JYVÄSKYLÄ STUDIES IN BUSINESS AND ECONOMICS

50

Jukka Lahtonen

Matching Heterogeneous Job Seekers and Vacancies

Empirical Studies Using Finnish Data

JYVÄSKYLÄN YLIOPISTO

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UNIVERSITY OF JYVÄSKYLÄ

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ABSTRACT

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This thesis consists of introductory chapter which reviews the theoretical and empirical literature on labour market matching function, and four self-contained empirical studies on that field. The matching function introduces market frictions into the textbook Walrasian equilibrium model. Because of the frictions workers and vacant jobs have to engage in a search process before a job match may occur. The literature provides several micro-level processes consistent with the aggregate function. The most common empirical specification is the Cobb-Douglas form. The first empirical study in Chapter 2 describes the basic characteristics of job seekers and vacancies in Finland. Then, it estimates labour market matching function taking the first step to model agent heterogeneity: the pool of job seekers is disaggregated into three education groups. The results indicate that primary educated job seekers have a positive effect on matches whereas seekers with secondary education display negative effect. The effect of higher educated is almost zero. Chapter 3 estimates the labour market model more sophisticated than that in the previous chapter According to the results, an increase in the relative number of primary or highly educated job seekers increases the ability of the labour market to form new matches. The corresponding effect of secondary educated job seekers is negative. In addition, long-term unemployed job seekers, and seekers aged under 25 or over 50 have negative effect on the number of monthly matches. Chapter 4 studies the process of matching job seekers and vacancies in a collection of local labour markets. We find area heterogeneity and trace whether it can be explained by differing population densities across markets, or by differences in the distribution of job seekers by level of education. The results suggest that, on average, high-density areas are more productive than low-density areas in forming matches. The study in Chapter 5 uses non-linear model which deals with the temporal aggregation problem of the linear form. In addition, both random and stock-flow approaches on modelling are considered. The results suggest that unemployed job seekers match rather with the flow of new vacancies than with the stock of old ones. However, it seems that all job seekers have to spend time on searching before a match may occur.

Keywords: labour market, matching function, heterogeneity

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CONTENTS

CHAPTER 1

INTRODUCTION

ABSTRACT. This introductionary chapter surveys both the empirical and theoretical literature on the labour market matching function. It also summarizes the results of the four subsequent empirical papers and evaluates them in the light of literature. The matching function provides a way to model labour market frictions which are caused, for example, by incomplete information between employers and employees, their search behaviour, or by congestion owing to large numbers. Both employers and employees have to make investments to overcome these frictions. Under these conditions, a job matching function might be defined so that the number of job matches depends positively on the numbers of job seekers and vacant jobs, and positively or negatively on some additional variables.

1.1 Backround

Modern labour market models are typically characterized by the reallocation of workers across productive activities. This process of allocation is slowed down by various search frictions that workers looking for jobs and firms recruiting workers face[1]. The emphasis of these models is placed, not on stocks of unemployed and employed, but on worker and job flows between inactivity and market production; they represent the so-called flow approach to labour market analysis. The interest in going beyond textbook frictionless and perfectly competitive equilibrium models owes to documented empirical findings: labour market flows are reported as large compared to changes in related stocks[2]. In

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1 Recent literature on the subject is surveyed by Mortensen & Pissarides (1999).

2 See Blanchard and Diamond (1989), for example.

addition, a considerable wage dispersion across workers is found to exist, even between those with similar characteristics[3]. None of these findings can be satisfactorily explained by the textbook Walrasian labour market theory.

Modern equilibrium models, then, concern worker and job flows within the framework of forward-looking agents maximizing their discounted expected returns. The key assumption is that two-sided frictions exist in the process of matching employers and employees. Frictions derive, e.g., from imperfect information between traders, from their heterogeneity, and from slow mobility or congestion owing to large numbers. Both sides of the market have to make investments to overcome these frictions. Because of these frictions the number of new matches is not necessarily the minimum number of available workers and vacant jobs during the observation period, as it would be in a frictionless market. Instead, unemployed workers and vacant jobs might exist at the same time. Nevertheless, the flow of new matches is assumed to depend positively on the numbers of unemployed workers and vacancies. This relationship is known as the matching function:

$$M = m(U,V), \qquad (1)$$

where M is the number of worker-job pairs being matched during the observation period. U denotes the number of unemployed job seekers, at some moment within the period[4], and V is the number of vacancies, also measured within the observation period.

The matching function (1) is mainly an aggregate-level function with some desired properties, though several papers have founded on the development of convenient micro-level meeting processes which might induce (1). Usually, the function is assumed to be increasing and concave in both arguments, with the property $m(0,V)=m(U,0)=0$. Thus given at least one vacant job in the market, extra job seekers always increase the number of matches. However, because of concavity, the greater the total number of job seekers, the smaller will be the next increment. A constant returns-to-scale property – that is, if all of the inputs are doubled, output will double – is also typically imposed, as it implies a constant unemployment rate along a steady-state growth path in equilibrium models; see Pissarides (1990).

This dissertation consists of an introductionary chapter and four self-contained empirical studies on the labour market matching function. The main focus of the introductory chapter is devoted to theory; the choice is made for two reasons: first, empirical considerations are discussed broadly in the four subsequent empirical papers. Secondly, a comprehensive survey of the empirical literature has recently been made by Petrongolo and Pissarides (2001). Hence only the need to supplement their work with papers published after 2001 remains. This is done in Table 1.1, which summarises the main findings from

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3 See Burdett and Mortensen (1998); Acemoglu and Shimer (2000).

4 U might also denote all workers looking for a job. In that case it includes employed and out-of-the-labour-force job seekers.

empirical matching function studies. To ensure comparability between older and newer studies, it also includes some papers already discussed by Petrongolo and Pissarides. Next, before the review of the theory, I shall briefly discuss the contents of Table 1.1.

The early literature, omitted from the summary table, made inferences on the properties of the matching function by estimating a long-run vacancy-unemployment relationship, namely the Beveridge curve. The advantage of the method was that it exploits data on stock variables without any flow variables, which in any case were poorly available at that time. Nevertheless, the method suffers from several problems. It requires a steady-state assumption between the unemployment rate and vacancy rate, and the inferences on the micro structure of the underlying process are seldom unambiguous[5]. To overcome these difficulties, and helped by the increasing availability of flow data, authors have estimated matching functions directly since the late 1980s. The studies of interest are presented in Table 1.1. They were published after the early 1990s and several of them are considered in the survey of Petrongolo and Pissarides (2001). The focus is on aggregate and sectoral studies, leaving micro studies outside the scope of the survey.

For an empirical researcher, the key questions, also confronted in the empirical parts of this dissertation, include:

1. What is the right empirical specification of the matching function?
2. Which empirical variables correspond to the theoretical variables *U*, *V* and *M*? Should some additional explanatory variables be included?
3. What are the average elasticities of matching with respect to *U* and *V*?

Let us look at the first question in the light of the existing studies. Table 1.1 summarises 28 studies, of which the first 17 have been conducted at the aggregate level and 11 are sectoral studies. Only four papers do not utilise a log-linear specification. These are Warren (1996), using a translog form; Gregg & Petrongolo (2002) and van Ours & Ridder (1995), using non-linear models; and Münich & Svejnar & Terrel (1999), utilising a translog-form. Although not reported in the table, Blanchard & Diamond (1990) use also a function of the CES form, and Yashiv (2000) also employ the translog specification. Thus the log-linear seems to be the most popular specification. Popular alternatives are translog, non-linear and CES.

Building heavily on the existing studies, the present empirical studies mainly use the log-linear specification. The models in Chapters 2-3, and partly that in Chapter 4, derive from a log-linear Cobb-Douglas specification. The only exception is Chapter 5, which uses a non-linear specification to deal with the temporal aggregation problem from which the linear form typically suffers.

The second key question stresses the importance of finding empirical variables corresponding to the theoretical ones. If we look at Table 1.1, we find that in 11 papers the number of matches *M* is approximated by all hirings or by

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5 A steady-state means typically that the stock variables of the system remain constant.

hirings from unemployment. The outflow or the outflow rate from unemployment is used in 9 papers and 5 papers use filled vacancies. There seems to be some variability in the measure of *M*. This is, however, suspect since more important than the separate choice of the left-hand-side variable is the correspondence between the dependent and independent variables. Broersma and Van Ours (1999) show both theoretically and empirically that the measure of job matches should correspond to the measure of job searchers, otherwise the estimated matching elasticities will be biased.

If all hires or filled vacancies are used as a proxy for matches, one has to account for the fact that these variables are likely to contain more than just the flow from unemployment to employment: some vacancies will be filled by workers moving from one job to another or coming from outside the labour force. In that case, for the pool of job seekers and the flow of matches to correspond to each other, the former should also include employed job seekers, and those who are outside the labour force[6].

Some studies in Table 1.1 use the total unemployment outflow, or outflow rate, as a dependent variable. This measure of matches is problematic since many unemployed persons move outside the labour force[7]. Some studies deal with that problem by using the outflow rate of men as a dependent variable, since men's spells of unemployment are more likely to end in employment.

In Chapters 2-4 of this dissertation, the choice has been made to use filled vacancies as a dependent variable and all job seekers as an explanatory variable. All job seekers also include employed and out-of-the-labour-force job seekers. These variables correspond well to each other. Chapter 5 restricts the focus to unemployed job seekers. Therefore, the variable to be explained in the model is outflow from unemployment to employment, and the corresponding stock variable is the unemployment level. Again, the correspondence condition holds.

Should the matching function include some additional explanatory variables? According to the theory, job seeker characteristics affect reservation wages, or search intensities, and therefore have effect on the overall matching process. As a matter of fact, the estimated functions reported in the empirical literature have included several additional variables. The most often-used variable is the proportion of long-term unemployed (Mumford & Smith, 1999; Broersma 1997; Burgess 1993; Ilmakunnas & Pesola, 2003). In several papers job seekers are differentiated according to their labour market status (Mumford & Smith, 1999; Kangasharju & Pehkonen & Pekkala, 2004). In addition, several studies add flows of new job seekers and new vacancies to the specification to

6 Blanchard and Diamond (1989), for example, document the importance of job-to-job switches and movements from outside the labour force. They estimate that in the United States, 15 per cent of the vacancies are filled by the employed job searchers and 40 per cent by searchers coming from outside the labour force. In Finland, Ilmakunnas and Maliranta (2000) estimate that on average during the years 1994 – 1996, 42 per cent of worker inflow to the main industries consisted of within-industry transitions, 17 per cent originated from unemployment and 41 per cent from outside the labour force. These estimates are based on workers' end-of-the-year labour market status.

7 According to Rantala (1998), in Finland less than 50 per cent of the transitions from unemployment ended up in employment and 24 per cent exited the labour force.

control for the stock-flow properties of the process (Gregg & Petrongolo, 2002; Coles & Smith, 1998; Kangasharju & Pehkonen & Pekkala, 2004).

Fifteen papers in Table 1.1 add time trend or time dummies to the function to reveal changes in the matching process over time. Real wages and energy prices (Gross, 1997), GDP growth (Fahr & Sunde, 2002) and change in employment (Anderson & Burgess, 2002) are used as the proxy for the overall economic situation. Other frequently used variables include replacement ratios and demographics in sectoral studies.

This dissertation contributes to the existing literature by adding more variables to the matching function. These variables aim to measure the effect of job-seeker heterogeneity, or heterogeneity across the labour markets where workers sell their labour, on the matching process. By heterogeneity is mainly meant differences in job seekers' educational level. In Chapter 3, the model disaggregates job seekers also according to their age and duration of spell of unemployment. In Chapter 4, matching is allowed to differ according to density of the population of the market in which they are selling their labour. In Chapter 5, job seekers are divided into new and old job seekers depending on how long they have been searching. Job seekers' characteristics are found significantly to affect the process of matching.

The third key question concerns the value of the elasticity of matching with respect to both U and V. On average, the coefficient for job seekers is higher than that for vacancies when unemployment outflow or the unemployment outfow rate is the target variable. In turn, when hires or filled vacancies are explained, the matching elasticity with respect to vacancies is higher. The average estimate across all the studies presented in Table 1.1 is 0.5 for job seekers and 0.3 for vacancies. Chapter 2 of the present study provides the corresponding estimates for Finnish data. The estimated coefficients for job seekers and vacancies are 0.25 and 0.6, respectively. It seems that a similar relationship subsists between the variables captured by the matching functionin in our Finnish data sample as in the international data.

Some research problems have been deliberately excluded from this dissertation. These include spatial aspects such as the magnitude of the estimation bias originating from the aggregation of local markets, and interactions between local markets. These issues are discussed in Petrongolo and Pissarides, and empirical results from Finnish data are provided by Kangasharju, Pehkonen and Pekkala (2004) and Hynninen (2005).

TABLE 1.1 Empirical Matching function studies.

Authors	**Data**	**Job seekers, coefficient.**	**Vacancies, coefficient.**	**Other explanatory variables**
Aggregate studies:				
Dependent variable: hires				
Specification: log-linear				
Blanchard, Diamond (1990)	U.S. 1968-81 (monthly)	Unemployed	Help-wanted index (adj.)	time trend
		0.4	0.6	
Gross (1997)	Western Germany 1972-94 (quarterly)	Unemployed	notified V	real wages, real energy price
		-	-	
Yashiv (2000)	Israel 1975-89 (monthly)	Unemployed	notified V	structural breaks
		0.5	0.9	
Specification: translog				
Warren (1996)	U.S.manuf. 1969-73 (monthly)	Unemployed from manuf.	Help-wanted index (manuf.)	-
		-	-	
Dependent variable; unemployment outflow or outflow rate				
Specification: log-lin				
Layard,Nickell, Jackman (1991)	Britain 1968-88 (quarterly)	Unemployed	Notified V	time trend, search intensity index
		0.8	0.2	
Burda, Wyplosz (1994)	France 1971-93 (monthly)	Unemployed	Notified V.	time trend
		0.7	0.3	
	Germany 1968-91 (monthly)	Unemployed	Notified V.	
		0.7	0.3	
	Spain 1977-92 (monthly)	Unemployed	Notified V.	
		0.7	0.3	
	U.K 1985-93 (monthly)	Unemployed	Notified V.	
		0.7	0.2	
Mumford, Smith (1999)	Australia 1980-91 (quarterly)	Survey based job seekers	Survey based measure of vacancies	new hires, groups of job seekers, LTU/U, seasonal dummy
		0.9	0.1	
Broersma (1997)	Netherlands 1966-91 (yearly)	U rate	vacancy rate	hiring rate, income, RR, LTU, demogr. variables.
		-	-	
Specification: non-lin				
Gregg, Petrongolo (2002)	Britain 1967-96 (quarterly)	Unemployed	Notified V	U inflow, V inflow quadratic trend
		0.1	0.2	

Dependent variable vacancy outflow, male U outflow rate, referrals, hires from U, U outflow by duration				
Specification: log-lin				
Van Ours (1991)	Netherlands 1961-87 (annual)	Dep. var: vacancy outflow		RR, LTU/U
		Unemployed	Notified V adj.	
		0.5	0.7	
Burgess (1993)	U.K., men 1968-85 (quarterly)	Dep. var: male U outflow rate		male hires, RR, demogr. variables, LTU/U
		male U rate	-	
		0.6	0.4	
Berman (1997)	Israel 1978-90 (monthly)	Dep. var: referrals		time trend
		Unemployed	Notified V	
		0.3	0.4	
Bleakley, Fuhrer (1997)	U.S. 1979-1993 (monthly)	Dep. var: hires from U		structural breaks, time trend
		U rate	help-wanted index, adj.	
		0.6	0.3	
Coles, Smith (1998)	Britain 1987-1995 (monthly)	Dep. var: U outflow by duration		time trend, U and V inflows
		U stock	V stock	
		-0.3-0.2	0.2-0.9	
Kano, Ohta (2002)	Japan 1964-2000 (monthly)	Dep. var.: Filled Vacancies		time trend, transitions prob. between regimes
		effective js	active openings	
		0.6	0.4	
Fahr, Sunde (2001)	Western Germany, 1980-95 (yearly)	Dep. var.: hirings		time trend, time and occupational dummies, GDP (growth)
		registered U	registered V	
		0.4-0.5	0.4	
Specification: non-lin				
Van Ours, Ridder (1995)	Netherlands October 1980-83, September 1984, January 1986-88	Dep. var: Filled vacancies		occupational dummies
		-	-	
		-	-	
Sectoral studies:				
Dependent variable hires from U				
Specification: log-lin				
Burda (1993)	Czech 1990-92 (monthly)	Unemployed	Notified V	-
		0.4	0.4	
	Slovakia 1990-92 (monthly)	Unemployed	Notified V	
		0.6	0.1	
Boeri, Burda(1996) Profit (1997)	Czech 1992-94 (quarterly)	Unemployed	Notified V	time dummies, area dummies, lagged dep. vars.
		0.4-0.6	0.1	

Burda, Profit (1996)	Czech 1990-94 (monthly)	Unemployed	Notified V	time dummies, spillover across areas
		0.8	0.1	
Broersma, van Ours (1999)	Netherlands 1988-94 (quarterly)	Dep. var: hires from U		Industry dummies
		unemployed	Notified V	
		0.6	0.01	
		Dep. var: filled vacancies		
		unemployed	Notified V	
		-0.1	0.5	
Specification: translog				
Münich, Svejnar, Terrel (1999)	CzechSlovakia 1991-96 (monthly)	Total outflows from U		human capital, output per head, demogr. variables
		Unemployed	Notified V	
		1-1.8	0.7-1	
	Slovakia 1991-96 (monthly)	Total outflows from U		
		Unemployed	Notified V	
		0.4-2.5	0.2-0.3	
Dependent variable:				
Specification: log-lin				
Coles, Smith (1996)	England&Wales 1987 (monthly)	Dep. var: Filled Vacancies		wages, size of TTWA, demogr. variables
		Unemployed	Notified V.	
		0.3	0.7	
Burgess, Profit (2001)	U.K 1985-95 (monthly)	Dep. var: U outflow		time trends, spillover across areas
		Unemployed	Notified V	
		0.7	0.03	
		Dep. var: Filled vacancies		
		Unemployed	Notified V	
		0.003	0.4	
Anderson, Burgess (2000)	U.S 1979-84 (quarterly)	Dep. var: all new hires		change in E, RR, demographic variables.
		U rate	Help-wanted rate	
		0.4	0.8	
Bunders (2003)	Finland 1988-02 (yearly)	Dep. var: avg. duration of V		time, regional and occupational dummies
		Unemployed	Notified V	
		0.3	-0.05	
Kangasharju, Pehkonen, Pekkala (2004)	Finland 1991-02 (monthly)	Dep. var: U outflow		regional dummies, flows of new U and V, labour market states of job seekers
		Job seekers	Notified V	
		0.6	0.2	
		Dep. var: Filled vacancies		
		Job seekers	Notified V	
		0.1	0.4	
Kangasharju, Pehkonen, Pekkala (2005)	Finland 1991-2002 (monthly)	Dep. var.: Filled Vacancies		time dummies, flows of new U and V
		Specification; log-lin		
		Job seekers	Notified V	
		0.1	0.3	

		Specification: translog		
		Job seekers	Notified V	
		0.6	0.4	
Ilmakunnas, Pesola (2003)	Finland 1988-97 (annual)	Dep. var: U outflow		time trend, age structure, education, LTU, log GDP, spillovers from neighboring regions, excess job reallocation, churning flow
		Unemployed	Notified V	
		0.9	0.2-0.4	

Notes: V refers to vacancies, U to unemployment, LTU is long-term unemployment, RR is replacement rate, E is employment; and – means that additional variables are not used or reported, or that the estimate in question is not reported or it is not comparable to those reported in other studies.

1.2 Micro foundations

Several micro-level meeting processes consistent with the desired properties of the aggregate matching function have been provided. A common starting point is a so-called urn-ball problem analyzed by several probability theorists[8]. In these models, homogeneous job seekers apply for homogeneous vacancies without knowledge about each others' actions. The matching frictions are induced by a coordination problem which occurs as the likelihood of some vacancies attracting several applications while some attract no applications at all. Typically, this approach yields a matching function with an exponential form. This exponential matching function has some drawbacks, as shown in Section 1.2.1, which discusses the urn-ball model in more details. Therefore, it can not be used as an empirical specification without modifications. It, however, provides some insights into the problems associated with the modelling the process of matching.

The most common empirical specification is of the Cobb-Douglas form. The Cobb-Douglas form is widely used also in the empirical part of this thesis. Its drawback is that theoretical literature does not directly suggest the using of it. An important exception is Stevens (2002): her model which is based on a "telephone line" Poisson queuing process implies a CES matching function, which is approximately Cobb-Douglas under the assumption of constant marginal search costs. Note that this model includes congestion or coordination failure similar to that in the urn-ball model[9]. Actually, it may be regarded as a continuous time version of the urn-ball model. Thus, it preserves the insights provided by the urn-ball model and modifies it to suit better for empirical applications. In the model agents choose their search intensities, but because these are endogeneous, the only arguments of the matching function are U and V. These agents can therefore

8 See, e.g., Hall (1979) or Pissarides (1979).

9 Congestion means a negative externality that workers/firms cause each other. A more formal definition is provided later.

be regarded as homogeneous. Section 1.2.2 presents Stevens model in more detail.

Two alternatives for coordination failure as a source of market frictions are the directed-search model and the stock-flow model. The former presumes several worker-employer micromarkets where the short side of each market clears without frictions, but no mobility exists between these markets. Thus the source of frictions is imperfect mobility. The directed search model is discussed in section 1.2.3. In the stock-flow model frictions are rather caused by the heterogeneity of agents and mismatch between them, than by a coordination failure. It differs from all the previous models by presuming differences in the characteristics of agents or, in other words, agent heterogeneity. It also has several implications that can be empirically tested, these implications are discussed more carefully in section 1.2.4, and some of them are tested in essay 5 of this thesis.

The subsequent three sections continue the discussion on the models that include agent heterogoneity. These models are important for the purposes of this study because they are modifications of the urn-ball coordination failure approach, and they suggest that the heterogeneity of agents is a relevant factor in the process and should be therefore expicitely modelled. Section 1.2.5 discusses so-called ranking models. In these models workers are differentiated by employers according to their personal characteristics. The implication is that less attractive applicants do not cause congestion to preferred ones. Therefore, for differentiated worker groups the processes of matching also differ.

Section 1.2.6 extends the coordination failure model by adding a parameter that allows differences in workers' search intensity. The implication is that the probability of transition from unemployment to employment for a particular worker may differ from that for an average worker. This approach is used in essay 2 and 4 to interprete the estimation results.

Section 1.2.7 presents an additional assumption that a wage offer made by entrepreneurs to workers is a random variable. Under this assumption, a worker chooses her reservation wage by maximizing her expected consumption, and rejects all offers below it. Also this model provides a theoretical justification for the addition of various aggregate variables, such as the proportion of higher educated job seekers, or a particular demographic variable, into the estimated matching function. Therefore, this model is important in motivating all the empirical essays in this thesis.

Table 1.2 summarizes these matching processes by providing for each process the functional form of the matching function and some of its key properties.

TABLE 1.2 Summary of the micro-level models.

	Matching function	Properties
Static urn-ball model		
Butters (1977)	$M(U,V) = V(1-e^{-\frac{U}{V}})$.	Constant returns to scale; M(0,V) = M(U,0) = 0 ; Increasing in U and V (with U and V large).
Continuous time urn-ball model		
Stevens (2002)	$m = m^*(U,V,\alpha^*(U,V),\gamma^*(U,V))$ α* is worker's optimally chosen search intensitites. γ* is firm's optimally chosen search intensitites. Both depends on the form of the search and recruitment functions.	Constant returns to scale; The rate of matching tends to 0 as U and V tend to 0; Increasing and concave in U and V.
Directed-search model		
Lagos (2000)	$M(U,V) = \min\{U,\phi V\}$ ϕ depends on the expected profits of cabs conditional on being in a specific location and picking up a passenger.	Increasing returns to scale (not homogeneous); M(0,0)=0 ; Increasing in U and V.
Stock-flow model		
Coles & Smith (1998)	$M(S_t,s,B_t,b) = b\left(1-(1-\lambda)^{S_t}\right) + s\left(1-(1-\lambda)^{B_t}\right)$ S_t is the stock of open vacancies posted during a period t-1 or earlier. B_t denotes job seekers who have started to search during a period t-1 or earlier. s is the flow of new open vacancies posted during a period t. b is the flow of new job seekers starting to search during a period t.λ is the probability that a job seeker accepts a job offer.	Constant returns to scale; M(0,V) = M(U,0) = 0 ; No substitutability between U and V.
Ranking model		
Blanchard & Diamond (1994)	$M = M(U^H + U^L, V)$ U^H and U^L are the stocks of higher and lower educated job seekers.	Properties depend on the exact form of M.
Search intensity		
e.g. Petrongolo& Pissarides (2001)	$M(sU,V) \approx V(1-e^{-\frac{sU}{V}})$ s is the average search intensity across all job seekers.	Constant returns to scale; M(0,V) = M(U,0) = 0 ; Increasing in U and V (with U and V large).
Reservation wage		
e.g Petrongolo & Pissarides (2001)	$M = (1-G(R))m(U,V)$ G(R) is the average reservation wage across all job seekers.	Properties depend on the exact form of M.

