

43rd Congress of the European Regional Science Association
Jyväskylä, Finland

Matches, vacancies and job seekers : panel data evidence from Finland, 1991-2002

Aki Kangasharju,
Government Institute for Economic Research

Jaakko Pehkonen,
University of Jyväskylä, School of Business and Economics

Sari Pekkala
Government Institute for Economic Research

23.5.2003

Abstract

The study presents evidence on the matching function by using different measures of job matches, the pool of potential job seekers and time aggregation. This allows us to test various hypotheses put forward in the matching literature. The properties of a matching function are examined by using a large panel dataset from Finland. The monthly data is highly disaggregated, comprising 173 work-to-travel areas from a 12-year period between 1991 and 2002. The interpretation of the empirical analysis benefits from the register-based data that has detailed information on the types of open vacancies and unemployed job seekers. The results imply that the main economic activity of the job seekers affects matching performance of local labour offices significantly. Seekers not in labour force have a positive impact on matches while unemployed seekers display a negative effect. A greater share of employed job seekers does not lead to better matching performance. These findings can be explained by the characteristics of open vacancies and job seekers as well as the ranking behaviour of the employers. Furthermore, the time aggregation bias is likely to cause severe underestimation of the returns to scale in the matching function. Finally, regional characteristics do not explain under- or over-performance of matching.

1. Introduction

The matching function postulates a relationship between flow of new matches and stocks of job seekers and vacancies. This relationship has attracted considerable, both theoretical and empirical attention during the last decade. The current state of the art in the field is well-documented in a comprehensive survey by Petrongolo and Pissarides (2001). The reference list of the study comprises a total of 105 theoretical and 27 empirical studies.

There are a number of interesting features that emerge from the survey. First, most of the empirical studies are published in the late 1990s. This indicates the importance of the topic in current research agenda. The data sets analysed in these studies are, however, mainly from the 1980s or early 1990s. The investigation period ends prior to 1989 in 13 of the total of 32 different studies and there are only three studies where data spans to mid 1990s. Second, cross-section studies on the matching function tend to rely on data that covers only three or four cross-sections. The augmentation of sectoral or spatial dimension is thus done at the expense of time dimension. Third, the main frequency of data is year or quarter. This suits poorly with the “flow idea” of the matching function, especially as we know that most vacancies are filled within weeks. Fourth, typically there is no detailed information on job seekers or filled vacancies. Only aggregate numbers of jobs and seekers are used in econometric analysis. In short, the survey suggests that there is a distinct lack of empirical analyses that (i) employ high frequency data with detailed information on job applicants and filled vacancies (ii) utilise cross-section variation between local or sectoral markets a markets while spanning over business cycle. We can thus agree to Andersson and Burgess (2000) who recently pointed out that Hall’s (1989) comment on Blanchard and Diamond (1989), noting that the matching literature lacks disaggregate evidence, remains generally valid even today.

In this paper the properties of a matching function are examined by using a large panel dataset from Finland. The data is high frequency and highly disaggregated, comprising 173 work-to-travel areas from a 12-year period between January 1991 and August 2002. The data set contains information on the types of open vacancies and job seekers, and thus on types of potential matches. The data set at hand allows the exploration of a number of interesting theoretical and empirical questions. In this study we confine the focus on three distinct features: Namely, the measurement of job matches, the measurement of potential job seekers, and time aggregation bias.

Job matches are approximated either by the flow out of unemployment or by filled vacancies.¹ Typically both statistics are compiled and provided by (local) job centres or employment offices. Both measures have their shortcomings. The former can be blamed for not constituting an accurate measure of job matches since transitions out of labour force usually account for a considerable part of unemployment flows. For example, in Finland about 15 per cent of the flows out of unemployment end in work relief programs and about 40 per cent transit out of labour force. Although the latter measure is better in this respect, it can be criticised for not accounting for job matches that are mediated by private agencies and alike. Typically, approximately only 40 percent of all filled vacancies are mediated by labour offices. This Finnish figure is a comparable to most other countries. The difference between these two measures, filled vacancies and unemployment outflow, shows up in data sets. This can be seen well, e.g., in a recent study by Burgess and Profit (2001) that demonstrates how job matches move in a pro-cyclical manner whereas unemployment outflows move counter-cyclically. As Figure 1 shows, this also seems to be the case with our data. Thus the choice of the dependent variable is likely to show up in results.

The choice of the empirical counterpart of the dependent variable of the matching function is an important question since evidence on whether the matching function has constant returns to scale may depend on this choice. Constant returns to scale suggests, in turn, that average exit and filling rates are not affected by the number of job seekers or vacancies. This issue is recently examined in Broersma and van Ours (1999) who suggest that returns to scale are likely to be upward biased if job matches are approximated by the flow out from unemployment. To quantify for the possible bias, we estimate matching functions using both measures.

Job matches are commonly explained by the stock of the unemployed job seekers.² The procedure where the stock of all potential job seekers is approximated only by the stock of unemployed job seekers is typically defended by the lack of information on other job searchers, including those that are employed or out of labour force. This practice may cause problems since a large number of job matches are transitions from other jobs or directly from out of the labour force to employment. For example, Mumford and Smith (1999) report that in their data of UK only 20 % of the total flows

¹ For the former measure, see, e.g., Pissarides (1986), Layard et al. (1991), Burgess (1993), Burda and Wyplosz (1994), Antolin (1994), Eriksson and Pehkonen (1998), Broersma (1997). For the latter measure, see, e.g., Gorter and Ours (1994), Coles and Smith (1996), Munich et al. (1999), Petrongolo and Wasmer (1999), Anderson and Burgess (2000). Both measures are used only in Boersma and van Ours (1999) and Burgess and Profit (2001).

² See, e.g., Blanchard and Diamond (1989), Van Ours (1991), Gorter and Van Ours (1994), Coles and Smith (1995), Gorter and Ours (1994), Munich et al (1999), Petrongolo and Wasmer (1999), Anderson and Burgess (2000), Boersma and van Ours (2000) and Burgess and Profit (2001).

into jobs constitute of flows from unemployment. Flows between jobs and flows from outside of the labour market make up about 43 % and 37 % of the total flows, respectively. The Finnish aggregate labour market data have similar features. About 20 per cent of job openings in local labour offices are filled by employed job seekers. In fact, only about 60 percent of all job seekers are unemployed and a considerable fraction of job seekers are either employed (20 percent) or not in labour force (7 percent).

The consequences of a case where the flow measure to be explained does not correspond to the correct stock are taken up in Broersma and van Ours (1999). They argue that if the non-unemployed job seekers are ignored from the pool of job searchers, the returns to scale are likely to be downward biased. More ... In this study we will consider this possibility by augmenting the pool of possible job seekers by unemployed job searchers, employed job searchers, job searchers not in labour force, and inactive (passive) job searchers. The last group includes those waiting for pensions or temporarily laid-off. The control and measurement of these non-unemployed job seekers will be one of the main contributions of the study.

