ECONSTOR
Make Your Publications Visible.

A Service of
ZBW
Leibniz-Informationszentrum Wirtschaft
Leibniz Information Centre for Economics

Gottfries, Nils; Stadin, Karolina

Working Paper

The Matching Process: Search or Mismatch?

CESifo Working Paper, No. 6300

Provided in Cooperation with:
Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

Suggested Citation: Gottfries, Nils; Stadin, Karolina (2017) : The Matching Process: Search or Mismatch?, CESifo Working Paper, No. 6300, Center for Economic Studies and ifo Institute (CESifo), Munich

This Version is available at:
https://hdl.handle.net/10419/155542

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

WWW.ECONSTOR.EU

Mitglied der Leibniz-Gemeinschaft

The international platform of Ludwig-Maximilians University's Center for Economic Studies and the Ifo Institute

CESifo Working Papers

www.cesifo.org/wp

The Matching Process: Search or Mismatch?

Nils Gottfries
Karolina Stadin

CESIFO WORKING PAPER NO. 6300
CATEGORY 4: LABOUR MARKETS
JANUARY 2017

An electronic version of the paper may be downloaded
- *from the SSRN website: www.SSRN.com*
- *from the RePEc website: www.RePEc.org*
- *from the CESifo website: www.CESifo-group.org/wp*

ISSN 2364-1428

CESifo
Center for Economic Studies & Ifo Institute

CESifo *Working Paper No. 6300*

The Matching Process: Search or Mismatch?

Abstract

We examine the matching process using monthly panel data for local labour markets in Sweden. We find that an increase in the number of vacancies has a weak effect on the number of unemployed workers being hired: unemployed workers appear to be unable to compete for many available jobs. Vacancies are filled quickly and there is no (or only weak) evidence that high unemployment makes it easier to fill vacancies; hiring appears to be determined by labour demand while frictions and labour supply play small roles. These results indicate persistent mismatch in the labour market.

JEL-Codes: J230, J620, J630, J640.

Keywords: structural unemployment, frictional unemployment, matching function, labour demand, labour supply.

Nils Gottfries
Department of Economics
Uppsala University
P.O. Box 513
Sweden - Uppsala 75120
nils.gottfries@nek.uu.se

Karolina Stadin
Ratio Institute
Box 3203
Sweden - 103 64 Stockholm
karolina.stadin@ratio.se

24 November 2016
This paper builds on Chapter II in Stadin (2014). We are grateful for helpful comments on earlier versions from Timo Boppart, Mikael Carlsson, Per-Anders Edin, Anders Forslund, Håkan Gustavsson, John Hassler, Bertil Holmlund, Erik Mellander, Eran Yashiv, Johnny Zetterberg and seminar participants at Jönköping University, Nordic Summer Institute for Labor Economics, Ratio, the Riksbank (GSMG), and Uppsala University. We also want to thank employees at the Public Employment Service (Arbetsförmedlingen) for providing us with data and helpfully answering questions. Financial support from the Jan Wallander and Tom Hedelius Foundation and Marianne and Marcus Wallenberg Foundation is gratefully acknowledged.

1. Introduction

Vacancies and unemployment coexist in the labour market. In good times, there are many vacancies and unemployment is low, while in bad times there are few vacancies and unemployment is high. The standard explanation of these observations is that there are search and matching frictions: it takes time for workers and firms to find each other. Normally, search frictions are modelled with the help of a matching function, which is a reduced-form relationship; the underlying microeconomic mechanisms are usually not spelled out.[1]

The word "search" suggests that frictions arise because of *imperfect information*. Workers are imperfectly informed about jobs, and it takes time to contact firms and investigate job opportunities. If vacancies and job seekers are trying to find each other within a finite space, more vacancies should make it easier for unemployed workers to find jobs, and high unemployment should make it easier to fill vacancies.

To this we can add *heterogeneity* and *mismatch*. Suppose that there are two types of jobs, A and B, and two types of workers, A and B, and only A-workers can do A-jobs while only B-workers can do B-jobs. Then, with a given probability of meeting, and equal numbers of each type of worker and job, the flow of hiring will be half as large. If most workers are of type A while most jobs are of type B, this will further reduce hiring for given stocks of unemployment and vacancies. So, within this framework, changes in heterogeneity and mismatch are expected to shift the matching function in a similar way as changes in search intensity. In the standard search-matching literature, mismatch is typically thought of as one factor that may cause a shift the matching function and the Beveridge curve; see, e.g., Daly, Hobijn, Sahin and Valletta (2012) and Håkanson (2014).

[1] For surveys of this literature, see Petrongolo and Pissarides (2001), Yashiv (2007) and Elsby, Michaels and Ratner (2015).

However, this way of thinking about heterogeneity and mismatch is still fundamentally based on imperfect information. With perfect information, the A-workers will queue up for the A-jobs, the B-workers will queue up for the B-jobs, and there will be excess supply, balance, or excess demand in each submarket.

In this paper we investigate the matching process using a monthly panel from the Public Employment Service (Arbetsförmedlingen) covering all 90 local labour markets in Sweden 1992:1-2011:12. Our focus is on how the hiring of unemployed workers and the filling of vacancies are related to stocks of unemployment and vacancies at the beginning of the month as well as to the inflows of vacancies and unemployed workers during the month.

As a background to our empirical study, we present two simple models of the labour market. One is the standard matching function. The other is a model with perfect information where unemployment is caused by persistent mismatch between supply and demand. In the latter case, we assume that each local labour market consists of a mixture of submarkets, with excess supply in some and full employment in other submarkets. Such a model is motivated by the observation that in many markets – typically those for less skilled workers – there appears to be constant excess supply while other markets have (close to) full employment – typically those for highly qualified workers. We derive the implications of these two models for the relations between the stocks and flows of vacancies and unemployment in a local labour market. Compared to a standard matching function, a model with persistent mismatch has very different implications for the relations between stocks and flows. First, if a large fraction of the vacancies arise in markets with full employment, an increase in vacancies will have a limited effect on the job prospects for unemployed workers. Second, and most importantly, higher unemployment will *not* increase the rate at which vacancies are filled. The reason is simple: in markets with unemployment, workers are queuing for the jobs and in markets with full employment there is, by definition, no unemployment.