Notes: *M* is number of matches, *U* is stock of (unemployed) job seekers, *V* is stock of open vacancies.

1.2.1 "Urn-ball" model

An "urn-ball" model provides intuitively appealing and systematic framework to analyse, what it means if the labour market lacks of information and coordination. A model produces an aggregate level matching function which is of exponential form, but is not very usefull in its plain form for advising the choise of the empirical specification of the function. Notwithstanding, several more sophisticated models base on the urn-ball framework and therefore it is a good starting point for the theory review.

Let us suppose fixed numbers of balls and urns at the beginning of an observation period. During the period, every individual ball is randomly placed in an urn without information about the locations of the other balls. The immediate inference from this limited information is that even with the same number of urns and balls, it is possible that some urns will receive several balls and some urns remain empty.

In labour market applications, the balls correspond to workers and the urns correspond to vacancies. All workers, as well as vacancies, are identical to each other. Identical workers know the locations of all vacancies but, because of the coordination problem, it is possible that some vacancies attract several applications and some attract no applications at all, and therefore cannot be filled during the period in question. Vacancies attracting several applications are filled by one of the applicants, while the rest remain unemployed, continuing to search during the next period. Therefore vacant jobs and unemployed workers can co-exist in the marketplace, even in market equilibrium conditions.

More carefully, denote the numbers of vacancies and unemployed workers by *V* and *U*, respectively. Because a job seeker chooses randomly the job he is going to apply for, the probability of a particular vacancy being chosen by that worker is *1/V*. Furthermore, the total number of applications for a particular vacancy follows the binomial distribution:

$$f(x) = \binom{U}{x}\left(\frac{1}{V}\right)^{x}\left(1-\frac{1}{V}\right)^{U-x}, \tag{2}$$

where x denotes the total number of applications. Given that, the probability for a vacancy will not attract any applications is $(1-1/V)^U$, the number of vacancies that attract at least one application, denoted by y, follows the binomial distribution[10]:

$$f(y) = \binom{V}{y}\left(\left(1-\left(1-\frac{1}{V}\right)\right)^{U}\right)^{y}\left(\left(1-\frac{1}{V}\right)^{U}\right)^{V-y}. \tag{3}$$

Because all the vacancies attracting at least one application are filled, the number of matches can be expressed as the expected value of the previous random variable:

$$M(U,V) = E[f(y)] = V\left[1-(1-1/V)^{U}\right]. \tag{4}$$

10 The probability that a vacancy will not attract any applications increases if the number of vacancies increases: by posting vacancies entrepreneurs are causing negative externality to each other. This is called the congestion effect. The same applies in reverse: the probability that a particular unemployed worker will find a job decreases as the number of unemployed workers increases.

Letting $U,V \to \infty$ so that V/U remains constant yields:

$$\lim_{\substack{U,V\to\infty \\ \frac{V}{U}=\theta}} \frac{M(U,V)}{V} = m(\theta) = \lim_{\substack{U,V\to\infty \\ \frac{V}{U}=\theta}} 1-(1-1/V)^{U} =$$

$$\lim_{\substack{U,V\to\infty \\ \frac{V}{U}=\theta}} 1-\left(1-\frac{(U/V)}{U}\right)^{U} = 1-e^{-\frac{U}{V}}. \tag{5}$$

Hence, for large but finite U and V, we have

$$M(U,V) \approx V(1-e^{-\frac{U}{V}}). \tag{6}$$

This matching function (6) clearly satisfies the desired properties of the matching function. It has constant returns to scale and it is increasing in U and V[11]. On the other hand, it is rather naive, and implies a combination of levels and durations of unemployment that is not empirically feasible.[12]

1.2.2 "Telephone line" model

The "telephone line" Poisson queuing process was originally presented by Cox and Miller (1965). Its application to the labour market has been suggested by Stevens (2002). This model is interesting because under certain conditions it produces an aggregate matching function of Cobb-Douglas form. It provides a micro-level theory that justifies the use of the Cobb-Douglas form as an empirical specification. It is also usefull for interpreting the results of the regressions that use a Cobb-Douglas specification.

Suppose workers send applications to firms randomly at Poisson rate a while firms respond to applications at Poisson rate γ. Because an exponentially distributed length of time with expectation $1/\gamma$ will be taken for a firm to process one application, an application sent to a firm already processing another application, will fail. This might happen because applicants are unaware of each others' actions. Therefore the model includes the congestion or coordination failure effect similar to that in the urn-ball model; in fact, it can be regarded as a continuous time version of the urn-ball model.

More formally, let U denote the number of unemployed workers, V the number of vacancies and V_0 the number of vacancies for which applications are not being processed. Because workers send applications at Poisson rate a, the total number sent out per unit time is aU, and the arrival rate of applications for each vacancy is aU/V. Accordingly, the total number of applications arriving for

11 With U and V small this function exhibits decreasing returns to scale.

12 This is shown in Petrongolo and Pissarides (2001).

vacancies for which applications are not being processed is aUV_0/V. In equilibrium, the inflow for processing is equal to the outflow, which is $\gamma(V-V_0)$. Equating these, yields the probability P that a given application will encounter a vacancy belonging to V_0:

$$P = \frac{V_0}{V} = \frac{\gamma V}{\alpha U + \gamma V}. \tag{7}$$

Under these conditions, the matching function can be expressed as a product of the probability (7) and the number of applications, aU:

$$m(U,V,\alpha,\gamma) = \frac{\alpha U \gamma V}{\alpha U + \gamma V}. \tag{8}$$

In addition to the congestion effect, the matching function (8) has several desirable properties. It is increasing and concave in U, V, α and γ. It has a constant returns-to-scale property. The rate of matching tends to zero as U or V tend to zero, and tends to aU as V tends to infinity.

The function (8) includes arguments a and γ which are seldom observable. Therefore this function can not be of empirical interest. Matching functions, however, are typically embedded in the equilibrium model in which a and γ are endogenous variables, and thus their optimal value can be solved. In the study by Stevens, the optimal search intensities a and γ depend on the forms of the search and recruitment cost functions. Under specific conditions, the function $m(U,V, a, \gamma)$ can be solved in the form

$$m = m^*(U,V,\alpha^*(U,V),\gamma^*(U,V)), \tag{9}$$

where U and V are the only unknowns. Stevens shows that given a constant elasticity search cost function, the matching function (9) is CES. Moreover, with the elasticity of the search cost function close to one, (9) is approximately Cobb-Douglas. In addition, the function (9) provides an interpretation for the elasticity of matching with respect to unemployment: it is determined by the costs of search relative to the benefits, for workers relative to firms. To illustrate this, consider a Cobb-Douglas matching function with a positive estimated unemployment elasticity below 0.5. The interpretation is, on the one hand, that the search costs relative to benefits are lower for workers than for firms, resulting in workers higher total search effort in equilibrium. On the other hand, an estimated elasticity above 0.5 would suggest lower congestion between workers than in the first case, resulting from their lower search effort, the search costs relative to benefits being now higher for workers.

We can use this theory to interprete the results achieved in the empirical parts of this dissertatation. For example, the model I in Table 2.7 reports that the elasticity of matches with respect to vacancies is 0.6 and that with respect to unemployment 0.2. That suggest the search costs relative to benefits are lower for workers than for firms. Therefore, the greater share of the total search intensity comes from the behaviour of job seekers and they cause a greater congestion effect on each other. I discuss this interpretation more in summary of this introduction chapter.

1.2.3 Directed-search model

The reason I present a directed-search model is that it provides an alternative for the coordination failure as a source of frictions. The form of it provided here does not guide us very much towards the adequate empirical specification, but it motivates to seek various result interpretations behind the coordination failure.

In this framework, contrary to these previously described, frictions are not assumed to arise out of information imperfections, but are shown as a feature of a specific type of equilibrium. The model presumes several frictionless micromarkets without agents having mobility between them. Thus the frictions exist due to imperfect mobility. Lagos (2000) presents an indirect search model which can be described in tems of a dynamic market for taxi rides, where taxi drivers seek passengers on a grid[13]. As in reality, passengers are able to perceive each others' actions: a light on the roof tells whether a taxi is free or not. There is no coordination failure, but it is possible that some passengers are located in areas empty of free taxis nearby. Thus, within every micromarket the number of matches is the minimum of taxis and passangers, and given more passengers than taxis, or vice versa, some agents will remain unmatched during that period.

Let us assume that time is discrete and continues forever, and a city consists of $n \geq 2$ locations where people and taxis can position themselves. There is a continuum of people and cabs. The continuum of people is normalized to 1 and the continuum of cabs is measured by v. The numbers of people and cabs in location i are l_i and v_i, respectively. Passangers' needs to move between locations are assumed to be exogenously determined by a Markov chain process.

In this model, taxis distribute themselves optimally across distinct locations. Given that at least one location is better than another, there is a possibility that cabs oversupply that position leaving some another location with unserved passengers. As mentioned before, there are no frictions within locations; in each location matches are determined by the short side of the market:

$$M_i = \min\{U_i, V_i\}. \qquad (10)$$

Still, agents may be distributed across locations so that vacant cabs and unserved customers exist simultaneously. Under certain conditions, the matches within each location can be aggregated to form the following matching function:

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13 This model provides three appealing features for the analyses of matching frictions. First, it is simple, but still adequate for the present purposes. Second, it is a market where frictions are readily visible: normally vacant taxis spend time waiting for passengers in some parts of the city, and at the same time some passengers wait for cabs in others. Third, the price of the industry is typically regulated, like the price of labour.

$$M(U,V) = \min\{U, \phi V\}, \tag{11}$$

where ϕ depends on the expected profits of cabs conditional on their being in a given location and serving some passengers[14].

This matching function has constant returns to scale. However, it allows for no substitutability between U and V. When there is an excess supply of cabs in each location, an additional cab does not increase the aggregate number of matches; only an extra customer increases matches.

1.2.4 The stock-flow model

The idea behind the stock-flow model, which makes it different from all the previous ones, is that agents are not seen as homogeneous. They are disaggregated into old and new traders depending on how long they have been in the market. The key feature is that the stock of old traders on one side of the market matches only with the flow of new traders on the other side. The intuition is the following: imagine a buyer visiting a market for the first time. She starts by sampling the stock of available goods. If she manages to find a good satisfying her needs, she buys it and exits the market. On the other hand, if she is not fortunate in finding a suitable good, she has to wait until some new goods arrive. To put the idea in the context of labour markets, the stock of vacancies matches only with the flow of new workers but not with the stock of old workers, and vice versa.

The stock-flow approach to labour market analysis has two clear empirical predictions that depart from the outcomes of a random search model. First, the stock of buyers matches with the flow of new sellers, but not with the stock of old sellers. In other words, unemployed persons who belong to the stock of unemployment does not cause congestion with respect to the flow of new unemployed, but create congestions for each other by applying for the same new vacancies. Second, a trader's hazard rate to match should at first be high, and then to fall if he fails to match with the current stock of buyers.

Formally, let us assume two types of agents in a marketplace: buyers and sellers. Each seller has one unit of a differentiated good for sale, and each buyer seeks to buy one unit of a good. Buyers have heterogeneous preferences over a good, because the model presumes that the value of a good for a buyer is an independent random draw from some underlying distribution. A suitable distribution is the Bernoulli distribution, in which λ denotes the probability that a buyer will like a seller's good. Correspondingly, $1-\lambda$ denotes the probability that a buyer does not like that good. The marketplace provides agents with perfect information about each other, and hence they can meet without costs. Contrary to

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14 The original idea of using aggregation across a large number of micro markets to express an aggregate function dates back to Hansen (1970). His approach differs from the directed-search model in assuming an exogeneously determined distribution of traders across micro markets. In the directed-search model, traders are optimally located, and thus their distribution is endogeneously determined.

the urn-ball model, market frictions between current buyers and sellers do not exist.

Assume that the market operates over an infinite sequence of discrete time periods. At each point in time, the stock of old buyers B_t and the stock of old sellers S_t exist in the market. New buyers and sellers arrive in the marketplace according to the Poisson process, with arrival rates b and s, respectively.

Given the length of a discrete time period close to zero, the probability for a new buyer to match a seller immediately after arrival in the market is:

$$P(\text{new buyer matches}) = 1 - (1-\lambda)^{S_t} . \qquad (12)$$

And the probability that a given old seller will trade with this new buyer is

$$P(\text{particular old seller trades with the new buyer}) = \frac{1-(1-\lambda)^{S_t}}{S_t} . \qquad (13)$$

Since the rate at which sellers contact new buyers is b, the old sellers' exit or hazard rate h can be written as

$$h = \frac{b}{S_t}\left(1-(1-\lambda)^{S_t}\right). \qquad (14)$$

It should be emphasized, that the probability for an old seller to match with a new buyer decreases given an increase in the number of sellers S_t. This can be interpreted as the standard congestion effect that old sellers cause each other by seeking the same new buyers.

Due to the assumption of symmetry between traders, the above analysis holds for new sellers. It follows that the matching function is:

$$M(S_t, s, B_t, b) = b\left(1-\left(1-\lambda\right)^{S_t}\right) + s\left(1-\left(1-\lambda\right)^{B_t}\right). \qquad (15)$$

The first term of the sum depicts the flow of new buyers matching with the stock of old sellers. The second term expresses the flow of new sellers matching with the old buyers. This matching function exhibits increasing returns to scale, although it is not homogeneous[15]. All traders become better off when the flow of new buyers and sellers increases[16].

1.2.5 Ranking

The idea of ranking was first introduced by Blanchard and Diamond (1994). Their model is based on the "urn-ball" model, but it additionally assumes

15 This implies the possibility of multiple Pareto-rankable equilibria and trade cycles.

16 This stems from assumption b=s, which is necessary for stationary equilibrium to exist. Increasing b (and s) makes old sellers and buyers better off.

entrepreneurs to prefer some workers to others, meaning that in the case of several applications for a vacancy, the one that is successful is not the result of random selection. Instead, an entrepreneur first ranks the applicants and then matches with the one deemed the best.

Blanchard and Diamond (1994) used their ranking model to explain differences between the labour market behaviour of short and long-term unemployed job seekers. Similarly, entrepreneurs may rank job applicants on the basis of characteristics other than the duration of unemployment; for example, their level of education.

Let us assume higher and lower educated job seekers apply randomly for the same vacancies, and that an entrepreneur always chooses a higher over a lower educated applicant. The consequence is that lower educated job seekers do not create congestion for their higher educated counterparts during a search. Thus the hazard rate of a higher educated job seeker is greater than that of lower educated one.

More formally, assume the matching function for higher educated job seekers to be $M^H(U^H,V)$, where V denotes all vacancies, and U^H denotes the number of higher educated job seekers. Since lower educated job seekers do not affect the matching of higher educated ones, they are not included into function. The corresponding function for low educated seekers is $M^L(U^H+U^L, V)$, where the first argument also includes higher educated seekers. The aggregate function can be written as

$$M = M(U^H + U^L, V). \tag{16}$$

The transition probability for higher educated job seekers is $M^H(U^H,V)/U^H$. It decreases given an increase in the number of higher educated seekers. The corresponding probability for lower educated job seekers is $M(U^H+U^L, V)/U^L$ - $M^H(U^H,V)/U^L$. This results from subtracting the matches of higher educated job seekers from the total seekers.

1.2.6 Differences in search intensity

A convenient way of introducing the influence of agent heterogeneity on the matching process is presented by Petrongolo and Pissarides (2001). They use a simple matching function arising from the urn-ball process, in which they add a parameter s_i to denote the search intensity of worker i. Thus, they assume some seekers put more effort into searching than others. In this model the differences in search effort is usually related to the differing expected returns from searching.

Let us denote the sum of search intensities over all job seekers by s. The matching function can be written as

$$M(sU,V) \approx V(1 - e^{-\frac{sU}{V}}). \tag{17}$$

The function (17) implies that the transition probability of a particular worker differs from that of an average worker, the former being now $s_i m(U,V)/sU$.

Usually the search intensity parameter *s* is endogenous in the equilibrium model. The model may be constructed to allow workers to choose how much effort to put into searching. Given positive search costs, a worker chooses her search intensity to maximize her expected returns from searching

1.2.7 Differences in reservation wages

Another way of includíng agent heterogeneity in the model is to assume wage offers made by entrepreneurs to job seekers have a probability distribution. Under this assumption, a worker chooses a reservation wage that maximises her expected net consumption, and rejects all offers below it. We assume that a meeting technology is $m(U,V)$, wage offers are drawn from a probability distribution $G(w)$, and the reservation wage of job seeker i is R_i. The hazard rate of this seeker can be written as

$$(1-G(R_i))\frac{m(U,V)}{U}. \tag{18}$$

By assuming, further, that the average reservation wage over all individuals can be defined, and denoting it by R, the aggregate matching function can be written as:

$$M=(1-G(R))m(U,V). \tag{19}$$

This function provides a theoretical justification for the addition of various aggregate variables into the estimated matching function. Such variables might, for example, be the proportion of higher educated job seekers, or some demographics.

1.3 Macro-level framework

Although the matching function captures the complex process of employment production, we still have need of the equilibrium model in order to assess the effect of matching efficiency on unemployment, employment and other macro-level variables. The equilibrium model is necessary in inferring consequensies of the estimation results reported in subsequent essays to the unemployment or employment. The equilibrium model presented in this section follows the papers of Mortensen and Pissarides (1994), Rogerson (1997) and, especially, Pissarides (2000).

Figure 1.1 illustrates the activity of the labour market. Expanding firms constantly create new jobs and thereby increase the number of vacant jobs. This is indicated by flow 4 in Figure 1.1. At the same time, some jobs are terminated, increasing the stock of unemployed persons (flow 1). Another source of flows to unemployment is quitting (flow 2) and job seekers entering the labour force (flow 8). Unemployed persons and vacant jobs, in turn, meet each other according to the matching technology, giving birth to new filled vacancies (flows 6 and 5). Eventually, some matches cease to exist due to job loss or quitting thus maintaining circulation in the market. In addition, some unemployed job seekers may move out of labour force, as indicated by flow 7. In addition, some theoretical studies have pointed out that a certain share of employed workers is possibly searching for a job, because they are willing to change between jobs. Those job-to-job movers create a worker flow which goes directly from quits to matches, and is indicated by the arrow number 9 in the figure. Another direct flow to matches would be compricing of workers out of the labour force moving to the employment pool. That channel is drawn in the figure by a dash line because in principle, as the period of analysis is made sufficiently short, all those who enter employment pass first from the unemployment pool.

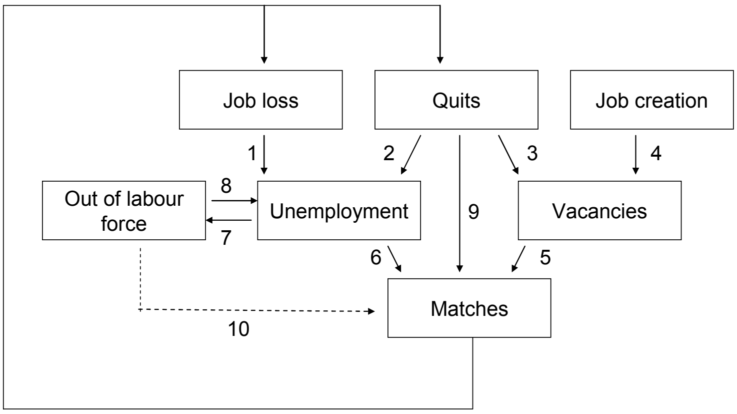

FIGURE 1.1 Labour market flows.

To predict the level of unemployment it is necessary to model flows 1, 2 and 6-8, of which the matching function itself captures only flow 6. At first, I present a simplified model which omits the flows 7-10. Then some extended versions of the model are discussed. The modle presented is quite standard and is elaborately presented for example by Pissarides (2000), thus only key features are provided here.

It can be shown that the mean number of unemployed job seekers entering the employment pool (flow 6) can be expressed as $\theta q(\theta)uL*dt$, where $\theta q(\theta)*dt$ is the probability that an unemployed job seeker receives a job offer, and uL is the total number of job seekers, written as a product of unemployment rate u and labour force L. The parameter θ is the proportion of vacancies to unemployed job seekers, v/u.

That expression comes more understandable if we remind that the matching function gives us the total number of matches during a unit time and vacancy- worker pairs to be matched are randomly chosen from the respective pools of agents. Thus, the process that changes the state of vacancies to occupied jobs is Poisson distributed at rate $m(uL,vL)/vL$. The stationary Poisson process has the property that the probability of one offer to arrive in any short time interval is approximately proportional to the length of that period. We assume that all offers are accepted, therefore the probability of a vacant job to be occupied is *m(uL,vL)/vL*dt*, with *dt* denoting a short time interval. The mean number of vacancies becoming occupied is *m(uL,vL)/vL*vL*dt=mLdt*. If the homogeneity of degree one -assumption is imposed to the matching function, the above Poisson rate depends inversely only on *v/u* –ratio, denoted by θ;: This dependence can be written as; $q(\theta) \equiv m(u/v,1)$ Likewise, the rate at which unemployed workers become employed is $\theta q(\theta)$. And the flow out of unemployment is now $\theta q(\theta)uL*dt$.

The corresponding expression for the flow in unemployment (sum of flows 1 and 2) is $\lambda(1\text{-}u)Ldt$, where λ is the Poisson rate for technology shocks that make jobs unprofitable. By ignoring flows 7-10 at the first stage, the equilibrium mean unemployment can be calculated from the equivalence of the flows into and out of unemployment:

$$\lambda(1-u) = \theta q(\theta)u \Leftrightarrow u = \frac{\lambda}{\lambda + \theta q(\theta)}. \tag{20}$$

In equation (20), the parameter λ is exogenous but the equilibrium value for θ has to be calculated. The solution to this problem comes from the optimizing behaviour of firms and workers. For firms, vacant jobs are like assets; search costs are related to posting them, but the investment is expected to yield a return after a successful match. The optimizing behaviour of firms ensures that the demand for labour follows the equation:

$$w = p - \frac{(r+\lambda)pc}{q(\theta)}, \tag{21}$$

That equation is not derived here, but it can be understood to correspond to the standard marginal condition for the demand for labour: the wage equals the value of the job's output *p*. Because frictions appear in the model, search costs have to be subtracted from *p*. The second term in the right side of the equation is the expected capitalized value of the firm's hiring costs, where r is the interest rate and pc is a search cost per unit time. Pissarides (2000) gives the detailed derivation of that equation.

Because the labour force is constrained to remain constant, job seekers are able to influence equilibrium only through wages. The aggregate wage equation that holds in equilibrium is

$$w = (1-\beta)z + \beta p(1 + c\theta), \tag{22}$$

where β is workers' bargaining power and *z* is real returns from unemployment. Again, we take this here as given, but the details can be found in Pissarides (2000).

The equilibrium model is summarized by equations (20)-(22), the first of which is known as the Beveridge curve; see Figure 1.2. The three unknown parameters are wage rate *w*, labour market tightness θ and equilibrium unemployment u. Equations (21) and (22) together yield the wage rate and tightness, and the Beveridge curve the unemployment rate. Given u and v, the fall in the number of matches shifts the Beveridge curve upwards and to the right, away from the origin. Since the rate of job seekers filling vacancies at a given market tightness is reduced, the job creation curve shifts to the left and downwards in the wage-tightness space, reducing both equilibrium wages and tightness. This causes a downward rotation of the equilibrium job creation line in the u-v space. Thus, unemployment rises and the number of vacancies falls. The increase in matching efficiency has the opposite effects.

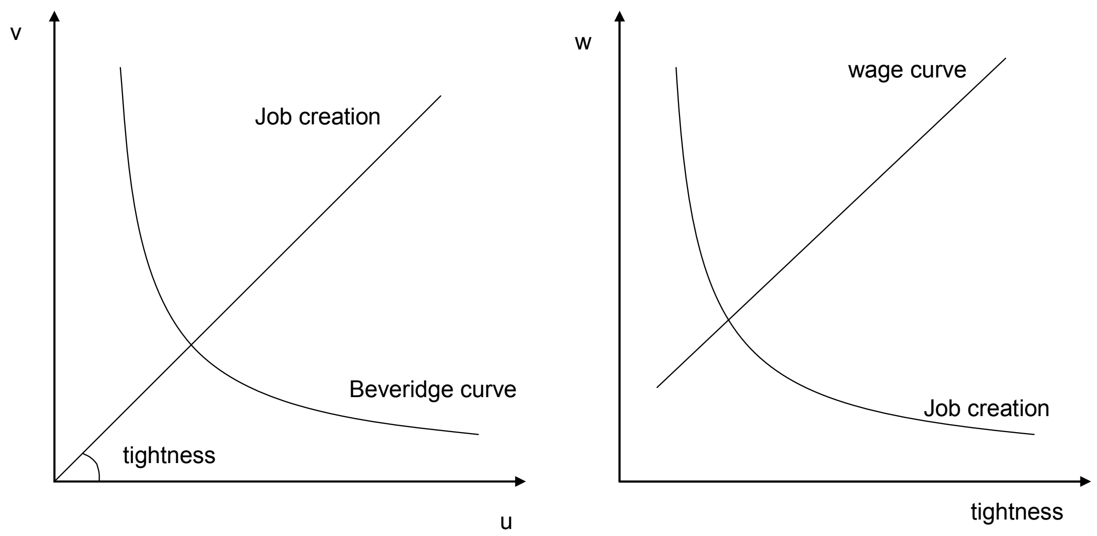

FIGURE 1.2 Beveridge, job creation and wage curves.