Possible problems caused by time aggregation will also be examined. This is done by means of a stock-flow specification of the matching model and by analysing both monthly and quarterly data. In the stock-flow specification we will construct the conditioning stock variables such that they include proxies of the outflow originating from the inflow during the measuring interval. This accounts for cases where the number of job matches exceeds the number of (beginning-of-the-period) vacancies, i.e., we observe vacancy filling rates that are above unity. We will follow the example set out in Gregg and Petrongolo (1997) and use auxiliary models that rely on the estimation of hazard rates for unemployment and vacancies. The results of the experiments on bias in matching elasticities due to time aggregation can, e.g., be compared to the results of Burdett, Coles and van Ours (1994), who argue that the size of the bias is approximately a linear function of the measuring interval. In our case the length of the measurement interval is tripled.

The interpretation of our empirical analysis will also benefit from the fact that the register-based data has detailed information on the types of open vacancies and unemployed job seekers. This allows us to contribute to the discussion as to whether matching problems are due to the job characteristics and to what extent they are due to the characteristics of job seekers. For example, it can readily be seen that most vacancies have no requirement concerning potential employees' education, indicating that the wage level is likely to be relatively low. On the other hand, a

considerable number of job seekers have either a secondary or tertiary education, meaning that they are in fact skilled workers.

The paper is organised in the following way. Section 2 describes the data, compiled by Ministry of Labour. This register data from the period 1991-2002 records the end of month situation by local job office areas. The total number of offices is 173. We look at the types of vacancies and unemployed job seekers. We have information on open vacancies by required education and industry. Information on job seekers includes that of age, industry and education. Basic information on regional features and outline regional characteristics of unemployment outflow and vacancy filling rates are depicted. Section 3 starts with theoretical considerations. The basic setup for the matching model follows that of Burgess and Profit (2001). The model is then augmented to account for different groups of job seekers and for a stock-flow specification. Section 4 reports our findings. Finally, section 5 concludes the paper.

2. The anatomy of vacancies and job seekers in Finland, 1991-2002

The data used in the study are from the Ministry of Labour unemployment register that records the end of the month situation by local labour office area. There are 173 local labour offices in Finland and the time span of our data is January 1991 to September 2002.³

The data on employment services include open vacancies reported in the local labour offices by private employers, public bureaus or institutions. In principle employers are required by law to report an open vacancy in the labour office. Nevertheless, approximately only 40 percent of all filled vacancies are mediated by labour offices. This is a comparable figure to most other countries. It should be noted, however, that considerable regional variation is likely to exist in the proportion of filled vacancies mediated by the local labour office. Data on unemployment outflow is also available and hence we will be able to compare these two measures. Data on filled vacancies indicate the total flow during a month while unemployment outflow compares the end of the month situation to that of the previous month.

Job seekers can be divided into various categories by their main economic activity. Most importantly, unemployed persons are those actively seeking for a job and not currently employed. Job seekers also include those who are working but hope to switch jobs, are threatened by unemployment or in subsidized jobs looking for other type of employment. Job seekers not currently in labour force include students, persons doing household work or in the armed services looking for a job. Finally, job searchers include also those who are working a shortened week or are temporarily laid off and not receiving a pay. Importantly for our purposes different types of job seekers are reported separately enabling us to use the proper definitions of job seekers corresponding to filled vacancies or unemployment outflow. We also have information on other characteristics of the job seekers, e.g. age, duration of unemployment and education. All data on job seekers refer to the end of month situation.

³ It should be noted that unemployment statistics are also compiled by Statistics Finland using a questionnaire. Statistics Finland provides the official unemployment rate in Finland, comparable to that of other EU member countries. Due to the relatively small sample size of the Statistics Finland unemployment survey regional unemployment information is available on a much more aggregated regional level than that used here. Moreover, the unemployment register includes much more detailed information on job applicants and filled vacancies.

2.1 Types of open vacancies and unemployed job seekers

Let us first have a look at typical vacancies offered at local employment offices. A breakdown for the years 1991-2002 is shown in Table 1. In Finland, like in most other European countries, local labour offices mainly concentrate on jobs requiring less formal education and offering a relatively low wage. The jobs directed to the most highly educated and other “high end of the scale” –jobs are typically advertised in newspapers and are not registered in the offices. In most countries, however, surprisingly little information exist on the types of job matches. In this paper we were able to look at open vacancies by required education and industry. This may help us understand why, e.g. a high share of employed job seekers in a region does not contribute to a greater matching rate.

Table 1: Open vacancies 1991-2001

Year	Number	Open (days)	% not filled	% full time	% over 1 year	% under 3 mth	% services	% health / soc.	% manufact.
1991	196 856	26	7	75	61	34	21	19	12
1992	127 781	16	7	76	52	39	20	12	14
1993	114 188	16	7	75	47	44	18	8	19
1994	153 790	15	7	73	51	40	17	9	23
1995	169 558	15	5	72	54	39	19	10	22
1996	192 982	16	6	74	53	40	17	12	21
1997	242 014	17	5	74	66	36	16	11	22
1998	254 727	20	5	74	59	34	18	11	20
1999	264 578	18	4	73	59	34	19	12	19
2000	301 981	19	4	74	39	30	18	13	21
2001	318 905	20	3	74	39	30	19	15	18
2002	327 554	22	3	73	39	31	19	16	17

At the aggregate level three points should be noticed. First, many of the advertised jobs are in sales (11 %), often offering a commission based wage, or in the service sector (18 %). Relatively many jobs are also in the health care and other caring services (12 %). Based on this we might expect that job seekers not belonging in the labour force would find it easier to find a job match as, in many cases, women returning from maternity leave will be employed in the caring and service sectors. Secondly, most open vacancies advertised in local offices have little of any requirement concerning the potential employees’ education (not reported here). For example, in the 2001-2002 monthly data

only about 6-12 percent of open vacancies required a specific level of education, and only about 4 percent required secondary or tertiary education. This indicates that such vacancies likely offer a relatively low wage level, which may not exceed the reservation wage of those already employed. Finally, during summer months the number of agricultural and short-term (summer) jobs increases drastically. These jobs are popular among students, school kids and short-term immigrants, leading one to expect a positive effect on matching by the non-labour force job seekers.

The average share of jobs that cannot be filled has been less than 5 percent during 1990-2002. The average time a vacancy is open has varied somewhat over the years, but was just 20 days in 2002. This varies across regions from just over 10 days to almost 30 days. Overall, unemployment rate and the vacancy filling time appear to be negatively correlated. Vacancies are typically filled fastest in Lappi, Kainuu and the Pohjanmaa area (north and west of Finland) and slowest in Pohjois-Savo and Häme (east and middle of Finland). Many (around 50 percent) of the vacancies are filled within 2 weeks and most (80 percent) within a month. Vacancies in building and mining industry are filled fastest while finding employees in agricultural and forestry jobs is more difficult.