Our empirical findings point in the direction of persistent mismatch rather than information problems as the main explanation of unemployment. More vacancies do lead to more unemployed workers being hired, but the effect is surprisingly weak; it appears that only a small fraction of vacancies are filled by unemployed workers. Higher unemployment does not increase the rate at which vacancies are filled – or it has a weak effect in some specifications.

Our empirical results are in line with some recent empirical studies on macro and micro data. Christiano et al. (2011) estimated a macro model where the recruitment cost per hired worker could potentially depend on labour market tightness. However, they found no evidence that recruitment costs depend on labour market tightness. Michaillat (2012) simulated a model with wage rigidity and showed that, with reasonable parameter values, search frictions play a small role in bad times but may be more important in a tight labour market. Michaillat and Saez (2015) found that fluctuations in employment are mostly due to aggregate demand shocks. Carlsson, Eriksson and Gottfries (2013) and Stadin (2015) used firm-level data and found that higher unemployment does not make firms hire more workers.

Although many researchers have estimated matching functions, they have typically used more limited data than we use and they have often imposed relatively tight specifications. Many studies use aggregate data and assume the existence of a constant returns-matching function. Thus, they relate the job finding rate to labour market tightness and since both variables are pro-cyclical they find a positive regression coefficient. We do not impose CRS à priori; instead we investigate the separate roles of vacancies and unemployment using panel data for local labour markets. In our baseline estimation, we include fixed effects and time dummies to reduce the risk of spurious correlations. Following the stock-flow matching literature, we investigate the separate roles of inflows and initial stocks, and we estimate identical equations with the filling of vacancies and the hiring of unemployed workers as dependent variables.

We find that the filling of vacancies and the hiring of unemployed workers are very different variables; there is no such thing as a stable matching function that explains both of these flows. Vacancies are filled quickly and, it appears, often by a worker who already had a job (or was not in the labour force). Unemployed workers appear to be unable to compete for many of the vacancies. We discuss previous empirical results in Section 6 and show that qualitatively similar results have, in fact, been found in other studies when similar empirical strategies were used.

Shimer (2007) brought renewed attention to heterogeneity and mismatch by explicitly allowing for many separate submarkets and perfect competition within each submarket, so that the number of matches is determined by the short side in each market.[2] In Shimer's model, there is high mobility: jobs and workers move randomly between markets every time they close/quit and because of this high random mobility, each worker has some chance of matching with each vacancy. As a result, the two stocks are complements in the matching process, and Shimer's model produces a reduced-form relationship between stocks and flows, that is similar to a Cobb-Douglas matching function (Shimer 2007, page 1093). We go to the opposite extreme compared to Shimer (2007) and assume that workers cannot move between markets and that there is constant excess supply in some markets and constant full employment in other markets. Thus, our model highlights, starkly, the implications of a *persistent* mismatch problem in terms of skills and experience. Our simple model yields a different and testable prediction: vacancies will not be filled more quickly if there is high unemployment, and this is also what we find in our empirical analysis. Obviously, a more realistic model would allow for *some* mobility between markets and also for some markets to switch from excess supply to balance or excess demand, but if heterogeneity is related to skills and experience, this will be a slow process.

[2] Shimer (2007) reviews some earlier work in this tradition. The model by Lagos (2000) is closely related.

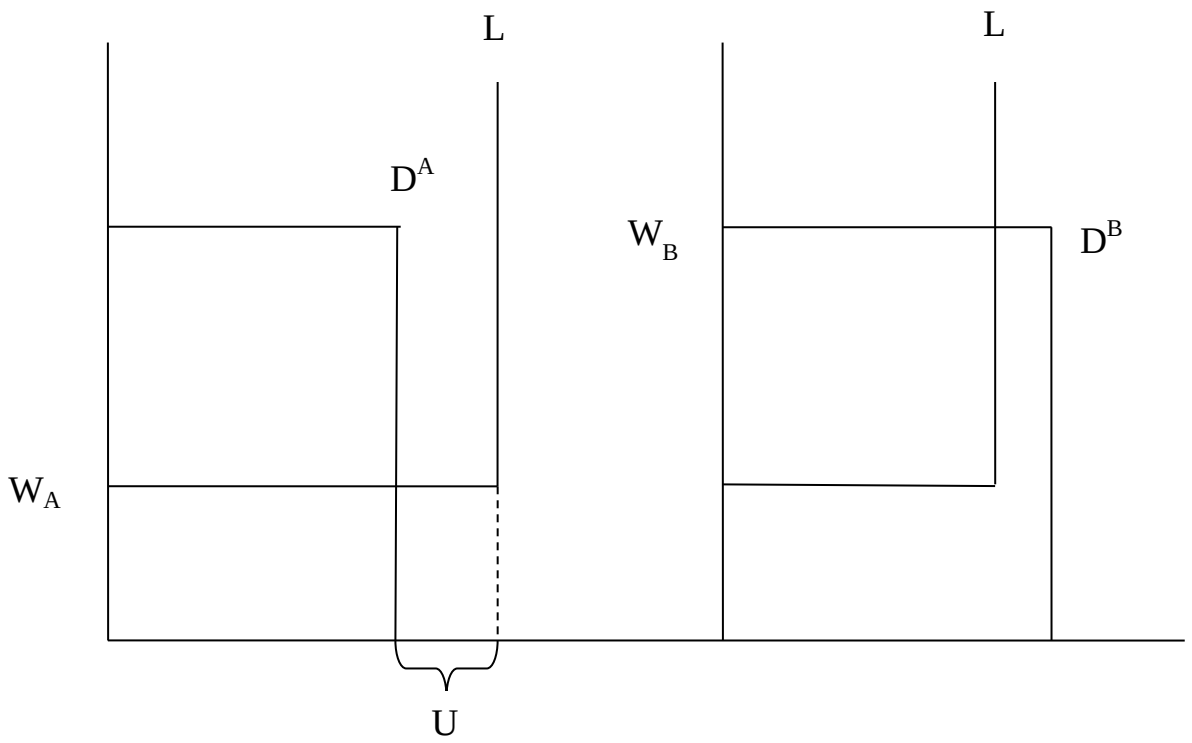
So how can there be unemployment in some submarkets and full employment in other submarkets? Clearly, there must be limited mobility among submarkets, and wage rigidity may also play a role. In Shimer's (2007) model, wages are flexible and adjust to clear each submarket. If there are fewer jobs than workers in a particular submarket, wages fall to the reservation wage and some workers are voluntarily unemployed. If there are more jobs than workers, wages rise to equal productivity and all workers are employed. However, wages play no role in the allocation of jobs and workers across submarkets; instead, the allocations of jobs and workers are determined by exogenous random processes.[3] Alternatively, we can think of a model where wages affect the allocation but where they do not adjust enough to clear each submarket. As in Lagos (2000), some markets are characterized by excess supply (involuntary unemployment) while there is balance or a shortage of workers in other markets. *Figure 1* illustrates these two models of mismatch. In this paper, we do not take a stand on what drives labour demand, how wages adjust, or whether unemployment is voluntary or involuntary. The purpose of our simple model is to try to understand how labour market stocks and flows are related when unemployment is caused by persistent mismatch rather than imperfect information.

