Finnish Economic Papers – Volume 20 – Number 1 – Spring 2007

FINNISH EVIDENCE OF CHANGES IN LABOR MARKET MATCHING

HEIDI SOININEN

The Swedish School of Economics and B.A., HECER and The Bank of Finland, Snellmanninaukio, 00100 Helsinki, Finland; e-mail: heidi.soininen@bof.fi

This paper models the Finnish labor market matching process for the period 1982:1–2002:3 using cointegrated VAR-analysis. The data is split into two periods. For the years prior to the economic crisis in the early 1990s a Beveridge-curve is found as the long-run relationship. The post-crisis period is dominated by a traditional matching-like relationship with strong negative association between unemployment and matching, stemming mainly from long-term unemployment. This suggests that some of the Finnish unemployment persistence can be traced back to changes in the matching process and particularly to the matching of the long-term unemployed. (JEL: J41, J64)

1 Introduction

In the beginning of the 1990s Finland experienced a serious economic crisis. The crisis followed financial deregulation, but also the fall of the Soviet Union affected the outcome. Koskela and Uusitalo (2006) and Honkapohja and Koskela (1999) argue that the Finnish economy consequently experienced a strong structural change. As other economic indicators, such as GDP growth, recovered rapidly from the crisis, the unemployment rate refused to fall to earlier levels. The proportion of long-term unemployed increased from 10% to 30% and has since fallen slowly. The Beveridge curve[1] shifted outward and has since failed to shift back in a similar manner (Honkapohja and Koskela, 1999).

It hence appears clear that the initial rise in Finnish unemployment was due to the economic crisis, during which 450 000 jobs were destroyed (Koskela and Uusitalo, 2006). The reasons for the persistence of the unemployment rate are however unclear. Blanchard and Wolfers (2000) argue that the interaction between shocks and institutions is vital for understanding European unemployment, while Saint-Paul (2004) finds that labor market reform is important for getting out of a period of high unemployment. Contrary to these, Nickell et al. (2005) show that the Finnish unemployment experience cannot be explained by institutions, as is the case in many countries.

In this paper I investigate if the persistent unemployment prevalent in Finland can be a consequence of matching related issues. I model vacancies, unemployment and hirings using

* *I am grateful to two anonymous referees as well as Rune Stenbacka, Erkki Koskela and Mikael Juselius for fruitful comments. The Academy of Finland is acknowledged for financial support. All remaining errors are mine.*

[1] *The Beveridge curve or the u/v-curve (unemployment/vacancy) is a theoretical description of the process that matches unemployed to available vacancies. It is assumed to be convex and downward sloping in the vacancy-unemployment space.*

cointegrated vector autoregression (VAR) analysis for both a pre-crisis period and a post-crisis period in order to determine if the matching process has changed. Judging by the stability of model parameters I split the sample into a pre-crisis period (1982:1–1988:1) and a post-crisis period (1993:1–2002:3).

In the analysis I seek to establish whether the theoretical relationships, the matching function or the Beveridge curve, can be found as long-term relations in the data and how the relations differ between the periods. I also separate long- and short-term unemployment in the analysis. The main findings are that for the 1980s a one-to-one Beveridge curve can be distinguished, while for the 1990s, a corresponding long-run relationship resembling the Cobb-Douglas matching function, but with a negative unemployment coefficient, is found. When splitting the unemployment variable into long- and short-term unemployment in the post-crisis period, long-term unemployment is found to have a strong negative influence on matching while short-term unemployment has a strong positive effect on matching. This result is in line with among others Mumford and Smith (1999) and Burgess (1993) who show that the share of long-term unemployed has a negative impact on matching.

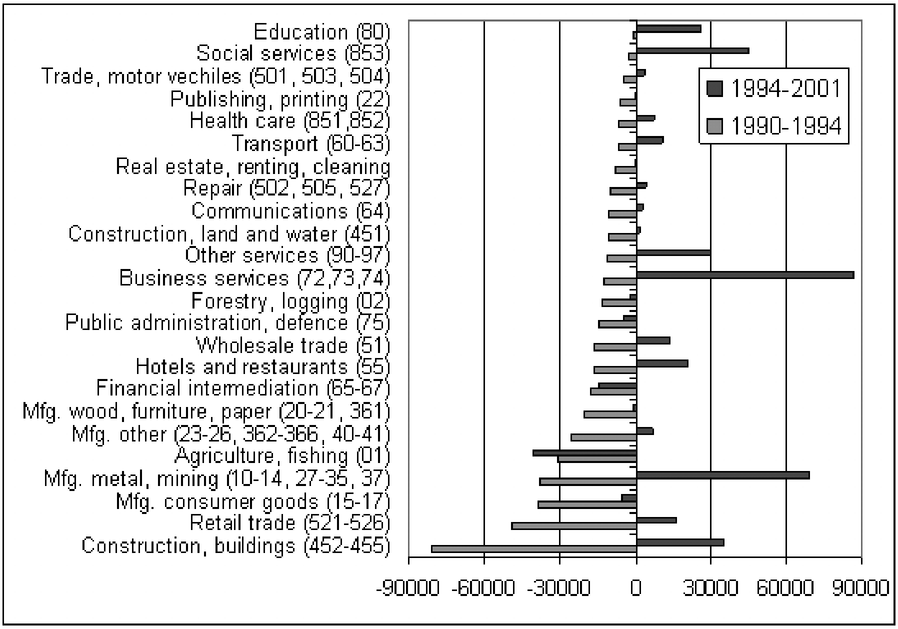
The implications of the findings are the following: The matching process has changed, indicating two different regimes, a pre-crisis low unemployment regime and a post-crisis high unemployment regime. In the low unemployment regime unemployed and vacancies can find each other with a smaller amount of effort, while after the initial rise in unemployment during the economic crisis this mechanism collapsed. The separation between long- and short-term unemployment underlines that it is the increased amount of long-term unemployed that congests matching. This helps to explain the persistence of Finnish unemployment during the whole 1990s.