Most open vacancies are in private sector firms (71 %) and consist of regular full-day work (75 %). In 1991-2002, on average 54 percent of vacancies were meant to last over a year while the share of short-term jobs was about a third. This indicates that a considerable number of open vacancies can be termed as “attractive”. It is then no wonder that almost all open vacancies will be filled within just two months. Matching problems may thus not be so much due to the job characteristics as the characteristics of the unemployed job seekers.

The number of unemployed has varied drastically over the period studied; see Table 2. The average length of job search has also changed over the years, ranging from 22 to 58 weeks. Regional variation in the length of search is also great: fastest times are consistently recorded in Etelä-Pohjanmaa and Pohjois-Pohjanmaa (west and north-west) while in the slowest regions, Satakunta (south-central) and Etelä-Savo (south-east), job search may take up to twice as long. Those who do find a job will do so relatively quickly (within a couple of months), and currently even the average length of ended unemployment periods is just 18 weeks. This indicates that a great number of unemployed are experiencing long-term unemployment, and even when they terminate job search they may not do so because they have found a job. Indeed, about one third of unemployment outflow is to labour market training or out of labour force.

Table 2: Unemployed job seekers 1991-2001

Year	Number	Search (wks)	Ended per. (wks)	% found job	% high educ.	% sec. educ.	% aged 45-55	% aged 55+	% services	% health / soc.
1991	719 421	22	13	64	6	44	13	6	10	5
1992	907 261	30	18	64	7	46	14	7	20	12
1993	1 028 647	37	21	64	9	47	15	8	10	8
1994	1 047 032	46	25	67	9	48	16	8	10	9
1995	1 022 964	58	25	67	10	49	17	9	11	9
1996	1 008 236	52	24	67	10	49	18	10	11	10
1997	972 425	55	22	67	10	50	19	11	11	11
1998	921 744	56	21	68	10	51	20	12	12	12
1999	890 982	54	19	68	11	50	21	13	12	12
2000	849 321	55	18	69	11	50	21	13	12	12
2001	816 474	54	18	69	18	43	21	14	12	12
2002	810 361	54	17	69	18	44	21	15	11	10

The characteristics of some of the unemployed job seekers may not correspond to what potential employers are looking for. Many of the job seekers are relatively old, and on average more than 10 percent are over 55. A definite trend of aging among the pool of unemployed job seekers is also evident during 1991-2002.⁴ Most job seekers have just the basic education (41 % on average) or secondary education (48 %). Those with tertiary education seldom become unemployed in the first place, but if they do they may face problems finding employment through local job centres due to the nature of vacancies on offer. Over half of the unemployed job seekers were employed before registering at the local labour office, and their most common occupations were in manufacturing, services, health care and administration/secretarial. About a third of those who had not been in labour force before registering as unemployed came directly from school and over 10 percent had previously been doing household work (not reported in table 5). The large number of previous students suggests that the non-labour force job seekers may have a positive effect on the number of matches.

⁴ It should be noted that the unemployment benefit system in Finland operates through two different systems: unemployment benefit societies (unemployment funds) and the Social Security Institution of Finland (KELA). The benefit covers a maximum of 500 days of unemployment after which the person can apply for a labour market subsidy. If the person is over 60, he/she may be entitled to an unemployment pension. Hence the age of the person is likely to determine how intensively he/she is looking for a job.

2.2 Regional characteristics of the data

Local labour market areas in Finland differ widely in size and other characteristics; see Table 3. There are only a handful of regions where population is over 100,000 whereas there are plenty of areas with population less than 10,000. Variation in unemployment is also relatively high. If we look at different types of job seekers across local labour office areas an interesting picture emerges. The pool of potential new employees does not correspond to the pool of unemployed job seekers in any region. On the contrary, only 60 percent of all job seekers are unemployed on average. A considerable fraction of job seekers are either employed (20 percent) or not in labour force (7 percent). Moreover, the characteristics (age, gender, education, unemployment duration) of the job seekers vary drastically from region to region, and over time. While some regions have mainly very young job seekers, others are characterised by a large pool of elderly seekers. The same is true for education and unemployment duration. These differences would indicate that any differences in matching efficiency may be caused by structural factors. It should be emphasized that differences are large both across regions and over time, due to the nature of the period in question.

Table 3: Description of data: the local labour offices (averages of monthly data, 1991-2002)

	<i>Mean</i>	<i>Min / Max</i>	<i>St. dev.</i>
Population in region	29 589	1 213 / 559 718	50 799
Unemployment rate in region (%)	17.9	2.0 / 39.1	6.3
Unemployed job seekers	2 071.7	45 / 49 864	3 676.1
Unemployment outflow	314.6	7 / 6 591	454.5
Employed job seekers	712.0	29 / 11 440	1 034.9
Non-labour force job seekers	244.2	0 / 6 424	424.8
All job seekers	3 455.3	153 / 67 206	5 589.8
Open vacancies	74.43	0 / 6 591	217.2
Filled vacancies	95.4	0 / 5 116	238.1
Seekers aged under 25 (%)	15.9	1.4 / 45.1	5.6
Seekers aged 25-49 (%)	58.6	37.0 / 80.5	5.3
Seekers aged over 50+ (%)	25.5	6.5 / 55.3	8.4
Female job seeker (%)	44.7	11.5 / 65.5	7.0
Male job seekers (%)	55.3	34.4 / 88.5	7.0
Long-term unemployed job seekers (%)	20.3	0 / 48.6	10.2

The rates of matches also differ across the labour offices, indicating differences in matching efficiency; see Table 4. Typically, when comparing the rate of unemployment outflow across

offices the greatest rates can be observed in the smallest regions. Those regions do not (necessarily) have a low unemployment rate and actually have a rather low per capita income. The unemployment outflow also displays clear pro-cyclicality, whereas the vacancy filling rate appears to be counter-cyclical. Highest vacancy filling rates can also be observed in the smallest regions where unemployment rate is relatively high, employment rate is low and taxable income relatively low. The rate of open vacancies to unemployed, on the other hand, tends to vary widely both across offices and over the business cycle. Both in 1991 and 2001 the lowest category had just 0.03 open vacancies per each unemployed, while in the highest category there were four times more open vacancies per job seeker (not shown here). The highest number of open vacancies per unemployed can be observed in largest regions both in 1991 and 2001. In those regions the unemployment rate is also fairly low, employment rate fairly high and taxable income per capita relatively high (though not in 2001).