In Sections 2 and 3, we use a standard matching function and a simple model of mismatch unemployment to derive equations for the hiring of unemployed workers and the filling of vacancies. In Section 4, the data and the estimation method are presented, and we also illustrate the relations between stocks and flows graphically. Section 5 contains the results of the baseline econometric analysis, and in Section 6 we compare with previous studies. In section 7 we consider alternative functional forms, and Section 8 concludes.

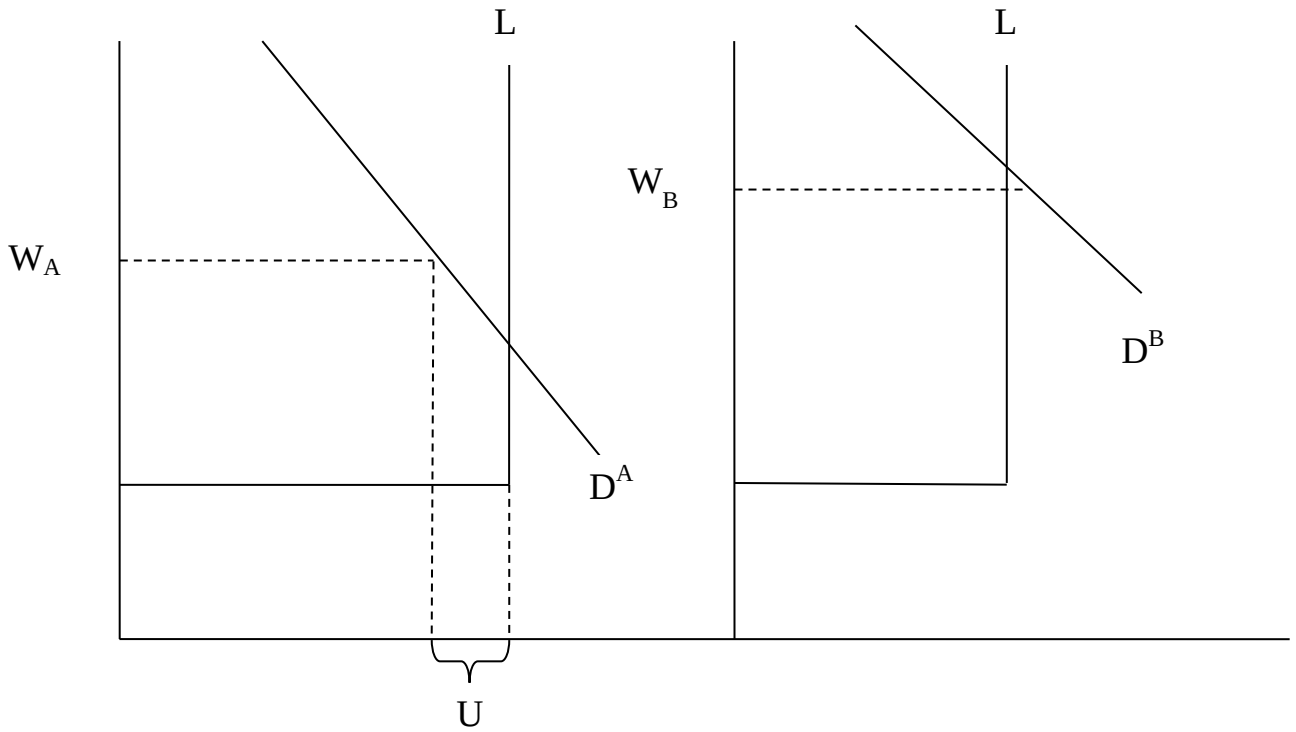
[3] In an extension, Shimer (2007) allows for limited endogenous mobility, but this does not change the basic mechanism of the model.