A large number of empirical studies have been conducted in the field, most of which are based on OLS-analyses. Examples are Blanchard and Diamond (1989), who use US data, Pissarides (1986), Layard e al. (1994) and Coles and Smith (1996), who study British data and Burda and Wyplosz (1994), who utilize data for many continental European countries. Most earlier international studies find evidence of constant returns to scale in the matching function, for example Blanchard and Diamond (1989) and Petrongolo and Pissarides (2001). There are studies such as Edin and Holmlund (1991) and Anderson and Burgess (2000) which indicate that there would be decreasing or increasing returns to scale. When using aggregate data the estimated functions usually satisfy constant returns to scale while disaggregate data mostly suggest mildly increasing returns to scale. Generally, studies using hirings instead of unemployment outflow as the third variable tend to have a larger coefficient for vacancies than otherwise. For an excellent overview of earlier studies see Petrongolo and Pissarides (2001). Related issues have been studied using Finnish data by Koskela and Uusitalo (2006), Pesola (2002) and Ilmakunnas and Pesola (2003). Ilmakunnas and Pesola (2003) find evidence for both constant returns to scale and increasing returns to scale using two different methods on Finnish disaggregate data. Albaek and Hansen (2004) is an exception in the literature, as they utilize cointegrated VAR-analysis on matching issues using Danish data between 1974 and 1988. They find evidence for both a Beveridge curve and a matching function, which is homogenous of degree one, when they model shifts in the Beveridge curve and the matching function as smooth transition functions. They suggest that mismatch, as opposed to reallocation, is the cause of the outward shift of the Beveridge curve.

The main contribution of the present paper is that I analyze the matching process before a crisis, in a low unemployment regime, and after a crisis, in a high unemployment regime. The differing matching patterns in the two periods indicate that matching issues can explain a part of the stickiness of unemployment during the post-crisis period.

The remainder of the paper is organized as follows. Section 2 gives a brief presentation of the Finnish economy. In 3 the theoretical framework is presented and in section 4 the data and the statistical model are presented. Section 5 conducts the empirical analysis. Section 6 concludes.

Figure 1. Change in employment by industry during the recession and subsequent recovery.



The source of this figure is Koskela (2004). It is based on their own calculations based on data from the Labour Force Survey. Industry classification according to ISIC 2–3 digit classification as used in the LFS.

2. The Finnish economy 1982–2002

The Finnish economy was rather closed in the beginning of the 1980s. However, while most other European economies suffered from high unemployment during the 1980s, the Finnish unemployment rate remained at 5%. Finland relied heavily on trade with the Soviet Union and can be considered to have been even more closed than other Western European countries due to the bilateral trade agreements with the Soviet Union. One result of the bilateral trade agreements was that the oil shocks did not hit the Finnish economy as hard as they hit many other economies. This was because an increase in the prices of Soviet goods (including oil) led to a corresponding increase in the demand for Finnish goods (Koskela and Uusitalo, 2006).

During the 1980s the economy started to open up. The financial markets were deregulated leading to an increased openness of the economy. As most European countries, Finland's economy experienced a serious crisis at the beginning of the 1990s. The Finnish crisis was, however, exceptionally deep. Between 1991 and 1993 GDP fell by 13%, the employment level fell by 18% and almost 450000 jobs were destroyed (Koskela and Uusitalo, 2006). This extreme crisis was a result of a combination of many things; the fall of the Soviet Union, deregulation of the financial markets in combination with extensive borrowing and high real interest rates. Finland devalued in 1991 and let the Finnish markka float freely in 1992 (Honkapohja and Koskela, 1999).

The Finnish economy, however, recovered quite quickly from the crisis. The only serious problem that remained was the extensive and persistent unemployment. Koskela and Uusitalo (2006) argue that one reason for this is that jobs destroyed and created during and after the crisis were in different sectors, adding to the stickiness (see figure 1 for a graphical description of job destruction and creation during and after the crisis). A slow decline in the unemployment rate has taken place, but only recently has the unemployment rate fallen below 8%.

There are many potential explanations for persistent unemployment. For the European unemployment problem both aggregate demand and aggregate supply shocks along with real wage rigidity have been suggested as possible causes (Blanchard and Summers, 1986). Unemployment benefits and structural changes can both be seen as aggregate supply shocks in this framework. Ljungqvist and Sargent (2002) point at the generous benefit system along with other aspects, while Lindbeck and Snower (1986) emphasize Insider-Outsider theories. Hysteresis is an additional explanation for persistent unemployment. It can occur when a country is far down on its Beveridge curve as Finland was in 1993. At this point a movement along the curve can transform into an outward shift of the curve. The reason for this is that long periods of unemployment can decrease the possibilities to find a job (Blanchard and Summers, 1986).

Nickell et al. (2005) argue that institutions do not matter for the Finnish unemployment experience, while Saint-Paul (2004) underlines the importance of changes in institutions as a response to high unemployment. Blanchard and Wolfers (2000) emphasize the importance of the interaction between institutions and shocks. There is still no consensus on what determines high and persistent unemployment. In the Finnish case most observers agree that a severe restructuring of the economy has taken place along with the collapse of the economy in the early 1990s.

3. *The theoretical matching framework*

The matching framework utilized in this paper is based on the model described in Pissarides (2000). The matching function gives the number of formed jobs as a function of the number of vacancies and the number of unemployed. In its simplest form the matching function can be written as

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

where M is the number of hirings or matches during the period, V is job vacancies during the period and U is the number of unemployed during the period. It is usually assumed that m is increasing and concave in both of its arguments and $m(0, V) = m(U, 0) = 0$. The matching function is in most theoretical contributions assumed to exhibit constant returns to scale. Constant returns to scale imply a proportional increase in hirings given a change in vacancies or unemployment.

The functional form usually used is the Cobb-Douglas form

(2) $M_t = \delta V_t^{\alpha} U_t^{\beta}$,

where

(3) $\alpha + \beta = 1$

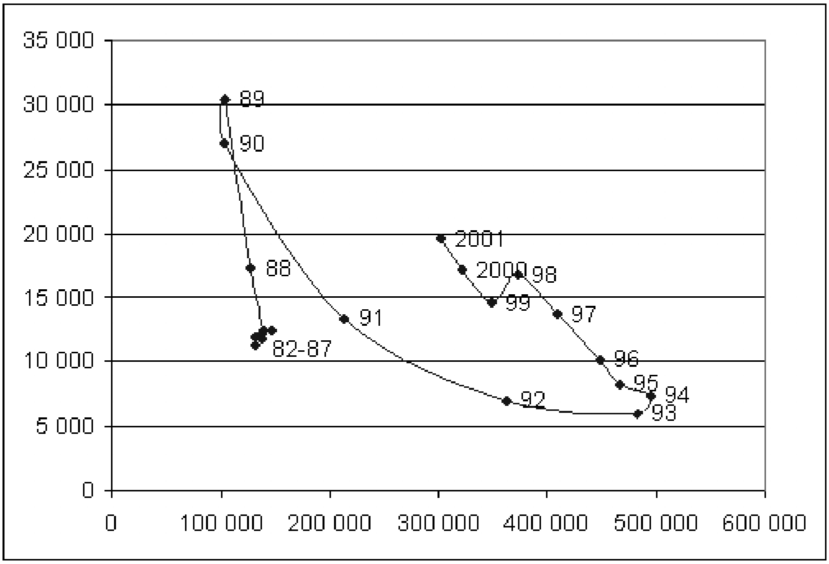
if there are constant returns to scale. The Cobb-Douglas functional form is very popular and highly successful in empirical applications, but has been questioned because there are no micro foundations for it in the existing literature. Alternative specifications suggested include translog and CES functional forms. Lately Stevens (2002) has shown, using a "telephone line" Poisson queuing process[2], that when marginal search costs are approximately constant the Cobb-Douglas matching function gets theoretical support.

