier and the efficiency term can be estimated jointly by maximising the log-likelihood of the model (Coelli 1997; Coelli et al. 1998). The conditional estimates of the efficiency coefficients $TE_{i,t}$ are computed as

$$TE_{i,t} = [\exp(-u*_{i,t}) \mid M,S,V,Z]. \tag{3}$$

The efficiency measure is absolute, not relative to the best in the sample. It is equal to 1 when matches lie on the frontier, otherwise $TE_{i,t} < 1$.

5.3 Data description

The data comprise filled vacancies during a month and the stocks of registered job seekers and vacant jobs at the end of a previous month from 145 Local Labour Offices (LLOs) in Finland. The research period spans from January 1995 to September 2004. Following the examples of Fahr and Sunde (2002, 2005), Ilmakunnas and Pesola (2003), and Ibourk et al (2004) we include in the model control variables that capture labour market heterogeneity and possibly affect technical efficiency of the production of matches. These inefficiency regressors consist of the structure of the job-seeker stock according to labour market status, age, and education. Shares of long-term unemployed (over one year), job seekers out of the labour force, employed job seekers, job seekers below 25 years and over 50 years and primary educated as well as highly educated job seekers are included in the inefficiency terms.

Table 1 summarises the descriptive statistics of the data by LLOs. On average in a LLO there are 4 066 job seekers and 114 vacant jobs. A large share of the job-seeker pool, 14 % on average, is of long-term type. Employed job seekers account for 24 % and job seekers out of the labour force for 9 % of the job-seeker stock. By age, almost 20 % of job seekers are over 55 years old and 7 % are younger than 25 years. In educational composition the registered job seekers are predominantly the primary and secondary educated; only 9 % are highly educated (see Appendix 1 for the educational classification).

TABLE 1 Descriptive statistics

	Average	**Min / Max**	**Std. Dev**
Matching rate	0.04	0 / 1.0	0.04
Filled vacancies	142	0 / 7 717	426
Job seekers	4 066	183 / 106 329	7 809
Vacant jobs	114	0 / 7 566	370
Share long-term unemployed	0.14	0.01 / 0.33	0.05
Share job seekers out of the labour force	0.09	0.01 / 0.44	0.05
Share employed job seekers	0.24	0.08 / 0.47	0.05
Share job seekers < 25 years	0.07	0 / 0.2	0.03
Share job seekers > 50 years	0.18	0.08 / 0.31	0.03
Share primary educated job seekers	0.49	0.32 / 0.7	0.06
Share highly educated job seekers	0.09	0.01 / 0.27	0.05

Figure 1 provides preliminary information on regional differences by tabulating matching probabilities (M/S) and labour market tightness (V/S) across regions[15]. The relationship between matching probability and tightness is clear: R^2=0.82. The picture indicates differences in matching efficiency: at a given tightness LLOs produce deviating amounts of matches. Figure 2 in turn describes the changes in matching probability and labour market tightness by years. Both factors have increased continuously over the period. The change in the matching rate was notably slower, especially in the early 2000s. As a result, the gap between the matching rate and tightness also widened over the period. This indicates deterioration in matching efficiency: at a given labour market tightness the local labour markets are able to produce fewer matches. These figures furnish a starting point for our stochastic frontier analysis, which takes

15 The flow of new vacant jobs during a month is included in the tightness in the figure. Owing to simultaneity bias problems, they are not, however, used in the matching function estimations. See Gregg and Petrongolo (2005) for stock-flow matching.

into account factors affecting efficiency and allows for time-wise variation in the efficiency estimates.