Figure 1.2 helps to interpret the regression results of the subsequent empirical papers. For example, Table 2.10 gives information that holding other factors constant, the number of matches increased during the period 1991-1996. Then our theoretical model predicts that during that period, the Beveridge curve is likely to move to the origin reducing both the unemployment and vacancy rates. Because the rate at which job seekers fill vacancies increases, job creation curve tends to move up, which will increase equilibrium tightness. From the left-side picture we see that an increase in the tigthness increases vacancy rate and decreases unemployment rate.

The model presented above contains several simplifications that can be, and already have been, relaxed by several authors. Acemoglu (1999) extends the equilibrium unemployment model which contains the urn-ball random meeting process. In his model, firms decide what kinds of vacancies to advertise. In other words, the distribution of worker skills is assumed to be exogeneous in the model, but the distribution of skill requirements across jobs is now endogeneous[17]. Under these conditions an economy is shown to have two types of equilibria. In the first, firms open "middling" jobs, meaning that they are targeted at all job seekers regardless of their skills. In the second, firms create separate jobs for skilled and unskilled workers.

[17] One way to measure the ability of a worker is to relate it to her education.

Acemoglu shows that when high-skilled workers are relatively few and the productivity gap between higher and lower educated workers is small, firms create middling jobs. But an increase in the productivity gap or in the proportion of high-educated workers may switch an economy to a separating equilibrium. Such an upward change in the average skill requirements of jobs is shown to increase unemployment for all workers.

Whereas Acemoglu's model relies on a random search process, the model proposed by Mortensen and Pissarides (1999) builds around a directed-search assumption and endogenous job destruction. In their model, there is a perfect match between job seeker skills and the skill requirements of firms, but all kind of jobs face productivity shocks. These shocks, in turn, give rise to wage dispersion.

Gautier (2002) and Albrecht & Vroman (2002) add to the framework the spillover effect of higher-educated job seekers on the creation and filling of unskilled job vacancies. In Gautier's model high-skilled job seekers might accept a low-skill job offer and continue to search on-the-job for a high-skill job. However, they assume that wage determination ignores overall labour market conditions. In Albrecht & Vroman (2002) wages are formed by the Nash bargaining process, but they do not allow on-the-job search. Finally, Dolado et al. (2003) include both Nash-bargaining and on-the-job search assumptions in their model.

1.4 On-the-job search

Many empirical studies report that a considerable proportion of new hirings consists of job-to-job movements: workers do not necessarily enter the unemployment pool between jobs. These findings have stimulated several theoretical studies that allow employed workers to search for better jobs[18].

Pissarides (1994) includes the on-the-job search assumption in the conventional search equilibrium framework with a random meeting process. He presumes job heterogeneity to occur as differences in the net productivity of filled vacancies. The type of job, "good" or "bad", is perceived only after a match. Also the operating costs are higher for good than bad jobs. An entrepreneur can choose whether to advertise a good or a bad job, but because of the randomness of the meeting process, he receives applications from all job seekers. However, only unemployed workers are ready to match with a bad job.

Under these conditions, employed workers may create congestion for unemployed job seekers by starting to search for another job. But then again, by starting to search they will increase the flow of applications to firms, providing an incentive for entrepreneurs to advertise more good jobs. As a result, the existing job structure will change in favour of employed workers. In the

18 The early literature is surveyed by Mortensen (1986).

framework of Pissarides the search of employed workers is related to the level of economic activity: they search during booms. The outcome of the model is that an increase in the number of vacancies during an economic upswing does not decrease unemployment by the same amount because of the increase in the number of employed job seekers.

In empirical matching function studies employed job seekers play an important role. Broersma and Van Ours (1999) show both theoretically and empirically that the measure of job matches should correspond to the measure of job seekers. Otherwise the estimated matching elasticity will be biased. Some vacancies are filled by workers moving from one job to another. To make the pool of job seekers to correspond to the flow variable, the pool of job seekers should also include employed job seekers.

In the majority of empirical studies, employed job seekers are ignored because of the scarcity of data. An exception for example, is Van Ours (1995), who uses data from the Dutch labour force survey which includes the requisite information on employed job seekers and on all vacancies (not only notified). He builds a general model which enables him to test whether the search process of employed job seekers is the same as that of unemployed seekers. He also tests for job competition between these groups. First, he finds differences in matching between employed and unemployed seekers. Second, competition exists between the two groups, and it is caused by employers who use different recruitment channels in seeking to fill their vacancies.

1.5 Job competition

The origin of the concept of job competition is found in papers aiming to explain why unemployment rates are higher among lower than higher educated workers, especially during downturns. The literature provides two major explanations. The first is that firms invest more in job-specific capital for higher educated workers, and therefore they are more reluctant to lay off these than lower educated workers. That is, higher educated workers are hoarded during recessions. Hoarding implies that the inflow rate of lower educated workers to unemployment increases during downturns relatively more than that of higher educated workers. The second explanation for the higher unemployment rates of lower educated workers is job competition. This, in turn, implies a decrease in the unemployment outflow rate of lower educated workers.

The concept of job competition or the crowding-out effect owes in part to the ranking literature. Van Ours and Ridder (1995) state that job competition between workers exists, "if employers prefer higher over lower educated workers for jobs that were previously occupied by lower educated workers". On the one hand, this definition assumes employers' ability to rank higher over lower educated applicants, while on the other, the definition includes the idea that ranking is preceded by a match between the employer and a lower educated worker. In addition to this, job competition is usually related to business cycles. According to Van Ours and Ridder (1994), employers may raise their hiring standards during times of high unemployment, meaning that they are willing to match only with better educated workers. The other alternative is that hiring standards remain constant, but employers rank applicants according to their education. In this case, a lower educated worker is hired only if a vacancy attracts no applications from higher educated workers.

A synonym for job competition is the concept of crowding-out. Gautier et al. (2001) define crowding-out as "the process by which during recessions lower educated workers are replaced by higher educated workers". There is a minor distinction between the definitions of Van Ours & Ridder and Gautier et al. According to Van Ours and Ridder, job competition occurs only when a worker switches from unemployment to employment, whereas Gautier et al. include also the flow from employment to unemployment in their concept.

One of the first models to include a crowding-out effect was presented by Okun (1981). Okun proposed the idea that it is costly to adjust wages down during cyclical downturns. Therefore, instead, firms increase their hiring standards. In the search theory framework, the crowding-out effect can be explained by the optimal search strategy of higher educated workers. Under certain conditions, it may be optimal for a worker to accept a low-skill job temporarily in order to continue searching as an employed job seeker.

Studies which discuss on the topic of job competition or the crowding-out effect have potentially important policy implications. If job competition exists, there is no reason to educate unemployed workers because this leads only to redistribution of unemployment. If the unemployment rate of lower educated workers is high and is caused by crowding-out, then policy makers should encourage higher educated workers to vacate low-skill jobs. This can be done, for example, by increasing the rate of creation of high-skill jobs. If there is no evidence of crowding-out but the unemployment rate of lower educated workers is high, policies should focus on creating more vacancies with low skill requirements.

In the job competition model of Burgess (1993), two groups of job seekers distinguished are employed and unemployed seekers. Employed workers start to search for jobs during upturns, since then the probability of getting an offer is higher. By starting to search, employed workers are causing congestion for unemployed searchers. Pissarides (1994) takes the issue one step further. He argues that when employed workers start to search, the probability that employers will receive an application from an employed searcher increases. This gives employers an incentive to create vacancies suitable for employed workers.

The empirical evidence on the existence of job competition between workers disaggregated by education have been presented by Teulings and Koopmanschap (1989). They study the relationship between the distribution of employees by education and the distribution of jobs by level of difficulty. Their results suggest that in regions with high unemployment, the proportion of higher educated workers in jobs where only lower education is required, is higher than in regions with lower unemployment. Their results give only indirect evidence for job competition, since they do not measure differences in unemployment outflow rates. However, their results are consistent with the job competition hypothesis.

Van Ours and Ridder (1994) build a theoretical model in which a necessary condition for job competition is that higher educated workers are better off when searching for jobs with low educational requirements. If wages at a higher skill-level are bigger than or equal to wages at a lower level, the necessary condition for workers to search at lower level is smaller U/V –ratio at a lower level. This is because then the probability of receiving an offer is higher[19]. The empirical results suggest that only at the higher vocational level was the flow of filled vacancies affected by the number of unemployed at the next higher level. At lower levels of education there was no evidence of job competition.

Gautier et al. (2002) use a combined firm-worker dataset to test the occurrence of job competition at firm level. Their emphasis differs slightly from that of Van Ours & Ridder (1995). Their definition of job competition covers both unemployment inflows and outflows, whereas the study by Van Ours & Ridder concentrates only on the unemployment outflow. Gautier et al. test whether differences in years of schooling between the inflows and outflows of workers, for a particular job level and firm, are larger during low employment years. In other words, they test whether firms are upgrading their workers' education level at given job level during downturns. In addition, they have data on wages that enables them to test between pure job competition and substitution: they test whether higher educated workers are more productive than lower educated workers controlling for job complexity. They measure a productivity gap as a wage differential between the groups in question. Gautier et al. find that at each job complexity level it is mainly low educated workers who are laid off during downturns, but still, they is no evidence for higher educated workers crowding out lower educated workers. In addition, at each job complexity level, higher educated workers are not more productive that low educated workers. This result implies the substitutability between education and some other characteristics, such as job tenure.

1.6 Discussion on literature and the results of subsequent empirical papers

This chapter surveyed both the empirical and theoretical literature on the labour market matching function. The matching function provides a way to model labour market frictions Both employers and employees have to make

[19] In the Netherlands, however, this condition is satisfied only for unemployed workers with an academic education. Their data comes from eight vacancy surveys conducted by Dutch Central Bureau of Statistics, in the months October 1980-1983, September 1984 and January 1986-1988.

investments to overcome these frictions. Under these conditions, a job matching function might be defined so that the number of job matches depends positively on the numbers of job seekers and vacant jobs, and positively or negatively on some additional variables. The subsequent empirical papers report regression results from alternative specifications that base on the standard theoretical matching function $M=f(U,V)$. This section summarises main results from these empirical papers and discusses the results in the view of literature.

The first empirical study estimates a base specification, in which monthly number of filled vacancies in a labour office district is regressed on the corresponding number of vacancies and job seekers. In the alternative specification job seekers are classified into three groups and each group is allowed to have its own matching elasticity parameter. Both specifications are of log-linear or Cobb-Douglas form, as in most international studies of Table 1.1. The results indicate that the estimates of the base specification are in line with the international studies. The elasticity of matches with respect to vacancies is 0.6 when district and time effects are not controlled, and 0.4 after controlling for these effects. The corresponding estimate for job seekers is 0.2 in base specification without district and time effects, and 0.1 after controlling those effects. Using the information given in Table 1.1, and restricting ourselves to studies that use filled vacancies as dependent variable, we can calculate the average estimate for vacancies, 0.4, and for job seekers, 0.2, which are very close to our estimates.

The interpretation of these results is that congestion caused by job seekers on other job seekers is 0.1 – 1 = –0.9. That negative externality is higher than that caused by employers on each other, which is 0.4 – 1 = –0.6. It seems that, because the proportion of vacancies to job seekers was low during the estimation period (1991:1-2002:8), new vacancies were more likely to speed the process of matching than new job seekers. Including fixed effects for time and district into regression cuts both the effect of vacancies and job seekers, giving us a reason to suspect there are other variables that affect the dependent variable and that correlate with these two regressors.

Another interpretation comes from the telephone line model discussed is Section 1.2.2. Because the estimated congestion effect of job seekers is high their relative costs of search relative to benefits are low. Therefore they search with very high intensity resulting in high congestion on each other.

Regressions that allow variation in the elasticity parameter across education groups of job seekers show that only primary educated job seekers have a positive effect on monthly matches. An increase in the number of secondary educated seekers decreases the number of monthly matches, and the effect of highly educated job seekers is not statistically significant. The explanation for this empirical result is not clear. Although using slightly different regression, partly similar results have been reported by Fahr and Sunde (2001) who show that an additional job seeker with low education creates a new match with a relatively higher probability than job seekers with higher education. Especially a person belonging to intermediate education group has relatively lower probability to form a match. According to them, it could mean that the group of low educated job seekers are particularly affected by cyclical variations or that many matches in that group split up after a short period of time making the stock of low educated job seekers very dynamic. This is quite a data-oriented explanation, but should be taken into account also in our study.

The second empirical paper of this dissertation considers the issue of job seekers' education using a slightly different approach. At first, we check whether the previous results are driven by a certain set of omitted explanatory variables. It should be noted that the education variable is now a proportion of a certain education group to all job seekers, so this minor change in the definition of the variable might also have an effect on estimated coefficient. In any case, we find that the coefficient for job seekers increases when we control for the effects of education composition, and job seekers age, and the effect of long-term unemployment. The coefficient for vacancies does not chance between these specifications.

In addition, the coefficient for job seekers increases up to 0.4 when the GLS estimator is used. A plausible explanation for that higher figure in the latter specification is that the within-estimator does not exploit a between-districts variation. Anyway, we can conclude that the estimate for vacancies is in general more reliable than that of job seekers.

It is conceivable that many secondary educated job seekers are aged above 25 and the previously estimated negative coefficient for them as a group could be partly explained by the age-effect. These control variables, however, do not change the basic result. The estimated coefficient for secondary educated seekers is still negative although the interpretation slightly differs from the previous one. Because education variables appear in the specification as relative shares of all seekers, the estimated effect is that the education composition of the market has on the number of monthly matches. The results indicate that the change in the composition that increases the relative shares of primary or highly educated seekers speeds up the matching process, whereas an increase in the relative share of secondary educated seekers has a negative effect on the ability of the market to form new matches.

In the second empirical paper, the results are interpreted by the theory which points out job seekers' reservation wages may vary individually and therefore, different job seeker compositions might result in varying local matching processes. That theory was also discussed in Section 1.2.7 of this introduction chapter. The estimated model, however, do not support the hypothesis that higher education leads to higher reservation wages and therefore, the higher share of highly educated job seekers would slow down a local matching process. Instead, an increase in the share of highly educated seekers has a positive effect on the number of monthly matches. Instead, a relative growth of the group of secondary educated seekers has a negative effect. It means, assuming that the model is appropriate, that the hypothesis in its literal form should be rejected.

Although the paper does not provide any alternative theories that might explain the result better, this kind of exercise can be done here. Let us first assume the characteristics of matching process are better captured by the urn-ball model than by the directed search or stock-flow model. We can also exclude ranking models as a source of interpretation because even if employers rank members of a certain education group ahead of another, there is no reason why this should affect the total number of matches. Secondly, as we already noted, the reservation wage hypothesis as an interpretation obligates us to explain why the reservation wage of secondary educated seekers would be higher than that of other groups, especially, why it is high compared to highly educated job seekers. It seems that the hypothesis of varying search intensities across groups of job seekers provides a better theoretical interpretation. And that is why a growth in the relative share of a certain group has an effect on a total number of matches.

The third empirical paper changes focus more clearly on the characteristics of local labour markets. Although the regressions of the previous papers included district-specific effects, their purpose was more or less to control for several uninteresting factors, while the main interest was to estimate parameters common to all districts. In the third paper, instead, district-specific factors are of interest. The hypothesis of the study is that the speed of the local matching process depends more on the population density than on the numbers of job seekers and vacancies. That argument alone would suggest we will find efficient matching processes in cities or in other areas where population density is high. We expect, however, to find signs of another factor: heterogeneity of both workers and jobs tends to increase in densely populated areas implying less efficient matching process.

We choose to control for the heterogeneity effect by the education composition of the labour market. In principle, we could include more control variables into the specification, but it would certainly complicate the specification without certainty of the improving measurement of heterogeneity.

The analysis of the estimates for fixed effects reveals that on average they are higher in high density labour market district. These fixed effect estimates, however, not unambiguously measure the efficiency of the market, because efficiency in its standard meaning should be measured in relation to some upper limit. Rather it measures the effect of those district-specific factors that are omitted from the specification. Or in other words, it is the net-effect of all district specific factors except the numbers of vacancies and job seekers, and education composition, which are explicitly included in the specification.

We use a so-called mixed effect model including both random and fixed effects to achieve more information on the factors captured by the fixed effects alone in the previous specification. This specification uses random parameters to capture the effects of all the omitted variables, and fixed effects to capture that part of random parameters which can be explained by labour office areas belonging to a certain group, where grouping variable is population density. We find that when we control for heterogeneity by including the education composition variable in the regression, the estimates for intercepts are higher in the densely populated areas. However, when the education composition variable is omitted, or its effect is a part of the random parameter of the model, the highest intercepts are found in the LLOs constituting a middle density group. This observation is in line with the hypothesis that holding heterogeneity constant matching "efficiency" is the higher the higher the population of the area is. Also, it seems that heterogeneity plays a role in the matching process of densely populated areas, although its importance is not completely clear after this exercise.

The final of the empirical papers returns to estimate global parameters. The main empirical issue of this paper is to deal with the time aggregation problem that appears in regression models which explain a flow variable by stock variables. That problem is discussed also in context of Table 1.1, where empirical studies are summarised. The economics theory behind the regressions is related to the stock-flow approach presented in Section 1.2.4. The results show some evidence for the stock-flow hypothesis: the stock of unemployed jobseekers matches rather with the flow of new vacancies than with the stock of old vacancies. Another finding is that the flow of new job seekers doesn't seem to match with the stock of vacancies. Although this finding does not contradict the hypothesis, it is highly unexpected, and therefore casts doubts on the validity of the stock-flow hypothesis.

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CHAPTER 2

JOB SEEKERS AND VACANCIES IN FINLAND

ABSTRACT. The aim of this study is to estimate the labour market matching function. The paper is innovative because the pool of all job seekers is disaggregated into three groups by education. In addition, the data allows the matching function to be estimated not only on the aggregate but also spatially disaggregate level. The monthly data are drawn from 173 labour office areas over a 12-year period between 1991 and 2002. The results indicate that primary educated job seekers have a positive effect on matches whereas seekers with secondary education display a negative effect. The effect of higher educated seekers is almost zero. The results suggest that labour offices are a relevant market place mainly for primary educated job seekers.

2.1 Introduction

In recent years labour market research has made extensive use of the concept of the matching function[20]. It connects the stocks of unemployed job seekers and vacant jobs to the flow of filled vacancies. The matching function is used to model labour market frictions caused by, for example, incomplete information between trading parties, their search behaviour, slow mobility, and differences between worker skills and the requirements of employers. On account of such frictions, unemployed workers and vacant jobs do not match immediately, but after a time-consuming search process. Therefore vacancies and unemployed job

[20] For a comprehensive survey of the matching function literature see Petrongolo & Pissarides (2001).

seekers are likely to exist simultaneously on the market, even in a state of market equilibrium[21].

Traditionally, the matching function relates the three aggregate variables to each other without describing in more detail the process underlying it. Indeed, the term "black box" has been used to describe the matching function. During the last few years, the theoretical literature has tried to open the black box by adding explicit variables into the function. As a consequence, more properties of the matching process have come to light. The additional variables include, e.g., employed job seekers and their individual characteristics. Empirical research has tried to follow in the wake of the theory, but progress has been hindered by the lack of applicable data.

In this study, I utilize a rich panel data set which covers the years 1991-2002 and is especially suitable for matching function studies for several reasons[22]. First, as monthly data its frequency is relatively high, as required for empirical research purposes since the majority of vacancies is known to be filled, and the majority of unemployment spells is known to end, within a month or two. Secondly, the data provide information about the characteristics of both job seekers and vacancies, allowing the former to be grouped on the basis of their educational background. The data also offer several demographic variables and provide for regional disaggregation at the local labour office (n=173) level. Thus it enables empirical knowledge to be obtained about the influence of the characteristics of individuals in the matching process.

The aim of this paper is twofold. First, It describes the data, thereby providing an intuitive picture of labour market matching performance during the observation period. The second objective is to model a matching process, first at the aggregate level, making no distinction between individuals with different characteristics, and then at disaggregate level, taking job seeker heterogeneity into account. The aggregate model provides estimates comparable to these in the previous literature, and functions as a baseline for the further analysis.

The results indicate the educational background of job seekers affects matching performance. Primary educated seekers have a positive effect on matches whereas seekers with a secondary level of education have a negative impact. The effect of the higher educated job seekers is almost zero.

The study proceeds as follows. Section 2.2 describes the data, giving an intuitive picture of the characteristics of job seekers and of vacancies. Section 2.3 discusses the coverage of the data. Section 2.4.1 introduces the model and 2.4.2 reports the results of the estimations. Finally, Section 2.5 concludes.

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21 There are two main approaches to the definition of equilibrium unemployment. Either an attempt is made to determine the non-accelerating inflation rate of the unemployment rate, NAIRU, or equilibrium unemployment is defined as the equivalence between unemployment inflows and outflows. Equivalence can be achieved with different combinations of unemployed persons and vacant jobs.

22 Data are from the unemployment register of the Finnish Ministry of Labour.

2.2 Job seekers and vacancies

The monthly data span January 1991 to September 2002, and comprise 189 labour office areas, LLOs. The data contain information on the variables of interest at the end of each month. For the estimations the 189 LLOs have been aggregated into 173 LLOs, which is the current number of labour offices in Finland.

Table 2.1 provides descriptive statistics for the key variables. The majority of the LLOs are rather small in size, but there are few large offices: the ninetieth percentage point for all job seekers is 7 617, whereas the maximum value is no less than 67 206. Another marked labour market feature is the low proportion of vacancies to job seekers. Calculated from the mean numbers, there are approximately fifty job seekers per one vacant job. The average number of filled vacancies 98, exceeds the number of vacancies 76, because some openings become filled within a month, and therefore become not registered as a vacancy in our data.

Figure 1 plots the monthly average values over all the LLOs for the key variables. As a consequence of the severe recession in the 1990s, the number of job seekers increased markedly up to the end of 1993. At the same time, the numbers of filled vacancies and openings decreased. The turning point for the both vacancy series appears to be the year 1993. The number of job seekers peaked sligthly later, at the beginning of 1994. Since then recovery from the recession has been constant.

TABLE 2.1 Descriptive statistics, 1991:1-2002:8.

	All job seekers	Vacancies	Filled vacancies
Mean	3522	76	98
Std. dev	5645	220	241
Min	153	0	1
10th percentile	711	3	9
25th	1070	8	18
50th	1781	22	38
75th	3415	62	87
90th	7617	164	195
Max	67206	5115	5116

Notes: All the variables are measured at the end of each month in each of the 173 labour office areas.

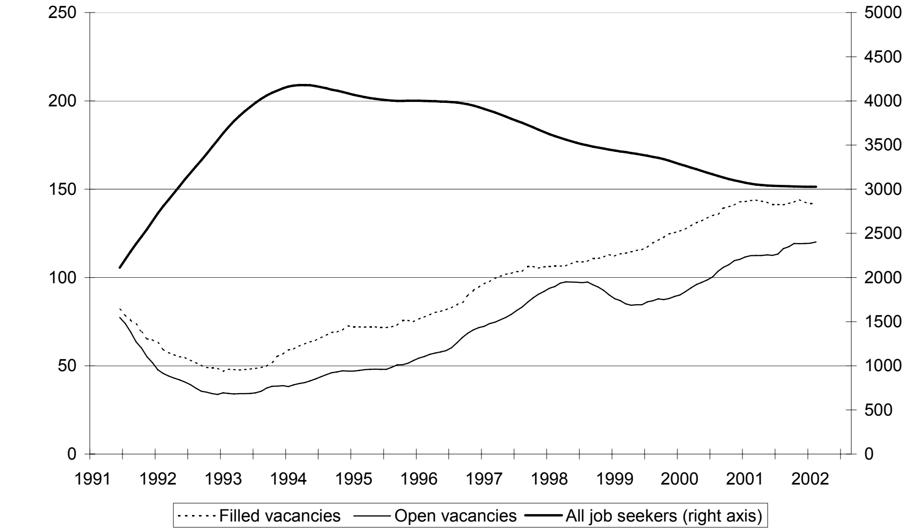

FIGURE 2.1 Filled vacancies, vacant jobs and all job seekers at the end of each month, averages over labour offices, 1991-2002 (12-month moving average).

As can be seen from Figure 2, the recession temporarily increased differences between the areas for all variables, especially vacancies. After 1994, however, the regional coefficient of variation for vacancies decreased from 3.5 to 2.2, and from the beginning of 1996, it again increased ending slightly above 2.5. As a result, only the regional differences for filled vacancies seem to show a permanent change during the observation period.