Figure 1. Models of Mismatch

Shimer (2007)



Wage rigidity



2. Frictional Unemployment

In this section, we specify a matching function that we estimate on monthly panel data from the Public Employment Service. We take the effective number of job seekers to be $U_{t-1} + \lambda u_t^{in} + E_t$ where U_{t-1} is the number of unemployed workers who are registered at the beginning of the month, u_t^{in} is the inflow during the month and E_t is the number of job searchers who are not registered at the Public Employment Service. The parameter λ reflects the importance of the inflow for the formation of matches. With random matching we would expect λ to be smaller than unity because workers who enter during the period are available for a shorter time than the workers who are looking for jobs already at the beginning of the month. With stock-flow matching we may instead expect λ to be larger than unity so the inflow matches at a higher rate than the initial stock. The stock-flow matching argument is that the new inflow of workers can match with both the stock and the inflow of vacancies, while the workers who were unemployed at the beginning of the month have already exploited all matching possibilities with the vacancies that were available at the beginning of the month.[4] E_t is unobserved and consists of two groups: job seekers without jobs who were not registered as unemployed with the Public Employment Service and employed workers searching on the job.[5]

Similarly, we take the effective stock of vacancies to be $V_{t-1} + \theta v_t^{in} + \Omega_t$ where V_{t-1} is the stock of vacancies that are registered at the beginning of the month, v_t^{in} is the inflow of new vacancies during the month and Ω_t is the number of vacancies that are not registered at the Public Employment Service. Using a similar argument as above, θ may be larger or smaller

[4] Studies of stock-flow matching include Coles and Smith (1998), Gregg and Petrongolo (2005), Coles and Petrongolo (2008) and Ebrahimy and Shimer (2010).
[5] Allowing the two types of job searchers to have different search intensities would not change the conclusions.

than unity depending on the matching technology. The matching function is specified as follows:

$$M_t = \phi_t \left(U_{t-1} + \lambda u_t^{in} + E_t \right)^{\alpha} \left(V_{t-1} + \theta v_t^{in} + \Omega_t \right)^{\beta} \tag{1}$$

where M_t is the total number of matches and we assume that α and β are smaller than unity. We do not impose constant returns to scale because we see no compelling reason to do so.[6] The variable ϕ_t represents variations in "matching efficiency," which may be due to changes in incentives, efficiency of the public employment service, and mismatch. With this specification, the job-finding rate for someone who is unemployed at the beginning of the period is $F_t = M_t / \left(U_{t-1} + \lambda u_t^{in} + E_t \right)$ and hiring from registered unemployment is

$$u_t^{out} = F_t \left(U_{t-1} + \lambda u_t^{in} \right) = \left(U_{t-1} + \lambda u_t^{in} \right)^{\alpha} \left(V_{t-1} + \theta v_t^{in} \right)^{\beta} \varepsilon_t \tag{2}$$

where $\varepsilon_t = \phi_t \left(1 + \dfrac{E_t}{U_{t-1} + \lambda u_t^{in}} \right)^{\alpha-1} \left(1 + \dfrac{\Omega_t}{V_{t-1} + \theta v_t^{in}} \right)^{\beta}$.

The rate at which vacancies are filled is $Q_t = M_t / \left(V_{t-1} + \theta v_t^{in} + \Omega_t \right)$ so the number of registered vacancies that are filled during the month is

$$v_t^{out} = Q_t \left(V_{t-1} + \theta v_t^{in} \right) = \left(U_{t-1} + \lambda u_t^{in} \right)^{\alpha} \left(V_{t-1} + \theta v_t^{in} \right)^{\beta} \eta_t \tag{3}$$

where $\eta_t = \phi_t \left(1 + \dfrac{E_t}{U_{t-1} + \lambda u_t^{in}} \right)^{\alpha} \left(1 + \dfrac{\Omega_t}{V_{t-1} + \theta v_t^{in}} \right)^{\beta-1}$.

[6] If unemployed workers and firms search in a limited space we would expect increasing returns to scale in the meeting technology, but as pointed out by Petrongolo and Pissarides (2006) reservation wages may respond in such a way that an estimated matching function shows constant returns to scale.

The outflows of registered unemployed and vacancies are positively related to the registered stocks, and the inflows and ε_t and η_t are the unobserved parts. To test the predictions of the model we estimate log-linearized versions of these equations:

$$\ln u_t^{out} = a_{11} \ln U_{t-1} + a_{12} \ln u_t^{in} + a_{13} \ln V_{t-1} + a_{14} \ln v_t^{in} + \ln \varepsilon_t \tag{4}$$

$$\ln v_t^{out} = a_{21} \ln U_{t-1} + a_{22} \ln u_t^{in} + a_{23} \ln V_{t-1} + a_{24} \ln v_t^{in} + \ln \eta_t \tag{5}$$

where $a_{11} = a_{21} = \frac{\alpha U}{U + \lambda u^{in}}$, $a_{12} = a_{22} = \frac{\alpha \lambda u^{in}}{U + \lambda u^{in}}$, $a_{13} = a_{23} = \frac{\beta V}{V + \theta v^{in}}$ and $a_{14} = a_{24} = \frac{\beta \theta v^{in}}{V + \theta v^{in}}$.

Values without time indexes denote steady-state values. We chose to estimate a log-linear specification as baseline because it is easy to understand and gives us a clear idea of how the different variables are correlated.