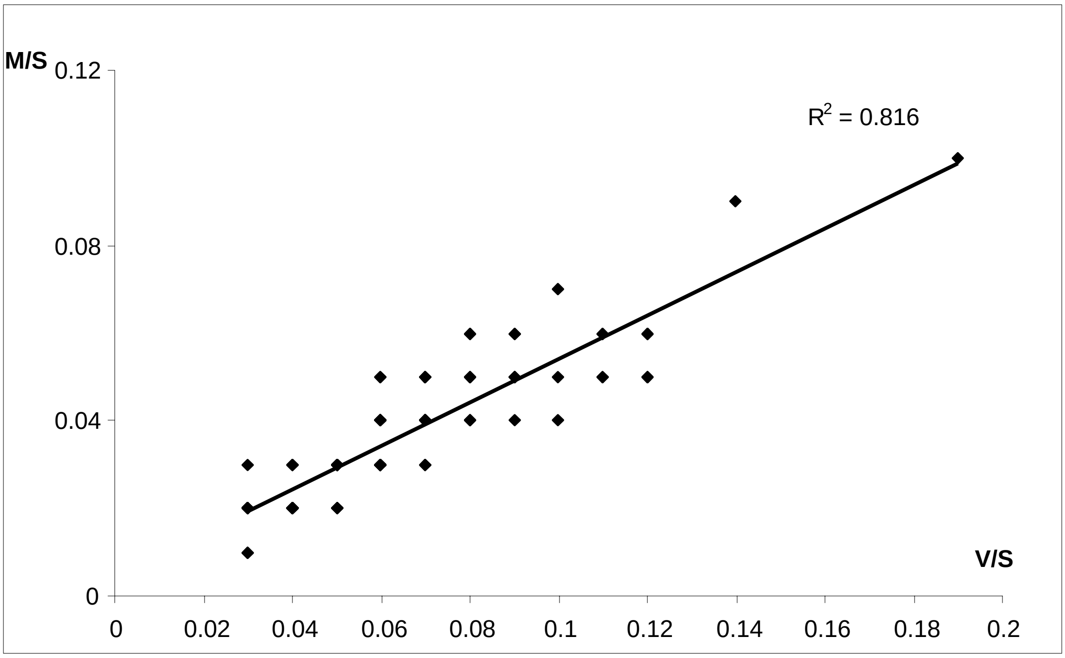

FIGURE 1 Matching probabilities and labour market tightness by LLOs

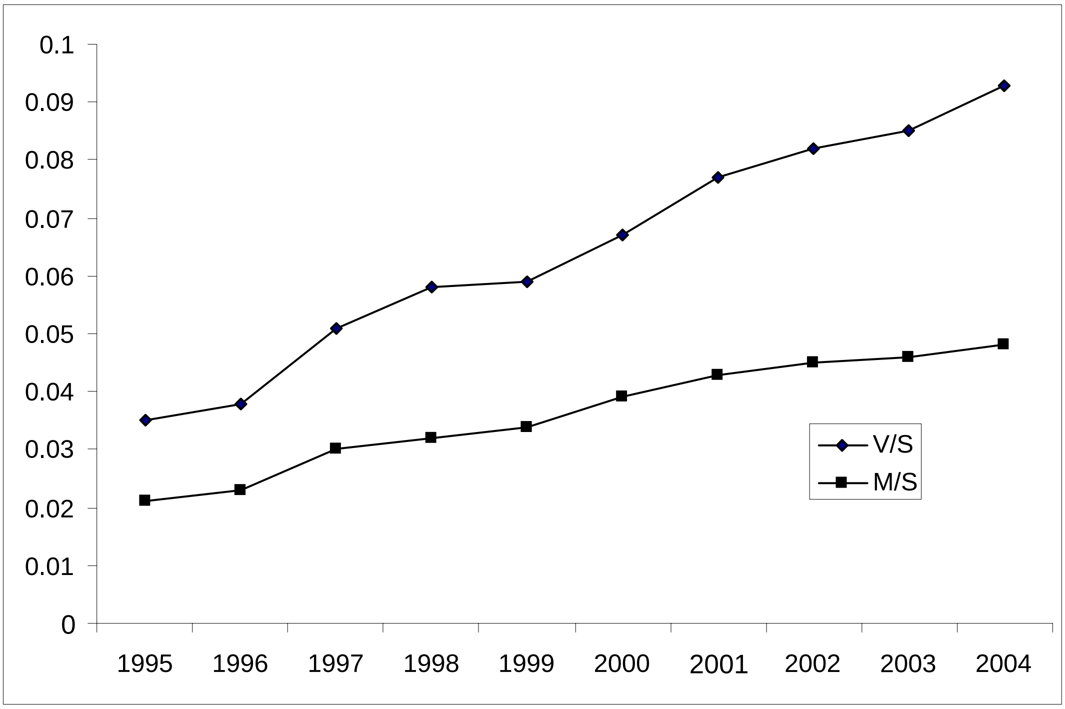

FIGURE 2 Matching probabilities and labour market tightness by years

5.4 Results

Five alternative specifications are reported in Table 2. Specification 1 is a conventional random-effects model and specification 2 a fixed-effects model. Specifications 3-5 are different kinds of stochastic frontier models. Specification 3 is a SFA model of the Battese and Coelli (1995) type without any panel-specific effects. Cross-sectional heterogeneity is added into the model through the inefficiency regressors, where it enters into the mean of the distribution of the inefficiency effects. Model 4 combines the Battese and Coelli -type of inefficiency effects with Greene's (2005a and b) true fixed-effects model by adding LLO-specific dummies into the function to capture time-invariant heterogeneity in the matching production. Specification 5, in addition, includes the time trend in the inefficiency term. In addition, in order to capture cyclical and seasonal variation in the matching function, we include yearly and monthly dummies in the function in all of the models[16].

[16] We also estimated all of the models with a trend in the function instead of yearly dummies. The models with dummies proved to have more explanatory power. The results on the estimations with a trend are available from the author.

TABLE 2 Estimation results

Variables	Conventional panel data models		Stochastic frontier models		
	Random	Fixed	Battese and Coelli	True fixed 1	True fixed 2
Dependent variable: ln M_t	(1)	(2)	(3)	(4)	(5)
ln S_{t-1}	0.45***(0.02)	0.3***(0.06)	0.47***(0.01)	0.31***(0.05)	0.24***(0.05)
ln V_{t-1}	0.42***(0.005	0.42***(0.005)	0.47***(0.005)	0.42***(0.005)	0.43***(0.005)
Constant	-1.75***(0.24)		-0.68 (175.7)		
Inefficiency controls			**-ln(efficiency)**		
t					0.025***(0.001)
(Share LTU) $_{t-1}$	-1.73***(0.2)	-1.21**(0.2)	4.68***(0.14)	0.97***(0.21)	-2.32***(0.45)
(Share OUT) $_{t-1}$	1.84***(0.19)	2.12***(0.2)	-0.41**(0.14)	-2.57***(0.21)	-9.28***(0.55)
(Share EMP) $_{t-1}$	0.3 (0.18)	0.47* (0.19)	1.01***(0.15)	-0.85***(0.2)	-4.44***(0.41)
(Share < 25) $_{t-1}$	0.48 (0.44)	0.64 (0.45)	-0.19 (0.35)	-1.7***(0.49)	-7.79***(1.01)
(Share > 50)t-1	0.38 (0.32	0.73*(0.35)	0.13 (0.24)	-0.1 (0.38)	-7.77*** (0.85)
(Share PRIMARY) $_{t-1}$	0.36 (0.21)	0.65** (0.23)	0.31**(0.12)	-0.31 (0.22)	4.13*** (0.47)
(Share HIGH) $_{t-1}$	2.64*** (0.3)	2.79*** (0.32)	-1.45***(0.2)	-3.83***(0.35)	-7.92***(0.35)
Constant				1.99***(0.22)	2.18***(0.35)
Returns to scale	0.87*	0.75***	0.94***	0.74***	0.67***
R^2	0.8	0.79			
Number of observations	16 965	16 965	16 965	16 965	16 965
sigma-squared			0.29	0.24	0.37
gamma			0.00006	0.3***	0.57**
log likelihood			-13 449	-11 479	-11 270
AIC			26 966	23 313	22 898
Hausman, Chi^2		146.5***			
LR-test, t=0, Chi^2					417***
Average efficiency			0.47 (0.12)	0.52 (0.16)	0.74 (0.17)