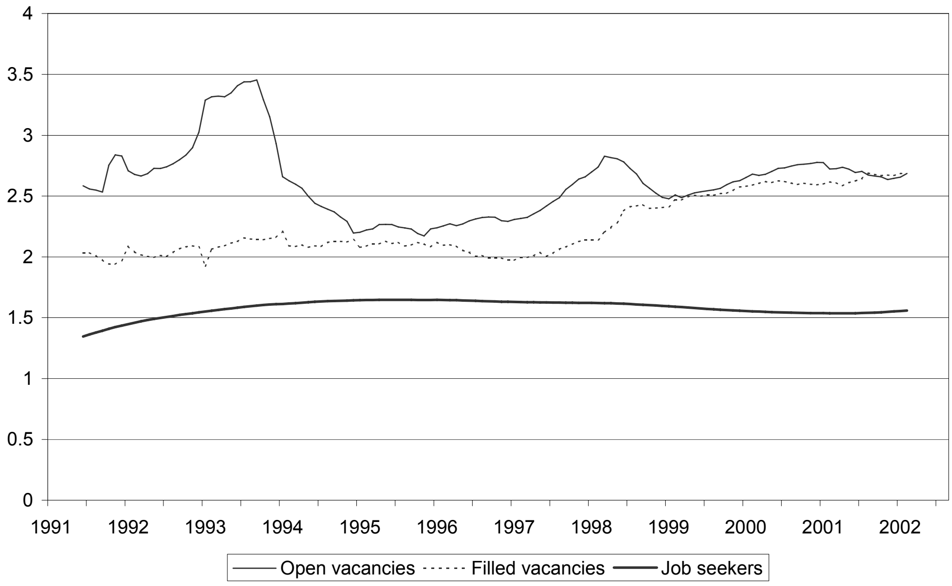

FIGURE 2.2 Regional coefficient of variation in vacant jobs, filled vacancies and job seekers, 1991-2002 (12-month moving average).

Figure 3 plots the distribution of job seekers by their labour market status[23]. The annual average number of job seekers peaked at approximately 750 000 persons in 1994. Since then the number of job seekers has steadily decreased. The majority of job seekers were in the unemployment category, although their relative number steadily decreased since 1994. At the end of the period, only slightly over half of all job seekers were unemployed. The proportions of employed and out-of-the-labour-force job seekers, in turn, increased since 1994, accounting at the end of the observation period for approximately 20 and 10 per cent of the total, respectively. The share of unemployment pension recipients was then also relatively high, almost 10 per cent, whereas the proportions of laid of and shortened week workers were relatively small.

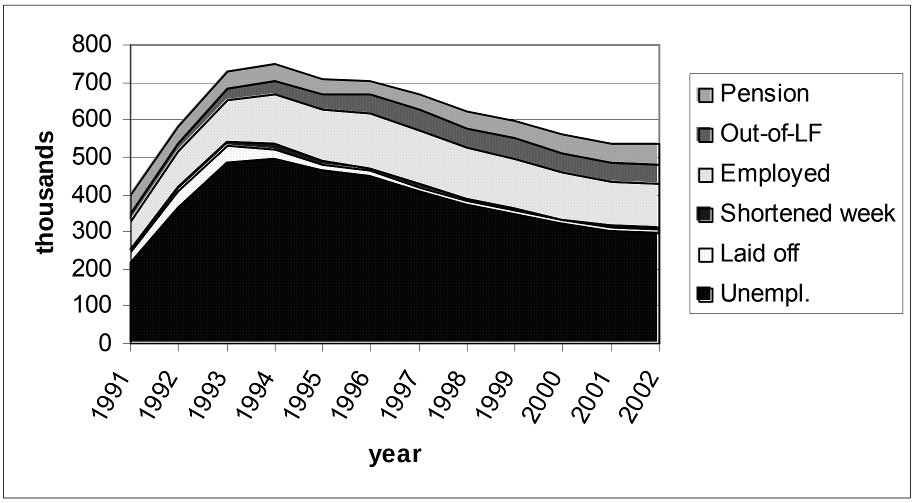

FIGURE 2.3 Annual average number of job seekers by labour market status, 1991-2002. Average is taken over monthly aggregate numbers from all LLOs.

The data provide some further information about the characteristics of unemployed job seekers; see Table 2.2. Towards the end of the decade, almost half of the unemployed workers consisted of women, as compared to only 37 per cent in 1991. Marked changes were found in the age structure of unemployed workers and in the average duration of unemployment spell as well. The

[23] To become a job seeker in the labour office requires that the individual sign on in person. Job seekers are differentiated according to their labour market status: (i) unemployed, (ii) employed (iii) out-of-the-labour-force, (iv) working a shortened week, (v) laid off without pay and (vi) receiving an unemployment pension. A job seeker becomes registered as unemployed if available for a full-time job but does not have one at a moment, or if waiting for already agreed employment to start. In addition, laid-off workers receiving pay are registered as unemployed workers. Employed job seekers consists of those seeking to change their jobs, those under threat of unemployment, or whose employment is state-subsidised. Out-of-the-labour-force job seekers are not employed, nor at the moment available for full-time work. But they will be available at some future time and have therefore already signed on. If earlier agreed weekly working hours are reduced by an employer, the worker in question becomes registered as a job seeker working a shortened week. If a person is aged over 60 and has been receiving unemployment benefit for a long time, he is entitled to an unemployment pension.

proportion of job seekers aged over 50 increased steadily from 14 to 33 per cent during the observation period. In 1991, only 2.3 per cent of unemployed workers experienced a spell of unemployment lasting over 1 year, whereas in 2001, the corresponding figure was almost 30 per cent. Thus, at the end of the eleven-year period, many of the unemployed job seekers were relatively old and their spells of unemployment relatively long duration.

TABLE 2.2 Unemployed job seekers by gender, age and duration of spell of unemployment.

Year	Total	Women %	Men %	Age <25 ,%	Age >50 ,%	Duration >1 year,%	Duration >2 years,%
1991	213 201	37	63	21	14	2	0.3
1992	363 121	39	61	21	14	8	0.4
1993	482 173	42	58	20	15	18	2
1994	494 247	44	56	19	17	27	7
1995	466 013	45	55	17	20	30	12
1996	447 987	46	53	15	23	30	13
1997	408 964	47	53	13	27	30	14
1998	372 431	49	51	13	29	30	15
1999	348 140	49	51	13	30	28	15
2000	321 119	50	50	12	32	28	14
2001	302 177	49	51	12	33	27	13

Notes: Figures are monthly averages.

The data allows job seekers to be grouped according to their level of education. The original data utilised 9 levels of education. This classification has been used by Statistics Finland between 1971 and 1997, when it was revised to correspond to the international standard ISDEC 1997. For the estimations, the 9 educational groups were clustered into 3 groups. Table 2.3 presents the relation between the 3-group classification and ISDEC 1997.

TABLE 2.3 Classification of education

ISCED 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 education	2 Secondary
Level 5	First stage of tertiary education	
	5B-programmes	3 High
	5A-programmes	3 High
Level 6	Second stage of tertiary educ.	3 High

Notes: The name for education level 2, "Lower secondary" is somewhat misleading, as it corresponds to grades 7-9 (ages 13-16 years) in the Finnish school system, and should therefore be regarded as a part of primary education.

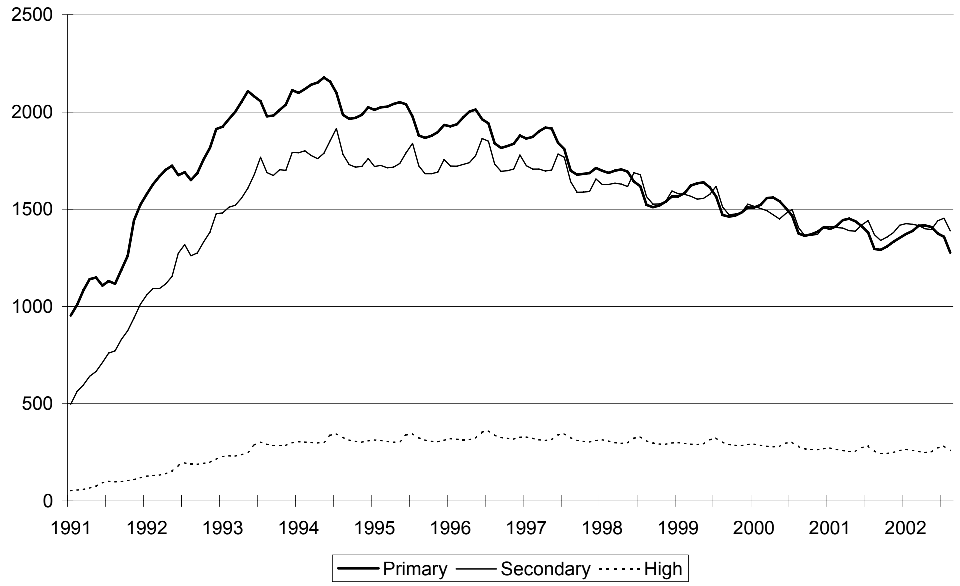

FIGURE 2.4 Job seekers by education in the area of the average LLO, 1991-2002.

At the beginning of 1991, there were 1000 primary educated job seekers in the average LLO; see Figure 4. Approximately 500 seekers had secondary education and above 100 were higher educated. At the end of the 1990's there were nearly as many primary as secondary educated job seekers.

Unfortunately, the data at hand do not provide direct information about the skill level requirements of the vacant jobs. Information is, however, provided about their occupational category, thereby giving an approximate picture of the distribution of skills required across vacancies; see Table 2.4. A large proportion of vacancies belongs to the category 'professional, technical and related work'. These jobs typically require an educational level beyond primary. The proportion of these jobs has increased since 1994, accounting for 24 per cent of the total in 2002. The remaining categories do not permit such an inference regarding skill requirements. Nevertheless, as in many European countries, LLOs mainly mediate jobs requiring less education and offering lower wages. Sales work which accounts for approximately 15 per cent of all vacancies, for example, typically offers a commission-based wage.

TABLE 2.4 Vacancies by occupational group, years 1991 and 2002.

year	Professional, technical (%)	Clerical (%)	Sales (%)	Agicultural, forestry (%)	Production (%)	Transport (%)	Service (%)
1994	16.2	5.4	14.9	20.3	27.0	2.0	12.2
2002	24.1	6.0	14.4	11.6	21.3	2.3	19.4

TABLE 2.5 Vacancies by duration, years 1991 - 2004.

Year	Total	Duration >1 month,%	Duration >3 months,%	Duration >6 months,%
1991	12 453	45	19	8
1992	6 378	38	16	9
1993	5 293	36	12	3
1994	6 341	30	7	2
1995	7 104	32	9	3
1996	8 652	33	9	4
1997	11 671	36	9	5
1998	15 112	42	17	9
1999	13 560	30	6	2
2000	13 792	30	5	2
2001	17 934	33	7	3
2002	19 820	33	8	4
2003	21 744	36	9	4
2004	23 304	35	8	4

Notes: Figures are monthly averages.

Table 2.2 reported that the proportion of unemployed workers experiencing a spell of unemployment lasting over 1 year was as high as 30 per cent at the end of the 1990s. Table 2.5 shows that vacant jobs became filled much faster. Measured at the end of each month, below ten per cent of the total number of vacancies had been unoccupied over six months. Actually, since 2000 less than ten per cent of the vacancies had duration over three months.

2.3 Data coverage

Because the data are extracted from the unemployment register of the Ministry of Labour, they cover only LLO-registered job seekers and vacancies. Fortunately, other data sources are available that provide a means assessing the coverage of the register-based figures.

Statistics Finland publishes regularly survey-based figures using all workplaces in Finland as the population. Figure 5 plots the number of vacancies in Finland starting from the first quarter of 2002. The upper graph depicts the figures given by Statistics Finland. At the beginning of the period only 50 per cent of all vacancies were advertised in the LLOs. Thereafter the gap between the graphs decreased rapidly. On average, the register figure accounts for 59 per cent of the corresponding survey-based figure.

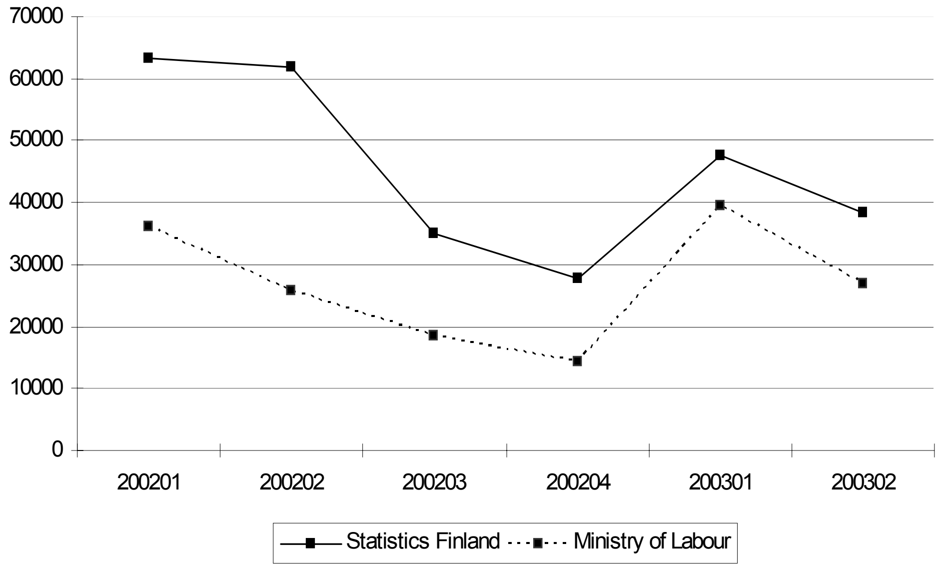

FIGURE 2.5 Vacancies in Finland, 2002:01-2003:02.

Since 1993, employers have been asked to give their views on the recruitment prospects. The information is collected every year, and from the beginning of 2002 also quarterly. The market share of the LLOs of all public sector recruiting was at its highest during 1995-1997; see Table 2.6. This period was characterized by a post-recession recovery and a time when a lot of job seekers were clients of LLOs, including higher educated ones. Possibly, therefore, it was an attractive market place for employers as well. The average market share of the LLOs between 1993-2002 was 64 per cent, as against 69 per cent during 1995-1997.

TABLE 2.6 Market share of the LLOs (1993-2002).

Year	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Market share	49 %	66 %	67 %	71 %	68 %	62 %	65 %	65 %	62 %	60%

The Finnish Centre for Pensions provides annual statistics about the number of new matches in the private sector. In Figure 6, these figures are compared to the numbers of register-based filled vacancies. Although the graphs slightly approach each other, the figure supplied by the Ministry of Labour is approximately 40 per cent smaller than that of the Finnish Centre for Pensions at the end of the period.

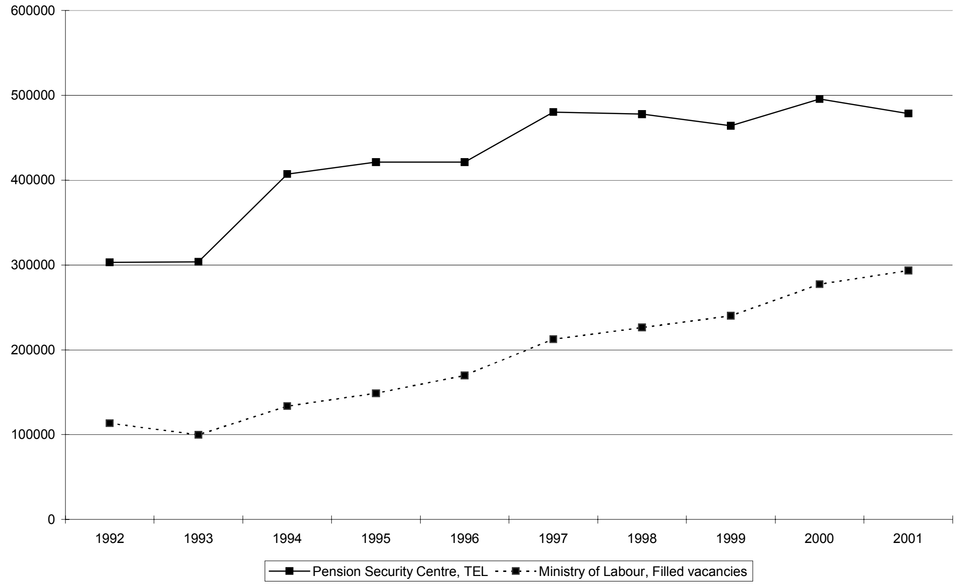

FIGURE 2.6 New matches, 1992-2001.

Depending on the baseline, about 50-60 per cent of all vacancies are mediated through LLOs. This figure is high compared to many other countries. In fact, public-sector employers are required by law to report their vacant jobs, but firms are under no such obligation.

2.4 The role of heterogeneity in matching: some preliminary results

2.4.1 Model

When, after a search, a job seeker finds a suitable vacancy and the employer is willing to hire him, a new filled vacancy or a match is generated. This process can be summarized by the matching function

$$M = m(U,V), \qquad (1)$$

where M is the number of jobs formed during a given time period. U is the number of unemployed job seekers and V is the number of vacancies, both measured at some moment during the period. Usually, it is assumed increasing in both arguments, concave and homogenous of degree one. The simple matching function contains all the frictions that exist in the market, however, it gives us no further details of them.

Several micro-level theories have been presented that indicate the aggregate matching function (1)[24]. Although these theories do not suggest an exact form for

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24 A common approach is to rely on the urn-ball problem analyzed by probability theorists. In these models, the matching function arises in environments where agents

the function, the Cobb-Douglas specification has become predominant in the empirical literature. The Cobb-Douglas matching function is written as follows:

$$M_t = cU_t^{\alpha}V_t^{\beta}, \tag{2}$$

where the subscript t denotes time, α and β are the elasticity of the matching parameters with respect to U and V, and c is a scale parameter. The scale parameter can be regarded as containing the properties of job seekers and jobs, such as search behaviour, capability and geographical location.

Broersma and Van Ours (1999) show, both theoretically and empirically, that the measure of job matches should correspond to the measure of job seekers, otherwise the matching elasticities will be biased[25]. In this paper, I use the flow of filled vacancies as a dependent variable. The corresponding stock of job seekers includes not only unemployed seekers but also those who are employed or outside of the labour force[26]. In addition, job seekers include those working a shortened week or temporarily laid off and not receiving a wage.

In recent literature, increased emphasis has been placed on additional variables that can be included in the function (1) in order to reveal the properties of the matching process in more detail. One relevant variable is job seekers' level of education. There are several ways to introduce the influence of education into the matching technology. I let the search intensities of job seekers vary by using the Cobb-Douglas function, in which job seekers are classified into three groups.

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engage in random search. Thus the matching frictions are due to a coordination problem between traders with imperfect imformation on each others' actions. Alternative approaches include the stock-flow model of Coles and Smith (1998) and the directed search model of Lagos (2000).

25 Traditionally the explanatory variables of the empirical matching function are the stocks of vacancies and unemployed job seekers. In this case, the measure of matches, M, should be a flow from unemployment to employment to ensure that stocks and flows correspond to each other. In several studies, however, the flow is approximated by the number of filled vacancies or by the total outflow from unemployment. The former approximation is used, for example, in Blanchard and Diamond (1989), and in Burgess and Profit (2001). For the latter measure see, for example, Burda and Wyplosz (1994), and Eriksson and Pehkonen (1998). Filled vacancies is a problematic measure because some vacancies will be filled with workers moving from one job to another. In addition, a flow from outside the labour force fills some vacancies. Blanchard and Diamond (1989) estimate that in the United States 15 per cents of vacancies are filled by employed job searchers and 40 per cents by searchers coming from outside the labour force. In Finland, Ilmakunnas and Maliranta (2000) estimate that on average during the years 1994-1996 42 per cent of worker inflow to the main industries consisted of within-industry worker transitions, 17 per cent originated from unemployment and 41 per cent from outside the labour force. These estimates are based on workers' end-of-the-year labour market status. Total unemployment outflow is also an inaccurate measure of matches since a number of unemployed will be moving outside the labour force. According to Rantala (1998), in Finland less than 50 per cent of the transitions from unemployment ended up in employment and 24 per cent were exiting the labour force.

26 Theoretical models in which employed job seekers are included are few. An example of such a model is the search theoretic model presented by Pissarides (1994). It provides a theoretical reason for using all job seekers as an explanatory variable. Searchers outside the labour force can be dealt with as unemployed seekers.

Because of these possible differences in search intensity, job seekers might not be complete substitutes in the matching process, which is now written as:

$$M = c(U_p)^{\alpha_1}(U_s)^{\alpha_2}(U_h)^{\alpha_3}V^{\beta} \qquad (3)$$

In (3), parameters α_1, α_2 and α_3 are the search intensities of primary, secondary and higher educated job seekers, respectively. The indices *p, s* and *h* denote the corresponding group of job seekers.

In only a few former empirical studies job seekers have been differentiated according to their educational background. One such example is Fahr and Sunde (2001) who estimate matching functions using data from Western Germany. They disaggregate the pool of unemployed job seekers into three educational groups, as in this paper. They report that the elasticity of matching with respect to primary and higher educated unemployed job seekers is higher than the corresponding elasticity for secondary educated workers. However, the frequency of their data is only annual, thereby failing to capture much valuable dynamic information.

2.4.2 Results

The present study uses a Cobb-Douglas specification of the matching function in log-linear form. The model can be written as

$$\ln M_{i,t} = \mu_i + n_t + \alpha_p \ln(U_p)_{i,t-1} + \alpha_s \ln(U_s)_{i,t-1} + \alpha_h \ln(U_h)_{i,t-1} + \beta \ln v_{i,t-1} + \varepsilon_{i,t}, \qquad (5)$$

where $M_{i,t}$ is the flow of filled vacancies in area *i* during month *t*, μ_i is a fixed effect term controlling for regional characteristics, η_t is a fixed effect for time, $U_{i,t-1}$ is the stock of job seekers at the end of month *t-1* according to three levels of education: primary *p*, secondary *s* and higher *h*. $V_{i,t-1}$ is the stock of vacancies in area *i* at the end of month *t-1* and $\varepsilon_{i,t}$ is an error term with the usual properties. The stocks are lagged with one period to avoid simultaneity bias.

Table 2.7 reports the results. Model 1 is the baseline. It is estimated by OLS, restricting μ_i and n_t to constant across areas and time. The coefficients for the vacancies and for the all job seekers are 0.6 and 0.25, respectively. They are in line with existing theoretical and empirical studies[27]. A Durbin-Watson test indicates the presence of autocorrelation for all the models and a likelihood ratio test shows that heteroscedasticity is present. Therefore, the calculation of standard errors does not treat observations as independent within an office, but the offices themselves are independent[28].

Model 2 accounts for the efficiency differencies across labour offices and variation over time by including fixed effects in the model. This lowers the

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27 See Petrongolo and Pissarides (2001) for a summary of recent studies.

28 See Rogers (1993): Regression standard errors in clustered samples, or Williams (2000): A note on robust variance estimation for cluster-correlated data.

coefficients for vacancies and job seekers, but they remain positive and significant. Specification 3 disaggregates job seekers into three groups according to their educational backround. The elasticity for primary educated job seekers appears to be rather high, about 0.5, whereas secondary educated seekers have a large negative effect on the number of monthly matches. The impact of higher educated seekers is almost zero and just significant.

The results are in line with those obtained by Fahr and Sunde (2001), who estimate matching functions disaggregated by educational level using annual data from Western Germany. According to their results, the group of lower educated job seekers produces the highest coefficient for the stock of unemployed.

TABLE 2.7 Results of the estimations.

	I: OLS	II: LSDV	III: LSDV
Ln(V)t-1	0.592 (0.02)	0.431 (0.01)	0.427 (0.01)
Ln(Uall)t-1	0.244 (0.02)	0.132 (0.07)	
Ln(Uprimary)t-1			0.451 (0.10)
Ln(Usecondary)t-1			-0.357 (0.09)
Ln(Uhigh)t-1			0.010 (0.04)
R2	0.72	0.81	0.81
RTS	0.836 (6.70)	0.563 (6.13)	0.531 (6.55)
DW	1.17	1.60	1.67
LR (Heterogenity)	267.64	32 875.94	33020.32
N	23 500	23 500	23 497

Notes: Constants and fixed effects are not reported, robust standard errors are given in parentheses. Models II and III include annual and seasonal dummies. RTS (returns to scale) is the sum of the coefficients for log vacancies and log unemployment. In parentheses next to RTS is the value of the t-test for H_0: RTS = 1.

In the early 1990s Finland experienced a deep recession recovery from which took place towards the end of the decade[29]. Thus, the matching efficiency of the labour market probably changed during the 90s. To reveal the possible changes, the data is split into two periods and estimations separately performed for each period. The first period contains observations 1991:1–1994:12, and the second 1995:1-2002:8. Although the choice of the cut-off point is somewhat ad hoc, it can be justified by the graphic analysis performed in Section 2.2: the year 1994 marked the start of recovery from the recession: e.g., the number of job seekers reached its peak at the beginning of 1994.

The results are reported in Tables 2.8 and 2.9. The most notable differences between the whole period (Table 2.7) and the sub-periods (Tables 2.8 and 2.9) are found in the coefficients for job seekers. The elasticity of the vacancies appears to be rather stable, at around 0.4, regardless of the estimation period. In Table 2.7, the elasticity of all job seekers in the fixed effect model is relatively small (model 2). This seems to result from the exceptional character of the 1990s recession. This interpretation gains support from Tables 2.8 and 2.9: the elasticity is negative

29 See, for example, Kiander and Vartia (1996) for a more detailed description of the 1990s recession.

during the recession (Table 2.8, model 2), but after that it exceeds the elasticity of vacant jobs (Table 2.9, model 2).