Note that $a_{11} + a_{12} = a_{21} + a_{22} = \alpha$ and $a_{13} + a_{14} = a_{23} + a_{24} = \beta$ so the deep parameters α and β could potentially be inferred from the estimates.[7] However, unregistered job searchers and vacancies enter the error terms, and thus the estimated parameters may not correspond to those of the underlying matching function. The bias depends on how the unobserved variables co-vary with registered unemployment and vacancies. If on-the-job search is either constant or pro-cyclical, $E_t / \left(U_{t-1} + \lambda u_t^{in}\right)$ will fall when unemployment increases and since $\alpha - 1 < 0$ this means that the estimated effect of unemployment on the outflow from registered unemployment will be larger, i.e. the sum of the estimates $a_{11} + a_{12}$ will be larger than α. Furthermore, if E_t increases when vacancies increase (pro-cyclical

[7] Alternatively, we can think of these equations as log-linear approximations of the matching functions that arise in the stock-flow matching model – see equations 7-13 in Coles and Petrongolo (2008).

on-the job search), the net effect of vacancies on the outflow from registered unemployment will be smaller; the sum of the estimates $a_{13} + a_{14}$ will be smaller than β.[8]

The effects of pro-cyclical on-the-job search on the coefficients in equation (5) go in the opposite direction: the effect of registered unemployment on the vacancy outflow will be smaller and the effect of vacancies increases. Thus, we see that pro-cyclical on-the-job search changes the interpretation of the coefficients, but we would still expect all coefficient estimates to be positive. For the effect of unemployment on the vacancy outflow to be zero, an increase in unemployment would have to be fully countered by a decrease in on-the-job search (see equation (1)), and this is unlikely.[9] Simultaneity and measurement problems are discussed in Section 4.

3. Mismatch Unemployment

In this section we present an alternative model with persistent mismatch of workers and jobs. The basic idea is that each local labour market consists of many submarkets with specific job characteristics and skill requirements. In some submarkets (type A), there are more workers willing and able to work than there are jobs, and in other markets (type B) there is full employment. We take demand for labour as given; what we attempt to understand is how labour market stocks and flows are related when unemployment is caused by persistent mismatch rather than search costs and information problems.

[8] These biases are discussed in Petrongolo and Pissarides (2001). Whether search on the job is procyclical is not clear; Elsby, Michaels and Ratner (2015) construct a measure of on the job search and find it to be slightly countercyclical

[9] If workers searching on the job face convex search costs and weigh the marginal benefits of search against the marginal costs, an increase in unemployment will make them search less, but not so much less that the effective number of job seekers decreases.

Demand, Supply, and Turnover

To match the empirical data, we let the period length be one month. There is a representative firm and an exogenous labour force L in each market, and we let N_t^A and N_t^B denote employment at the end of the period in the two types of markets. In a market of type A, labour demand is always smaller than *L*, firms can hire as many workers as they want and unemployment is

$$U_t^A = L - N_t^A. \tag{6}$$

In the B-markets, all workers are employed, so $N_t^B = L$ and $U_t^B = 0$.

At the beginning of each period, some fractions s_t^A and s_t^B of the employed workers quit their jobs, or they are fired for exogenous reasons, and some fractions z_t^A and z_t^B of the employed workers decide to apply for other jobs and quit if they get new jobs. Then, firms in both markets announce new vacancies v_t^A and v_t^B resignations and hires occur, and workers remain employed or unemployed until the end of the period. Vacancies remaining at the end of a period are denoted V_t^A and V_t^B.

Markets with Unemployment (type A)

We assume that a vacancy that exists at the beginning of the period generates *Q* hires during a month and a vacancy that is announced during the month generates *q* hires during the month, so hires in a market with unemployment are

$$h_t^A = QV_{t-1}^A + qv_t^A. \tag{7}$$

We take the rates Q and q as exogenous, reflecting practical delays in collecting applications and deciding whom to hire. It takes some time to hire a worker, but this time is independent of the level of unemployment. We expect q to be smaller than Q because the new vacancies enter during the period and thus have less time to be filled.

All workers who were unemployed at the beginning of the period and those who quit exogenously search for jobs together with the workers who are trying to switch jobs. Firms hire randomly among the job applicants, so the probability that a job searcher finds a job during the month is

$$F_t^A = \frac{h_t^A}{U_{t-1}^A + s_t^A N_{t-1}^A + z_t^A \left(1 - s_t^A\right) N_{t-1}^A}. \tag{8}$$

Markets with Full Employment (type B)

Even if there is full employment in markets of type B, it is normally possible to hire workers because there are workers who are ready to switch jobs. Vacancies can be filled by those who have already quit $\left(s_t^B L\right)$ and those who have not yet quit but are applying for other jobs $\left(\left(1 - s_t^B\right) z_t^B L\right)$. Assuming that $\mathrm{Q} V_{t-1}^B + \mathrm{q}\, v_t^B$ workers are hired if there are applicants to all jobs, hiring in the typical B-market is

$$h_t^B = \min\left(\mathrm{Q} V_{t-1}^B + \mathrm{q}\, v_t^B, \left(s_t^B + \left(1 - s_t^B\right) z_t^B\right) L\right). \tag{9}$$

If there are enough applicants for all jobs, hiring will be equal to $\mathrm{Q} V_{t-1}^B + \mathrm{q}\, v_t^B$, but there could also be congestion if there are not enough workers willing to switch jobs. This function is kinked and concave. With some heterogeneity across markets, hires will be a smooth concave function of the effective number of vacancies.

Outflow from Unemployment

The above equations describe a simple model of persistent mismatch. But we do not have data for individual submarkets, so we need to understand the implications of the model for data on a local labour market consisting of many submarkets. Thus, we assume that there is a continuum of submarkets and that a fraction λ of the markets are markets with full employment (type B). Then, aggregate unemployment at the end of the period is

$$U_t = (1-\lambda) U_t^A, \tag{10}$$

the inflow into unemployment is

$$u_t^{in} = (1-\lambda) s_t^A N_{t-1}^A \tag{11}$$

and the outflow from unemployment is

$$u_t^{out} = (1-\lambda) F_t^A \left(U_{t-1}^A + s_t^A N_{t-1}^A \right). \tag{12}$$

Using (10), (11), (12), (8) and (7) we can write the outflow from unemployment as

$$u_t^{out} = F_t^A \left(U_{t-1} + u_t^{in} \right) = \frac{(1-\lambda)\left(QV_{t-1}^A + qv_t^A \right)}{1 - z_t^A + z_t^A (1-\lambda) L / \left(U_{t-1} + u_t^{in} \right)}. \tag{13}$$

The outflow from unemployment increases with the initial stock and with the inflow into unemployment and the function is concave because unemployed workers compete with each other for jobs.[10] As in the frictional model, hiring from unemployment increases with unemployment, but not because more unemployed workers can locate more jobs. Rather, the reason is that the unemployed get some of the jobs that would otherwise have gone to the job switchers.