Notes: All models include yearly and monthly dummies in the function. Standard deviations reported in parentheses. *** denote statistical significance at the 0.1 % level, ** at the 1 % level, and * at the 5 % level. In tests for returns to scale, *** denote deviation from unity at the 0.1 % level. Of the conventional panel data models, Hausman test favours the fixed-effects model at the 0.1 % level. The LR test rejects the hypothesis that model 5 is nested in model 4 with a signifigance level of 0.1 %.

According to the results, the coefficient for vacancies is more stable across the specifications than the coefficient for job seekers, varying between 0.42 and 0.47. The job-seeker coefficient is more volatile, varying between 0.24 and 0.47. Random specifications report notably higher job-seeker coefficients. They take into account between-units variation in addition to within-unit variation, which might yield the higher job-seeker coefficients. Among these conventional panel data models, the Hausman test, however, favours the fixed-effects specification against the random model. All models, independent of the type of panel effects or inclusion of the inefficiency terms, exhibit decreasing returns to scale.

The γ coefficients in the SFA models correspond to the estimated share of the inefficiency term in the variance of the composed error term, i.e., it is an indication of two-sided errors. In the Battese and Coelli specification the inefficiency term is insignificant, since γ is almost zero and not statistically significant. This indicates that all deviations from the frontier are due to random errors $v_{i,t}$ and that the model collapses to the basic OLS-model with inefficiency regressors in the matching function (Battese and Coelli 1995).

In the true fixed-effects model 1 (column 4) γ is 0.3 and highly significant, indicating that when we control for cross-sectional differences in the matching technology, stochastic inefficiency terms explain 30 % of the total variation in the composed error term[17]. This indicates that fixed effects are necessary in order to separate inefficiency effects; we have 145 cross-sections with wide heterogeneity. When, further, we add the time trend into the inefficiency term, γ rises to 0.57. Adding the time trend thus increases the fraction of inefficiency to the composed error term.

The log likelihood and AIC values favours specification 5 against the others. In addition, the likelihood ratio test rejects the hypothesis that the coefficient of the trend is zero. Hence, efficiency appears to have a negative trend, i.e. an exogenous decline occurred in matching efficiency during the period, as already indicated by the curves in Figure 2. It should be noted that adding the time trend has a marked affect on the results by decreasing the coefficient for job seekers in the function and attributing to the job-seeker stock variables in the inefficiency term more importance. This means that variations in the composition of the job-seeker stock contribute to efficiency notably more than in the model without the time trend.

5.4.1 Determinants of the matching efficiency

Many previous studies have reported that the search intensity of job seekers (e.g. Budd et al 1988; Layard and Bean 1989; Pissarides 1992) and the ranking behaviour of firms (Burgess 1993; Blanchard and Diamond 1994; Pissarides 1994; Van Ours 1995; Broersma 1997; Broersma and Van Ours 1999; Mumford and Smith 1999; Anderson and Burgess 2000; Burgess and Turon 2003) are crucial determinants of the size of the matching frictions. In line with this, we assume the matching inefficiency to be a linear function of the composition of the job-seeker stock. We control for the composition of the job-seeker stock regarding labour market position, age and education. With respect to labour market position, we define unemployed job seekers with an unemployment spell shorter than a year as the "base" group of job seekers with respect to age, job seekers aged between 26-49 years and with respect to education, secondary educated job seekers form the base groups. The efficiency effects of other groups are studied in relation to these base groups.

Our results for long-term unemployment are not straightforward. In a conventional fixed-effects model (Table 2, column 2) long-term unemployment negatively affects matches by the coefficient -1.21, as expected. According to the true fixed-effects model 1 (Specification 4), a one percentage point increase in the group of long-term unemployed decreases matching efficiency by about 1 %[18]. Adding the time trend into the true fixed-effects model, however, changes

---

17 The estimated inefficiency is clearly stochastic, not deterministic, which favours stochastic frontier analysis against data envelopment analysis, where all deviations from the frontier are assumed to be due to inefficiency.

18 Note that in SFA models a negative sign means a positive effect on efficiency: inefficiency = -(ln efficiency)

the sign and magnitude of long-term unemployment (Specification 5): according to that specification, a one percentage point increase in long-term unemployment increases matching efficiency by over 2 %. Evidently, the negative time trend captures the efficiency-decreasing effect of an increase in long-term unemployment. Long-term unemployment fell continuously during the research period, while efficiency also fell: the correlation between the trend and long-term unemployment is -0.40. The result is in line with Ilmakunnas and Pesola (2003) who report that long-term unemployment has a positive effect on hiring efficiency in Finland. Either Blanchard and Diamond (1989) did not find a statistically significant negative effect of long-term unemployment on matches.

The unequal employability of different job-seeker groups is clearly implied by the results for job seekers out of the labour force and employed job seekers. Both of these groups reduce matching frictions in LLOs. The negative inefficiency effect of job seekers out of the labour force is over two times larger than that of employed job seekers (Specification 5). This reflects that job seekers trying to enter the labour market are favoured by employers possibly due to their flexibility and freshness of skills that at least lately graduated students have. Their own search effort might also be higher than the effort of other groups. The same explanations hold for the efficiency enhancing effect of young job seekers who have found to improve efficiency also in Fahr and Sunde (2002) in Western Germany and in Ilmakunnas and Pesola (2003) in Finland. Older job seekers also improve efficiency in LLOs reflecting the value accorded the experience of older job seekers by firms seeking workers through state-run employment agencies.