The third columns of Tables 2.8 and 2.9 reveal the differences between the sub-periods in the estimates for primary and secondary educated job seekers. During the recession years the coefficient for primary educated seekers is only half of that during the second sub-period. The effect of higher educated job seekers is negative and insignificant during the first period, but turns out to be positive and significant in the latter period. It seems that the no-effect result for higher educated seekers reported in Table 2.7 originates in the recession period 1data.

TABLE 2.8 Results, estimation period 1991:1 - 1994:12.

	I: OLS	II: LSDV	III: LSDV
Ln(V)t-1	0.588 (0.02)	0.425 (0.02)	0.419 (0.02)
Ln(Uall)t-1	0.214 (0.02)	-0.185 (0.07)	
Ln(Uprimary)t-1			0.412 (0.15)
Ln(Usecondary)t-1			-0.471 (0.12)
Ln(Uhigh)t-1			-0.047 (0.04)
R^2	0.68	0.79	0.79
RTS	0.802 (7.12)	0.240 (11.12)	0.314 (9.48)
DW	1.14	1.66	1.76
LR (Heterogenity)	15.70	11563.30	11 620.53
N	7826	7826	7826

Notes: Constants and fixed effects are not reported, robust standard errors are in parentheses. Models II and III include year and seasonal dummies. RTS (returns to scale) is the sum of the coefficients for log vacancies and log unemployment. In parentheses next to RTS is the value of the t-test for H_0: RTS = 1.

TABLE 2.9 Results, estimation period 1995:1 - 2002:8.

	I: OLS	II: LSDV	III: LSDV
Ln(V)t-1	0.568 (0.02)	0.414 (0.02)	0.411 (0.02)
Ln(Uall)t-1	0.286 (0.03)	0.497 (0.16)	
Ln(Uprimary)t-1			0.713 (0.12)
Ln(Usecondary)t-1			-0.437 (0.14)
Ln(Uhigh)t-1			0.144 (0.05)
R^2	0.73	0.82	0.82
RTS	0.853 (5.83)	0.911 (0.55)	0.831 (1.16)
DW	1.19	1.69	1.69
LR (Heterogenity)	327.421	23 387.37	23 490.50
N	15 509	15 509	15 509

Notes: Constants and fixed effects are not reported, robust standard errors are in parentheses. Models II and III include year and seasonal dummies. RTS (returns to scale) is the sum of the coefficients for log vacancies and log unemployment. In parentheses next to RTS is the value of the t-test for H_0: RTS = 1.

It is worth noting that the theoretical assumptions of the matching function hold better during the latter sub-period. The constant-returns-to-scale property, which we have previously rejected, seems to be valid now (Table 2.9). This result underlines the exceptional character of the recession period.

The next model includes interactions between the year-dummies and the independent variables. The first specification tried was a general model consisting of all the independent variables, year-dummies and interaction terms. Because the interactions between vacancies and the time dummies were not statistically significant, they are omitted from the final specification presented in Table 2.10. The insignificant interactions between secondary educated job seekers and the year-dummies are omitted as well. The insignificance of secondary educated seekers was anticipated as tables 2.8 and 2.9 show no differences between the two sub-periods.

According to the results, an increase of one per cent in the number of primary educated job seekers increases matches on average by 0.4 per cent; see Table 2.10. This varies such that during the years 1991-1994 the increase was on average 0.5 and during the years 1995-2002 it was 0.3. An increase of one per cent in the number of higher educated seekers leads to an increase in the number of matches by 0.01 per cent. This effect varies from -0.09 during the years 1992-1994 to 0.06 during the years 1995-2002. This is in line with the earlier prediction that the effect of higher educated job seekers on matches turns to be positive after 1995. This probably reflects the fact that there were not many higher educated job seekers in the LLOs before the recession. They begin to visit LLOs during the slump and only after that were employers with high skill vacancies attracted to the idea of using labour offices as a recruiting channel.

TABLE 2.10 Results of the estimations. The model includes interaction terms between yearly dummies and independent variables.

Explanatory variables:	
$Ln(V)_{t-1}$	0.420 (0.015)
$Ln(Uprimary)_{t-1}$	0.536 (0.129)
$Ln(Usecondary)_{t-1}$	-0.318 (0.010)
$Ln(Uhigh)_{t-1}$	-0.079 (0.055)
Constant	0.900 (0.572)
1991	-0.070 (0.383)
1992	-0.432 (0.341)
1993	-0.283 (0.270)
1995	0.213 (0.251)
1996	0.572 (0.288)
1997	0.487 (0.311)
1998	-0.103 (0.340)
1999	0.242 (0.362)
2000	0.177 (0.374)
2001	0.426 (0.400)
2002	0.375 (0.386)
Seasonal2	0.427 (0.023)
Seasonal3	0.177 (0.018)
Seasonal4	-0.122 (0.014)
1991* $Ln(Uprimary)_{t-1}$	-0.062 (0.082)
1992* $Ln(Uprimary)_{t-1}$	0.075 (0.076)
1993* $Ln(Uprimary)_{t-1}$	0.042 (0.062)
1995* $Ln(Uprimary)_{t-1}$	-0.043 (0.061)
1996* $Ln(Uprimary)_{t-1}$	-0.130 (0.070)
1997* $Ln(Uprimary)_{t-1}$	-0.096 (0.075)

1998* $Ln(Uprimary)_{t-1}$	-0.001 (0.078)
1999* $Ln(Uprimary)_{t-1}$	-0.117 (0.085)
2000* $Ln(Uprimary)_{t-1}$	-0.084 (0.090)
2001* $Ln(Uprimary)_{t-1}$	-0.172 (0.095)
2002* $Ln(Uprimary)_{t-1}$	-0.156 (0.090)
1991* $Ln(Uhigh)_{t-1}$	0.090 (0.05)
1992* $Ln(Uhigh)_{t-1}$	-0.067 (0.05)
1993* $Ln(Uhigh)_{t-1}$	-0.048 (0.04)
1995* $Ln(Uhigh)_{t-1}$	0.033 (0.04)
1996* $Ln(Uhigh)_{t-1}$	0.103 (0.05)
1997* $Ln(Uhigh)_{t-1}$	0.100 (0.05)
1998* $Ln(Uhigh)_{t-1}$	0.071 (0.05)
1999* $Ln(Uhigh)_{t-1}$	0.185 (0.06)
2000* $Ln(Uhigh)_{t-1}$	0.170 (0.06)
2001* $Ln(Uhigh)_{t-1}$	0.241 (0.06)
2002* $Ln(Uhigh)_{t-1}$	0.229 (0.06)

Notes: The dummy for the year 1994 is leaved out from the estimated model to avoid perfect multicollinearity.

2.5 Conclusions

The paper estimated an empirical matching function using monthly data on 173 labour office areas over a 12-year period between 1991 and 2002. As required, if unbiased results are to be obtained, the explanatory stock variables and the dependent flow variable showed good correspondence: the job seeker variable on the right side of the equation comprised all workers looking for a job, including those who are not officially in the labour force, and those already have a job, whereas the dependent variable was filled vacancies during each month. Furthermore, the pool of all job seekers was disaggregated into three educational groups.

According to the results, the level of education of job seekers affects the matching performance of local labour offices. Primary educated seekers have a positive effect on matches while seekers with secondary education display a negative effect. Seekers with high education do not affect matching performance significantly. However, some evidence for the positive effect of higher educated seekers after the recession of the 1990s was found.

In general, the results reflect the characteristics of both vacancies and job seekers. It is estimated that only 40 percent of all filled vacancies are mediated by labour offices and those are mainly vacancies with low educational requirements. These vacancies are also likely to offer a low wage level which may not exceed the reservation wage of higher educated job seekers. Therefore an increase only in the number of primary educated job seekers improves matching performance. Jobs directed at higher educated seekers are advertised elsewhere, such as in newspapers. But then again, with respect to higher educated seekers, there are indications that the market share of labour offices increased after the recession, and led to the better matching performance. The most problematic group seems to be secondary educated workers. Perhaps jobs offering a low wage rarely exceed the reservation wages of this group. On the other hand, they probably compete unsuccessfully with higher educated job seekers for high-wage jobs.

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CHAPTER 3

LABOUR MARKET MATCHING WITH HETEROGENEOUS JOB SEEKERS*

ABSTRACT. This paper studies an empirical matching function which takes account of differences in educational background across job seekers. Our data is well suited for estimating matching function. Its frequency is high, it allows regional disaggregation, and provides additional information about the characteristics of both job seekers and vacant jobs. The monthly data comprise 173 Finnish labour office areas and cover the years 1991 to 2002. According to the results, an increase in the relative number of primary or highly educated job seekers increases the ability of the labour market to form new matches. The corresponding effect of secondary educated job seekers is negative. In addition, long-term unemployed job seekers, aged under 25 and over 50 have negative effect on monthly matches.

3.1 Introduction

Modern equilibrium models of the labour market are typically characterized by search and recruiting frictions, and by the constant need to reallocate workers across productive activities. Both job seekers and employers have to make investments in overcoming these frictions. As a result of these factors, the job creation flow depends on the numbers of unemployed workers and vacant jobs. This relationship is known as the matching function $M = M(U,V)$, where U denotes the number of unemployed workers and V is the number of vacant jobs. The value of the function, M, denotes the number of new jobs occupied by workers. The matching function can be used to model the frictions of the labour

* An earlier version of this paper was presented in EALE conference 2004 in Lisbon.

market which include, for example, incomplete information between traders, their search behaviours, slow mobility, and differences between the skills of workers and the requirements of employers. Owing to such frictions the matching of workers and vacancies does not take place immediately but requires a time-consuming search process. As a result, vacant jobs and unemployed job seekers can exist simultaneously on the market.

The disadvantage of the typical matching function is that it does not distinguish between job seekers. The only thing that matters is their total number. It follows from $M=M(U,V)$ that the probability that an unemployed worker will find a job during a given observation period is $M(U,V)/U$[30]. But this holds only for the average job seeker. The function says nothing about the probability of a specific job seeker with specific characteristics.

An important personal characteristic of a job seeker is level of education[31]. Yet, empirical researchers have paid little attention to the effect of education on job seekers' reservation wages and further, on the efficiency of labour market matching processes. This is mainly because of the scarcity of suitable data.

In this study I utilize a rich Finnish panel dataset which allows the addition of various aggregate variables into the estimated matching function. These variables include the proportion of long-term unemployed workers of all jobseekers, the proportion of unemployed persons aged under 25, and the proportion of the same aged over 50. Most importantly, the data allow the division of all job seekers into primary, secondary and highly educated seekers. As a theoretical standpoint for the empirical specification I use the matching function extended by Petrongolo and Pissarides (2001). This is discussed in Section 3.2 in more detail.

The results clearly indicate that the level of education of a job seeker affects local matching performance. An increase in the proportion of primary or highly educated seekers has a positive effect on the number of monthly matches, whereas an increase in the proportion of secondary educated job seekers has a negative impact. These estimates are in line with the results obtained by Fahr and Sunde (2001), who estimate matching functions using data from Western Germany[32].

These empirical findings can be explained by the differing reservation wages across differently educated job seekers, and by the ranking behaviour of employers. The labour offices in Finland mainly mediate vacancies with low

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30 In addition, the following condition is needed: At any point of time workers and vacancies are randomly matched from the respective stocks, and the process that changes the status of an unemployed person in the labour market is Poisson-distributed.

31 See e.g. the job competition model of Van Ours & Ridder (1995). According to them employers may prefer higher over lower educated workers. In addition, education may have an effect on job seekers' reservation wages and search intensities.

32 They disaggregate the pool of job seekers into three education groups, as in this paper, and find that the elasticity of matching with respect to primary and highly educated unemployed job seekers is higher than the corresponding elasticity on secondary educated seekers. However, the frequency of their data is only annual. Therefore a lot of dynamic information is lost.

education requirements, but a certain proportion of vacancies is directed at highly educated workers[33]. The results give some evidence that the reservation wage of a secondary educated worker is higher than that of a primary educated seeker, leading to a smaller matching probability for a secondary educated job seeker. On the other hand, secondary educated seekers may be ranked behind highly educated workers in the job queues for high-skill vacancies.

The study continues as follows. Section 3.2 presents the basic properties of the matching function, Section 3.3 describes the data. The results of the estimations are reported in Section 3.4, and Section 3.5 concludes the paper.

3.2 Matching function with heterogeneous job seekers

In general, the matching function tells us how many new jobs are generated in the labour market, given a certain number of job seekers, denoted by U, and a certain number of vacant jobs, denoted by V, in the market. It is assumed that there are frictions in the market. Open jobs and job seekers do not find each other immediately, but after a time-consuming search process. If there were no frictions, the M would be the same as the minimum of the variables U and V. Very often the function is written in the Cobb-Douglas form as follows:

$$M_t = cU_t^{\alpha}V_t^{\beta}, \tag{1}$$

where the subscript t refers to time, α and β are the elasticities of matching with respect to U and V, and c is a scale parameter. The scale parameter can be assumed to contain the properties of job seekers and jobs which are relevant to the matching efficiency. These are, for example, search behaviour, capability, and geographical location.

When forming an empirical matching function, extra care should be taken to ensure the correspondence between the flow variable on the left-hand side of the equation, and the stocks on the right-hand side of the equation. Broersma and Van Ours (1999) show that the measure of job matches should correspond to the measure of job searchers, otherwise matching elasticities will be biased[34]. In this

33 The share of vacancies in which the higher education required is 2 percent of the total, and 37 percent of all vacancies in which the education requirement is known.

34 Problems may occur when the filled vacancies include more than just the flow from unemployment to employment. Some vacancies are filled by workers moving from one job to another. In addition, a flow from outside the labour force to jobs fills some of the open vacancies. Blanchard and Diamond (1989) estimate that in the United States 15 percent of the vacancies are filled by employed job seekers coming from outside the labour force. In Finland, Ilmakunnas and Maliranta (2000) estimate that during the years 1994-1996 on average 42 percent of the inflow of workers to the main industries consisted of internal worker transitions, 17 percent of the inflow came from unemployment and 41 percent from outside the labour force. The total size of the outflow is also an inaccurate measure of matches since there are always a number of unemployed persons moving out of the labour force. According to Rantala (1998), in

study, I use filled vacancies as a dependent variable and the corresponding stock of job seekers includes not only unemployed searchers but also those who are employed or outside the labour force. Job searchers also include those who are working a shortened week or are temporarily laid off and not receiving pay.

In the recent literature, an increased emphasis has been placed on additional variables explicitly included in the matching function[35]. The main aim of these variables is to reveal the effect of job seekers' individual characteristics on the matching process. There are several ways of introducing this effect. In this study, I make the assumption that wage offers made by employers to workers have a distribution. The approach is presented for example in Petrongolo and Pissarides (2001).

Let us assume that a worker chooses her reservation wage so that her expected net consumption is maximized, and rejects all offers below it. Assume furthermore that the meeting technology is *m(U,V)*, wage offers are draws from a probability distribution *G(w)*, and the reservation wage of a worker *i* is R_i. Then the hazard rate of this worker *i* can be written as

$$(1-G(R_i))\frac{m(U,V)}{U}\,. \tag{2}$$

If we further assume that the average reservation wage over all individuals can be defined, and denote it by *R*, the aggregate matching function is

$$M=\left(1-G(R)\right)m(U,V)\,. \tag{3}$$

The term *(1-G(R))* depends on the individual reservation wage R_i. A natural assumption would be that the reservation wage of a highly educated seeker is higher that of a low-educated worker; hence an increase in the proportion of highly educated seekers would decrease the aggregate matching rate.

The term *(1-G(R))* may include several variables other than the proportion belonging to a certain education group. For example Burgess (1993) relates it, at the aggregate level, to the proportion of long-term unemployed and to demographic variables. Other typical related variables are time dummies (Burda and Profit, 1996) and the replacement ratio (Anderson and Burgess, 2000). In

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Finland less than 50 percent of the transitions from unemployment ended up in employment and 24 percent exited labour force.

35 An often-used variable is the proportion of long-term unemployed (e.g. Mumford & Smith, 1999; Broersma 1997; Burgess 1993; Ilmakunnas & Pesola, 2003). In several papers job seekers are distinguished according to their labour market status (e.g Mumford & Smith, 1999; Kangasharju & Pehkonen & Pekkala, 2004) Flows of new seekers and vacancies are added to the specification to control the stock-flow properties of the process (e.g. Gregg & Petrongolo, 2002; Coles & Smith, 1998; Kangasharju & Pehkonen & Pekkala, 2004). Used as a proxy for overall economic situation are e.g. real wages and energy prices (Gross, 1997) GDP growth (Fahr & Sunde, 2002) and change in employment (Anderson & Burgess, 2002). Other frequently used variables are time trend or time dummies, the replacement ratio, the proportion of long-term unemployed and demographic variables in sectoral studies.

addition, wages (Coles and Smith, 1996), sizes of regions, spillover effects (Burgess and Profit, 1998), output per capita (Münich, Svejnar, and Terrel, 1999) and labour market status of job seekers (Kangasharju, Pehkonen, Pekkala, 2004) are used in sectoral matching function studies.

The question of heterogeneities can be approached in the opposite direction by including them in the search behaviour of employers. Examples are Blanchard and Diamond (1994) and Van Ours and Ridder (1995). The latter paper provides a matching function in which employers rank applicants on the basis of their educational background.

3.3 Data

The data used in the empirical analysis is combined data from the unemployment register of the Ministry of Labour. It contains monthly observations from the areas of 173 labour offices and its time span is from January 1991 to August 2002. The variable on the left-hand-side of the estimated function is filled vacancies during each month. The explanatory variables are the stock of vacancies and the stock of all job seekers, both measured at the end of each month. The additional explanatory variables are the proportions of primary, secondary and highly educated seekers of all job seekers, the proportion of long-term unemployed seekers, and the relative proportions of unemployed seekers aged under 25 years and over 50 years.

Local labour market areas in Finland differ widely in size and time; see the descriptive statistics of the data given in Table 3.1. On average the number of vacancies is only 2 percent of the number of job seekers. However, this varies between regions and over time. The recession of the 1990s, in particular, gives rise to variation over time.

The data set allows the division of the job seekers into categories according to their educational background. The three groups distinguished are primary, secondary and highly educated job seekers[36].

[36] Comparing the three groups to the European standard ISDEC 1997, primary educated job seekers consist of levels 0-2, secondary educated seekers of levels 3-4, and higher educated of levels 5-6.

TABLE 3.1 Descriptive statistics of the data.

	Mean	St. dev.	Min	Max
Population	29 589	50 799	1 213	559 718
Filled vacancies	95	238	0	5116
Open vacancies	74	217	0	5115
All job seekers	3459	5584	153	67 206
Share(Primary)	0.52	0.07	0.33	0.83
Share(Secondary)	0.42	0.06	0.14	0.58
Share(Highly)	0.06	0.04	0	0.3
Share(long-term)	0.13	0.07	0	0.33
Share(under 25)	0.1	0.04	0.01	0.26
Share(over 50)	0.15	0.04	0.03	0.29

Figure 3.1 plots the proportion of job seekers by level of education to the whole country. At the beginning of the 1991 the majority of job seekers were primary educated. However, their share diminished during the observation period. At the beginning of the year 1991 the share of the primary educated seekers was about 60 percent of all seekers, whereas in the middle of 2002 it was only 45 percent. Seekers with a secondary level of education account for about 30 percent of the total at the beginning of the 1991. Their share increased smoothly, ending up at almost 50 percent by the end of the observation period. The proportion of highly educated job seekers showed only a faint rise, however, remaining all below 10 percent throughout.

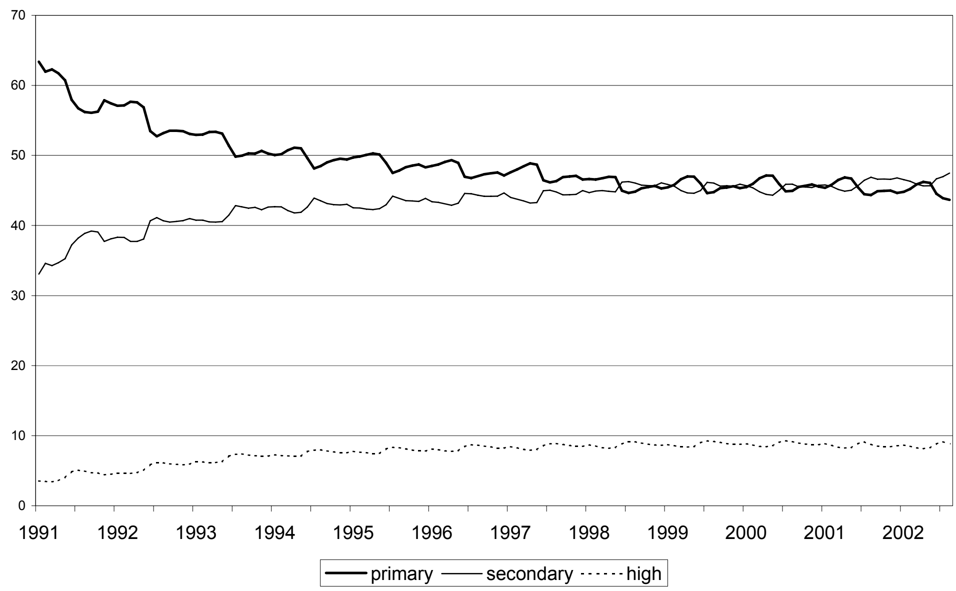

FIGURE 3.1 Job seekers by educational level (%).

The data at hand does not provide direct information about the skill levels required of the vacant jobs. However, the vacancies can be divided into occupational categories, thereby giving an approximate picture of the distribution of the skills required across vacancies; see Table 3.2. A large share of the open vacancies belongs to the category professional and technical work.

These jobs typically require an educational level beyond primary. The share of these jobs has increased since 1994, accounting for about 24 percent of the total in 2002. The remaining categories do not permit clear discrimination between different skill requirements. Nevertheless, as in many European countries, local labour offices mainly mediate jobs requiring less education and offering lower wages. Sales work which accounts for approximately 15 percent of all vacant jobs, for example, often offers a commission-based wage.

TABLE 3.2 Open vacancies by occupational category (%), 1991-2002

Year	Professional, technical	Clerical	Sales	Agricultural, forestry	Production	Transport	Services
1994	16.2	5.4	14.9	20.3	27	2	12.2
2002	24.1	6	14.4	11.6	21.3	2.3	19.4

3.4 Results

The study uses a Cobb-Douglas specification of the matching function in log-linear form:

$$\log M_{it} = \alpha + \beta_1 \log U_{i,t-1} + \beta_2 \log V_{i,t-1} + \beta_j X_{i,t-1} + u_{it}, \qquad (4)$$
$$u_{it} = \mu_i + \lambda_t + v_{it}$$

In (4), M_{it} denotes the flow of filled vacancies in area i during month t, $U_{i,t-1}$ is the stock of all job seekers at the end of month $t-1$, V_{it-1} is the stock of open vacancies, and $X_{i,t-1}$ consists of explanatory variables other than U and V, including the education variables. All the explanatory variables are lagged with one period to avoid simultaneity bias. The term u_{it} can be decomposed into time-invariant area-specific effects μ_i and area–invariant time effects λ_t; v_{it} is an error term for which the usual properties apply. In the final specification the time effects are replaced with dummy variables and are therefore a part of X_{it}[37]

First, we transform the data into deviations from area means and apply the OLS estimator to the transformed data. This yields a within-areas or fixed effect estimator. As long as $E[x_{it}\ v_{it}] = 0$, the within estimator is consistent for β, but it ignores between-areas information and may therefore be inefficient. The between-areas information may be utilised by applying GLS which in principle can be expressed as a combination of between and within estimators.

[37] In addition to time dummies the explanatory variable matrix X_{it} includes the proportion of primary/secondary/highly educated seekers of all job seekers, the proportion of long-term unemployed, and the relative proportions of unemployed aged under 25 and over 50.

TABLE 3.3 Results, estimation period 1991:1 - 2002:8.