[10] As $U_{t-1} + u_t^{in}$ approaches its maximum, $(1-\lambda) L$, the outflow approaches $(1-\lambda)\left(QV_{t-1}^A + qv_t^A \right)$.

The outflow from unemployment increases with the number of vacancies – but only if the vacancies appear in the markets where the unemployed workers are. Vacancies in markets with full employment $\left(V_{t-1}^{B} \text{ and } v_t^{B}\right)$ will not increase the job chances of unemployed workers. Thus, the effect of an increase in total vacancies on the outflow from unemployment will depend on where the vacancies appear.

Outflow of Vacancies

The outflow of vacancies is

$$v_t^{out} = (1-\lambda)\left(QV_{t-1}^{A} + qv_t^{A}\right) + \lambda \min\left(\left(\mathrm{Q}V_{t-1}^{B} + \mathrm{q}\, v_t^{B}, s_t^{B} + \left(1-s_t^{B}\right)z\right)L\right) \qquad (14)$$

The outflow of vacancies will increase with the inflow and the initial stock of vacancies, and this function may be linear or concave depending on whether there are enough workers willing to switch jobs.

An important implication of this model is that variations in unemployment have *no* effect on the rate at which vacancies are filled. Intuitively, this follows from two observations:

- in markets with unemployment, vacancies are filled at given rates;
- in markets with full employment, there is, by definition, no unemployment.

This prediction differs markedly from the implications of the matching function. If unemployment is due to information frictions, the presence of more unemployed job seekers should always increase the rate at which vacancies are filled.

4. Data and Estimation Method

We want to investigate how the hiring of unemployed workers and the filling of vacancies during a month are related to the stocks of unemployment and vacancies at the beginning of the month as well as the inflows of unemployed workers and vacancies during the month. We begin by estimating equations (4) and (5), which are approximations of the matching function. Alternative functional forms are considered in Section 7.

Data

We use register data from the Public Employment Service (Arbetsförmedlingen) for the period 1992:1-2011:12. Data from the Public Employment Service are available at the municipality level at a monthly frequency. We aggregate the data to obtain a dataset with variables for local labour markets, which consist of one or more municipalities and are constructed by Statistics Sweden based on commuting patterns. Local labour markets are constructed to be geographical areas that are as independent as possible from the rest of the world with respect to labour demand and labour supply.[11]

The stock of unemployment, U_t, is measured as the number of openly unemployed workers that are registered at the Public Employment Service at the end of the month. There is a strong incentive to register because doing so is required to qualify for unemployment benefits. In the baseline estimation, workers in labour market program participants are not included because earlier research indicates that they contribute to matching to a significantly smaller extent than do openly unemployed workers; see Forslund and Johansson (2007). (We include program participants in a robustness check.) The inflow into unemployment, u_t^{in}, is measured as the

[11] The 90 local labor markets are listed in the Appendix. Johansson and Persson (2000) reported that 80-90 percent of all hired workers came from the local labor market area where the firm was located. Survey data for vacancies and unemployment are not sufficiently large to allow panel estimation based on local labor markets.

number of workers who are newly registered as unemployed during the month and hires from unemployment, u_t^{out}, are measured as the number of workers who left registered unemployment, reporting to the employment service that they found jobs.

V_t is the stock of vacancies registered at the Public Employment Service at the end of the month, and v_t^{in} is the inflow of new vacancies during the month. We measure the outflow of vacancies as the inflow of new vacancies over the month minus the change in the stock:

$$v_t^{out} = v_t^{in} - \left(V_t - V_{t-1}\right). \tag{15}$$

A weakness of these data is that we do not know if all vacancies are filled. Firms may abandon their recruitment efforts without actually hiring a worker and if the fraction of firms that does this varies in a systematic way we may draw incorrect conclusions. [12]

In our sample, unemployment was, on average, 7.2 percent of the labour force, the monthly inflow into unemployment was 0.97 percent of the labour force and the outflow from unemployment to jobs was 0.92 percent of the labour force; some of those who deregistered did not report that they found a job. Vacancies were on average 0.53 percent of the labour force, and the monthly inflows and outflows of vacancies were both 0.82 percent of the labour force.[13] Thus, the flows are similar but the stock of vacancies is more than ten times smaller than the stock of unemployed workers.

Not all unemployed workers are registered at the Public Employment Service. According to Aranki and Löf (2008), vacancies reported to the Public Employment Service corresponded to 30-45 percent of total hirings in the 1990s and 2000s. Thus, we should view our measures of

[12] A recruitment survey, which is issued irregularly by the employer´s federation, shows that about 4/5 of all attempts to recruit result in hiring.

[13] These are unweighted means across local labor markets. If we instead consider aggregate numbers, we find that unemployment was, on average, 6.2 percent and the monthly inflow into unemployment was 0.45 percent of the labor force, while vacancies were 0.54 percent and the monthly inflow of new vacancies was 0.42 percent of the labor force.