The matching function describes how the actual match between vacancies and job-seekers takes place at each moment in time. If there are no frictions in the matching process, i.e. if unemployed and vacancies are instantaneously matched, this number is the minimum of vacancies and unemployed. Obviously if there are frictions, the number of matches will be lower (Petrongolo and Pissarides, 2001). Increased inefficiency in the matching process means less matches at the same level of vacancies.

The process that matches the unemployed to available vacancies is often graphically described as a convex Beveridge curve in the vacancy-unemployment space. The Beveridge

[2] *A telephone line Poisson queuing process is when workers send out applications randomly at a specific Poisson rate to firms with vacancies. Firms respond to applications at another Poisson rate. If an application arrives when the firm is not ready to receive it, there is no answer. When a contact is made, the match is consummated if it is sufficiently productive. Otherwise both parties continue to search. For more on the issue see Stevens (2002).*

Figure 2. The Finnish Beveridge Curve for the period 1982–2001, annual data.



curve slopes downward if the outflow from unemployment is described by equation (1). The steady state Beveridge relationship can easily be derived from equation (1). Let U be the number of unemployed and V the number of vacancies and N and L the level of employment and the labor force. The unemployment rate is given by $u = U/L$ and the vacancy rate is given by $v = V/L$. Assume that the job separation rate is λ and total separations are given by $S = \lambda N$. Imposing constant returns to scale on $m(.)$ the Beveridge curve is given by[3]

(4) $\lambda = m[u/(1-u), v/(1-u)]$.

The further away from the origin the curve is, the less effective is the process of matching jobs and unemployed.

The Finnish Beveridge curve for the period 1982–2002 slopes downward but has shifted out and has then partially shifted back again (see Figure 2), as is the case for most European countries (for example Layard et al. (1994)). When looking at the curve there seem to be three different stages; The 1980s, the turbulent years around 1990 and the period stretching from 1993 onwards.

4. Data and statistical model

4.1. Data

The data used in the analysis is Finnish monthly data from the Finnish Ministry of Labor spanning the period 1982:1–2002:3. Availability of the hirings series restricts the data period to start in 1982. In order to investigate if there are differences in matching before and after the economic crisis in early 1990s the data was split into two parts; 1982:1–1988:1 and 1993:1–2002:3. The first period will hereafter be called *Period 1* or the *pre-crisis-period*, while the second will be called *Period 2* or the *post-crisis-period.*

The dates for the cut out period, 1988:2–1992:12, were decided on the examination of the data and based on what happened to the es-

[3] Sometimes, e.g. in Petrongolo and Pissarides (2001), the Beveridge curve is given by $\lambda = m[u/(1-u), v]$, due to a different specification of the vacancy rate, $v = V/N$. In this paper the vacancy rate is calculated as the number of vacancies divided by the number of labor force participants, while it sometimes is calculated as the number of vacancies divided by the number of employed. Hence the vacancy rate used here is not linked to the number of employed, but is instead easy to compare with the unemployment rate.

timates when the periods were made longer. For period 1 adding just one month made the estimations impossible to interpret and changed the key relations. The same applies to period 2. Making the periods shorter does not change the results significantly indicating that for the periods chosen the results are robust.

The study is restricted by the data cutting, but the procedure is motivated by extreme turbulence during the period and the impossibility to make the model fit. The drawbacks of the cutting are, however, limited since the aim of the study is to compare matching before and after the crisis. The partial nature of the study needs to be underlined also concerning the fact that neither wage setting behavior nor additional macro variables are linked to the model.[4]

The variables used are *unemployment* (the logarithm of the number of unemployed/labor force), *vacancies* (the logarithm of the number of vacancies / labor force) and *hirings* (the logarithm of the number of hirings/labor force). Hirings is here measured as vacancy-outflow. Unemployment-outflow could be used as an alternative measure for hirings. Both series have their flaws; unemployment-outflow also includes outflow to retirement and outflow to outside the labor force, while vacancy-outflow also includes vacancies filled by other applicants as well.

Problems arise from using search and match measures that are based on different pools of people, which do not correspond to the underlying theoretical variables. Vacancy-outflow consists of vacancies filled by the unemployed, the employed job-seekers and the job seekers from outside the labor force while only data on unemployed is used as the search measure. Broersma and Van Ours (1999) and Petrongolo and Pissarides (2001) discuss the topic and emphasize the bias arising from using a search measure that only corresponds to a part of the vacancies filled. The unemployment coefficient only measures the effect of the number of unemployed on matching and not the effects from all job seekers. Hence the unemployment coefficient is much smaller than the all-job-seeker coefficient would be. It is, on the other hand, very interesting to measure the influence from unemployment on matching, but the misspecification issues need to be remembered.

Long-term and *short-term unemployment* data for the period 1994:3–2002:3 is also used for additional analysis. Long-term unemployed are those that have been unemployed for more than 12 months. The series used are logarithms of long-term unemployment/labor force and of short-term unemployment/labor force. Additionally an analysis with the share of long-term unemployed is conducted.

The data is based on information reported by local workforce offices and therefore only includes unemployed, vacancies and hirings reported to the workforce offices. Quite a significant amount of all of the vacancies are never posted at workforce offices but are only posted in newspapers, on company websites or advertised through recruitment agencies, neither do all newly unemployed report to workforce offices. The general view is that high skill jobs are not matched through workforce offices, which may result in a low-skill bias in the data. This view is, however, challenged by the fact that most large Finnish corporations and all governmental sectors report all their vacancies also through local workforce offices, so the bias towards low-skill jobs might not be that large after all. For example, in July 2004 there were in total 33.900 vacancies available through workforce offices, 19.000 vacancies were filled during July and out of these only 8.900 where filled with applicants found through workforce offices. Roughly half of the vacancies are filled by workers not reported in any way to workforce offices. This is probably a result of vacancies being simultaneously posted in many different places and the applicants are then not only registered unemployed using information given by the workforce office but also workers conducting on-the-job-search and newly graduated. Hence it seems that vacancies and hirings

[4] *In earlier versions of the paper macro variables (real GDP, real interest rate, openness indicator etc.) were linked to the study but without being able to stabilize the results for the full period. Hence these variables were omitted. This result underlines the difficulty to find suitable variables for modelling cointegrating vectors through a severe economic crisis. Most vectors collapse during such periods, which motivates leaving the period out of the analysis if the interest is put on the long-run relations and not on studying the crisis itsel.*

Figure 3. The time series for vacancies and hirings, 1982:1–2002:3.