Table 4: Region characteristics by outflow- and vacancy filling rate

	High		Average		Low	
Unemployment outflow rate:	1991	2001	1991	2001	1991	2001
Outflow/Unemployed	0.26	0.29	0.17	0.22	0.13	0.17
Unemployment rate	0.12	0.15	0.10	0.16	0.09	0.14
Employment rate	0.58	0.60	0.61	0.59	0.64	0.63
Population	13 802	14 995	26 973	19 056	45 873	55 845
Net in-migration rate	-0.12%	-0.72%	0.01%	-0.74%	0.27%	-0.06%
Taxable income per capita	2492	4899	3556	4870	4234	6913
Vacancy filling rate:	1991	2001	1991	2001	1991	2001
Filled/open vacancies	1.94	2.52	1.23	1.35	0.84	0.99
Unemployment rate	0.12	0.17	0.10	0.14	0.09	0.14
Employment rate	0.58	0.57	0.62	0.62	0.63	0.63
Population	18 350	13 285	29 333	42 833	39 007	34 188
Net in-migration rate	-0.26%	-1.12%	0.11%	-0.14%	0.25%	-0.24%
Taxable income per capita	2486	4153	3643	5553	4155	6988

The 1990s recession is clearly depicted in our data, even though the observation period begins somewhat after the actual recession began (figure 1). The number of unemployed job seekers expanded vastly in all local labour office areas, in most cases until the end of 1993, while the number of open vacancies dropped and continued falling until the beginning of 1994. Regional variation in unemployment increased drastically until the summer of 1993, but the variation in the open vacancies across the local labour offices changed less (figure 2). Similar observation can be made from the series of filled vacancies: the average number of job matches fell until the end of

1993 and remained at a fairly low level until the summer of 1994, while the regional variation showed a slight declining trend. The economy started to pick up in 1994 resulting in a declining number of unemployed job seekers (accompanied with a similar decline in regional variation) and increasing number of both open and filled vacancies (with increasing regional variation). There was a temporary drop in the number of open vacancies already in 1998-1999 (not accompanied with a decreasing number of filled vacancies), after which the number started increasing again. The positive labour market development continued until 2001 when the economy started to experience a slight decline. In 2002 the situation has remained almost unchanged.

Figure 1: Unemployment, vacancies and matches in 1991-2002 (12-month moving average)

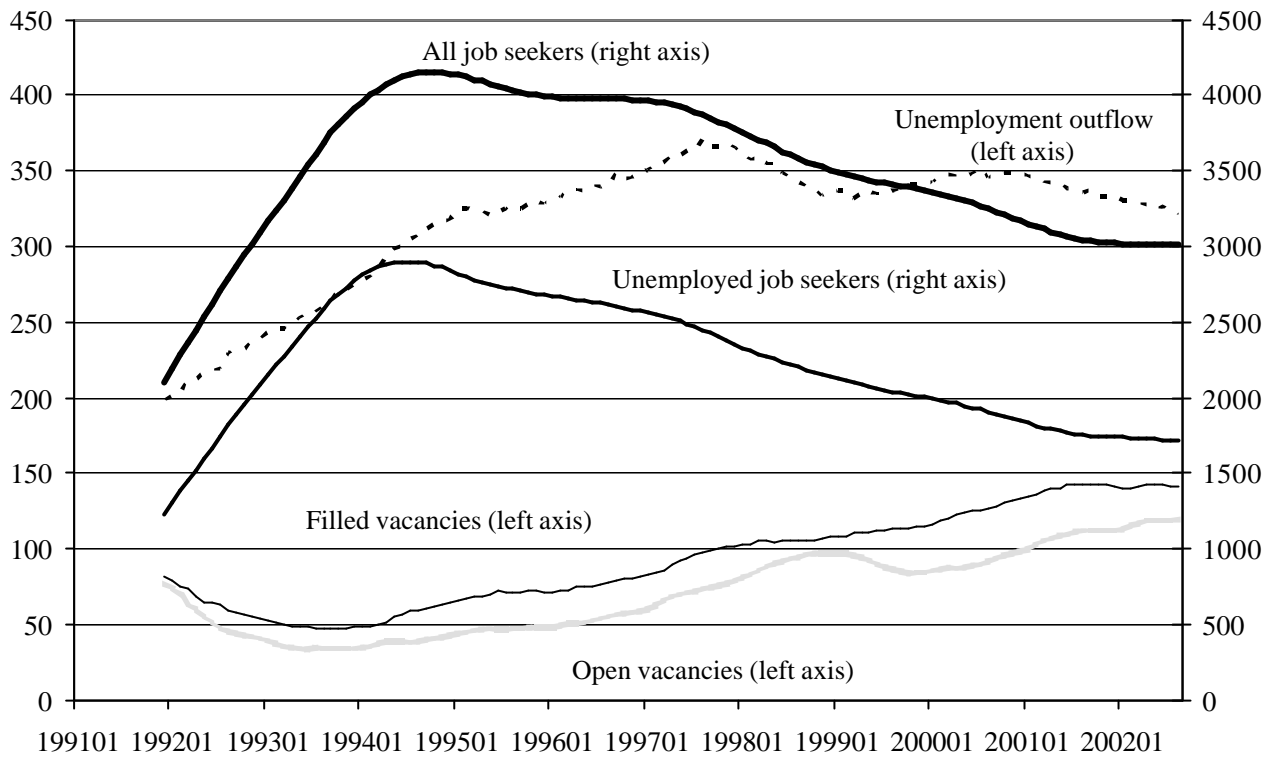
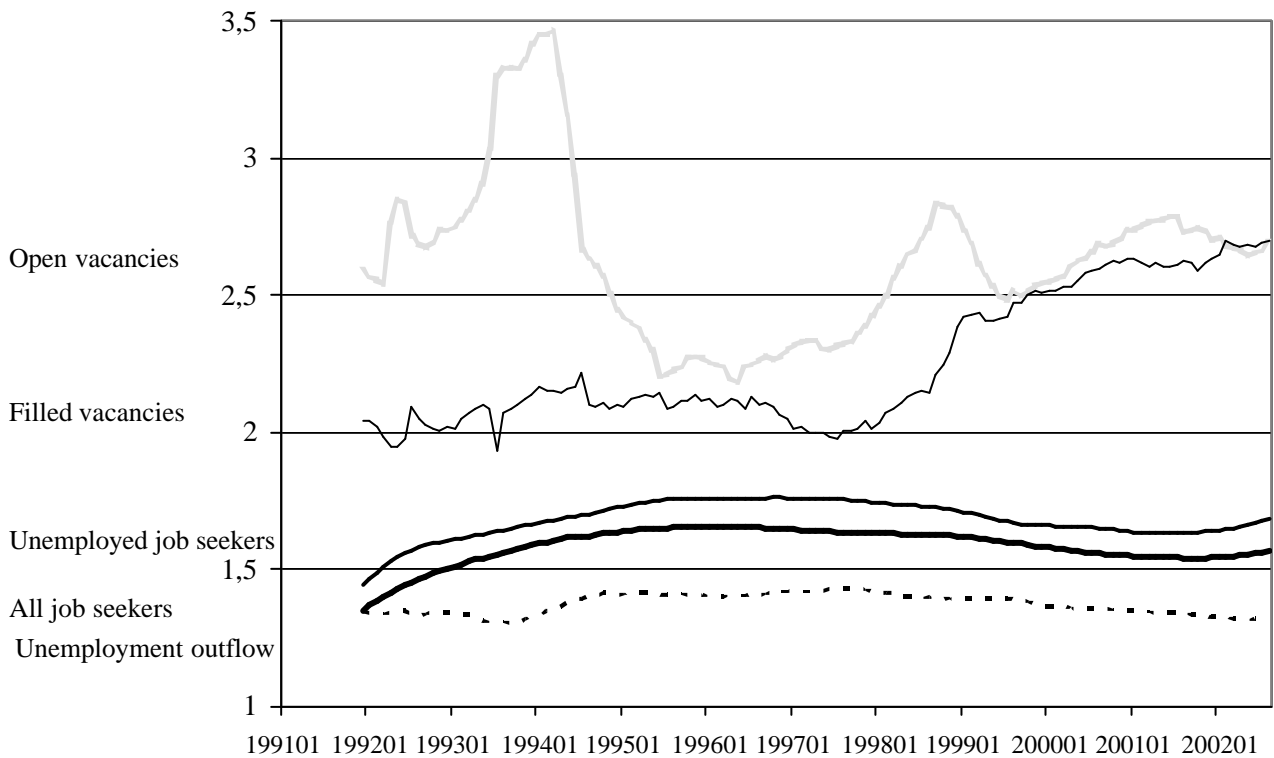