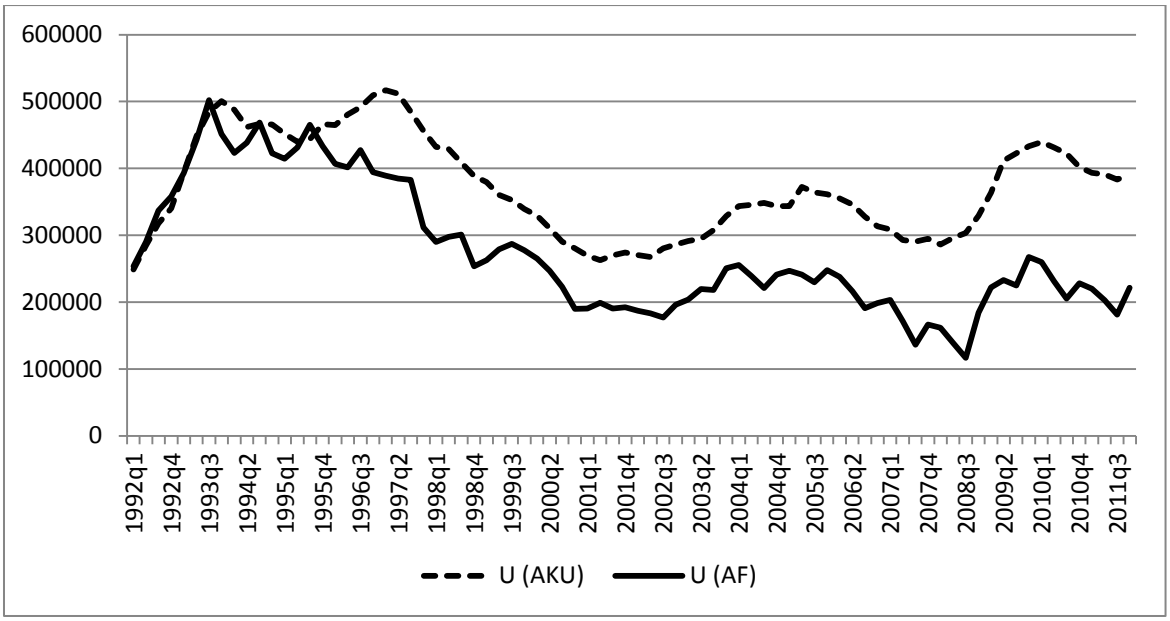
unemployment and vacancies as imperfect measures of the total stocks and flows of unemployed workers and vacancies in the economy as a whole.

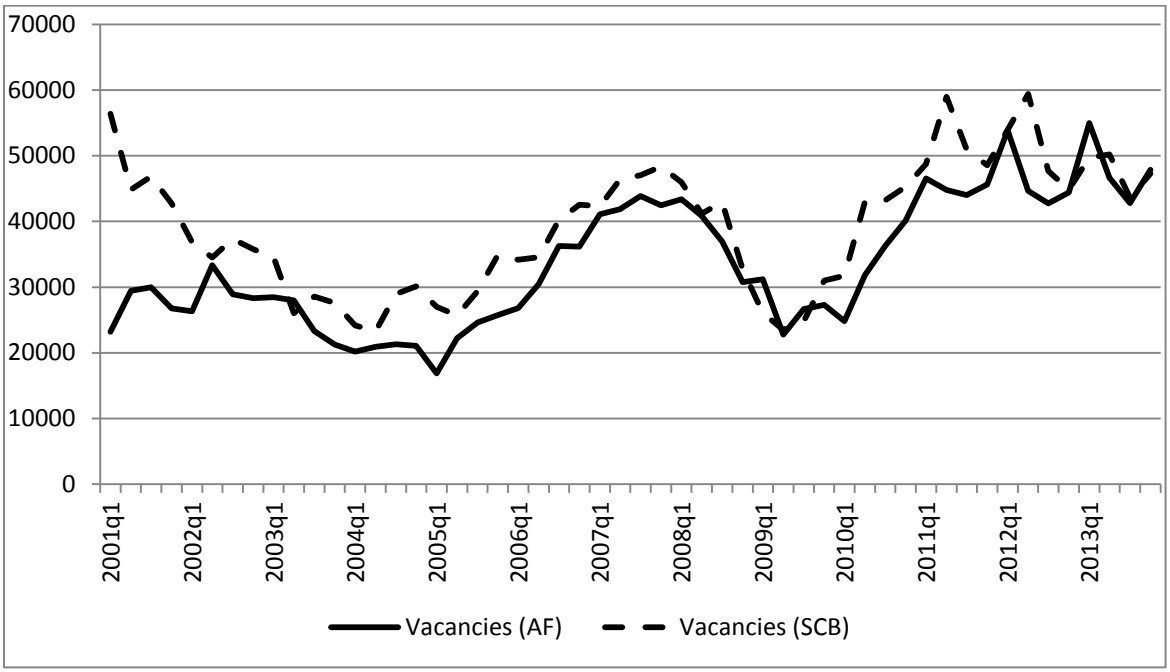
An important question, then, is how representative registered unemployed workers are of the total population of unemployed workers. We have no direct evidence on this, but *Figure 2* shows that, for Sweden as a whole, unemployment registered at the Public Employment Service has fluctuated in a similar way as unemployment according to the labour force survey conducted by Statistics Sweden (AKU). However, the number of unemployed workers that are registered at the Public Employment Service has declined over time compared to the survey measure.[14] The lower panel in *Figure 2* shows that aggregate vacancies registered at the Public Employment Service (AF) are closely correlated with available jobs according to a survey conducted by Statistics Sweden that began in the year 2001 (except for the first year of the survey). The survey data are too limited to do analysis on the local labour market level.

Thus we see that, at the aggregate level, these measures vary similarly to the alternative measures; they appear to be sufficiently broad and representative to make it worth studying how stocks and flows are related. The long-term trend in the fraction of unemployed workers that register at the employment service makes it important to account for underlying trends and structural changes in the estimation.