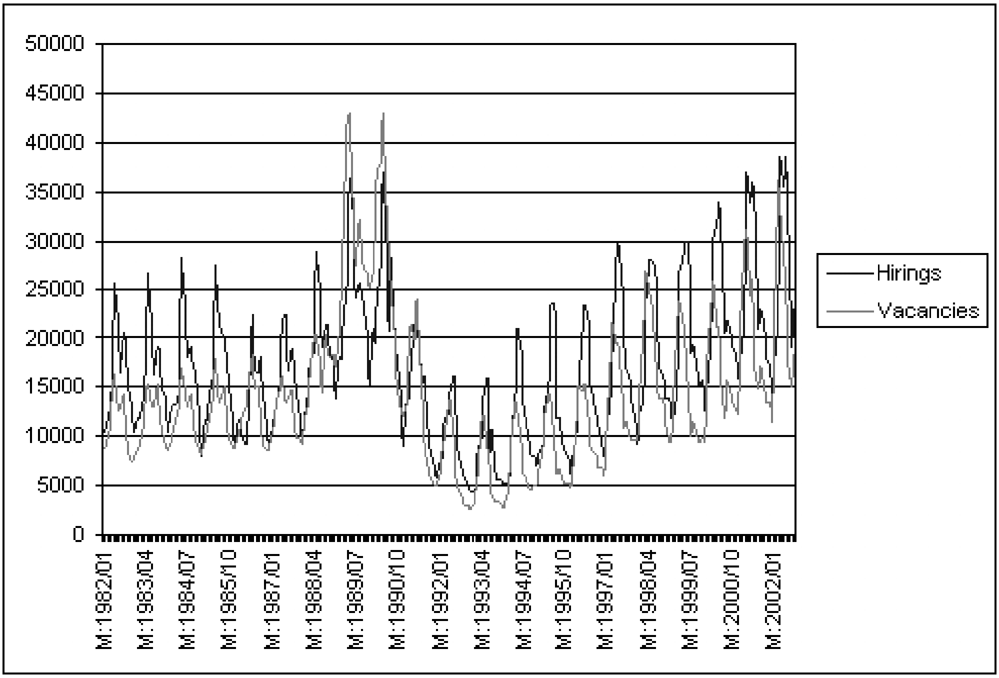
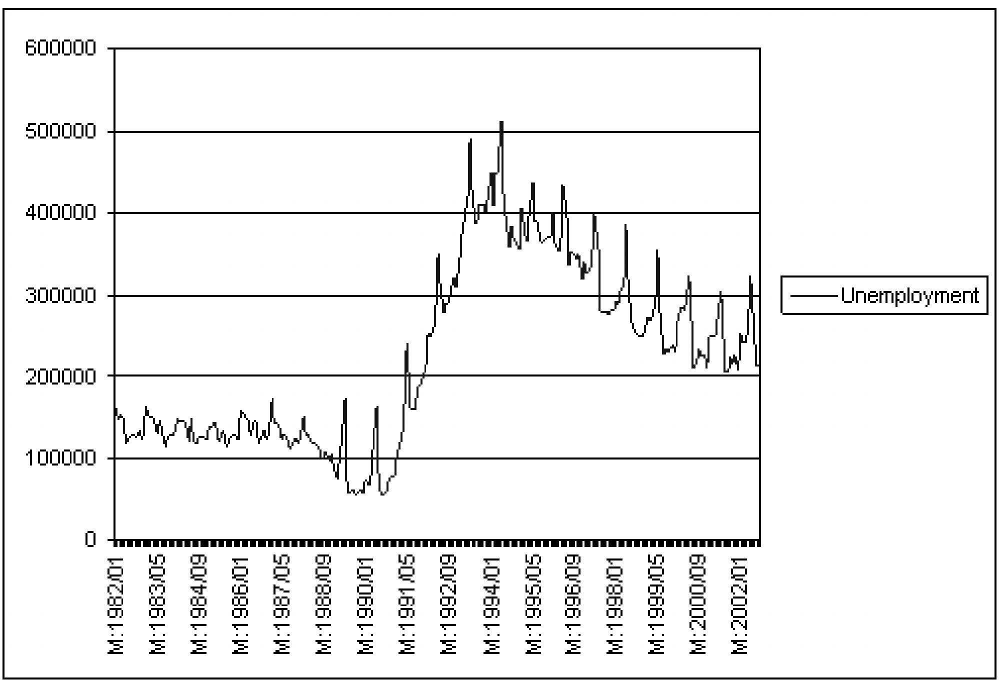


Figure 4. The time series for unemployment, 1982:1–2002:3.



are quite extensively reported. It is the job applicants we know less about.

One aspect that also requires mentioning is that the labor force data, which originally comes from Statistics Finland, but which is also used by the Ministry of Labor, is in its basic form quarterly data reported as an average of the labor force during the period. This average has been used as the observation for all months within each quarter. The fluctuation in labor force is, however, very limited and therefore this action cannot be seen as something that would seriously affect the results. The aspects of interest are the long-term fluctuations and not the variations within a quarter.

4.2. The statistical model

Most time series in macroeconomics are non-stationary, as are all series used in this study, and unreliable results follow if this non-stationarity is ignored. Cointegrated vector autoregression analysis is especially suitable when dealing with the kind of data used here, because it finds long-term relationships which are kept separate from short-term adjustments (Engle and Granger, 1987). A short overview of the most fundamental aspects of the cointegrated VAR method is given here. Readers requesting a more thorough description of the model are advised to turn to Hendry and Juselius (2000) and Hendry and Juselius (2001) for a survey.

The baseline statistical model used is the p-dimensional k:th order cointegrated VAR-model, which in its error correcting form, is given by

$$(5) \quad \Delta X_t = \Pi X_{t-1} + \sum \Gamma_i \Delta X_{t-i} + \mu + \Psi D_t + \varepsilon_t,$$

$$(6) \quad \varepsilon_t \sim N_p(0, \Sigma)$$

where the Π-matrix includes both the long-run relations, β, and the loadings to the long-run relations, α, such that $\Pi = \alpha\beta'$ if there exists cointegration. The vector process X_t is a p-dimensional vector assumed to be I(1). μ is a vector of constants and D_t consists of other deterministic components, including seasonal dummies. The Γ_i-matrices consist of short term components.

One of the main parts of the analysis is to test linear restrictions on the cointegrating vectors, β. Johansen (1995) derives an LR-test for testing these hypotheses.