Figure 2: Regional coefficient of variation in unemployment, vacancies and matches, 1991-2002 (12-month moving average)



3. Labour market matching in Finland

3.1 The matching function: specifications

The basic idea of the matching function is simple. Due to imperfect information, lack of regional and occupational mobility as well as other frictions in the labour market, matches between job seekers and firms looking for applicants to fill their vacancies involve time consuming search and finding appropriate matches on both sides. This relation is typically modelled as a production function where matching technology is captured by efficiency and elasticity parameters. The matching model is often formalised by the Cobb-Douglas technology:

$$M_t = m(U_t, V_t) = cU_t^a V_t^\beta \quad (1)$$

where M is the number of jobs formed during an interval, U is the number of job searchers looking for work, V is the number of vacant jobs and c is a scale parameter. The function is increasing in both of its arguments and concave such that $m(0,V) = m(U,0) = 0$ and $m(V,U) < \min(U,V)$. The scale parameter c measures the efficiency of the matching process. It reflects characteristics of jobs and job searchers, including search behaviour of job seekers as well as differences in skills and geographic location of jobs and workers. The model implies that an unemployed job seeker finds a job during the interval with probability $m(U,V)/U$ and a vacancy is filled with probability $m(U,V)/V$. Constant returns to scale suggests that $a + \beta = 1$, implying that average exit and filling rates are not affected by the size of U or V .

Existing empirical research on matching functions has pinpointed several issues that deserve attention; see Petrongolo and Pissarides (2001) for an excellent survey. As noted at the outset, in this study we will focus on three, frequently neglected features. These were (i) the measurement of job matches, (ii) the measurement of potential job seekers, and (iii) time aggregation bias.

The empirical analysis will proceed in the following order. First, we will separately analyse two flow variables, filled vacancies and unemployment outflows. We start the analysis with a setup similar to Burgess and Profit (2001). Allowing for fixed effects for time and districts, we rewrite equation (1) both for filled vacancies (M) and unemployment outflows (F) as follows:

$$\ln M_{it} = u_i + n_t + a^m \ln U_{it-1} + \beta^m \ln V_{it-1} + \eta_{it}^m \quad (2)$$

$$\ln F_{it} = u_i + \eta_t + a^f \ln U_{it} + \beta^f \ln V_{it} + \varepsilon_{it}^f \quad (2')$$

where M and F are the flow variables in area i during month t , the explanatory variables U_{it} and V_{it} are stocks of registered unemployment and vacancies at the beginning of period t . Fixed districts effects are captured by u_i . Seasonal variation in matching and changes in aggregate cycles are controlled by η_t . Error terms ε_{it}^f and ε_{it}^m are normally distributed.

In the second stage we will augment the pool of possible job seekers by controlling for unemployed job searchers (Uu), employed job searchers (Ue), inactive (passive) job searchers (Up) and job searchers not in labour force (Uo). Passive job searchers include those waiting for pensions or temporarily laid-off. We reformulate equations (2) and (2') as follows:

$$\ln M_{it} = u_i + \eta_t + a_1 \ln Uu_{it-1} + a_2 \ln Ue_{it-1} + a_3 \ln Uo_{it-1} + a_4 \ln Up_{it-1} + \beta \ln V_{it-1} + e_{it}^m \quad (3)$$

$$\ln F_{it} = u_i + \eta_t + a_1 \ln Uu_{it-1} + a_2 \ln Ue_{it-1} + a_3 \ln Uo_{it-1} + a_4 \ln Up_{it-1} + \beta \ln V_{it-1} + e_{it}^f \quad (3')$$

It should be emphasised that our priors for matching elasticities are not entirely clear-cut for a number of reasons. First, employers may prefer the employed job seekers to the unemployed. Thus in the model: $a_2 > a_1$. Similarly, it can be assumed that out of labour force seekers are preferred to the unemployed seekers and inactive seekers. Thus we may anticipate that $a_3 > a_1$ and $a_3 > a_4$. Support for these priors can be found in different ranking and job competition models; see, e.g., Mumford and Smith (1999), Anderson and Burgess (2000) for job competition between non-unemployed and unemployed job seekers and van Ours and Ridder (1995) for job competition between unemployed workers with different levels of education.⁵ On the other hand if employed and out of labour force job searchers have higher reservation wages than unemployed searchers and the distribution of vacant jobs is towards low-skill jobs, we may expect the reverse be true, i.e., $a_2 < a_1$ and $a_3 < a_1$. Information on the distribution of vacancies tabulated in Table 1 indicates that the latter assumption, in fact, might be more appealing in our case.

Time aggregation bias is examined, first, by augmenting the conditioning variables U_{t-1} and V_{t-1} by measures that proxy the outflow from the inflow during the unit of measurement, i.e., during the

⁵ See also Blanchard and Diamond (1989, 1994) for ranking between the short- and long-term unemployed.

month. This brings our analysis to the class of stock-flow matching models where the number of job matches exceeds the number of (beginning-of-the-period) vacancies, i.e., we observe vacancy filling rates that are above unity. Following Gregg and Petrongolo (1997), we assume that these flows can be approximated by $[(1-e^{-\lambda})^{-1} - 1/\lambda] u$ and $[(1-e^{-\lambda})^{-1} - 1/\lambda] v$, where u and v denote the unemployment and vacancy inflows during the measuring interval and λ stands for the hazard rate. For computational burden, these new variables are constructed only for the basic models, given in (2) and (2'). Second, we will deal with time aggregation problems and thus a possible bias in matching elasticities by estimating our models both with monthly and quarterly data. The results of this experiment can be compared to those of Burdett, Coles and van Ours (1994) who argue that the size of the bias is approximately a linear function of the measuring interval.