The educational structure of the job-seeker stock is also of significance. The share variables capture the effect of primary and highly educated job seekers in relation to the secondary educated. A one percentage point increase in the high education group increases efficiency by almost 8 %. This is in line with results of Lahtonen (2006) in Finland and with those of Fahr and Sunde (2002) in the SFA framework in Western Germany. Fahr and Sunde argue that highly educated job seekers might have a higher search intensity and that the search process may be more directed in the high-education segment of the labour market, thereby contributing to higher matching efficiency.

Primary educated job seekers seem to decrease matching efficiency. These results could indicate job competition between job seekers with different levels of education. Employers might prefer highly educated to primary and secondary educated job seekers even where the job does not necessarily require high education. The existing evidence on job competition is not, however, unproblematic (Sicherman 1991; Van Ours and Ridder 1995; Gautier et al. 2002): Van Ours and Ridder found evidence of job competition between academic and higher vocational education, but not at lower levels of education, while others found no educational-related evidence of job competition.

5.4.2 Quantitative effects of inefficiency on matches

The average efficiency levels vary from 0.47 in a Battese and Coelli to 0.74 in the true fixed effects model with the time trend in the inefficiency term. (Table 2). We face the familiar problem that the efficiency estimates are not robust across SFA models, as previously reported, e.g., in Giannakas et al. (2003). Both the LR test for the significance of the trend in the inefficiency estimates and the AIC favour specification 5, as already reported above. On the basis of these tests we end up using the estimates given by them in our further calculations.

Regional variation in the mean efficiency varies from 0.36 to 0.89 (Appendix 2). If we consider all 16 965 efficiency estimates, the variation ranges from 0.06 to 0.95 with a standard deviation 0.17. On average, the matching process works rather efficiently; however, there are also inefficient regions which are permanently far from the frontier. The ranking of regions according to efficiency remained, however, rather stable during the research period: the Spearman rank correlation coefficient between the estimates for 1995 (the first year) and 2003 (last full year of the period) is 0.74.

We clarify the quantitative dimension of regional inefficiency from a somewhat different perspective from that of Ibourk et al. (2004) who also calculate efficiency slacks and the explanatory power of environmental variables. Our focus is on the magnitude of inefficiency and its direct effects on the number of monthly matches. Table 3 reports the results of those calculations. If there was no inefficiency at all, i.e., the efficiency level were 1 in all regions, we would obtain 2 727 more filled vacancies in a month. This implies a 23.7 % monthly increase in matches compared to the level of matches obtained at the current average levels of inefficiency. Comparing the number of matches obtained at the prevailing inefficiencies with the hypothetical number of matches obtained with zero-level inefficiency implies that inefficiency decreases matches by 19.2 %.

It is, however, unrealistic to assume that inefficiency plays a zero-role in the matching function. It is more appropriate to set the efficiency frontier at the highest level found in the sample. The highest average efficiency level, 0.89, is obtained in Vaasa (in Ostrobothnia). If we set all LLOs at the efficiency level of Vaasa we would achieve 1 174 new matches in a month, which would increase matches by 10.2 %. Comparing the number of matches obtained at the prevailing inefficiencies with the hypothetical number of matches obtained with Vaasa's inefficiency implies that inefficiency decreases matches by 9.3 %.

TABLE 3 Quantitative effects of inefficiency on matches

Efficiency calculations		Increase in matches
Predicted matches	11 484	
Matches with highest efficiency in the sample	12 658	1 174, 10.2 %
Matches with efficiency level of 1	14 211	2 727, 23.7 %
The weight of Z-variables in the inefficiency determination, mean	61 %	
Correlation between the weight of Z-variables and inefficiency level	0.25	

As defined in Section 2, the inefficiency estimates consist of two parts: $u_{i,t} = Z_{j,it}\delta_j + w_{i,t}$, i.e., of the part explained by inefficiency regressors and a random error. The Z variables contain the variables describing the composition of the job-seeker stock, the time trend and a constant. We have calculated the weight of the Z variables in the determination of the inefficiency estimates by comparing the absolute value of the inefficiency level predicted by the Z variables to the sum of this prediction and the absolute value of inefficiency predicted by random terms $w_{i,t}$ [19] (Appendix 2). The greater the particular absolute value, the greater the importance in the inefficiency term. According to the calculations, the weight of the $Z_{j,it}\delta_j$ set is on average 61 % in the inefficiency estimates. There is, however, weak positive dependence between the importance of the Z variables and the level of inefficiency: the correlation coefficient between inefficiency and the weight of the Z variables is 0.25. This indicates that, at lower levels of efficiency, the Z variables play a more important role while factors not related to the composition of the job-seeker stock become relatively more important at higher efficiency levels.

5.5 Conclusions

We studied the process of matching job seekers and vacant jobs in local labour markets taking a stochastic frontier approach. We applied true fixed-effects modelling in order to decompose the time-invariant cross-sectional heterogeneity that directly affects the matching technology from inefficiency that causes deviations from the frontier. The inefficiency terms were modelled as functions of the job-seeker stock composition in the regions.

Notable differences in matching efficiency between regions were found, and these differences were shown to have significant effects on the number of filled vacancies. If all regions were as efficient as the most efficient one, the number of total matches in a month would increase by over 10 %. If there were no inefficiency at all in the matching function, matches would increase by almost 24 %.

[19] Note that parts of the efficiency estimates can predict negative inefficiency. Together they determine level of inefficiency higher than 0 (Battese and Coelli 1995).