	I: Within	II:GLS
$Ln(V)_{t-1}$	0.42 (92.82)**	0.43 (95.84)**
$Ln(U_{all})_{t-1}$	0.25 (7.14)**	0.42 (24.63)**
$Share(Primary)_{t-1}$	1.60 (9.79)**	1.25 (8.13)**
$Share(High)_{t-1}$	2.67 (8.35)**	2.77 (9.18)**
$Share(long\text{-}term)_{t-1}$	-1.47 (10.04)**	-1.87 (13.26)**
$Share(under\ 25)_{t-1}$	-1.75 (7.06)**	-1.71 (7.03)**
$Share(over\ 50)_{t-1}$	-0.92 (3.66)**	-0.99 (4.10)**
RTS:	0.67 (91.58)**	0.85 (80.37)**
N	23497	23497
R2	0,55	0,76
Joint significance	1337.6**	30916.07**
Fixed effect=0	28.99**	
Wald	7017.35**	
DW	1,682	1,676
Hausman test:		
Model I vs. model II	Chi2(20) = 213.87**	

Notes: Constants and fixed effects are not reported. Standard errors are in parenthesis. All the models include year and seasonal dummies. RTS (returns to scale) is the value of an F-test (Within) or Wald-test (GLS) for H_0: RTS = 1. Absolute value of t (within) and z (GLS) - statistics in parentheses: * significant at 5%; ** significant at 1%. Wald is a modified Wald Statistics for groupwise heteroscedasticity in the residuals of the model, H_0: $sigma_i^2$ is the same for all i. DW is the Durbin-Watson test for panel data. In Hausman test, H_0 is the case: difference in coefficients not systematic. ** denotes significant at 1%

Table 3.3 summarizes the results from the within-groups and GLS estimations. More detailed results can be found in Appendix. It can be seen from Table 3.3 that the elasticity of matches with respect to open vacancies and all job seekers are both positive and significant. The former coefficient, especially, seems to be stable over different estimators. A rise in the number of vacancies by one percent leads to a rise of 0.4 percent in the number of monthly created matches. The elasticity of all job seekers varies depending on the estimator selected. When the within-estimator is used (model I) a rise in the number of job seekers by one percent increases monthly matches by 0.2 percent. When the GLS is applied, the coefficient is larger, at around 0.4 (model II). All the models imply that a rise in the relative share of primary or highly educated job seekers increases the ability of the labour market to produce new matches. The coefficient for the primary educated seekers is 1.6 higher than that for secondary educated seekers which is left out from specification to avoid multicollinearity, then the coefficient for higher educated seekers is 2.67-1.6=1.07 higher than that for primary educated. These outcomes weakly indicate the existence of different types of vacancies, some of suit workers with primary education and the others suit workers with higher education.

The secondary educated seekers would appear to constitute a problematic group. Possibly their reservation wages are too high for vacancies with low educational requirements. On the other hand, they might be ranked below the highly educated seekers by employers when applying for jobs with high skill requirements. Of course this is only one possible explanation. Notwithstanding, the results obtained here are in line with those of Fahr and Sunde (2001) who estimate matching functions disaggregated by education level using yearly data from Western Germany. According to them, the elasticity of matching with respect to primary and highly educated unemployed job seekers is higher than the corresponding elasticity to secondary educated seekers.

The estimates for the rest of the additional variables are all negative and therefore in line with those of former studies[38]. The first test reported in Table 3.3, RTS, is the F-statistic from the linear hypothesis test for the constant returns to scale property. All the models give evidence on the behalf of the decreasing returns to scale. On average the estimate of returns to scale is 0.76.

The major problem with the GLS estimator is that it is inconsistent when the area effects are correlated with the regressors. Hausman (1978) suggested a test for checking the uncorrelation assumption. Under the null hypothesis there is no correlation which implies that both the GLS and within are consistent, although the former is more efficient. Under the alternative the GLS is inconsistent, while the within is consistent and efficient. I used the Hausman test procedure to decide between the within and GLS estimators (Table 3.3). The tests strongly favour the use of the fixed effect or within-area estimator.

As was pointed out in the context of the data description, Finland experienced a deep recession in the early 1990s from which the recovery did not took place until the end of the decade[39]. As a consequence, the number of job seekers increased strongly, peaking in 1994. At the same time, the numbers of open and filled vacancies fell. Table 3.4 summarizes the results related to the time dummies. The coefficients for the years 1991-1993 are negative, indicating that, compared to the year 1994, the matching efficiency was lower during these years. The dummies for the years 1995-2002 have, in turn, positive coefficients. In fact, the changes between consecutive years were positive from 1991 to 1997. Evidently the slump forced the labour market to operate more effectively.

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38 Burgess (1993) reports negative coefficients for the proportion of long-term unemployed, and the proportion of employed aged 16-19. In his model a dependent variable was unemployment outflow. Mumford and Smith (1999) report a negative coefficient for the proportion of long-term unemployed when total matches were explained.

39 See, for example, Kiander and Vartia (1996) for a more detailed description of the 1990s recession.

TABLE 3.4 The coefficients of yearly dummies.

	Model I	Model II
1991	-0.23 (6.33)**	-0.14 (4.58)**
1992	-0.22 (8.48)**	-0.20 (8.04)**
1993	-0.21 (10.71)**	-0.22 (10.93)**
1995	0.07 (3.63)**	0.08 (4.29)**
1996	0.12 (5.70)**	0.12 (6.13)**
1997	0.23 (9.57)**	0.24 (10.15)**
1998	0.17 (6.26)**	0.18 (7.07)**
1999	0.23 (8.30)**	0.25 (9.14)**
2000	0.30 (10.26)**	0.32 (11.34)**
2001	0.10 (2.56)*	0.12 (3.29)**
2002	0.06 (1.61)	0.08 (2.10)*

Thus the matching efficiency of the labour market changed during the 1990s. In order to study this change more carefully, the data has been divided into two periods and the estimations performed each period separately. The first period contains observations from the beginning of the year 1991 to the end of the year 1994. This period can be characterized by the recession. The second period starts at the beginning of the year 1995 and ends at August 2002. During the period the labour market is assumed to be recovering from the recession and operating more normally.

It can be seen from Table 3.5 that the aggregate matching function is not well defined during the slump. The coefficient of all job seekers has a negative sign contrary to theoretical assumptions. During that time the number of job seekers increased considerably, perhaps exceeding the capacity of labour offices. Under these conditions, it might be reasonable to think that extra job seekers decrease the monthly number of matches. The effects of primary and secondary educated seekers do not change markedly across sub-periods and the whole period. The effect of highly educated seekers, in turn, is negative in some models, but usually it is not statistically significant.

The elasticity of vacancies seems to be stable, at around 0.4 irrespective of the estimation period. Likewise, the effects of the long-term unemployment and age groups are negative in all models.

TABLE 3.5 Results, estimation period: model I 1991:1 - 1994:12; model II 1995:1 - 2002:8.

	I: Within	II: Within
$Ln(V)_{t-1}$	0.42 (25.14)**	0.41 (24.33)**
$Ln(Uall)_{t-1}$	-0.11 (1.49)	0.44 (3.31)**
$Share(Primary)_{t-1}$	1.55 (2.66)**	2.05 (5.06)**
$Share(High)_{t-1}$	-2.37 (1.61)	1.97 (3.73)**
$Share(long\text{-}term)_{t-1}$	-0.43 (0.99)	-1.78 (4.26)**
$Share(under\ 25)_{t-1}$	-1.16 (2.36)*	-0.96 (1.84)
$Share(over\ 50)_{t-1}$	-3.73 (4.19)**	-1.53 (2.62)**
R2	0,78	0,82
RTS	0.31 (88.15)**	0.85 (1.35)
DW	1,76	1,74
LR (Heterogeneity)	11692.71**	23934.30**
N	7826	15671

In the above empirical specifications, education and the other additional variables used affect the matching process via a constant term, or in other words, they change the efficiency of the matching process. One might suspect that the education variable has an effect on matching technology, too. In order to study this effect, the model estimated next includes the interactions of the relative shares of education groups with the number of job seekers and vacancies. The results are in shown Table 3.6. Since the interaction between vacancies and secondary educated job seekers has a negative coefficient, a greater share of secondary educated seekers means a lower positive effect of vacancies on job matches. For primary and highly educated seekers the opposite applies. Only a increase in the relative share of secondary educated seekers strengthens the positive effect of job seekers on matches. So, the greater the share of primary or highly educated seekers, the more congestion job seekers cause on each other.

TABLE 3.6 Model with interaction terms, period 1991:1-2002:8.

	Within I	**Within II**
Ln(V)$_{t-1}$	0.22 (2.84)**	0.46 (8.75)**
Ln(Uall)$_{t-1}$	0.65 (4.56)**	0.04 (0.36)
Share(Uprimary)$_{t-1}$	5.07 (3.72)**	
Share(Usecondary)$_{t-1}$		-5.07 (3.72)**
Share(Uhigh)$_{t-1}$	3.44 (1.32)	-1.62 (0.77)
Ln(V)t-1*Share(Uprimary)$_{t-1}$	0.25 (2.00)*	
Ln(V)t-1*Share(Usecondary)$_{t-1}$		-0.25 (2.00)*
Ln(V)t-1*Share(Uhigh)$_{t-1}$	1.34 (5.12)**	1.09 (5.05)**
Ln(Uall)t-1*Share(Uprimary)$_{t-1}$	-0.62 (3.20)**	
Ln(Uall)t-1*Share(Usecondary)$_{t-1}$		0.62 (3.20)**
Ln(Uall)t-1*Share(Uhigh)$_{t-1}$	-0.92 (2.18)*	-0.31 (0.89)
Share(long-term)$_{t-1}$	-1.63 (5.15)**	-1.63 (5.15)**
Share(under 25)$_{t-1}$	-1.77 (4.16)**	-1.77 (4.16)**
Share(over 50)$_{t-1}$	-0.70 (1.38)	-0.70 (1.38)
N	23497	23497
R2	0.81	0.81
DW	1.689	1.689

Notes: Constants and fixed effects are not reported. Robust standard errors are in parentheses: * significant at 5%; ** significant at 1% All the models include year and seasonal dummies. DW is the Durbin-Watson statistic for the fixed-effects model. LR tests groupwise heteroscedasticity. N is the number of observations.

3.5 Conclusions

This paper was motivated by the matching function -related theories suggesting that individual characteristics of job seekers affect their reservation wages and search behaviour. We measured worker heterogeneity by educational composition in the area of the labour office and employed monthly data, comprising 173 Finnish labour office areas, from a 12-year period between 1991 and 2002. All persons looking for a job, including those who are out of the labour force and those who already have a job was used as an explanatory variable. The variable on the left-hand side was filled vacancies during each month. As is required, the flow variable on the left-hand side of the equation corresponds well to the stocks of the right-hand side.

The pool of all job seekers was categorized into three education groups. According to the results, the average educational level of a job seeker affects the matching performance of local labour offices. An increase in the proportion of secondary educated seekers of all job seekers was found to have a negative effect on matching efficiency while an increase in the corresponding proportions of primary or highly educated seekers displayed a positive effect. In addition, long-term unemployed job seekers, both those aged under 25 and over 50, was found to have a negative effect on monthly matches.

During the years of the recession, the coefficient of all job seekers was negative and statistically not significant. It suggests that a stable relationship between the aggregate variables did not hold during the recession.

The results give some evidence for higher reservation wages among secondary educated than primary educated job seekers. This leads to a smaller matching probability for secondary educated. On the other hand, it seems that secondary educated job seekers are ranked below higher educated workers in job queues for high-skill vacancies.

The results can also be explained by the characteristics of the open vacancies mediated by the labour offices. It has been estimated that only 40 percent of all filled vacancies are advertised in labour offices. Furthermore, the labour offices in Finland mainly mediate vacancies with low educational requirements. These vacancies are likely to offer a low wage level at a below the reservation wage of highly educated job seekers. Therefore, a greater share of primary educated job seekers leads to better matching performance. It seems that highly educated job seekers also improve the matching performance, as was shown especially during the period after the recession. Until then, their proportion of total job seekers had been small, as had the proportion of high-skill vacancies. The high-skill jobs are typically advertised elsewhere than in labour offices, for example in newspapers. Therefore labour offices are a market place with especial relevance for primary educated seekers.

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Appendix

TABLE 3.7 Estimation results, 1991:1-2002:8.

	I: Within	IV:GLS
$Ln(V)_{t-1}$	0.422 (92.82)**	0.429 (95.84)**
$Ln(Uall)_{t-1}$	0.246 (7.14)**	0.421 (24.63)**
$Share(Low)_{t-1}$	1.598 (9.79)**	1.247 (8.13)**
$Share(High)_{t-1}$	2.669 (8.35)**	2.774 (9.18)**
$Share(long\text{-}term)_{t-1}$	-1.466 (10.04)**	-1.873 (13.26)**
$Share(under\ 25)_{t-1}$	-1.745 (7.06)**	-1.710 (7.03)**
$Share(over\ 50)_{t-1}$	-0.922 (3.66)**	-0.986 (4.10)**
1991	-0.227 (6.33)**	-0.140 (4.58)**
1992	-0.221 (8.48)**	-0.200 (8.04)**
1993	-0.213 (10.71)**	-0.217 (10.93)**
1995	0.065 (3.63)**	0.077 (4.29)**
1996	0.115 (5.70)**	0.123 (6.13)**
1997	0.226 (9.57)**	0.238 (10.15)**
1998	0.166 (6.26)**	0.184 (7.07)**
1999	0.226 (8.30)**	0.245 (9.14)**
2000	0.298 (10.26)**	0.323 (11.34)**
2001	0.096 (2.56)*	0.118 (3.29)**
2002	0.063 (1.61)	0.080 (2.10)*
2. quarter	0.384 (34.88)**	0.376 (34.27)**
3. quarter	0.158 (14.78)**	0.147 (13.87)**
4. quarter	-0.141 (12.99)**	-0.139 (12.83)**
Constant	-0.156 (0.53)	-1.300 (7.50)**
RTS	91.58**	80.37**
N	23497	23497
R2	0.55	0.76
Joint significance	1337.6**	30916.07**
Fixed effect=0	28.99**	
Wald	7017.35**	
DW	1.682	1.676

TABLE 3.8 Estimation results, interaction included, 1991:1-2002:8.

	Within
$Ln(V)_{t-1}$	0.217 (2.84)**
$Ln(Uall)_{t-1}$	0.652 (4.56)**
$Share(Uprimary)_{t-1}$	5.068 (3.72)**
$Share(Uhigh)_{t-1}$	3.444 (1.32)
$Ln(V)t\text{-}1{*}Share(Uprimary)_{t-1}$	0.246 (2.00)*
$Ln(V)t\text{-}1{*}Share(Uhigh)_{t-1}$	1.340 (5.12)**
$Ln(Uall)t\text{-}1{*}Share(Uprimary)_{t-1}$	-0.616 (3.20)**
$Ln(Uall)t\text{-}1{*}Share(Uhigh)_{t-1}$	-0.923 (2.18)*
$Share(long\text{-}term)_{t-1}$	-1.625 (5.15)**
$Share(under\ 25)_{t-1}$	-1.769 (4.16)**
$Share(over\ 50)_{t-1}$	-0.703 (1.38)
1991	-0.228 (3.44)**
1992	-0.232 (5.41)**
1993	-0.222 (8.18)**
1995	0.071 (3.48)**
1996	0.118 (3.68)**
1997	0.226 (5.44)**
1998	0.163 (3.26)**
1999	0.223 (4.27)**
2000	0.294 (4.97)**
2001	0.167 (2.29)*
2002	0.121 (1.62)
2. quarter	0.391 (17.13)**
3. quarter	0.172 (9.84)**
4. quarter	-0.133 (9.09)**
Constant	-2.307 (2.24)*
N	23497
R2	0,81
LR (Heterogeneity)	33544.23**
DW	1,689

CHAPTER 4

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

ABSTRACT*. This paper studies the process of matching job seekers and vacancies in a collection of local labour markets. We measure the differences in the ability of the local markets to form new matches and trace whether these differences can be explained by differing population densities across markets or by differences in the distribution of job seekers by level of education. We find that on average high-density areas are more productive than low-density areas in forming matches.

4.1 Introduction

In the recent literature on labour market matching, increased emphasis has been placed on the heterogeneity of both job seekers and vacant jobs (Burgess 1993; Pissarides 1994; Anderson and Burgess 2000; Burgess and Turon 2003; van Ours 1995; Broersma and van Ours 1998; Mumford and Smith 1999; Fahr and Sunde 2001). These heterogeneities appear to be the main source of frictions in the labour market and therefore are of crucial importance when assessing matching productivity. In addition, many recent studies have taken the labour market not as a single market but as a collection of several heterogeneous micro-markets.

This paper analyses the matching of vacant jobs and job seekers of different educational backround in local labour markets that differentiated by population density. The motivation to the study derives mainly from three sources. Firstly,

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* This paper is written together with Sanna-Mari Hynninen. The paper has been presented in 45th (2005) European Regional Science Conference in Amsterdam.

Coles and Smith (1996) argue that population density, not the numbers of vacant jobs and job seekers, determines the matching rates in the labour market. According to them, the matching process is the more effective the more concentrated the market is. This is because communication between parties close to each other requires lower effort and costs[40].

Secondly, Kano and Ohta (2005) offer an alternative view on the role of population density. Apart from the lower effort and costs of communication when parties are geografically close to each other, the matching process may be affected by another factor. Namely, the heterogeneity of job seekers and vacancies may be higher in densely populated areas than elsewhere[41], which may increase search frictions. Successful matches may appear easily if the consentrations of the skill-distribution of workers and the hiring standards of firms are on the same level. But in urbanised areas where the distributions tend to be wide, the characteristics of job seekers may differ in their consentration from that required by employers. It implies difficulties in the matching process despite the fact that the actors are located near each other in the geographical sense.

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, it will have a positive effect on matching efficiency. However, the effect may become negative in very densely populated areas because of the dominance of the opposing congestion effect.

In this paper, we estimate the abilities of Local Labour Offices (LLOs) in Finland to form successful matches at given levels of inputs in the matching process. In addition, we investigate whether the total factor productivity of the matching process deviates in areas with different population density. By controlling for the heterogeneity in the labour market by allowing job seekers with different education levels to have different employability, we can estimate a matching productivity unconfounded by the relative distributions of the education level of job seekers and the education requirements of vacancies. We choose to control for heterogeneity by education level because it is the best measure of worker-skill level we are able to obtain.

We use both fixed and random effects to control for various factors that might affect matching process. The advantage of a random effect model is that it

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40 They illustrate the argument by the following mind experiment: a blindfolded man and a woman wander around a field seeking to contact each other. Obviously, the contact rate of 1000 men and women wandering in a field of the same size would be more than 1000 times the contact rate of the original situation of one man and woman.

41 For example, Coles and Smith (1995) report several demographic variables that are significant in explaining matching rates. According to their results, matching rates increase in towns that have younger population and decreases in population with high education. Their matching process exhibits constant returns to scale. Thus, the results indicate that it is density that matters, not the numbers of job seekers and vacancies in the labour market. However, they conclude that successful matches may be of better quality in large cities than elsewhere since wages tend to be higher in large cities than elsewhere. There are larger markets for highly specialised workers in large cities.

exploits both within- and between-districts information in estimating model parameters, whereas a standard fixed effect model uses only within-districts information. On the other hand, a random effect model migh suffer from correlation between effects and other regressors, against with fixed effect model is robust. One important drawback of a fixed effect model is that it can not measure the effect of a factor that do not change over time. This is because all these kind of effects are captured by the fixed effects. Therefore, to include for example district indicator variables to the specification, we necessarily have to use a random effect model, or a mixed-effect model which includes bot fixed and random effect parameters.

Our data are informative and temporally, spatially, as well as by job seekers level of education and education requirements of vacancies highly disaggregated. The data consist of monthly panel from 146 LLOs in Finland over 10 years[42]. Job seekers are divided into three groups by their level of education. These groups are primary, secondary, and higher education. The data set has been extracted from the registers of the Ministry of Labour. It, therefore, includes job seekers and vacancies registered at the public employment agency, which has an important role in the labour market in Finland.[43]

The paper is organised as follows: Section 4.2 defines the concept of the productivity of the matching process. A brief discussion on the estimation technique is also presented. Section 4.3 introduces the model, Section 4.4 describes the data, and in Section 4.5 the results are presented. Finally, Section 4.6 concludes.

4.2 Productivity of the matching process

The total factor productivity of the matching process captures the ability of the labour market to form successful matches given the numbers of job seekers and vacancies. It is partly a product of the rate at which job seekers and employers meet and the probability that a contact leads to a successful match (Anderson and Burgess 2000). The total factor productivity is defined as the fraction of production output to production factors in the standard production theory. We estimate the total factor productivity of the matching process and focus on differences in it between areas with differing population density. By controlling for the educational structure of the stock of job seekers we clarify whether the heterogeneity of job seekers affects the productivity of the matching process.

42 Here we have LLOs fewer than in the previous studies, because some LLOs have merged into one before 1995:1. Therefore, despite the total number of LLOs varies we still consider the same group of LLOs, only the aggregation level of them is different.

43 The proportion of jobs mediated by LLOs in Finland is quite high. It varied from 49 per cent to 71 per cent between 1993 and 2002 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 open vacancies is in the private sector (Räisänen 2004).

In the case of a Cobb-Douglas matching function:

$$M_{i,t} = A_{i,t} U_{i,t-1}^{\alpha} V_{i,t-1}^{\beta} = A e^{\mu_i + \lambda_t + \varepsilon_{i,t}} U_{i,t-1}^{\alpha} V_{i,t-1}^{\beta}, \tag{1}$$

it is natural to interpret the parameter $A_{i,t}$ to denote the productivity part of the function since it is independent of U and V but may vary across LLOs (part μ_i), and over time (part λ_t) The error term is assumed to be identically and independently distributed with expectation 0 and constant variance. If, furthermore, we impose additional assumption that

$$\sum_{i=1}^{n} \mu_i = \sum_{t=1}^{T} \lambda_t = 0, \tag{2}$$

the equation becomes a fixed-effects model which can be estimated by the least squares dummy variables estimator, or equivalently by the within estimator. This estimator is, however, known to be problematic; see for example Ibourk et al. (2004). Fixed effects tend to capture the returns to scale effects, especially when district scales differ widely.

Our data is comprised of LLOs in which the proportion of vacant jobs to job seekers is on average very low (2 - 3 percent). In other words, the number of job seekers is high, meaning that after the log-transformation it shows little time-variation within the LLOs; see Figure 4.1. There is, however, some variation between LLOs. These features of the data are confirmed by the estimation results; see Table 4.3. When the fixed-effect estimator is applied (Specifications 2-4) the coefficient for job seekers is markedly lower than that estimated by the random-effect estimator (Specification 1). The value given by the random-effect estimator is higher because it exploits both between- and within -variations, but is inconsistent when random effects correlate with explanatory variables, as is the case here.

Bleakley and Fuhrer (1997) and Wall and Zoega (2002) estimate shifts in the efficiency of the matching process, interpreting region-specific fixed-effects as efficiency terms. While cognisant of problems with interpretations of the term efficiency in the context of the fixed-effects model (see i.e. Ibourk et al. 2004), we estimate the average productivity of the matching process in areas with differing population density. We control for the educational structure of job seekers to find out if this factor affects matches in LLOs and to find out if it explains part of the productivity. After controlling for educational structure, the estimated fixed effects measure the part of the total factor productivity independent of educational structure.

It is worth noting that of job seekers education, per se, does not make the matching process more productive. It is successful matching between the education level of job seekers and the education requirements of vacancies that leads to greater matching productively. Therefore, employability differences cannot directly be derived from search intensity or the ranking behaviour of firms but rather from matching between the supply and demand of education. Hence, with reference to Coles and Smith (1996), Kano and Ohta (2005), and

Wahba and Zenou (2003), it is interesting to investigate the population density of an area in relation to the education structure of job seekers. We assume that owing to the interactive nature of the production of matches, controlling for the educational heterogeneity of job seekers also controls the educational requirements of the vacancy side. There can be no positive effects due to the particular educational level of a job seeker on her employability if there is no demand for that level of education.

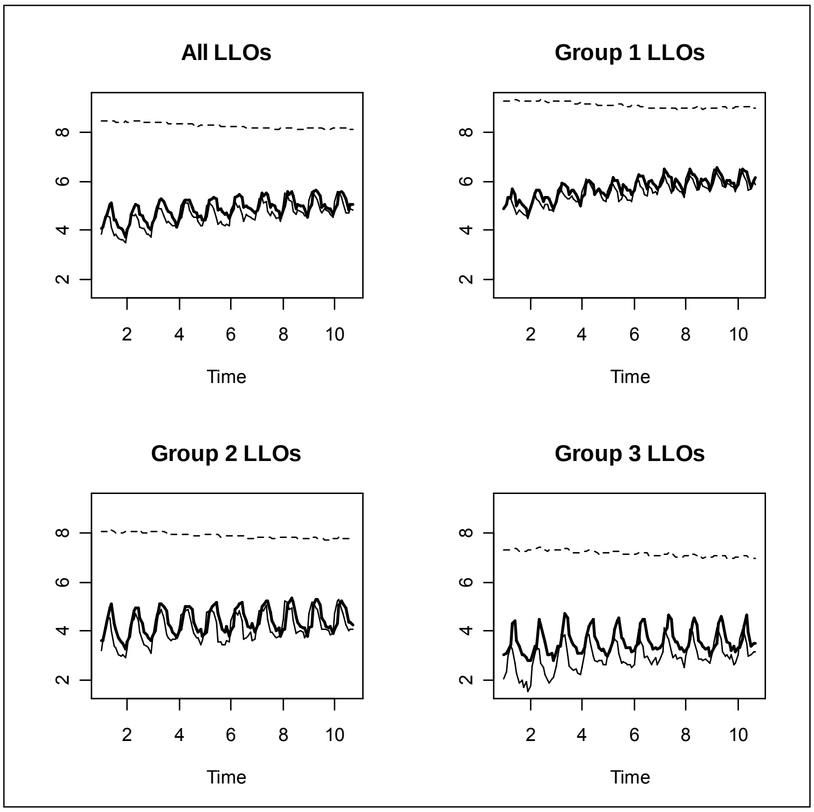

FIGURE 4.1 Job seekers, filled vacancies and vacant jobs. Time series of averages taken over LLOs.