3.2 Matching models: empirical results

The earliest matching studies used time-series information on vacancies and unemployed individuals. Recently the disaggregated data have gained more popularity; see Appendix 1 for a summary of findings in such studies. Included are studies that have at least some regional dimension in the analysis. Clearly the findings depend on the dependent variable used, and in most cases the dependent variable is chosen based on data availability. In studies where matches are approximated by filled vacancies or new hires the estimate for the stock of vacancies exceeds that of the unemployment stock. And if matches are approximated by the unemployment outflow the stock of unemployed seems to dominate as an explanatory factor. These differences are documented and summarised in Petrongolo and Pissarides (2001) and Broersma and van Ours (1999). They show that if the dependent variable is the flow from unemployment, the unemployment elasticity of matching is about 0.7 and vacancy elasticity is 0.3. In the case where matches is the flow variable, the unemployment elasticity is around 0.3 and the vacancy elasticity is 0.7. We take these findings as a point of departure when estimating the matching model both for filled vacancies and unemployment outflow.

Let us now turn to the estimation results. As explained in the theory section we have estimated matching models both for the actual job matches (filled vacancies) and the unemployment outflow, taking into account the different types of job seekers. In the following tables we report only the most important findings of our models.

Our results show that the coefficient of open vacancies is larger than that of job seekers when we model job matches (filled vacancies). The opposite is true when unemployment outflow is the LHS variable. This is consistent with many earlier studies. The reasoning behind this finding is clear: the number of those “at risk” of exiting the labour force is best explained by the actual number of unemployed job seekers, while in the case of filled vacancies it is the number of open jobs “at risk” of being filled that matters most. Our results also underline the importance of using a correct empirical specification: the coefficient for “unemployed/job seekers” is larger when the RHS variable is specified in line with the LHS variable than if the variable does not correspond to the measure of “matches”. In other words, when estimating a model for actual job matches the RHS variables should be “open vacancies” and “all job seekers” (as in models I and II). Otherwise the estimated coefficient will suffer from a downward bias.⁶ This is true both for monthly and quarterly data. In the model for unemployment outflow a wrong specification leads to a downward bias in the coefficient for vacancies and an upward bias in the unemployed-coefficient, both with monthly and quarterly data. To sum up, our baseline models are model II in table 6 for filled vacancies and model III in table 7 for unemployment outflow.

⁶ The coefficient of open vacancies is almost the same in the “correctly” and “wrongly” specified models when job matches is the LHS variable.

Table 6: Summary table for the Matching models; endog. var: $\ln(\text{filled vacancies})_t$

	Monthly data					Quarterly data		
	I	II	III	IV	V	I	II	III
Vacancies:								
$\ln(\text{vacancies})_{t-1}$.430 (29.0)	.415 (28.2)	.427 (29.3)	.0575 (4.7)	.0545 (4.5)	.224 (16.1)	.220 (15.8)	.223 (16.1)
$\ln(\text{vacancies during } t)$.785 (44.4)	.777 (43.3)			
Job seekers:								
$\ln(\text{All})_{t-1}$.121 (1.6)			.059 (1.59)		-.005 (- 0.1)		
$\ln(\text{Unemployed})_{t-1}$		-.203 (-3.1)	-.168 (-2.8)		-.113 (3.1)		-.140 (- 2.0)	-.126 (- 1.8)
$\ln(\text{Employed})_{t-1}$.067 (1.8)			.082 (3.5)		.037 (0.9)	
$\ln(\text{Out of labour force})_{t-1}$.168 (9.2)			.052 (4.7)		.124 (5.8)	
$\ln(\text{Other})_{t-1}$		-.064 (-1.2)			-.024 (-.9)		-.079 (- 1.5)	
R^2	0.81	0.81	0.81	0.91	0.91	0.85	0.85	0.85

Note: all models include year and seasonal dummies; no monthly dummies.

Table 7: Summary table for the Outflow models; endog. var: $\ln(\text{outflow})_t$

	Monthly data					Quarterly data		
	I	II	III	IV	V	I	II	III
Vacancies:								
$\ln(\text{vacancies})_{t-1}$.009 (2.3)	.014 (3.7)	.158 (4.2)	-.030 (-8.0)	-.029 (-7.6)	.008 (2.9)	.010 (3.8)	.013 (4.4)
$\ln(\text{vacancies during } t)$.091 (14.3)	.091 (14.6)			
Job seekers:								
$\ln(\text{All})_{t-1}$.609 (16.9)					.568 (14.7)		
$\ln(\text{Unemployed})_{t-1}$.567 (21.5)	.569 (22.6)	.572 (22.0)	.570 (22.8)		.494 (18.4)	.506 (17.4)
$\ln(\text{Employed})_{t-1}$.161 (6.9)		.163 (7.4)			.118 (5.2)	
$\ln(\text{Out of labour force})_{t-1}$		-.001 (-0.2)		-.013 (-1.9)			.029 (4.0)	
$\ln(\text{Other})_{t-1}$		-.082 (-3.7)		-.082 (-3.9)			-.054 (- 2.6)	
R^2	0.91	0.92	0.91	0.92	0.92	0.97	0.97	0.97

Note: all models include year and seasonal dummies; no monthly dummies.

As far as time aggregation is concerned the results show an interesting pattern (tables 6 and 7). Regardless of the LHS variable used, the coefficient of vacancies is larger when using monthly than quarterly data (both in job match- and unemployment outflow model, though not significantly in the latter). The opposite is true for the unemployment variable in the job match model: the coefficient is larger (or less negative) when using quarterly data. When estimating a model for the unemployment outflows the effect of time-aggregation on the unemployment variable is less clear. In specification III, however, the coefficients are larger with monthly data than with quarterly data. These results would indicate that time aggregation will generally bias the vacancy- and job seeker –coefficients downwards in a stock-flow context. Unemployment-coefficient might be biased upwards (becomes less negative) by time-aggregation in the job match model, yet this is not very clear. It should be noted that variation exists when looking at the sub-groups of job seekers.

The magnitude of the bias caused by temporal aggregation in the stock-flow model can be estimated by comparing the coefficients in the monthly and quarterly regressions. Burdett et al (1994) show that the bias is proportional to the length of the time-interval, i.e. the difference between monthly and quarterly estimates triples the downward bias. In the case of filled vacancies the bias is approximately 15 percents, and the corrected estimate for the elasticity with respect to open vacancies is just below 0.5 (models I-III in table 6). The estimate for job seekers is even more biased (almost 35 percent) and the corrected elasticity estimate would be around 0.16 (model I). A similar procedure for the unemployment outflow model yields an elasticity of 0.21 for vacancies and 0.59 for unemployed job seekers (model III in table 7). Another way of estimating the bias caused by time aggregation is to use the number of open vacancies during a month instead of those at the end of previous month. Using this procedure the estimate for vacancies is almost doubled indicating considerable bias. The results indicate that new vacancies are filled much faster than those already in the stock. However, the problem with this approach is that the variables used suffer from simultaneity bias. Preferably, we would like to estimate our models using both the stock and new inflow of vacancies and unemployed, yet these data are not available.