The results indicate that a continuous exogenous decline in matching efficiency occurred during the research period. The results also show that changes in the composition of the job-seeker stock strongly contribute to the efficiency estimates: the labour market status, age as well as educational structure of the job-seeker stock strongly affect the ability of local labour markets to form successful matches. In particular, job seekers out of the labour force and highly educated job seekers improve matching efficiency. The total weight of the set of inefficiency regressors in the inefficiency term is on average 61 %.

APPENDIX 1 Relation between 3-group classification and ISDEC 1997

ISDEC 1997	**Name**	**3-group classification**
Level 0	Pre-primary education	-
Level 1	Primary education	1 Primary
Level 2	Lower secondary education	1 Primary
Level 3	Upper secondary education	2 Secondary
Level 4	Post secondary non-tertiary ed.	2 Secondary
Level 5	1st. stage of tertiary education:	
	5B-programmes	3 Highly
	5A-programmes	3 Highly
Level 6	2nd stage of tertiary education	3 Highly

APPENDIX 2 Efficiency and inefficiency by LLOs

LLO	Efficiency	Inefficiency	Ineff. due Z-variables	Ineff. due other factors	Weight of Z-variables
Average	**0.737**	**0.324**	**0.792**	**-0.468**	**0.607**
Vaasa	0.891	0.116	-0.242	0.358	0.404
Tuusula	0.884	0.123	0.054	0.069	0.436
Jyväskylä	0.880	0.127	-0.292	0.419	0.410
Parainen	0.880	0.128	0.020	0.107	0.159
Kaarina	0.876	0.133	0.290	-0.157	0.649
Eura	0.875	0.134	0.746	-0.612	0.549
Tampere	0.873	0.136	-0.078	0.214	0.268
Helsinki	0.872	0.137	-0.083	0.220	0.274
Turku	0.870	0.139	-0.023	0.163	0.126
Ylöjärvi	0.862	0.148	0.302	-0.154	0.662
Kuopio	0.862	0.148	-0.161	0.309	0.343
Naantali	0.861	0.150	0.096	0.053	0.644
Valkeakoski	0.860	0.151	0.343	-0.192	0.641
Raisio	0.858	0.153	0.307	-0.154	0.666
Seinäjoki	0.857	0.154	-0.168	0.322	0.343
Hämeenlinna	0.857	0.154	0.257	-0.103	0.714
Mikkeli	0.857	0.155	0.090	0.065	0.579
Pietarsaari	0.856	0.155	0.466	-0.310	0.600
Oulu	0.856	0.156	-0.164	0.320	0.339
Kotka	0.855	0.157	0.128	0.029	0.818
Rauma	0.853	0.159	0.389	-0.230	0.628
Kouvola	0.853	0.159	0.318	-0.158	0.667
Pori	0.851	0.161	0.360	-0.198	0.645
Vihti	0.851	0.161	0.127	0.034	0.788
Varkaus	0.850	0.162	0.243	-0.080	0.752
Lahti	0.849	0.163	0.506	-0.343	0.596
Kirkkonummi	0.849	0.163	0.288	-0.124	0.698
Lappeenranta	0.849	0.164	0.360	-0.196	0.647
Mänttä	0.847	0.166	0.731	-0.565	0.564
Hyvinkää	0.846	0.167	0.426	-0.260	0.622
Paimio	0.846	0.167	0.169	-0.002	0.990
Kerava	0.845	0.168	0.554	-0.386	0.589
Kokkola	0.842	0.172	0.243	-0.071	0.774
Kajaani	0.841	0.173	0.078	0.095	0.450
Kemiö	0.841	0.173	0.860	-0.687	0.556
Kangasala	0.841	0.173	0.669	-0.496	0.574
Karjaa	0.840	0.174	0.512	-0.338	0.603
Salo	0.839	0.175	0.651	-0.476	0.578
Rovaniemi	0.838	0.177	0.196	-0.019	0.912
Loimaa	0.835	0.180	0.601	-0.422	0.588
Jämsä	0.835	0.181	0.734	-0.553	0.570
Kauhava	0.834	0.181	0.311	-0.130	0.706
Hamina	0.834	0.181	0.371	-0.190	0.662
Porvoo	0.834	0.182	0.400	-0.218	0.647
Lempäälä	0.832	0.184	0.555	-0.372	0.599
Joensuu	0.831	0.185	0.026	0.159	0.138
Kuusankoski	0.830	0.187	0.985	-0.799	0.552