Just as the cointegrating vectors can be restricted, the α-vectors can be restricted. A special case is when one or more rows in α consist of nulls. A variable with a row of nulls in α is not adjusting to the long-run relations and can be treated as weakly exogenous with respect to the β-parameters. Sometimes a weakly exogenous variable can be seen as a driving trend in the system. (Johansen, 1995)

5. The empirical results

In this section the results from the empirical study are reported. The analysis is conducted through a cointegrated VAR-analysis and hence there is both a long-run and a short-run part of the analysis. Only the dynamic long-run relations are presented in this section. The short-run parameters are presented in appendix 1.

5.1. Dynamic long-run relations

Sections 5.1 and 5.2 present results from the cointegrated VAR-analysis beginning in this section with the dynamic long-run relations. Results from both Period 1 and Period 2 are presented in parallel to improve readability. Section 5.2 presents results separating for long-term unemployment.

In order to investigate whether any long run properties resembling the Beveridge curve and the matching function exist in the model equation (5) was estimated for both periods with $X_t = [vac_t, une_t, hir_t]$, k = 2 and an unrestricted constant[5].

None of the variables were found to be stationary in either period, all variables are I(1) which means that if cointegrating relations can be found they will be I(0). Cointegrating rank in both periods is set at one. A rank of one indicates that there is one long-run relation in the data in each period.

[5] *The same lag length was given by both the Akaike information criterion (AIC) and the Bayes information criterion (BIC).*

Table 1. Tests for weak exogeneity and exclusion.

Period 1	Rank	χ^2	DGF	Hirings	Unemployment	Vacancies
Weak exogeneity (LR-test)	1	3.84	1	0.49	12.28	14.20
	2	5.99	2	0.61	19.04	19.62
Exclusion (LR-test)	1	3.84	1	0.03	12,39	17.16
	2	5.99	2	0.13	17.64	22.73
Period 2	Rank	χ^2	DGF	Hirings	Unemployment	Vacancies
Weak exogeneity (LR-test)	1	3.84	1	14.04	0.31	2.14
	2	5.99	2	31.12	1.32	18.75
Exclusion (LR-test)	1	3.84	1	14.57	7.65	6.34
	2	5.99	2	32.36	19.86	24.06

In Period 1 hirings are found to be excludable from the long-run analysis based on the tests reported in table 1. Based on these results the hirings series is excluded from the long-run analysis[6]. Hence in period 1 only two variables, unemployment and vacancies, remain in the analysis.

In Period 2 no variable was found to be excludable but unemployment was found to be weakly exogenous. In this setup there are two shocks driving the system. These are most likely demand and supply side shocks.

In the analysis for period 2, a trend was also allowed for in the cointegration relations, but the trend was rejected, as expected. In order to remove extreme observations a few dummies were added into the models[7].

Since the hirings variable was excluded from the long-run analysis in period 1 a natural first hypothesis to test for is if there is a long run relationship resembling a Beveridge curve. Given the choice of cointegrating rank the hypothesis corresponding to a Beveridge curve relation between unemployment and vacancies was tested in the cointegration space. The null hypothesis is that the relation is in the cointegration space, i.e. that it is stationary. A one-to-one relation between unemployment and vacancies could not be rejected (p-value 0.86). This indicates that the relation really is "one more vacancy = one less unemployed". Alternative restrictions were also imposed but no other significant relation was found and therefore the Beveridge curve is chosen as the long-run relation. The alpha coefficients suggest that the relation, if out of steady state, adjusts back through shifts in both variables. The alpha-coefficient for vacancies is –0.41 and the coefficient for unemployment is –0.31. The rather high α-coeffiecients suggest fast adjustment back to steady state. The results are reported in table 2.

It is interesting that the relation between vacancies and unemployed is negative and one to one. This indicates an uncomplicated matching process; one more vacancy, one less unemployed. These results go quite well with the

Table 2. The estimated α- and β-vectors, Period 1.

	β_1	α_1
Unemployment	1	–0.31
	(0.00)	[–3.87]
Vacancies	1	–0.41
	(0.00)	[–4.08]

t-value are reported in brackets and standard errors in parenthesis. Hirings was excluded from the model. Rank for the system is 1. There is one dummy to correct for outliers in the vacancy series for the observation 1986:6.

[6] *In an earlier version of the paper the variable was kept in the analysis despite the results from the exclusion test. No significant long run relations including hirings were however, found, giving even more support for excluding hirings.*

[7] *The dummies are usually added to this kind of models to correct for outliers in the data and make the model well specified. In Period 1 a dummy was added for 1986:6 correcting for an outlier in the data. In Period 2 adjustment dummies were added for the observations 1993:4 and 1993:8. The need for these dummies reflects the fact that the economy was still somewhat unstable during 1993.*

Table 3. The estimated α- and β-vectors, Period 2

	β_1	α_1
Hirings	1	–0.53
	(0.00)	[–6.95]
Unemployment	0.52	–
	(0.00)	–
Vacancies	–0.49	–0.20
	(0.031)	[–1.89]

t-value are reported in brackets and standard errors in paranthesis. Unemployment was restricted to be weakly exogenous. Rank for the system is 1. There are 2 dummies connected to the vacancy series for 1993:4 and 1993:8.

picture of the Beveridge curve for the period, figure 2.

For Period 2 the same test procedures were performed as for period 1. Here the natural hypothesis to initially test for is if the matching function without any specific restrictions on the coefficients is in the cointegration space. This hypothesis could not be rejected (p-value 0.97). The coefficient for unemployed is –0.52 and the coefficient for vacancies is 0.49. Again, a large number of other restrictions were also imposed and tested for. No support for the Beveridge curve was found and constant returns to scale was strongly rejected.

This matching-like function differs quite a lot from conventional matching functions in that the unemployment coefficient is negative. Due to this it cannot be interpreted as a matching function. The result also contradicts earlier aggregate matching studies.

The alpha-vector for this period consists of the coefficients –0.53 for hirings and –0.20 for vacancies. Hence, if the economy is hit by a shock this relation shifts back to steady state through shifts in hirings. The results from the analysis are reported in table 3.

These results are interesting since they tell something about the rigid Finnish unemployment during the 1990s. The more unemployed there are, the stickier does matching become, contradicting traditional theories that suggest that more vacancies and more unemployed create more matching.

The parameter constancy of the chosen vectors was tested using a recursive test (Hansen and Johansen, 1993). There are constancy problems in neither period 1 nor in period 2. Immediately when extending the sample periods towards the beginning of the 1990s constancy problems, however, appear. Hence it seems as if the long-run relations exist and are stable for the periods they are estimated for but not outside the sample. For the period 1988–1992 no constant relations exist using this data set, which is explained by the exploding unemployment rate during the period. The results are stable for the chosen periods but cannot be said to be robust outside the sample.