Finally, and most importantly, the results concerning different types of job seekers reveal useful information. In the job match –models unemployed job seekers have a large negative effect on matching whereas job seekers outside labour force have a noticeable positive impact. This may be caused by ranking behaviour displayed by the employers, i.e. those entering the labour force are likely to be “ranked” above the unemployed by potential employers. Moreover, in our baseline

specification employed job seekers have a positive, yet insignificant, impact on job matches. This may be due to the nature of jobs mediated by local labour offices, i.e. the wage level offered may not exceed the reservation wage of many of the already employed seekers. One curiosity is the negative coefficient for unemployment in model III (table 6), and the fact that the coefficient becomes even more negative when moving to the “correct” specification (model II). This indicates that holding constant the total number of job seekers in a region a higher share of unemployed seekers will reduce the number of actual matches. In order to further clarify the negative impact of unemployed job seekers on matches we would need to divide them into new and long-term unemployed and possibly look at these by age group.

The results are somewhat different when estimating a model for the unemployment outflows. Again, unemployed job seekers have a large positive effect on the outflow, as expected, whereas both employed job seekers and those not in labour force have a positive impact. Rather than indicating a greater likelihood for the unemployed of finding a job when there are more job non-unemployed seekers in the region the finding may reflect job competition between unemployed and other job seekers. This competitive pressure could make the unemployed exit the labour force altogether and quit their job search.

3.3 Performance of local labour offices

Even at the aggregate level we can see that the characteristics of open vacancies and those of unemployed job seekers are not perfectly matched. At the local level these discrepancies are even larger, which explains why some local labour offices have such a poor matching rate and long delays in matching jobs and workers. If we look at local labour offices that have performed better than expected we notice that there are many very small areas among the best performers. Yet the same is true for the worst performers. No clear geographical pattern is immediately observable either. The three best performers (given their number of vacancies and job seekers) are Pelkosenniemi, Utajärvi and Kuivaniemi. The worst performers, on the other hand, are Ranua, Kuusankoski and Liminka. It should be noted that the “performance” is by no means an indication of the actions taken by the local labour office. A bad performance may simply be a result of mismatch: a job match is difficult to conceive if the only vacancy is for a medical doctor and there are only unemployed labourers looking for a job.

In order to see if we can find common denominators for offices doing well or badly, we have estimated a model for the under- or over-performance of the offices (table 8). The dependent variable is the residual of the matching model and it is explained by various (exogenous) characteristics of the local labour office region. It is found that the region-specific fixed effect explains only a small part of the variation across regions. Indeed, there should be no fixed effect left in the residual as it was already included in the first-stage model. However, when including regional characteristics such as region size, population density and industrial structure the explanatory power of the model is hardly improved. For example, when estimating the residual from the filled vacancy –model (with no fixed effects) large regions appear to do better than expected, as well as those with a high share of employment in primary production or construction. Matching rate is also higher in regions that are more active in offering work relief programs. On the other hand, regions with a high employment share in commerce are doing worse than expected, and the same goes for high share of population outside labour force. No clear geographical pattern is evident, although regions in the north of Finland appear to be doing somewhat better than expected relative to the capital region.

When allowing a region-specific fixed effect most of the regional characteristics become insignificant. Only population density, industrial structure and population outside labour force remain significant. It should be noted, however, that all the above models do poorly in explaining why some regions have a better/worse matching performance than expected. This is partly due to the fact that regional variables are measured at the annual level, whereas the dependent variable is the error term of the first-stage monthly based regression. However, these findings would indicate that a more careful analysis of the characteristics affecting the matching rate is needed. It is also possible that the characteristics of the neighbouring region(s) need to be taken into account, especially in labour offices located close to larger cities. Taking such factors into account would call for a spatial autocorrelation model.

Table 8: Summary table for “performance” models

	Filled vacancies –model		Ue. outflow –model	
	OLS	FE	OLS	FE
Constant	-.309 (-1.3)	.407 (0.2)	.215 (1.8)	-6.58 (6.7)
Ln(labour force in region)	.199 (5.9)	-.094 (-0.4)	.147 (9.1)	.693 (7.0)
Ln(population density)	.007 (1.3)	1.991 (5.1)	.000 (0.1)	-.536 (2.3)
Ln(taxable income per capita)	.023 (0.9)	.113 (1.1)	-.015 (1.1)	.048 (1.0)
Ln(population not in labour force)	-.238 (-6.6)	-.647 (-4.5)	-.244 (14.0)	.037 (0.5)
Ln(persons in work relief programs)	.050 (5.7)	-.005 (-0.3)	.101 (20.0)	.167 (13.7)
Net in-migration / population	.004 (6.5)	.002 (1.4)	.002 (7.0)	.000 (0.6)
Primary production (% of employment)	.520 (5.1)	1.463 (1.9)	.244 (4.5)	.406 (1.0)
Manufacturing (% of employment)	.010 (0.1)	-1.424 (-1.8)	.123 (2.7)	.423 (1.0)
Construction (% of employment)	.870 (2.7)	3.345 (1.8)	.308 (1.9)	.928 (1.4)
Commerce (% of employment)	-.734 (-2.4)	-1.544 (-1.0)	-.059 (0.3)	.651 (0.7)
Hotel/catering (% of employment)	-.510 (-1.4)	-3.587 (2.4)	-.431 (2.7)	-1.45 (1.4)
Transport (% of employment)	.148 (0.7)	-1.317 (-0.9)	.408 (3.4)	2.03 (2.5)
Region Turku	-.025 (-1.7)	-	-.013 (1.5)	-
Region Tampere	-.011 (-0.7)	-	-.046 (5.2)	-
Region Lappeenranta	.007 (0.4)	-	-.015 (1.6)	-
Region Mikkeli	.002 (0.1)	-	-.022 (2.3)	-
Region Vaasa	-.022 (-1.2)	-	-.023 (2.2)	-
Region Jyväskylä	.011 (0.6)	-	-.018 (1.8)	-
Region Kuopio	.022 (1.2)	-	.000 (0.0)	-
Region Ilomantsi	.021 (1.0)	-	-.033 (2.9)	-
Region Kajaani	.048 (2.0)	-	-.030 (2.5)	-
Region Oulu	.014 (0.8)	-	-.015 (1.7)	-
Region Rovaniemi	.064 (2.6)	-	-.035 (3.1)	-
Region Lahti	.007 (0.4)	-	-.023 (2.5)	-
Region Seinäjoki	-.001 (-0.1)	-	-.018 (1.9)	-
Region Ahvenanmaa	-.052 (-1.3)	-	.000 (0.0)	-
Adjusted R2	0.008	0.020	0.023	0.035

4. Conclusions

In this study we have analysed the job matching process of local labour offices in Finland during 1991-2002. At our disposal we had monthly data on open and filled vacancies, and job seekers by their main economic activity. The aim of the study was to establish baseline estimates for the typical matching model, as well as to test various hypotheses put forward in the matching literature. Our data proved to be of much better quality and greater detail than those used in earlier empirical studies. Hence we were able to suggest possible answers to some empirical puzzles.