Notes: The line ----- represents job seekers; —— filled vacancies; — — vacant jobs. All the variables are measured in logs. The X-axis indicates time span from 1995:1 to 2004:9. Group 1 consists of high-density LLOs, Group 2 of middle LLOs and Group 3 of low-density LLOs.

4.3 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 job 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 the number of matches to increase, as if the matching technology or efficiency of the process had been improved. Thus, from now on let us denote the average search intensity, or employability of job seekers by s

and the corresponding employability of vacancies by *a*. The aggregate matching function is now (Pissarides 2000)

$$M = m(sU, aV) \tag{3}$$

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

$$M = m\left(\sum_{i=1}^{3} s_i U_i, aV\right) = m(sU, aV) \tag{4}$$

For estimation purposes, we measure the employability of different groups with respect to the employability of one particular group, let it be s_2 (secondary educated job seekers)[44]. In the model, the employability of these groups is set equal to 1. Our modelling follows Ibourk et al. (2004), taking, however, a somewhat different view on modelling heterogeneity in the matching model[45]. By adding and subtracting terms the function takes the following Cobb-Douglas form (See Appendix for more details):

$$M_{i,t} = A\left((U + (s_1 - 1)U_1 + (s_3 - 1)U_3)_{i,t-1}{}^{\alpha} V_{i,t-1}{}^{\beta}\right) \tag{5}$$

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

$$\ln M_{i,t} = c_i + \alpha \ln(U)_{i,t-1} + \alpha \ln(1 + \gamma(\frac{U_1}{U})_{i,t-1} + \eta(\frac{U_3}{U})_{i,t-1}) + \beta \ln(V)_{i,t-1}, \tag{6}$$

where γ = (s_1 – 1) and η = (s_3 – 1). Taylor-expansion provides linear approximation for the third term of the expression[46]:

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

44 Due to lack of data, we are not able to allow to different employability for vacancies with different education requirements.

45 Actually, this way to specify the model is used in several recent works that study production functions. These include, e.g., Hellerstein & Neumark (1995, 1999) and Hellerstein & Neumark & Troske (1999).

46 This gives a reasonable approximation if $\gamma(U_1/U)$ and $\eta(U_3/U)$ are small. When differences between group employabilities are small, also γ =s_1-1 =s_1-s_2 and η =s_3-1 are small. In addition, the values of share variables are between zero and one. Therefore the products are expected to be small as well.

The parameters of the expression have clear interpretation: α gives the overall elasticity of matches with respect to job seekers and β that for vacancies. The coefficients for the share variables state the average percentage change of matches given a change of one percentage point in the relative share of that education job seeker group. Furthermore, we can calculate the employability of other groups with respect to the group of secondary educated job seekers.

4.4 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. The variables are filled vacancies within a month, the number of vacant jobs at the end of each month and the number of job seekers at the end of each month. The last-mentioned variable is furthermore differentiated into three levels of education, namely primary, secondary and higher education[47]. Table 4.1 provides descriptive statistics for the variables at the LLO-level.

The distributions of the variables show that for all the variables the mean is clearly higher than the median. In addition, the maximum values are high. The statistics reflect the fact that the majority of LLOs in Finland are rather small in size, although some LLOs are large compared to the average. Logarithmic transformation of the data is thus indicated. There are also LLOs in which the number of filled vacancies or vacant jobs is zero within the observation period. To avoid missing observations we add one to all observations before applying the log-transformation.

TABLE 4.1 Descriptive statistics

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

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

To study the role of population density on matching productivity we order LLOs on the basis of their average population densities (population/km^2) during 1991-2001. This order remained stable during the research period despite some minor changes in population density within offices, Three groups of LLOs are formed

47 In the original data set there were nine distinguished levels of education. This system of classification has been used by Statistics Finland since 1971, and has been revised in 1997 to correspond to the international standard ISDEC 1997. For the estimations we aggregate the job seekers into groups of three education levels. Table 2 presents the relation between the three-group-classification and ISDEC 1997.

by setting group one contain the 36 LLOs with the highest population density, and group three the 36 LLOs with the lowest population density. Thus, the groups consist of LLOs belonging to the first and fourth quartiles of the population density distribution. The remaining offices belong to group two. Thus we consider the offices situated at the tails of the population density distribution as separate groups.

Figure 4.1 plots the time series of the average values of the key variables both for all the LLOs and separately for each density group. The log-transformation is applied before plotting. The strong time variation is observed for both vacancy series, but not for the series of job seekers. This, however, is mainly the product of the log-transformation. The number of filled vacancies seems to exceed the number of vacant jobs. The obvious explanation is that a major proportion of the vacancies advertised in a labour office are filled within a week or two, thus they become filled before they are registered in the pool of vacant jobs. Unfortunately, we do not have that kind of data on flows of new job seekers that would also differentiate between educational groups. That is why we do not add a flow variable in our model.

The time series of group 1 lies above the series of the other groups showing the difference in the amount of both inputs and output in the matching process. The variation in logged job seekers and its contribution to the variation in logged filled vacancies is small in all groups, while variations in vacancies contribute clearly to variation in successful matches. It seems that the connection is strongest in the highest population density group and weakest in the lowest population density group.

4.5 Estimation results

4.5.1 Fixed- and random-effects models

Fahr and Sunde (2001) estimate distinct matching functions for distinct markets, among others for job seekers with different education levels. They find that an additional job seeker in the lowest educational group creates a new match with a relatively higher probability than in the other education groups. We estimate the effects of the educational structure both in the whole data and in the groups formed according to population density. Then we put the density groups into the same model utilising the linear mixed model technique and investigate the importance and the significance of the density grouping in the matching model (Verbege and Molenberghs 2001).

As we already discussed in the introduction, the reason for using both fixed and random effects to estimate the model parameters owes to the properties of these effects. A fixed effect model estimated by the well-known fixed effect estimator, or by the least squares dummy variable estimator, has a drawback to ignore the information wich comes from between districts variation. That property is easy to see if we represent the fixed effect estimator as an ordinary

OLS estimator applied to the transformed data, which consists of deviations from district averages. For the same reason it is not possible to estimate effects that do not chance over time with this model. An alternative model, which enables estimating time invariable effects is a random effect model. It, however, will produce biased estimated if the regressors of the model correlate with random effects.

To get the overall picture of the matching function, we report the regressions using the whole data. We use the Prais-Winsten regression with panel-corrected standard errors (see StataCorp. 2001). Disturbances are assumed to be heteroscedastic, i.e., each cross-section unit is allowed to have its own variance. To handle possible dependencies across cross-section units, disturbances are assumed to be contemporaneously correlated, i.e., each pair of cross-section units is allowed to have its own covariance. We also assume there is first-order autocorrelation within all cross-section units and the coefficient of that AR(1) process is common to all the units. The regressions without these assumptions are also reported for the whole data. The Durbin-Watson coefficient 1.6 indicates, however, that the autocorrelation should be taken into account, and the test for groupwise heteroscedasticity shows that it is extremely important to allow the panels to have their own variances (Table 4.3., Specification 2).

The coefficient for job seekers (0.34) is lower than that for vacancies (0.42), which is common in the models with filled vacancies as a dependent variable (Table 4.3, specification 4). Positive externalities due to increases in inputs are not large enough on either side to cancel out negative congestion effects owing to a rise in inputs, and the matching process exhibits decreasing returns. With regard to the job seekers education level, both highly and primary educated job seekers improve the production of successful matches in LLOs in relation to the secondary educated. A percentage point increase in the share of highly educated job seekers increases matches by 2.3 per cent and a corresponding rise in the share of the primary educated by 1.8 per cent. These coefficients indicate that there is relatively higher demand for primary and higher educated than secondary educated workers. From these estimates we can calculate the employabilities of worker groups. Since we measured the employability of group two by 1, a corresponding figure for group one is $2.3/0.34+1 \approx 7.8$ and for group three $1.8/0.34+1 \approx 6.3$.

To clarify the total factor productivity of the matching process, i.e., the ability of a labour market to produce matches with given stocks of job seekers and vacancies, we calculate the LLO-specific fixed effects using specification 4 (Table 4.3). The average value of all fixed effects is –1.5, which means that independently of variations in the stocks of job seekers and vacancies, the number of successful matches produced is 0.22, i.e., the technology parameter *A* in the matching model is 0.22[48]. The average fixed effect for LLOs that belong to the high population density group indicates that the average productivity for that group is 0.25, for the middle group 0.22, and for the low population density

48 To calculate the estimate for the technology parameter A, the estimate for the constant which is in fact *ln(A)* have to be transformed: e.g. $\exp(-1.5) \approx 0.22$.

group 0.21. Therefore, according to this specification, the group with the highest population density has the highest total factor productivity and the group with the lowest population density has the lowest total factor productivity.

TABLE 4.3 Estimation results for the random- and fixed-effects models

Variables	**Specification**			
Dependent variable: ln M_t	(1)	(2)	(3)	(4)
ln U_{t-1}	0.41***(0.023)	0.25*** (0.048)	0.32***(0.081)	0.34**(0.077)
ln V_{t-1}	0.43***(0.005)	0.43***(0.005)	0.42***(0.008)	0.42***(0.008)
Education variables				
$(HIGH/U)_{t-1}$				2.3***(0.588)
$(LOW/U)_{t-1}$				1.8***(0.295)
Constant	-1.05***(0.183)			
Autocorrelation coefficient			0.2	0.19
Returns to scale	0.84***	0.68***	0.74***	0.76***
R^2	0.78	0.78	0.79	0.79
Number of observations	17 082	17 082	17 082	17 082
LR-test for groupwise heteroskedasticity		28 680***		
Durbin-Watson statistic		1.6		
The average value of fixed effects				
All				-1.5
Group 1				-1.39
Group 2				-1.52
Group 3				-1.57

the Notes: All models include annual and monthly dummies. Models 2-4 include LLO-specific fixed effects. Model 1 is a random-effects model. Standard errors (in specifications 3-4 panel-corrected) are shown in parentheses. In specifications 2-4 the error terms are assumed to be contemporaneously correlated and autocorrelated AR(1) with an autocorrelation coefficient common to all the panels. *** stand for statistical significance at 0.1% level, ** at the 1% level, and * at the 5% level. While testing for returns to scale, *** denote deviation from unity at the 0.1% level.

Next we estimate distinct matching models for distinct population density groups. According to the estimation results, in the group with the highest population density, the matching process seems to work independently of changes in the stock of job seekers (Table 4.4). The stock of job seekers is so large that the congestion effects cancel out all positive externalities due to increases in stocks. The coefficient for vacancies is quite high, 0.46. Changes in vacancies and dummies for LLOs, months, and years explain the changes in matches very well: R^2 is as high as 0.9. It is possible that the share of vacancies filled by job seekers not registered in LLOs is larger in densely populated areas than elsewhere. New vacancies produce successful matches with job seekers not registered in LLOs, and the congestion among job seekers in LLOs remains strong. The market share of the public employment agency in the job market tends also be lower in more urbanised areas than in the periphery (Hämäläinen 2004), which also complicates the job searching process of registered job seekers.

TABLE 4.4 Estimation results for fixed-effects models conducted separately for three groups of LLOs

Variables	Group 1 Specification		Group 2 Specification		Group 3 Specification	
Dependent variable: ln M_t	(3)	(4)	(3)	(4)	(3)	(4)
ln U_{t-1}	0.03 (0.077)	0.03 (0.077)	0.15 (0.087)	0.12 (0.086)	0.53***(0.145)	0.51***(0.145)
ln V_{t-1}	0.46***(0.013)	0.46***(0.013)	0.44***(0.01)	0.44***(0.01)	0.34***(0.012)	0.34***(0.012)
Education variables						
$(HIGH/U)_{t-1}$		0.03 (0.651)		-0.1 (0.584)		2.15***(1.022)
$(LOW/U)_{t-1}$		0.41 (0.409		1.5***(0.336)		1.43***(0.478)
Autocorrelation coefficient	0.15	0.15	0.18	0.18	0.14	0.13
Returns to scale	0.46***	0.46***	0.44***	0.44***	0.87***	0.85***
R^2	0.9	0.9	0.73	0.73	0.63	0.63
Number of observations	4 212	4 212	8 658	8 658	4 212	4 212

Notes: Group 1 includes LLOs with the high population density, group 3 is the low density group, and group 2 is the middle group. All specifications include annual and monthly dummies. Panel-corrected standard errors are shown in parentheses. 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.

In the group with the lowest population density, the coefficient for job seekers is high, 0.53. It is higher than the coefficient for vacancies, which is 0.34. A rise in the share of primary or highly educated job seekers also improves matches in these areas. The pools of job seekers and vacancies as well as the number of filled vacancies in these areas are very small compared to the group with the highest population density. In addition, unemployment rates are usually high. As a result of these factors, the vacancies reported in LLOs are more often filled by job seekers searching for jobs through LLOs. In addition, due to an imperfectly functioning labour market, the pool of job seekers is more stagnant than elsewhere, and small changes in it positively affect the production of new matches. Active labour market programmes might also induce dynamics in the pool of job seekers more than in LLOs with the highest population density.

In the middle group, the importance of additional job seekers in the production of matches is not significantly different from zero, as in the group with the highest population density. In the specification without education variables, the coefficient for job seekers is, however, nearly significant. The explanation might be that the coefficient for the primary educated captures the effect of all job seekers since their number increases in accordance with the number of job seekers. They constitute the largest group of job seekers. Higher educated job seekers seem not to have any significant effect.

Since it is somewhat misleading to compare results between separate estimations, next we estimate the model in which all the density groups are included. This enables us to investigate the statistical significance of the population density grouping.

4.5.2 Mixed-effects model

Next we employ a linear mixed model that provides additional information in two respects. First, we are able to estimate the coefficients for all density groups at the same time, which again allows statistical testing of possible differences. Secondly, we can relax the assumption of the same coefficients for vacant jobs and job seekers across LLOs. We are, after all, interested in the differences between LLOs.

The model may be expressed in a hierarchical, two-stage analysis form, or equivalently in the Laird-Ware form (Laird and Ware, 1982). Following the latter, the model can be expressed as:

$$\begin{aligned} y_{it} &= \beta_1 x_{1it} + \ldots + \beta_p x_{p1it} + b_{i1} x_{1it} + \ldots + b_{iq} x_{qit} + \varepsilon_{it} \\ b_{ik} &\sim N(0, \psi_k^2), Cov(b_k, b_{k'}) = \psi_{kk'} \\ \varepsilon_{it} &\sim N(0, \sigma^2 \lambda_{itt}), Cov(\varepsilon_{it}, \varepsilon_{it'}) = \sigma^2 \lambda_{itt'} \end{aligned} \tag{8}$$

where y_{it} is the value of the response variable (filled vacancies) for the tth observation in the ith of 146 LLOs; $\beta_1 \ldots \beta_p$ are the fixed-effect coefficients identical for all LLOs (intercept and coefficients for vacant jobs, all job seekers and relative shares of education groups); $b_{i1},\ldots,b_{iq}$ are the random-effects coefficients for LLOs, assumed to be multivariately normally distributed with covariance-variance structure $\psi_{kk'}$ that is constant across LLOs. ε_{it} is a normally distributed error term with specified covariance between LLOs. We assume the possibility that random effects will show correlation with explanatory variables, which is a common feature in econometric models. Therefore we do not inference strong causal statement from the results, instead, we estimate the effects that the explanatory variables have on response variables according to the data.

We fit a model to the data, including fixed effects for intercepts, vacant jobs, all job seekers and relative shares of education groups. We include a random intercept and slopes. The differences between density groups are estimated using dummy-variables. Thus, the estimated model is:

$$\begin{aligned} &\ln M_{i,t} = c + cD_1 + cD_2 + \alpha \ln(U_{i,t-1}) + \alpha D_1 \ln(U_{i,t-1}) + \alpha D_2 \ln(U_{i,t-1}) + \\ &\alpha\gamma \left(\frac{U_1}{U}\right)_{i,t-1} + \alpha\gamma D_1 \left(\frac{U_1}{U}\right)_{i,t-1} + \alpha\gamma D_2 \left(\frac{U_1}{U}\right)_{i,t-1} + \alpha\eta \left(\frac{U_3}{U}\right)_{i,t-1} + \alpha\eta D_1 \left(\frac{U_3}{U}\right)_{i,t-1} \\ &+ \alpha\eta D_2 \left(\frac{U_3}{U}\right)_{i,t-1} + \beta \ln(V_{i,t-1}) + \beta D_1 \ln(V_{i,t-1}) + \beta D_2 \ln(V_{i,t-1}) + \\ &b_{i1} + b_{i2} \ln(U_{i,t-1}) + b_{i3} \ln(V_{i,t-1}) + b_{i4} \left(\frac{U_1}{U}\right)_{i,t-1} + b_{i5} \left(\frac{U_3}{U}\right)_{i,t-1} + \varepsilon_{it} \end{aligned} \tag{9}$$

In the above formulation, α, β and c are fixed effects common for all LLOs. D_1 and D_2 are dummy-variables representing LLOs belonging to density group 1 and group 2, respectively. $U_{i,t-1}$ 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. The second line of the equation includes the proportion of primary/higher educated job seekers of the total number of seekers. The index 1 indicates primary education and 3 a high level of education. Finally, $b_{i1},...,b_{i5}$ are the random effect coefficients for LLO i; they are considered as random variables, not as parameters, so only their standard errors are estimated.

The results from the maximum likelihood estimation are reported in Table 4.5. The specification (1) 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 -2.6, the coefficient for job seekers 0.7 and that for vacancies 0.4. There appears to be increasing returns to scale in that group. The interactions between explanatory variables and group-dummies indicate that the intercept is 1.85 higher in the high-density group and 2.3 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 show the strongest contribution to total productivity in the middle group and the weakest in the low-density group. Comparison of the coefficients for job seekers reveals that congestion effects are stronger in the middle and high-density than low density LLOs. The elasticity of matches with respect to job seekers is 0.7 in the low-density group, 0.4 in the high-density group and 0.3 in the middle group. The coefficient for vacancies is 0.4 among low-density LLOs, and 0.5 in the middle and high-density groups.

In Specification (2) the effect of the education distribution across job seekers is controlled by including the education share variables in the model. Among low-density LLOs an increase in the relative share of primary educated job seekers has a positive effect on matches whereas the corresponding share of highly educated seekers displays a negative impact. The corresponding coefficients for the middle group do not deviate statistically from those estimated for the low-density group. Instead, among high-density LLOs the effect of highly educated job seekers is significantly negative.

The estimated standard errors for random effects are higher in specification (6) than in (5). The random effect terms can be interpreted as that part of variation across LLOs that cannot be explained by the density-group dummies. It seems that the share of variation across LLO-specific intercept terms unexplained by the group dummies increases after the insertion of the education share variables. That result is, however, hard to interpret in economic terms.

TABLE 4.5 Estimation results for mixed-effects model

Variables	**Specification**	
Dep. variable: ln M_t	(5)	(6)
Intercept	-2.63***(0.45)	-4.39***(1.07)
ln U_{t-1}	0.67***(0.06)	0.76***(0.11)
ln V_{t-1}	0.40***(0.02)	0.39***(0.02)
Education variables		
$(HIGH/U)_{t-1}$		-0.87*(0.43)
$(LOW/U)_{t-1}$		1.82**(0.56)
Interactions with d1:		
d1*Intercept	1.85**(0.62)	4.73**(1.54)
d1*ln U_{t-1}	-0.34***(0.08)	-0.56***(0.16)
d1*ln V_{t-1}	0.09**(0.03)	0.10***(0.03)
Education variables		
d1*$(HIGH/U)_{t-1}$		-1.01 (0.54)
d1*$(LOW/U)_{t-1}$		-2.00*(0.83)
Interactions with d2:		
d2*Intercept	2.30***(0.56)	3.83**(1.32)
d2*ln U_{t-1}	-0.37***(0.07)	-0.51***(0.14)
d2*ln V_{t-1}	0.07**(0.02)	0.07**(0.02)
Education variables		
d2*$(HIGH/U)_{t-1}$		-0.60 (0.49)
d2*$(LOW/U)_{t-1}$		-0.82 (0.69)
Random effects:		
Intercept	0.32	5.29
ln U_{t-1}	0.1	0.51
ln V_{t-1}	0.04	0.09
$(HIGH/U)_{t-1}$		0.27
$(LOW/U)_{t-1}$		2.53
residual	0.44	0.44

Notes: Although not reported here, time trend and monthly dummies are included in both specifications to capture time effects. Significance levels: *** significant at 0.1 % level, ** at 1% level, * at 5 % level. Dummy variable d1 refers to group of high density LLOs and d2 to the middle group. Low-density LLOs are the reference group.

4.6 Conclusions

This paper studied the process of matching job seekers and vacant jobs in local labour markets in Finland. We estimated the ability of the local market to form new matches, and traced whether the found differences across markets could be explained by population density or by the education distribution of job seekers.

The starting hypothesis was that high-density areas would otherwise prove more productive than the others but that their higher productivity may be negatively affected by the job seeker heterogeneity. Our results are in line with the hypothesis: after controlling for the effect of the average educational level of job seekers, high-density areas are more productive in producing successful matches than the others. Moreover, the heterogeneity of job seekers seems to contribute to the inefficiency of the matching process in high-density-areas more than elsewhere. In particular, there seem to be lower educated job seekers in high-density areas than needed to meet the requirements of employers. Therefore, we conclude that the greater job seeker heterogeneity seems to cause frictions in the matching process in densely populated areas but not in sparsely populated areas.

Appendix

An efficient stock of job seekers takes the following form:

$$ESS = U_2 + s_1 U_1 + s_3 U_3 \tag{A.1}$$

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

$$ESS = U_1 + U_2 + U_3 + s_1 U_1 + s_3 U_3 - U_1 - U_3 \tag{A.2}$$

which is equal to

$$ESS = U + (s_1 - 1)U_1 + (s_3 - 1)U_3, \tag{A.3}$$

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

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

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

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

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CHAPTER 5

RANDOM OR STOCK-FLOW MATCHING PROCESS

ABSTRACT. This paper estimates labour market matching model focusing on a choice between random and stock-flow models and dealing with temporal aggregation problem. The results suggest that unemployed job seekers match rather with the flow of new vacancies than with the stock of old ones. However, it seems that all job seekers have to spend time on searching before a successful match.

5.1 Introduction

In recent decades, there has been a growing interest among labour market researchers to model gross worker and job flows instead of stocks of employment or unemployment (see e.g. Mortensen & Pissarides, 1999). A prevailing empirical finding is that gross flows exceed stocks by volume many times (Blanchard & Diamond, 1989, for example). There appears to be a need to reallocate workers across productive matches. Under these circumstances the process of matching job seekers and vacant jobs becomes of a great importance.

The key assumption of matching models is that two-sided frictions exist in searching for workers or vacant jobs[49]. These frictions derive, e.g., from imperfect information between traders, or from their heterogeneity. Because of the frictions, the number of new matches within a particular observation period is not necessarily the minimum of available workers and vacant jobs, as it would be in a frictionless market. Instead, unemployed workers and vacant jobs might exist at the same time. Nevertheless, the flow of new matches is assumed to depend on the numbers of unemployed workers and vacancies. This relationship is known as the matching function, $M=m(U,V)$, where M is the number of matched worker-

49 See Pissarides & Petrongolo (2001) for a survey of the matching models.

job pairs within an observation period. U denotes the number of job seekers at some moment within the period and V is the number of vacancies, also measured within the observation period[50].

The literature has presented several micro-level meeting processes consistent with the properties of the aggregate matching function. A common starting point is an urn-ball problem analyzed by several probability theorists. In these models, homogeneous agents engage in random search, and matching frictions are caused by a coordination problem between these agents. Prominent alternatives for the urn-ball approach are directed-search model by Lagos (2000) and the stock-flow approach presented by Coles and Smith (1998). Of these the latter is of interest in this paper.

The difference between stock-flow and random search models is that the former does not presume a coordination problem between agents, instead, the lack of acceptable vacant jobs may prevent an immediate match of a job seeker. In other words, agents have preferences over possible matches. From a policy point of view the evidence in favour of stock-flow process would mean that the contact process of market parties need not be improved. Instead, their preferences should be worked to better cohere with each other. That may be achieved, for example, by encouraging employers to post vacancies that suit for existing job seekers, or by training job seekers to better meet vacancy requirements.

When estimating the matching model an extra care should be taken to deal with a time aggregation issue that arises because the dependent variable in the model (i.e. number of matches during a given period) is a flow variable, whereas explanatory variables are stock variables, measured at some point within the period. The problem arises because the explanatory variables are depleted by the response variable. Several studies have used lagged explanatory variables as conditioning variables or as instruments to account for this difficulty, but as will be discussed in the next section, they provide only a partial solution[51]. In this paper, I follow Gregg and Petrongolo (2005) to deal with the aggregation problem.

Section 5.2 presents the model focusing, at first, on the time aggregation issue and then, on the topic of nesting random search and stock flow approaches. Section 5.3 describes the data. Data consist of monthly aggregate time series spanning from January 1991 to January 2004. It is extracted from the unemployment register of the Ministry of Labour in Finland. It is high-frequent and provides information about the destination of the unemployment outflow;

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50 Usually, the function is assumed to be increasing and concave in both arguments, with $m(0,V)=m(U,0)=0$. Thus, given at least one vacant job in the market, an extra job seeker always increases the number of matches during an observation period. Concavity, however, implies that the greater the number of job seekers the smaller the increment.. Constant returns to scale –property is also regularly imposed.