The results reveal that there are differences between the two periods. The differences between the periods lie in both the functional form and the sign of unemployment coefficient. It seems there are two different regimes, which also gets support from the visual inspection of the Beveridge curve. During period 1 there was very low unemployment and a very close negative relationship between vacancies and unemployment, one less vacancy meaning one more unemployed and vice versa. In period 2 unemployment was very high and had a negative impact on matching. It appears as if the number of unemployed affect matching positively in a low unemployment regime where the supply side is characterized by scarcity, but that the effect is reversed when the unemployment level exceeds a certain point as in period 2. The strong negative impact on matching from unemployment during period 2 calls for more investigation. It is also likely that the efficiency of the matching process is time varying. Movements in long-term unemployment could then reflect shifts in δ. In section 5.2 long- and short-term unemployment are separated, in order to determine if there is a difference between these groups.

5.1.1. Elasticities

The coefficient estimates for the Cobb-Douglas matching function in period 2 were 0.49 for vacancies and –0.52 for unemployment. These elasticities are interesting compared to earlier estimations using hirings instead of unemployment outflow as the third variable in the system (Petrongolo and Pissarides, 2001). Vacancies have received very similar weight earlier. The negative coefficient for unemployed however, contradicts earlier studies.

A possible explanation for the negative unemployment coefficient in period 2 is that, as far as I know, no study has earlier studied an economy recovering from economic crisis with a very high unemployment rate. It is plausible that if unemployment is extremely high the effect from one more unemployed is marginal or even negative.

Another possible explanation for differing coefficient estimates in the studies are differences in data. As mentioned earlier the data used in this study is collected by local workforce offices. The general trend is that low skill jobs and unemployed are registered at these offices, while high-skill labor is matched elsewhere, for example through advertisements, word of mouth and private agencies. The data used here is therefore biased towards the low skill segment of the labor market, which most probably influences the results since it was mainly quite low skill jobs that were destroyed during the crisis. Hence these results, and especially the negative unemployment coefficient, probably magnify the actual situation.

5.2. Long-term unemployment

The matching function is usually assumed to be increasing in both its arguments. This assumption generally holds in empirical applications. The previous section, however, showed that this is not the case for post-crisis Finland, which makes the traditional interpretation difficult. This result leads to the question if the effect long- and short-term unemployed have on matching is the same. Given that the proportion of long-term unemployed in Finland increased from 10% in the beginning of Period 2 to around 30% a few years later and stayed roughly at that level thereafter, it is interesting to estimate how long- and short-term unemployment affect hirings in the matching setup.

The separation between long-and short-term unemployment is here only done for the post-crisis period, since it was only after the crisis that long-term unemployment began to rise and became a problem. The setup is analyzed in two ways; First a setup with long- and short-term unemployed separated is estimated and second a setup with unemployment and the share of long-term unemployed is estimated. The purpose of this separation is to determine if it is the share of long-term unemployed that is important or the sheer number of long-term unemployed. I first present the results from the analysis with long- and short-term unemployment and then the analysis using the share of long-term unemployed.

5.2.1. Long and short-term unemployed separated

When estimating the long-run structure of the model rank is, based on the cointegration rank test, set to be two. All series are non-stationary and no series should be excluded from the long-run analysis but vacancies were restricted to be weakly exogenous in the long-run analysis. Since I am intrested in how the coefficient estimate for unemployment is divided between long- and short-term unemployment in the matching function the natural first hypothesis to test for is whether there is a long-run relationship describing the Cobb-Douglas matching function when unemployment is split into short- and long-term unemployment.

When imposing the restriction of constant return to scale for the coefficients for vacancies and short-term unemployment, also including long-term unemployment in the relation, stationarity cannot be rejected (p-value 0.96). The coefficients are 0.40 for vacancies and 0.60 for short-term unemployment. Long-term unemployment has a negative coefficient of –0.90. Short-term unemployment has a very strong positive influence on matching and long-term unemployment has a negative influence on matching. It seems as if the strong negative effect from unemployment presented in the results in the previous section can be explained the by the large number of long-term unemployed. The negative effect from long-term unemployment pulls down the positive influence from short-term unemployment when the variables are pooled.

The second significant long-run relation found is a positive relation between long- and short-term unemployment. This relation reflects

Table 4. Restricted beta-vectors for system which separates for long- and short-term unemployment, Period 2.

	$\hat{\beta}_1$	$\hat{\beta}_2$	α_1	α_2
Hirings	1		–0.64	0.56
	(0.00)		[–6.78]	[5.95]
Vacancies	–0.40		–	–
	(0.00)		–	–
Short-term unemployment	–0.60	–1.32	–0.04	0.18
	(0.00)	(0.056)	[–0.58]	[2.32]
Long-term unemployment	0.90	1	–0.03	–0.02
	(0.05)	(0.00)	[–3.24]	[–2.83]

The sample period is 1993:1–2002:8. Standard errors for the beta vectors are reported in parenthesis. t-values for the alpha vectors are reported in brackets. V is restricted to be weakly exogenous in the long-run analysis.

Table 5. Restricted beta and alpha vectors for a system which separates for unemployment and the share of long-term unemployed, Period 2.

	$\hat{\beta}_1$	$\hat{\beta}_2$	α_1	α_2
Hirings	1	–0.64	0.12	
	(0.00)		[7.18]	[1.29]
Vacancies	–0.28		–0.39	0.11
	(0.00)		[–3.43]	[0.93]
Unemployment	0.69	–1.10	–0.01	0.15
	(0.044)	(0.034)	[–0.03]	[2.97]
Share long term unemployed		1	–0.02	–0.09
		(0.00)	[–2.43]	[–8.70]

Rank is 2. Standard errors for the beta vectors are reported in parenthesis. t-values for the alpha vectors are reported in brackets.

the statistical relationship that more short-term unemployed lead to more long-term unemployed. The p-value for the relation is 0.53. The alpha-coefficients for the matching function reveal that error correction takes place through shifts in the hirings-variable but also through the long-term unemployment variable. The second beta vector error corrects in both its elements. There are no constancy problems in this framework.

The results, which can be found in table 4, suggest that it indeed is so that long- and short-term unemployment have very different effects on matching. Short-term unemployment fits the traditional matching setup in that it has a strong positive effect on matching; More short-term unemployed leads to more matches. Long-term unemployment, however, has the opposite effect on matching.

5.2.2. Share of long-term unemployment separated

When estimating a system separating unemployment and the share of long-term unemployed the cointegrating rank is set at two based on the cointegration rank test. No variable is stationary and none are restricted to be weakly exogenous or excluded from the long-run analysis.