LLO	Efficiency	Inefficiency	Ineff. due Z-variables	Ineff. due other factors	Weight of Z-variables
Lohja	0.828	0.188	0.696	-0.507	0.578
Lapua	0.826	0.191	0.511	-0.320	0.615
Kristiinankaupunki	0.823	0.195	0.543	-0.349	0.609
Harjavalta	0.823	0.195	0.668	-0.472	0.586
Järvenpää	0.821	0.197	0.378	-0.182	0.676
Tammisaari	0.817	0.202	0.637	-0.436	0.594
Vammala	0.817	0.202	0.464	-0.262	0.639
Forssa	0.817	0.203	0.961	-0.758	0.559
Janakkala	0.816	0.204	0.660	-0.456	0.591
Ääneseutu	0.812	0.208	0.779	-0.571	0.577
Nurmijärvi	0.809	0.211	0.772	-0.560	0.579
Savonlinna	0.808	0.213	0.457	-0.244	0.652
Kemi	0.808	0.214	0.513	-0.299	0.632
Imatra	0.807	0.214	1.113	-0.899	0.553
Heinola	0.806	0.215	0.792	-0.576	0.579
Riihimäki	0.805	0.217	0.757	-0.541	0.584
Kurikka	0.804	0.218	0.572	-0.354	0.618
Lappajärvi	0.803	0.220	0.747	-0.527	0.586
Hämeenkyrö	0.796	0.228	0.565	-0.337	0.626
Nokia	0.796	0.228	0.737	-0.508	0.592
Anjalankoski	0.794	0.231	0.780	-0.549	0.587
Uusikaupunki	0.793	0.232	0.896	-0.663	0.575
Pieksämäki	0.791	0.235	0.482	-0.247	0.661
Leppävirta	0.790	0.236	0.446	-0.210	0.680
Laitila	0.789	0.237	1.053	-0.815	0.564
Kyrönmaa	0.785	0.242	0.479	-0.237	0.669
Loviisa	0.785	0.243	1.002	-0.760	0.569
Mäntsälä	0.784	0.243	0.789	-0.546	0.591
Karkkila	0.784	0.243	0.930	-0.687	0.575
Siilinjärvi	0.783	0.245	0.354	-0.109	0.764
Ylivieska	0.779	0.250	0.495	-0.245	0.669
Huittinen	0.776	0.254	0.934	-0.680	0.579
Keuruu	0.775	0.255	0.917	-0.663	0.581
Raahe	0.769	0.263	0.399	-0.136	0.746
Alavus	0.764	0.269	0.754	-0.485	0.608
Jalasjärvi	0.763	0.271	0.588	-0.318	0.649
Haukipudas	0.754	0.282	0.649	-0.366	0.639
Orivesi	0.754	0.283	1.083	-0.800	0.575
Iisalmi	0.753	0.284	0.533	-0.250	0.681
Juva	0.752	0.285	0.886	-0.601	0.596
Laukaa	0.749	0.289	0.749	-0.460	0.620
Kaustinen	0.745	0.294	0.443	-0.149	0.748
Parkano	0.743	0.297	1.086	-0.788	0.579
Sotkamo	0.741	0.300	0.564	-0.264	0.681
Virrat	0.740	0.301	0.757	-0.455	0.624
Mäntyharju	0.738	0.304	1.403	-1.099	0.561
Toijala	0.736	0.307	1.140	-0.833	0.578
Haapavesi	0.726	0.321	0.701	-0.381	0.648
Saarijärvi	0.725	0.322	1.140	-0.817	0.582

LLO	Efficiency	Inefficiency	Ineff. due Z-variables	Ineff. due other factors	Weight of Z-variables
Kemijärvi	0.724	0.323	1.066	-0.743	0.589
Parikkala	0.721	0.327	1.186	-0.859	0.580
Noormarkku	0.719	0.331	1.236	-0.905	0.577
Tornio	0.712	0.339	0.814	-0.475	0.632
Kerimäki	0.707	0.346	0.931	-0.585	0.614
Ylitornio	0.705	0.350	1.089	-0.739	0.596
Suupohja	0.701	0.356	1.053	-0.698	0.602
Kuusamo	0.691	0.370	0.694	-0.324	0.682
Alajärvi	0.683	0.381	1.094	-0.713	0.605
Haapajärvi	0.683	0.382	0.923	-0.541	0.630
Muonio	0.682	0.382	1.104	-0.722	0.605
Hanko	0.682	0.383	1.072	-0.689	0.609
Heinävesi	0.669	0.402	1.200	-0.798	0.601
Kankaanpää	0.658	0.419	0.980	-0.561	0.636
Kuhmo	0.657	0.420	1.269	-0.849	0.599
Kangasniemi	0.654	0.425	1.095	-0.670	0.620
Kiuruvesi	0.632	0.458	0.835	-0.377	0.689
Utsjoki	0.621	0.476	0.973	-0.497	0.662
Lieksa	0.618	0.481	1.274	-0.793	0.616
Lapinlahti	0.616	0.485	1.275	-0.790	0.617
Keski-Karjala	0.615	0.487	1.277	-0.791	0.618
Viitasaari	0.610	0.494	1.294	-0.801	0.618
Tervola	0.602	0.507	1.639	-1.132	0.591
Vaala	0.579	0.546	1.366	-0.820	0.625
Outokumpu	0.578	0.547	1.230	-0.683	0.643
Nilsiä	0.565	0.571	1.446	-0.874	0.623
Joutsa	0.564	0.572	1.295	-0.722	0.642
Paltamo	0.562	0.576	1.293	-0.717	0.643
Ylä-Karjala	0.561	0.578	1.414	-0.836	0.628
Sisä-Savo	0.559	0.582	1.201	-0.619	0.660
Suomussalmi	0.557	0.585	1.498	-0.913	0.621
Kittilä	0.545	0.606	1.781	-1.175	0.603
Pielavesi	0.543	0.611	1.651	-1.040	0.614
Savukoski	0.542	0.612	1.445	-0.833	0.634
Eno	0.525	0.645	1.700	-1.055	0.617
Pello	0.521	0.652	1.731	-1.079	0.616
Hyrynsalmi	0.508	0.676	1.723	-1.046	0.622
Sodankylä	0.501	0.691	1.161	-0.470	0.712
Juankoski	0.493	0.708	1.500	-0.792	0.655
Kolari	0.486	0.722	1.730	-1.008	0.632
Posio	0.471	0.752	1.634	-0.882	0.650
Pudasjärvi	0.469	0.758	1.587	-0.829	0.657
Ivalo	0.455	0.787	1.322	-0.536	0.712
Ranua	0.431	0.841	1.514	-0.673	0.692
Karstula	0.429	0.845	1.417	-0.571	0.713
Salla	0.418	0.873	1.899	-1.026	0.649
Ilomantsi	0.412	0.887	1.955	-1.069	0.647
Puolanka	0.381	0.966	1.792	-0.826	0.685
Enontekiö	0.359	1.024	1.855	-0.831	0.691

REFERENCES

Anderson, P. and Burgess, S. (2000) Empirical matching functions: Estimation and interpretation using state-level data, The Review of Economics and Statistics, 82, 93-102.