51 Lagged variables are used for example in the studies of Blanchard & Diamond (1990) for U.S data; and Burda & Wyplosz (1994) and Burgess & Profit (2001) for European data. For Finnish data estimations are reported in Kangasharju & Pehkonen & Pekkala (2005).

therefore exits from the labour force can be excluded from the outflow variable. Section 5.4 presents estimation results, and Section 5.5 concludes.

5.2 Model

TIME AGGREGATION

In an empirical matching function, stocks of vacancies V_t and unemployment U_t which are both measured at some point during the period, explain dependent variable M_t , which is measured as a flow over the period in question. It means that a flow variable is estimated as a function of stock conditioning variables, and a problem arises because U_t and V_t are depleted by matches M_t. That generates a downward bias in their estimated elasticity parameters.

The problem is often dealt with using lagged explanatory stock variables, U_{t-1} and V_{t-1} (equation (1) with a restriction $\delta=\lambda=0$). That, however, will not solve the whole problem: the dependent variable still measures an outflow both from a beginning-of period stock and from an inflow in progress, whereas the regressors measure only beginning-of-period stocks. If we include flows of new unemployed persons, u_t., and vacancies, v_t , as additional variables in the regression:

$$\ln M_t = c + \alpha \ln U_{t-1} + \beta \ln V_{t-1} + \delta \ln u_t + \lambda \ln v_t + \varepsilon_t , \qquad (1)$$

as a result, u_t. and v_t are depleted by matches and estimates are likely to be unreliable. Especially vacancies are filled quite fast, most within a month, and a large share of them within two weeks.

This study follows an approach used by Gregg and Petrongolo (2005). In the core of that approach lays the assumption of the exponential probability distribution of duration, with constant hazard λ_U with respect to duration during the measurement period[52]. The unemployment outflow within a month is generated by the beginning-of-period number of job seekers, U_{t-1}, and the inflow of new job seekers during the rest of the period, u_t. The whole flow equation is:

$$M_t = \left[1 - \exp(-\lambda_U)\right] U_{t-1} + \left[1 - \frac{1 - \exp(-\lambda_U)}{\lambda_U}\right] u_t , \qquad (2)$$

where λ_U can be estimated by several methods. According to equation (2), each agent belonging in u_t has a matching probability that is $(1 - \exp(-\lambda_U))^{-1} - 1/\lambda_U$ times the matching probability of each agent in U_{t-1}. Therefore, the pool of job seekers can be expressed as homogeneous search units as:

52 See Appendix 1 for more detailed description of the model.

$$U = U_{t-1} + \left[(1-\exp(-\lambda_U))^{-1} - \lambda_U{}^{-1}\right]u_t \quad (3)$$

By using the first or second order Taylor expansion to approximate $\exp(-\lambda)$ around $\lambda = 0$, the right side of equation (2) can be simplified to U_{t-1} or to $U_{t-1} + (1/2)u_t$, respectively. If the first order approximation is used and function (1) is assumed to be Cobb-Douglas with constant returns to scale, λ_U can be written as

$$\lambda_{U,t} = \exp\left(\alpha_0 + \alpha_1 \ln \frac{V_{t-1}}{U_{t-1}}\right). \quad (4)$$

This provides an approximate solution to the time aggregation problem by using the Taylor expansion, and by assuming uniform unemployment inflow within the observation period.

STOCK-FLOW MATCHING PROCESS

The key feature of the stock-flow model is a difference between the stock of old traders and the flow of new ones. When a new job seeker enters the market, she scans all vacant jobs and matches if at least one of the available jobs is acceptable. If she is not able to match within that period, the seeker has to wait for new vacant jobs to arrive in the market. That matching mechanism indicates that any stock-stock matches between *U* and *V* does not exist: newcomers match either immediately with an old trader or, during subsequent periods, with another newcomer.

We follow the paper of Gregg and Petrongolo (2005) to include the stock-flow matching model in the equation (2). Let us denote by *p* the probability that a new unemployed job seeker matches immediately upon entry to the market. Then, with probability *1-p* she must wait for new vacancies to arrive. The outflow equation is

$$M_U = \left[1-\exp(-\lambda_U)\right]U + \left[1-(1-p)\frac{1-\exp(-\lambda_U)}{\lambda_U}\right]u, \quad (5)$$

Those who do not match immediately (*U* and proportion *1-p* from *u*) match with hazard λ_U which is in the regression allowed to depend on the flow of new vacancies and on the stock of old ones according to the following equation:

$$\lambda_{U,t} = \exp\left(\alpha_0 + \alpha_1 \ln \frac{v_t}{U_{t-1}} + \alpha_2 \ln \frac{V_{t-1}}{U_{t-1}}\right). \quad (6)$$

Because stock-flow process implies that no stock-stock matches exist, the stock of old vacancies should not affect the hazard $\lambda_{U,t}$. Therefore, the estimate for α_2 is expected to be zero under the conditions of stock-flow hypothesis. On the other hand, estimation result $\alpha_2>0$ would imply random matching process. Also the result $p=0$ would be unlikely under the stock-flow hypothesis, although it does not literally contradict the hypothesis, because it is theoretically possible that the stock of vacancies does not include suitable jobs for new job seekers.

In addition, the parameter p may depend on the labour market conditions. We allow it to depend on the proportion of old vacancies to new jobseekers, because more old vacancies means more variation in available job characteristics and therefore, a higher probability to find a suitable one. On the other hand, an increase in the total number of newcomers would decrease the changes of one particular job seeker. Thus, p varies according to the equation

$$p_{U,t} = \exp\left(\gamma_0 + \gamma_1 \ln \frac{V_{t-1}}{u_t}\right). \tag{7}$$

5.3 Data description

The monthly data is extracted from the unemployment register of the Ministry of Labour. It span from January 1991 to January 2004. In a regression, the response variable is monthly unemployment outflow from which we exclude flows to outside the labour force, and to active labour market training programs. The regressors are the stocks of vacancies and unemployed job seekers, and flows of new vacant jobs and unemployed persons. All the variables are measured at the end of each month. We also exclude those who receive unemployment pension from the unemployment stock, since they are not considered as active job seekers.

Figure 5.1 compares the number of monthly matches (measured as flow from unemployment to employment) to the two vacancy series. The flow of new vacancies exceeds slightly the stock of old ones, and both of these are exceeded by the number of matches. Finland experienced a deep depression in the early 1990s which is the reason for the low level of vacancies at the beginning of the period. The number of vacancies increased over the whole observation period and seems to drive the number of matches prior to 1997. After that the number of matches turned into a slow decline.

Figure 5.2 presents the monthly matches together with the stock of unemployment and flow of new unemployed job seekers. The stock of unemployment is measured as tens of thousands whereas all the other series are measured as thousands. Again, because of the recession, unemployment was in the high level at the beginning of the period. It turned into a decline in 1993, and since then decreased together with the flow of new unemployed seekers[53].

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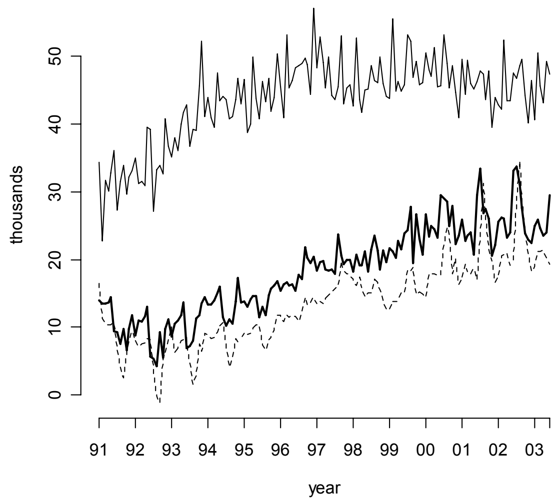
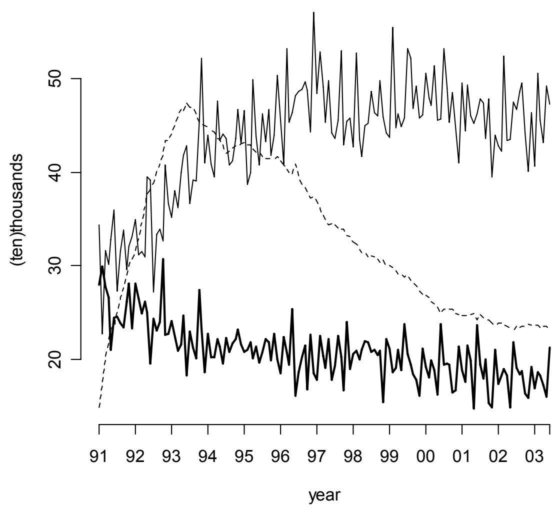
[53] The data is described in more detail by Lahtonen (2004).



Notes: — matches; —— new vacancies; ----- stock of vacancies.
Variables are seasonally adjusted.

FIGURE 5.1 Matches and vacancies (1991-2003).



Notes: — matches; —— new unemployed job seekers,
----- stock of unemployed job seekers (measured at tens of thousands).
Variables are seasonally adjusted.

FIGURE 5.2 Matches and unemployed job seekers (1991-2003).

Figure 5.3 depicts the proportion of vacancies to unemployed job seekers. That proportion was rather low, especially in the first half of the 1990s. The mean of that proportion is approximately 0.005 indicating that on average, there were two hundred job seekers per one vacant job.

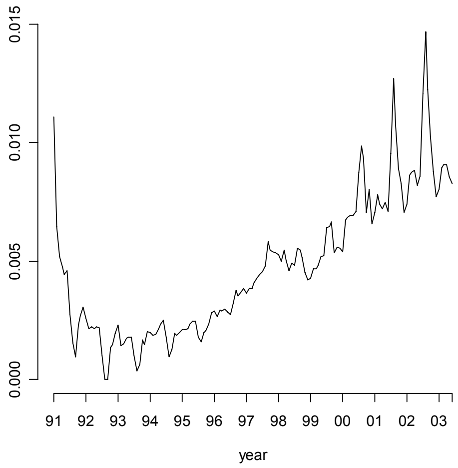
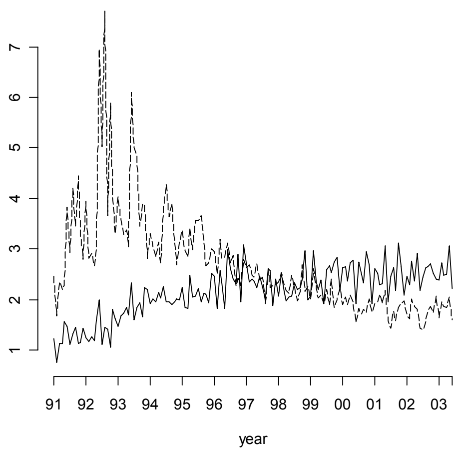


FIGURE 5.3 The proportion of vacancies to unemployed job seekers, calculated from stocks (1991-2003).

Figure 5.4 plots the proportion of matches to flows of new vacancies and new unemployed job seekers. Prior to 1997, monthly number of new job seekers exceeded the corresponding flow of new vacancies. After that, and clearly after 1998, the monthly number of new vacancies have been higher than that of new job seekers.



Notes: — matches/new unemployed job seekers; ----- matches/new vacancies, Variables are seasonally adjusted.

FIGURE 5.4 The proportion of matches to flow of new vacancies and unemployed job seekers (1991-2003).

5.4 Results

We estimate the parameters of the equation (2). First, we assume that the process of matching is of Cobb-Douglas form with constant returns to scale. Then the parameter λ_U can be substituted by equation (4) resulting in:

$$M_t = \left[1-\exp\left(-\exp\left(\alpha_0+\alpha_1\ln\frac{V_{t-1}}{U_{t-1}}\right)\right)\right]U_{t-1}+$$
$$\left[1-\frac{1-\exp(-\exp\left(\alpha_0+\alpha_1\ln\frac{V_{t-1}}{U_{t-1}}\right))}{\exp\left(\alpha_0+\alpha_1\ln\frac{V_{t-1}}{U_{t-1}}\right)}\right]u_t \tag{8}$$

This regression is a random matching model, and the estimated values for the parameters are reported in the first column of Table 5.1. Secondly, we allow a stock-flow matching process by estimating equation (5) in which parameter λ_U is substituted by Equation (6). This regression equation includes a new parameter p which is the probability of a new job seeker to match immediately upon entry. It also includes parameter α_1 which measures the effect of the flow of new vacancies on the matching rate of those job seekers who does not match immediately upon entry. Note that the parameter α_2 measures the corresponding effect of old vacancies. Therefore, the estimated value $\alpha_2>0$ would be in line with the random matching process, whereas $\alpha_2=0$ would indicate the stock-flow process.

Table 5.1 summarizes the results of non-linear regressions of unemployment outflow on the beginning-of-period stocks of unemployment and vacant jobs, and the flows of new unemployed persons and vacant jobs. Column 1 presents the random matching model. Column 2 presents an alternative specification that nests random and stock-flow matching models. Model 3 is the stock-flow model, in which the parameter p is allowed to depend on the labour market conditions according to Equation (7). We use seasonally adjusted data, because the alternative of adding seasonal dummies to nonlinear regression would substantially increase the number of estimated parameters.

In column 1, the significant and positive value for α_1 indicates that the stock of vacancies has strong effect on the unemployment outflow when the flow of new vacancies is not controlled. That result is even easier to see from the calculated elasticity estimates: the elasticity of the dependent variable with respect to the stock of vacancies is 1.2, whereas the corresponding elasticity for the new unemployed persons, u, and that for the stock of unemployment, U, are only 0.1.

Column 2 presents an alternative specification that nests random and stock-flow models, and controls for the flow of new vacancies. That affects the elasticity parameter of the stock of vacancies, which decreases from 1 to almost 0. The corresponding parameters for u and U are still approximately 0.1., suggesting that these estimates are likely to be reliable. The included flow variable, v, seems to have the strongest effect on unemployment outflow: its elasticity estimate is almost 1.2.

The results in column 2 do not give a clear answer to the question of choice between the random and stock-flow models. On one hand, the results are in line with the stock-flow hypothesis: the positive and statistically significant estimate for α_1 indicates that the flow of new vacancies has a strong effect on the matching probability of job seekers belonging to the stock of seekers. In addition, the estimate for α_2 does not deviate significantly from zero indicating that there is no stock-stock matching. In other words, those belonging to the stock of job seekers do not match with the stock of old vacancies. On the other hand, the estimate for the probability p that a job seeker matches immediately is not significantly different from zero. Under the stock-flow model, the interpretation would be that all job seekers have to wait for a suitable vacant job to arrive in the market before they will be able to find a job. The interpretation provided by the random matching model is, however, more convincing: there exist frictions in the market that prevents job seekers from immediate matches with vacancies.

Model 3 allows the parameter p to depend on the labour market characteristics. The estimate 1.02 for γ_1 indicates that an increase in the proportion of old vacant jobs to new job seekers increases the value of probability p, as was expected. The value for p computed by using sample averages and estimated values for unknown parameters, seems to be higher than in the previous specification. That provides some evidence in favour of the stock-flow model.

Table 5.1 also reports likelihood ratio tests that confirm the inferences made in context of Model 2: both tests indicate that the imposed restriction is valid. Actually, these results are quite intuitive because they are achieved by using data where V/U –ratio is relatively low meaning that job seekers have to compete more or less for same jobs. That competition is likely to result in to the random matching process with congestion. That is why the probability of job seekers to match immediately is not significantly different from zero. On the other hand, because the estimation period includes the recession of the 1990s, that parameter might have been changed during the whole period. In fact, in model 3, we allowed that parameter to change which led to the higher calculate value of the parameter.

TABLE 5.1 Results of non-linear regressions of unemployment outflow on the beginning-of-period stocks of unemployment and vacant jobs, and the flows of new unemployed persons and vacant jobs.

Parameter	Model 1	Model 2	Model 3
λ		[0.14]	[0.13]
α_0	-0.68 (0.08)	-0.47 (0.04)	-0.77 (0.13)
α_1	0.40 (0.02)	0.51 (0.02)	0.44 (0.03)
α_2	-	0.01 (0.02)	
p	-	0.07 (0.07)	[0.21]
γ_0	-		-1.14 (0.44)
γ_1	-		1.02 (0.33)
rho	0.31	-0.09	-0.01
No. obs.	149	149	149
Elasticities:			
dM/dU	0.08	0.07	0.07
dM/dV	1.23	0.03	-
dM/du	0.07	0.13	0.26
dM/dv	-	1.18	1.63

Test	L.ratio	p-value
p=0	1.082	0.298
α_2=0	0.781	0.377

Notes: All the models are estimated by maximum likelihood. Estimation period is 1991:1-2004:9. All the variables are seasonally adjusted. Elasticites are calculated using sample averages. Parameter values in square brackets are calculated using sample averages and estimated values for unknown parameters. Approximate standard errors are in parantheses. Rho is AR1 -coefficient estimated from residuals, and used in the Cochrane-Orcutt transformation to correct the serial correlation. The final three rows of the table contain the likelihood-ratio tests for the two restrictions of model 2, p-values are calculated under the true restriction.

5.5 Conclusions

This paper estimated labour market matching function focusing on two main issues: (i) a time aggregation problem, (ii) a selection between a random search and a stock-flow models. According to the results, only a minor proportion of total matches consist of stock-stock matches between unemployed persons and vacancies. Instead, unemployed job seekers are likely to match with the flow of new vacancies. These findings are in line with the stock-flow hypothesis. On the other hand, results show that almost all job seekers have to spend time on searching before a successful match may occur. This stems with the random search hypothesis.

The result seems to mirror exceptional labour market conditions during the observation period: the market experienced a deep depression in the beginning of the period which increased the relative number of traders, measured as *U/V* or *U/v*. Because there were a lot of job seekers per one vacant job, the matching process of job seekers resembles the random process with time-consuming search. Instead, firms with vacancies did not have to compete severely with each other for workers, and they can choose their trading partners from a larger pool of job seekers with various characteristics. Therefore, at least a certain share of new vacancies match immediately with the stock of old job seekers, the matching process of them being better characterized by the stock-flow approach.

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Appendix 1:

The Model

Assume a hazard rate λ implying that the survival probability (probability to stay in the unemployment pool) of an unemployed person is *exp(-λt)*, with *t* denoting the elapsed duration of search. Then, the probability of being matched within a period of length *t* is *1-exp(-λt)*. After normalizing the length of period to one, and assuming initial stock of unemployment *U* and flow of new unemployed u_t with $0 \leq t \leq 1$ the outflow from unemployment (i.e. matches) can be written as:

$$M = (1 - \exp(-\lambda))U + \int_0^1 (1 - \exp(-\lambda(1-t)))u_t dt \tag{A1}$$

Thus the flow of matches measured by unemployment outflow within a month is generated by the beginning-of-the-period number of job seekers, *U*, and the inflow of seekers during the rest of the period, u_t. The first term of the sum (A1) represents the flow from *U* and the second term that from u_t. Furthermore, if the assumption of uniform unemployment inflow within a month is made the equation (A1) simplifies to:

$$M_t = [1 - \exp(-\lambda)]U_{t-1} + \left[1 - \frac{1 - \exp(-\lambda)}{\lambda}\right]u_t \tag{A2}$$

Now, we can relate λ to the relevant variables, for its simplest it may depend on the labour market stocks in a following way:

$$\lambda_{U,t} = \exp\left(\alpha_0 + \alpha_1 \ln \frac{V_{t-1}}{U_{t-1}}\right) \tag{A3}$$

(A3) is in fact a standard Cobb-Douglas specification with a constant returns to scale restriction:

$$\lambda = \frac{M}{U} = c\left(\frac{V}{U}\right)^{\alpha} \tag{A4}$$

SUMMARY IN FINNISH (YHTEENVETO)

Väitöskirja koostuu johdanto-osuudesta sekä neljästä itsenäisestä, työmarkkinoiden kohtaantofunktiota käsittelevästä empiirisestä tutkimuksesta. Kirjan aloittava johdanto-osuus sisältää katsauksen aihepiiriä käsittelevään teoreettiseen ja empiiriseen kirjallisuuteen.

Kohtaantofunktion avulla walrasialaisia oppikirjatasapainomalleja voidaan laajentaa ottamaan huomioon markkinoiden kitkatekijät. Kitkatekijöistä johtuen työmarkkinoilla olevat työntekijät ja avoimien työpaikkojen haltijat eivät kohtaa välittömästi, vaan heidän on käytettävä aikaa sopivan vastapuolen etsintään, ennen kuin uusi työsuhde voi syntyä. Vaikka kohtaantofunktio on ennen kaikkea makroekonomistin työkalu, kirjallisuus tarjoaa funktion olemassaololle useita mikroperusteisia selitysmalleja. Lähtökohtana teorianmuodostukselle on oletus markkinoilla toimijoiden keskinäisen koordinaation puutteesta. Tällaisia malleja kutsutaan myös satunnaisen etsinnän malleiksi. Vaihtoehtoisia lähestymistapoja ovat ohjatun etsinnän malli, jossa kitka syntyy epätäydellisestä liikkuvuudesta, sekä varanto-virta -malli, jossa markkinoilla toimijat ovat ominaisuuksiltaan heterogeenisia. Empiirisistä tutkimuksissa eniten käytetty mallispesifikaatio on Cobb-Douglas -muotoinen, vaikka selvää teoreettista perustetta juuri tämän muodon käytölle ei voida esittää.

Kirjan ensimmäisen empiirinen tutkimus kuvaa Suomen työvoimatoimistojen työnhakijoiden ja avoimien vakanssien ominaisuuksia, sekä estimoi syntyneitä työpaikkoja kuvaavan kohtaantofunktio käyttäen pelkistettyä Cobb-Douglas –muotoista mallispesifikaatiota. Lisäksi tutkimuksessa laajennetaan alustavasti perusspesifikaatiota ottamaan huomioon työnhakijoiden heterogeenisuuden. Tämä tehdään jakamalla työnhakijat kolmeen koulutustasoluokkaan. Lisäksi malli sallii kohtaantofunktion parametrien alueittaisen vaihtelun. Tulosten mukaan peruskoulutetut työnhakijat vaikuttavat kohtaantoprosessiin sitä kiihdyttävästi, kun taas keskiasteen koulutetut hidastavat sitä. Korkeasti koulutettujen työnhakijoiden määrän kasvulla ei juurikaan ole vaikutusta prosessin kulkuun.

Väitöskirjan kolmannen luvun tutkimuksessa Suomen työmarkkinoita käsitellään kokoelmana alueellisia työmarkkinoita, Tutkimuksessa käytettävä malli on edellisen tutkimuksen mallia yksityiskohtaisempi mutta edelleen Cobb-Douglas -muotoinen. Käytetty malli sisältää useita muuttujia, joiden tarkoituksena on valottaa työnhakijoiden heterogeenisuuden vaikutusta kohtaantoprosessiin. Tulosten mukaan, perus- tai korkeakoulutuksen saaneiden työnhakijoiden osuuden kasvu markkinoilla parantaa sen kykyä tuottaa uusia työsuhteita. Vastaavasti keskiasteen koulutettujen suhteellisen määrän kasvulla on päinvastainen vaikutus. Lisäksi pitkäaikaistyöttömien, iältään alle 25-vuotiaiden tai yli 50-vuotiaiden osuuden kasvu heikentää markkinoiden kykyä tuottaa uusia työsuhteita.

Kolmas empiirisen tutkimus tarkastelee alueittaisia työmarkkinoita pyrkien mittamaan eroja niiden kyvyissä tuottaa uusia työsuhteita. Löytyneitä eroja selitetään sekä alueiden asukastiheyksillä että työnhakijoiden koulutusjakaumilla. Metodologisesti tämä tutkimus eroaa edellisistä hyödyntämällä ns. lineaarista sekamallia. Tulosten mukaan työmarkkinat, joilla asukastiheys on korkea, ovat keskimäärin tehokkaampia tuottamaan uusia työsuhteita matalan asukastiheyden alueisiin verrattuna.

Neljäs empiirinen tutkimus eroaa kirjan aikaisemmista tutkimuksista käyttämällä linearisoidun Cobb-Douglas -muotoisen spesifikaation sijaan epälineaarista mallispesifikaatiota. Mallin valinnalla pyritään ratkaisemaan aikaisempiin yhtälöihin liittyvä aika-aggregointiongelma. Käytettävällä mallilspesifikaatiolla voidaan myös testata satunnaisen etsintäprosessin ja varanto-virta -mallin implikaatioita. Jälkimmäisessä mallissa markkinoilla toimijat ovat heterogeenisia siinä mielessä, että juuri markkinoille saapuneiden toimijoiden kohtaantoprosessin oletetaan eroavan jo pitkään markkinoilla olleiden prosessista. Tulosten mukaan työttömät työnhakijat työllistyvät todennäköisemmin uusiin, markkinoille tuleviin vakansseihin, kun jo kauan markkinoilla olleisiin vakansseihin. Tulokset kuitenkin viittaavat siihen, että lähes kaikkien työttömien on käytettävä aikaa sopivan vakanssin löytämiseen, vain harva työllistyy heti markkinoille saapumisen jälkeen.