No significant long-run relation including all variables is found. Neither is any significant long-run relation between hirings and the share of long-term unemployed found. Instead a relationship between hirings, vacancies and unemployment cannot be rejected (p-value 0.90). This reflects a very similar setup as in the base framework. The coefficient for vacancies is 0.28 and the coefficient for unemployment is –0.69. There is, however, also another long-run relation between unemployment and the share of long-term unemployed, very similar to the one found in section 5.2.1. The p-value of this relation is 0.57. The matching relation error corrects in hirings while the second long-run relation error corrects in both its elements. The results can be found in table 5. Hence it appears as if there is no direct long-run relation between hirings and the share of long-term unemployed.

Based on these analyses it can be concluded that the poor matching of the long-term unemployed has played an important role in the persistent Finnish unemployment. This could be due to skill mismatch or human capital loss following structural changes, hysteresis, ranking (Blanchard and Diamond, 1994) or some other phenomenon. What we know is that almost half a million jobs were destroyed during a 4 year period around 1990. New jobs, demanding new skills, were rapidly created but in different disciplines (Koskela and Uusitalo, 2006). Some of the workers that became unemployed failed to find suitable jobs for long spells of time; They became long-term unemployed with very small chances of finding a job corresponding their skills. The failure to integrate all workers to the new demand created a situation in which matching in general works well, but in which the matching of the long-term unemployed has almost stagnated. Since this matching does not work, unemployment falls very slowly[8].

6. Conclusions

This paper estimates how matching in the Finnish labor market differs before and after the severe economic crisis that hit Finland in the beginning of the 1990s. The purpose is to find some explanation for the extreme persistence of the Finnish unemployment. The main finding is that a very evidential change has taken place in the matching process during the past 20 years, which helps explaining the persistence of Finnish unemployment.

The matching process during the 1980s can be described as a very simple Beveridge relationship between unemployment and vacancies. Basically one more vacancy led to one less unemployed. During the post-crisis period beginning in 1993 the matching process is instead described by a function resembling the Cobb-Douglas matching function. The peculiarity is, however, that the coefficient for unemployed is negative instead of the traditional positive, and can therefore not be interpreted in the traditional way. This suggests that more vacancies lead to more matches while more unemployed lead to fewer matches. It is hence not apparent that increasing the number of vacancies would lead to fewer unemployed as often believed. However a possible explanation for the results may be that the matching model does not fit the used data set.

When separating for long- and short-term unemployed it turns out that the coefficient for long-term unemployed remains strongly negative while the coefficient for short-term unemployed is positive. These results indicate that it is the large number of long-term unemployed that makes the unemployment coefficient negative. Long-term unemployed congest matching during this very high unemployment regime.

The persistence of the Finnish unemployment is in this paper explained by the fact that matching works differently in high and low unemployment regimes. In the Finnish high unemployment regime long-term unemployment enters the matching function with a negative coefficient. In such a regime it is very difficult to lower the unemployment rate fast. This result goes well with earlier results emphasizing the role of structural changes (Koskela and Uusitalo, 2006).

Appendix

The short-term structure of the model

The long-run relations from the previous section are in the short-run analysis taken as given and they are named $ECM1$ in period 1 and $ECM2$ in period 2. These are centered and normalized versions of the $\beta_1 : s$ in tables 2 and 3. The short run structure is then estimated for both periods by

$$(7) \quad \Delta X_t = \Gamma \Delta X_{t-1} + \alpha ECM_{t-1} + \mu + \Psi D_t + \varepsilon_t,$$

where $X_t = [var, une, hir]$.

There are no problems with autocorrelation, heteroscedasticity or normality in the model. The short-term relations are presented in table 6. All estimates are reported with t-values in the columns to the right of the estimates.

In period 1 an increase in unemployment during the previous period leads to a decrease this period, hence it corrects itself. An increase in vacancies the previous period has a positive effect on unemployment this period, which probably reflects some cyclicality. The change in hirings during t–1 does not affect any equation. A cointegration vector is error correcting in a variable if the vector contains the variable with a positive sign and enters the equation of the variable with a negative sign. The ECM in period 1 error corrects in both unemployment and vacancies since it enters the cointegrating relation with a positive sign for both unemployment and vacancies but enters the equations for both

[8] *Machin and Manning (1999) provide a comprehensive overview of the phenomenon of long-term unemployment.*

Table 6. Short-run relations, Period 1

	Equation 1		Equation 2		Equation 3	
	Δ_u		Δ_h		Δ_v	
Δ_{u-1}	–0.29	(–2.76)	0.02	(0.11)	0.19	(1.60)
Δ_{h-1}	0.11	(1.98)	–0.18	(–1.20)	0.07	(1.02)
Δ_{v-1}	0.18	(2.31)	0.27	(1.39)	–0.12	(–1.41)
$ECM1_{-1}$	–0.34	(–3.21)	–0.12	(–0.69)	–0.43	(–3.85)
D86	0.02	(1.35)	0.69	(11.8)	0.36	(10.8)
Constant	–0.03	(–3.67)	–0.019	(–0.82)	–0.03	(–2.79)
CSeasonal	0.08	(2.07)	–0.10	(–1.35)	–0.32	(–10.2)
CSeasonal1	0.17	(3.32)	–0.15	(–1.40)	–0.40	(–8.63)
CSeasonal2	0.03	(0.51)	–0.27	(–2.59)	–0.36	(–7.16)
CSeasonal3	0.004	(0.06)	–0.41	(–4.05)	–0.31	(–6.25)
CSeasonal4	0.19	(2.70)	0.10	(1.02)	–0.11	(–1.64)
CSeasonal5	0.0	(0)	–0.04	(–0.30)	–0.12	(–1.69)
CSeasonal6	0.03	(0.79)	–0.002	(–0.02)	0.02	(0.63)
CSeasonal7	0.01	(0.45)	0.01	(0.10)	0.05	(1.10)
CSeasonal8	–0.05	(–1.51)	0.4	(3.80)	0.12	(3.06)
CSeasonal9	0.13	(3.42)	–0.12	(–1.02)	–0.24	(–4.71)
CSeasonal10	0.12	(3.51)	–0.26	(–2.80)	–0.15	(–3.66)

t-values are reported in parenthesis.