Battese, G.E. and Coelli, T.J. (1995) A model for technical inefficiency effects in a stochastic frontier production function for panel data. Empirical Economics, 20, 325-332.

Blanchard, O. and Diamond, P. (1989) The Beveridge curve. Brookings Papers on Economic Activity 1, 1-76.

Blanchard O. and Diamond P. (1994) Ranking, unemployment duration, and wages, Review of Economic Studies, vol. 61, pp. 417-434.

Broersma L. (1997) Competition between employed and unemployed job searchers: is there a difference between the UK and The Netherlands?, Applied Economics Letters, vol. 4, pp. 199-203.

Broersma, L. and Van Ours, J. (1999) Job searchers, job matches and the elasticity of matching, Labour Economics, vol. 6, pp. 77-93.

Budd A., Levine P., and Smith P. (1988) Unemployment, vacancies, and the long-term unemployed, Economic Journal, vol. 98, pp. 1071-1091.

Burgess S. (1993) A model of competition between unemployed and employed job searchers: an application to the unemployment outflow rate in Britain, Economic Journal, vol. 103, pp. 1190-1204.

Burgess S. and Turon H. (2003) Unemployment equilibrium and on-the-job search, IZA Discussion Paper No. 753.

Coelli, T. (1997) A guide to FRONTIER Version 4.1: A Computer program for stochastic frontier production and cost estimation. CEPA Working paper 96/07.

Coelli, T., Perelman, S., and Romano, E. (1999) Accounting for environmental influences in stochastic frontier models: with application to international airlines. Journal of Productivity Analysis, 11, 251-273.

Coelli, T., Rao D.S., and Battese G. (1998) An introduction to efficiency and productivity analysis. Kluwer Academic Publishers.

Fahr, R. and Sunde, U. (2002) Estimations of occupational and regional matching efficiencies using stochastic production frontier models. IZA Discussion paper 552.

Fahr, R. and Sunde, U. (2005) Regional dependencies in job creation: an efficiency analysis for western Germany. IZA Discussion paper 1660.

Farrell, M.J. (1957) The measurement of productive efficiency. Journal of the Royal Statistical Society Series A, 120(3), 253-290.

Gautier, P., van den Berg, G., Van Ours, J., and Ridder, G. (2002) Worker turnover at the firm level and crowding out of lower educated workers. European Economic Review 46, 523-538.

Giannakas, K., Tran, K., and Tzouvelekas, V. (2003) On the choice of functional form in stochastic frontier modelling. Empirical Economics 28, 75-100.

Greene, W. (2005a) Fixed and random effects in stochastic frontier models. Journal of Productivity Analysis, 23, 7-32.

Greene, W. (2005b) Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. Journal of Econometrics, 126, 269-303.

Gregg and Petrongolo (2005) Stock-flow matching and the performance of the labor market. European Economic Review, 49, 1987-2011.

Hynninen, S., Kangasharju, A., and Pehkonen, J. (2006). Regional Matching Frictions and Aggregate Unemployment. VATT Discussion Paper 383.

Hynninen, S. and Lahtonen, J. (2007) Does population density matter in the process of matching heterogeneous job seekers and vacancies? Forthcoming in Empirica.

Hämäläinen H. (2003) Työvoiman rekrytointi toimipaikoissa vuonna 2002, [in Finnish], Ministry of Labour, Helsinki.

Ibourk, A., Maillard, B., Perelman, S., and Sneessens, H. (2004) Aggregate matching efficiency: A stochastic production frontier approach, France 1990-1994. Empirica 31, 1-25.

Ilmakunnas, P. and Pesola, H. (2003) Regional labour market matching functions and efficiency analysis. Labour 17 (3), 413-437.

Kim, Y. and Schmidt, P. (2000) A review and empirical comparison of Bayesian and classical approaches to inference on efficiency levels in stochastic frontier models with panel data. Journal of Productivity Analysis 14, 91-118.

Kumbhakar, S. and Lovell, C.A. (2000) Stochastic frontier analysis. Cambridge University press.

Lahtonen, J. (2006) Matching heterogeneous job seekers and vacancies: Empirical studies using Finnish data. Jyväskylä Studies in Business and Economics 50.

Layard R. and Bean C. (1989) Why does unemployment persist?, Scandinavian Journal of Economics, vol. 91, pp. 371-396.

Mumford K. And Smith P. (1999) The hiring function reconsidered: on closing the circle, Oxford Bulletin of Economics and Statistics, vol. 61, pp. 343-364.

Petrongolo B. and Pissarides C. (2001) Looking into the black box: a survey of the matching function, Journal of Economic Literature, vol. 39, pp. 390-431.

Pissarides C. (1992) Loss of skill during unemployment and the persistence of employment shocks, Quarterly Journal of Economics, vol. 107, pp. 1371-1391.

Pissarides C. (1994) Search unemployment with on-the-job search, Review of Economic Studies, vol. 61, pp. 457-475.

Pissarides C. (2000) Equilibrium unemployment theory, MIT Press.

Sicherman, N. (1991) "Overeducation" in the labor market. Journal of Labor Economics 9, 101-122.

Van Ours J. (1995) An empirical note on employed and unemployed job search, Economics Letters, vol. 49, pp. 447-452.

Van Ours, J. and Ridder, G. (1995) Job matching and job competition: Are lower educated workers at the back of queues? European Economic Review 39, 1717-1731.

SUMMARY IN FINNISH (YHTEENVETO)

Tämä väitöskirjatutkimus tarkastelee avoimien työpaikkojen ja työnhakijoiden kohtaamista työvoimatoimistojen alueilla sekä työssäkäyntialueilla Suomessa vuosina 1991-2004 keskittyen erityisesti ulkoisvaikutuksiin kohtaantoprosessissa sekä prosessin tehokkuuteen ja siihen vaikuttaviin tekijöihin. Kohtaannon tehokkuudella tutkimuksessa tarkoitetaan sitä, kuinka tehokkaasti työnhakijoista ja avoimista työnhakijoista muodostuu pareja – täyttyneitä työpaikkoja.