Firstly, the results underline the importance of defining the independent variables of the matching model such that they correspond to the definition of “matches”. When estimating a model for actual job matches the RHS variables should be “open vacancies” and “all job seekers”. Otherwise the estimated coefficient will suffer from a downward bias. In the model for unemployment outflow a wrong specification, all job seekers as independent variable, leads to a downward bias in the coefficient for vacancies and an upward bias in the unemployed-coefficient. Secondly, the main economic activity of the job seekers affects matching performance of local labour offices significantly. In other words, seekers not in labour force have a positive impact on matches while unemployed seekers display a negative effect. And interestingly, a greater share of employed job seekers may not lead to better matching performance. These findings can be explained by the characteristics of open vacancies and job seekers as well as the ranking behaviour of the employers. Thirdly, the extent of bias caused by time aggregation is estimated to be around 15 percent for vacancies and 35 percent for job seekers. Hence, the bias is likely to cause severe underestimation of the returns to scale in the matching function. And finally, regional characteristics do not seem to explain under- or over-performance of matching very well. There is some evidence that matching rate is higher than expected in larger regions, and that industrial structure of the region matters. A more thorough analysis is needed to explain why some regions perform better than others in matching vacancies and job seekers.

In general it seems that matching problems are likely to be due to the characteristics of unemployed job seekers rather than vacancies. The mismatch of vacancies and job seekers may also have become worse during the period 1991-2002: the average length of the search period has more than doubled and the average age of the job seekers has risen continuously. More work is needed to establish the cause of matching problems at local labour office level, however. And importantly, the possibility of spatial spill-overs needs to be taken into account in future empirical work.

References

- Anderson P. and Burgess S. (2000) Empirical matching functions: estimation and interpretation using disaggregate data, *Review of Economics and Statistics*, 82, 93-102.
- Antolin P. (1994) Unemployment flows and vacancies in Spain, Mimeo, Nuffield College Oxford.
- Bennet R. and Pinto R. (1994) The hiring function in local labour markets in Britain, *Environmental Planning*, 26, 1957-1974.
- Blanchard O. and Diamond P. (1989) The Beveridge curve, *Brookings Papers on Economic Activity* 0: 1, 1-76.
- Blanchard O. and Diamond P. (1994) Ranking, unemployment duration and wages, *Review of Economic Studies*, 61, 517-434.
- Broersma L. (1997) Competition between employed and unemployed job searchers: is there a difference between UK and the Netherlands, *Applied Economics Letters*, 4, 199-203.
- Broersma L. and van Ours J. (1999) Job searchers, job matches and the elasticity of matching, *Labour Economics*, 6, 77-93.
- Burda M. and Wyplosz C. (1994) Gross worker and job flows in Europe, *European Economic Review*, 36, 1287-1315.
- Burdett K., Coles M. and van Ours J. (1994) Temporal aggregation bias in stock-flow models, *CEPR Discussion Paper* 967.
- Burgess S. (1993) A model of competition between unemployed and employed job-searchers: an application to the unemployment outflow rate in Britain, *Economic Journal*, 103, 1190-1204.
- Burgess S. (1994) Matching models and the labour market flows, *European Economic Review*, 38, 809-816.
- Burgess S. and Profit S. (2001) Externalities in the matching of workers and firms in Britain, *Labour Economics*, 8, 313-333.
- Coles M. and Smith E. (1996) Cross-section estimates of the matching function: evidence from England and Wales, *Economica*, 63, 589-598.
- Eriksson T. and Pehkonen J. (1998) The unemployment outflow in Finland 1969-1995: A time series analysis, *Labour*, 12, 571-593.
- Fahr R. and Sunde U. (2001) Disaggregated matching functions. *IZA Discussion papers* No. 335.
- Gorter C. and Van Ours J. (1994) Matching unemployment and vacancies in regional labour markets: an empirical analysis for the Netherlands, *Papers in Regional Science*, 73, 153-167.

- Gregg P. and Petrongolo B. (1997) Random or non-random matching? Implications for the use of the UV curve as a measure of matching effectiveness, Institute for Economics and Statistics, Discussion Paper 13.
- Hall, R.E. (1989) Comment on Blanchard Oliver and Peter Diamond, Brookings Papers on Economic Activity 1, 61-64.
- Ilmakunnas P. and Pesola H. (2002) Regional labour market matching functions and efficiency analysis, EALE congress, Paris, 2002.
- Layard R., Nickell S. and Jackman R. (1991) Unemployment, macroeconomic performance and the labour market, Oxford U. Press, Oxford.
- Mumford K. and Smith P. (1999) The hiring function reconsidered: on closing the circle, Oxford Bulletin of Economics and Statistics, 61, 343-364.
- Münich D., Svejnar J. and Terrell K. (1999) Worker-firm matching and unemployment in transition to a market economy: (why) were the Czechs more successful than others? Davidson Institute, U. Michigan Business School, Working Paper, 107.
- van Ours J. (1991) The efficiency of the Dutch labour market in matching unemployment and vacancies, De Economist 139, 358-378.
- van Ours J. (1995) An empirical note on employed and unemployed job search, Economic Letters, 447-452.
- van Ours J. and Ridder G. (1995) Vacancies and the recruitment of new employees, Journal of Labour Economics, 10, 138-155.
- Petrongolo B. and Pissarides C. (2001) Looking into the black box: a survey of the matching function, Journal of Economic Literature, 39, 390-431.
- Petrongolo B. and Wasmer E. (1999) Job matching and regional spillovers in Britain and France, in Developments Recents et Economie Spatiale: Employ, Concurrence Spatiale et Dynamiques Regionales, Catin M., Lesier J-Y and Zenou (eds.), Economica, Paris.
- Pissarides C. (1986) Unemployment and vacancies in Britain, Economic Policy, 3, 676-690.

Appendix. Results of previous matching studies using regional data

Authors	Country and regions	Data frequency	Estimate: V	Estimate: U
<i>Dependent variable: Filled vacancies or new hires</i>				
Anderson and Burgess (2000)	US, 4 States	quarterly	0.813	0.429
Burgess and Profit (2001)	UK, 303 TWWAs	monthly	0.398	0.003
Coles and Smith (1996)	UK, 257 TWWAs	monthly	0.685	0.273
Gorter and van Ours (1994)	Netherlands	annual	0.7	0.3
Münich et al. (1999)	Czech R., 76 districts	monthly	0.68-1.19	1.31-1.93
van Ours (1995)	Netherlands, 8 regions	annual		
Petrongolo and Wasmer (1999)	UK, 11 regions	quarterly	0.736	0.039
Petrongolo and Wasmer (1999)	France, NUTS3	quarterly	0.315	0.546
<i>Dependent variable: Unemployment outflow</i>				
Bennet and Pinto (1994)	Britain, 104 districts	quarterly		
Burgess and Profit (2001)	UK, 303 TWWAs	monthly	0.034	0.659
Ilmakunnas and Pesola (2002)	Finland, 14 regions	annual	0.101	0.929
Münich et al. (1999)	Slovakia., 38 districts	monthly	0.17–0.25	0.4–2.5