Table 7. Short-run relations, Period 2

	Equation 1		Equation 2		Equation 3	
	Δ_u		Δ_h		Δ_v	
Δ_{u-1}	–0.24	(–2.46)	0.05	(0.35)	–0.32	(–1.52)
Δ_{h-1}	0.02	(0.72)	–0.10	(–1.27)	–0.10	(–1.20)
Δ_{v-1}	–0.002	(–0.05)	0.16	(1.59)	–0.01	(–0.20)
$ECM2_{-1}$	–0.02	(–0.39)	–0.51	(–3.88)	–0.18	(–1.51)
D93:4	0.03	(2.90)	–0.11	(–2.50)	0.68	(9.15)
D93:8	0.04	(1.75)	0.03	(0.88)	–0.69	(–12.4)
Constant	–0.006	(–1.45)	0.02	(2.23)	0.02	(2.09)
CSeasonal	0.06	(1.57)	–0.17	(–2.77)	–0.11	(–1.57)
CSeasonal 1	0.05	(1.84)	–0.15	(–2.90)	–0.07	(–1.28)
Cseasonal 2	0.04	(1.29)	–0.14	(–2.15)	–0.03	(–0.56)
CSeasonal 3	0.01	(0.27)	–0.29	(–3.92)	–0.09	(–1.32)
CSeasonal 4	0.13	(3.74)	–0.015	(–0.18)	0.40	(4.88)
CSeasonal 5	0.015	(0.28)	–0.08	(–0.71)	0.39	(3.73)
CSeasonal 6	0.03	(0.79)	0.22	(2.22)	0.15	(1.57)
CSeasonal 7	0.01	(0.31)	0.11	(0.99)	–0.03	(–0.29)
CSeasonal 8	0.18	(4.65)	0.23	(4.13)	0.02	(0.39)
CSeasonal 9	–0.07	(–1.38)	0.14	(1.87)	–0.18	(–2.27)
CSeasonal 10	–0.13	(–3.38)	–0.18	(–2.68)	–0.22	(–3.43)

t-values are reported in parenthesis.

unemployment and vacancies with a negative sign. Hence the unemployment equation is affected by many variables while the vacancy equation is only affected by the ECM and the hirings equation is only affected by a dummy and seasonal dummies.

In period 2 unemployment again corrects itself so that an increase in period t–1 corresponds to a decrease in period t. The ECM is error correcting in hirings but not in vacancies or unemployment. This means that if there is an imbalance in the relationship described in the *ECM* hirings will start to change in order to restore equilibrium. The change in hirings and vacancies the previous period does not influence any relation. The constant and the dummies are significant but some seasonal dummies could be excluded from the model.

References

Albaek, K., and H. Hansen (2004). "The Rise in Danish Unemployment: Reallocation or Mismatch?" *Oxford Bulletin of Economics and Statistics* 66(4), 515–536.

Anderson, P., and S. Burgess (2000). "Empirical Matching Functions: Estimation and Interpretation using state-level data." *Review of Economics and Statistics* 82, 93–102.

Blanchard, O., and P. Diamond (1994). "Ranking, Unemployment duration and wages." *Review of Economic Studies* 61(3), 417–434.

Blanchard, O., and P. Diamond (1989). "The Beveridge Curve." *Brookings Papers on Economic Activity* 1, 1–60.

Blanchard, O., and L. Summers (1986). "Hysteresis and the European Unemployment Problem." In *NBER Macroeconomics Annual*, 15–77. Ed. S. Fisher. MIT Press.

Blanchard, O., and J. Wolfers (2000). "The Role of Shocks and Institutions in the Rise of European Unemployment: The Aggregate Evidence." *Economic Journal* 110, 462.

Broersma, L., and J. Van Ours (1999). "Job searchers, job matches, and the elasticilty of matching." *Labour Economics* 6, 77–93.

Burda, M., and C. Wyplosz (1994). "Gross Worker and Job Flows in Europe." *European Economic Review* 38.

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.

Coles, M., and E. Smith (1996). "Cross-section Estimation of the matching function: evidence from England and Wales." *Economica* 63, 589–598.

Edin, P., and B. Holmlund (1991). "Unemployment, Vacancies and Labour Market Programmes: Swedish Evidence." In *Mismatch and Labour mobility*. Ed. P. Schioppa. Cambridge University Press.

Engle, R., and C. Granger (1987). "Co-integration and Error correction: Representation, Estimation and Testing." *Econometrica* 55(2), 251–76.

Hansen, H., and S. Johansen (1993). "Recursive Estimation in Cointegrated VAR-models." Institute of Mathematical Statistics, University of Copenhagen, Discussion paper 92–13.

Hendry, D., and K. Juselius (2001). "Explaining Cointegration Analysis: Part 2." *Energy Journal* 22, 1.

Hendry, D., and K. Juselius (2000). "Explaining Cointegration Analysis: Part 1." *Energy Journal* 21, 1.

Honkapohja, S., and E. Koskela (1999). "Finlands's depression: A tale of bad luck and bad policies." *Economic Policy*, October, 399–436.

Ilmakunnas, P., and H. Pesola (2003). "Regional labor market matching functions and efficiency analysis." *Labour* 17, 413–437.

Johansen, S. (1995). *Likelihood-based Inference in Cointegrated Vector Autoregressive Models.* Oxford University Press.

Koskela, E., and R. Uusitalo (2006). "The un-intended convergence: How the Finnish unemployment reached the European level." *In Structural Unemployment in Western Europe: Reasons and Remedies.* Ed. M. Werding. MIT Press.

Layard, R., S. Nickell, and R Jackman (1994). *Unemployment: Macroeconomic Performance and the Labour market.* Oxford University Press.

Lindbeck, A., and D. Snower (1986). "Wage setting, Unemployment and Insider-Outsider Relations." *American Economic Review* 76, 2.

Ljungqvist, L., and T. Sargent (2002). "The European Unemployment Experience." CEPR Discussion paper nr. 3543.

Machin, S., and A. Manning (1999). "The causes and consequences of long term unemployment in Europe." In *Handbook of Labor Economics*. Eds. Ashenfelter, and Card. Amsterdam: North-Holland.

Mumford, K., and P. Smith (1999). "The Hiring Function reconsidered: on Closing the Circle." *Oxford Bulletin of Economic and Statistics* 61(3), 343–64.

Nickell, S., L. Nunziata, and W. Ochel (2005). "Unemployment in the OECD since the 1960s. What do we know?" *Economic Journal* 115, 1–27.

Pesola, H. (2002). "Kohtaamisfunktio Suomessa 1988–1997 (The Matching function in Finland)" Studies in Labour Policy 235, Ministry of Labour, Helsinki.

Petrongolo, B., and C. Pissarides (2001). "Looking into the Black Box, a Survey of the Matching Function." *Journal of Economic Literature* 39, 390–431.

Pissarides, C. (1986). "Unemployment and Vacancies in Britain." *Economic Policy* 3, 499–559.

Pissarides, C. (2000). *Equilibrium Unemployment Theory*. MIT Press.

Saint-Paul, G. (2004). "Why are European Countries Diverging in Their Unemployment Experiences?" IZA, Discussion Paper 1066.

Stevens, M. (2002). "New Microfoundations for the Aggregate Matching Function, with Empirical and Theoretical Implications." University of Oxford, Department of Economics, Discussion Paper 95.