Työmarkkinoiden toimintaa mallitetaan kohtaantofunktion avulla, jolloin työnhakijat ja avoimet työpaikat ovat tuotantoprosessin panoksia ja täyttyneet työpaikat puolestaan sen tuotos. Tutkimusaineistona käytetään kuukausikohtaista tilastoa työvoimatoimistoihin ilmoitettujen työpaikkojen määristä sekä rekisteröityneistä työnhakijoista taustatietoineen.

Tutkimus koostuu neljästä empiirisestä artikkelista sekä makrotason kohtaantofunktion mikrotason perustaa esittelevästä johdanto-osuudesta. Johdanto myös kokoaa yhteen aihepiirin aiemmat suomalaiset empiiriset tutkimukset sekä pohtii väitöskirjan tuloksia. Artikkeleista ensimmäinen tarkastelee spatiaalisia riippuvuuksia työpaikkojen ja työnhakijoiden kohtaamisessa työssäkäyntialueiden välillä vuosina 1991-2004. Toisessa artikkelissa tutkitaan työnhakijoiden työmarkkina-aseman vaikutusta työllistyvyyteen ja työnhakijarakenteen vaikutusta alueen kykyyn tuottaa täyttyneitä työpaikkoja. Kolmannessa artikkelissa käytetään lineaarista sekamallia asukastiheydeltään erilaisten alueiden tehokkuuserojen mallituksessa. Neljäs artikkeli hyödyntää stokastista rintama-analyysia työvoimatoimistojen alueiden välisten tehokkuuserojen ja niiden syiden selvittämisessä.

Tulosten mukaan työnetsinnän ulottaminen oman alueen ulkopuolelle läheisille työssäkäyntialueille ei edistä työnhakijoiden ja työpaikkojen kohtaamista, vaan pikemminkin aiheuttaa ylimääräistä tungosta naapureiden työmarkkinoille. Negatiivinen vaikutus on lisäksi tiheän asutuksen työssäkäyntialueilla muita alueita selvästi voimakkaampi.

Tuloksista käy ilmi, että työvoiman ulkopuolisten työnhakijoiden, samoin kuin korkeasti koulutettujen työnhakijoiden määrän suhteellinen kasvu alueella edistää työpaikkojen täyttymistä. Tämä viittaa siihen, että työmarkkinoille tulossa olevat työnhakijat syrjäyttävät työttömiä työnhakijoita rekrytointitilanteissa. Pitkäaikaistyöttömien määrän kasvulla on puolestaan kielteinen vaikutus työpaikkojen täyttymiseen paikallisilla työmarkkinoilla: pitkäaikaistyöttömiä ei rekrytoida avoinna oleviin työpaikkoihin.

Työpaikat täyttyvät tulosten mukaan tehokkaammin tiheästi asutuilla alueilla kuin muualla. Työnhakijoiden osaamisen ja työpaikkojen vaatimusten yhteensovittamisessa on kuitenkin erityisiä ongelmia korkean asukastiheyden työmarkkinoilla: vaikka matalasti koulutettujen työnhakijoiden osuus kaikista työnhakijoista on muita alueita alempi, on se liian korkea avoinna olevien työpaikkojen vaatimuksiin nähden.

Työmarkkinoiden kohtaanto on yleisesti heikentynyt jaksolla 1995-2004. Työvoimatoimistojen alueiden välillä on kuitenkin merkittäviä ja ajassa pysyviä eroja siinä, kuinka tehokkaasti työnhakijoista ja avoimista työpaikoista muodostuu pareja: jos kaikki alueet toimisivat yhtä tehokkaasti kuin tehokkain toimii, täyttyneiden työpaikkojen määrä kuukaudessa kasvaisi yli 10 prosentilla. Vaikka osa eroista selittyykin työnhakijoiden ominaisuuksien ja työpaikkojen vaatimusten kohtaamattomuudella, merkittävä osa johtuu muista tekijöistä. Työvoimatoimistojen toimintakulttuureissa lieneekin vaihtelua esimerkiksi niiden suhteessa paikalliseen elinkeinoelämään, mikä vaikuttaa myös työpaikkojen täyttymisen tehokkuuteen.

Tulokset osoittavat pitkäaikaistyöttömyyden torjunnan tärkeyden kaikissa olosuhteissa. Työntekijöiden ja -hakijoiden on huolehdittava osaamisensa jatkuvasta päivittämisestä työelämän vaatimusten mukaiseksi. Tutkimuksen ajanjaksolla työmarkkinoilla oli kysyntään nähden erittäin paljon työnetsijöitä, jolloin työnantajat pystyivät valitsemaan työntekijänsä laajasta hakijajoukosta. Tämä epäsuhta edesauttoi työttömien ajautumista pitkäaikaistyöttömyyteen.

Tilanne työmarkkinoilla on kuitenkin muuttumassa pulaksi työvoimasta ainakin tietyillä sektoreilla, jolloin työnhakijoilla on aiempaa suurempi mahdollisuus valita itselleen mieluisa työpaikka. Tilanne asettaa haasteen työnantajille: työpaikkojen houkuttelevuuteen on kiinnitettävä entistä enemmän huomiota. Lisäksi julkinen työvoimapalvelu on uuden edessä. Sen on toimittava työllisyyden edistäjänä kasvavien kohtaanto-ongelmien oloissa. Paikallistasolla tämä edellyttää työvoimatoimistoilta läheistä yhteistyötä alueen yritysten kanssa sekä toimimista syvällisen informaation välittäjinä työnhakijoiden ja yritysten välillä.