[14] Register data from the public employment service (AF) covers all persons registered at AF while the labour force survey (AKU) is a survey of about 30 000 persons. The difference between the different unemployment measures has been analysed by Statistics Sweden (Statistics Sweden 2016, Table 3). In 2015, 376 700 persons were unemployed according to AKU. Of these, SCB estimates that 133 600 were not registered at AF and 105 500 were participating in labour market programs with "activity support" so they were not openly unemployed according to AF. On the other hand, 34 700 persons who were registered as unemployed at AF would count as out of the labour force according to AKU, e.g. because they did not fulfil the job search requirement. There were also differences in the criteria used to count a person as employed, where AKU has stricter criteria, leading to a net difference of 18 700. In 2015, 191 100 persons were openly unemployed according to the public employment service: $376\,700 - 133\,600 - 105\,500 + 34\,700 + 18\,700 \approx 191\,100$.

Figure 2. Alternative Measures of Unemployment and Vacancies





Note: The upper panel shows unemployment according to the labour force survey (AKU) age 15-74, (series obtained from Konjunkturinstitutet) and openly unemployed workers who are registered at the Public Employment Service (AF). The lower panel shows job openings (lediga jobb) according to a survey conducted by Statistics Sweden (SCB) and vacancies registered at the Public Employment Service (AF). The series are seasonally adjusted.

Estimation Method

To investigate how transition rates are related to stocks, we rely on differences in the variation over time across local labour markets. Thus, we include time dummies and fixed effects for local labour markets in our baseline specification. We include fixed effects because geography, density, and industry structure affect the matching process in different labour markets.

We include time dummies in the baseline specification for two reasons. First, cycles are highly correlated across local labour markets, so although we have a panel with 90 local labour markets, the results of a regression without time dummies will be driven mainly by the aggregate business cycle. Then, there will be a risk that the results are affected by some unobserved macroeconomic shocks that affected all local labour markets in the same way. When we use differences in variation over time across labour markets, it is much less likely that the results are affected by some specific unobserved shocks.

The second reason to include time dummies is that we have data for a long time period, and there have clearly been structural changes in the labour market during this period. As discussed above, there has been a decline in the fraction of unemployed workers that are registered at the Public Employment Service. Additionally, formal rules and firms' behaviour – with respect to the posting of vacancies – may have changed. By including time dummies, we can account for changes in rules and behaviour – provided that they had similar effects across local labour markets.[15]

[15] A number of structural changes have been noted in reports from the Public Employment Service: i) Until 2007, it was mandatory for all employers to announce their vacancies at the Public Employment Service, and this is still mandatory for the government. Although many vacancies went unreported before 2007, it is likely that this rule change affected firms' behavior. ii) Around 2006-2007, there was an increased tendency for firms to post the same job several times, but from 2008 onward, such behavior was policed by the Public Employment Service. iii) In recent years, increased use of IT systems has led to a dramatic increase in automatic transfers of job postings to the PES register, and this appears to have increased the share of job postings that are registered with the PES. iv) Vacant summer jobs are posted earlier in the year in the latter part of the period.

We also include seasonal dummies interacted with dummies for the local labour markets. We do this to account for differences in seasonal patterns depending on the importance of sectors such as agriculture and tourism. Finally, we include local linear and quadratic time trends to account for long-term structural changes in specific labour markets. *Table 1* shows that there is considerable variation remaining in the explanatory variables after removing fixed effects, common time effects, and local seasons and trends.

Table 1. Standard Deviations of Explanatory Variables

Variation removed:	lnU	lnV	lnUin	lnVin
Fixed effects for llm, local seasons	0.403	0.706	0.308	0.505
Fixed effects for llm, local seasons, time dummies	0.160	0.563	0.206	0.453
Fixed effects for llm, local seasons, time dummies, linear and quadratic local time trends	0.114	0.539	0.181	0.414

Note: Stocks are measured on the last day of the previous month and in relation to the labour force. The inflows during the month are also measured in relation to the labour force in each local labour market.

We estimate equations (4) and (5) by ordinary least squares (OLS) and instrument variable estimation (IV). In the IV estimation, we use five lags of the inflows and the stocks from six months ago as instruments. By instrumenting, we can alleviate two problems. First, there may be purely random variation in the fractions of all unemployed workers and all vacancies that register with the employment service. We can think of this as pure measurement errors that will lead to biased estimates.[16] Second, a simultaneity problem may arise because persistent shocks to the matching function (ϕ_t) may be correlated with the variables included on the right hand side. Suppose that there is a persistent increase in mismatch (e.g., because of a

[16] The sign of this bias is unclear. If some additional vacancies are randomly registered and deregistered within the month, the inflow and outflow of vacancies will both increase. If some additional vacancies are randomly registered but not deregistered within the month, the inflow of vacancies will increase but not the outflow. If some vacancies are randomly deregistered, the outflow will increase but not the inflow.

large inflow of immigrants) so that the typical unemployed worker matches with fewer jobs. This means that as ϕ_t falls, the outflow from unemployment decreases and the stock of unemployment increases over time. *Persistent* mismatch shocks of this type imply reverse causation that will make the coefficient on the initial stock of unemployed smaller. To address these problems, we use lagged stocks and inflows as instruments because they should be more exogenous to the matching process in a given period than recent stocks and current inflows.[17]

A Look at the Data

Figure 3 shows vacancies, unemployment and the outflow from unemployment for the three largest local labour markets: Stockholm, Göteborg and Malmö. The graphs for vacancies and unemployment mirror each other and are fairly similar for the different local labour markets; to a large extent, vacancies and unemployment reflect the general business cycle. The outflow from unemployment is positively correlated with unemployment, but it is hard to see how it is related to the number of vacancies.

Figure 4 shows the same data, aggregated to quarterly frequency, but here we have unemployment on the horizontal axis and vacancies on the vertical axis, and the size of the bubbles reflects the outflow from unemployment. By comparing the bubbles in the horizontal direction, we can examine how the hiring of unemployed workers is related to the stock of unemployed holding the stock of vacancies constant. We see clearly that the outflow from unemployment is higher when unemployment is high. Comparing the sizes of the bubbles in the vertical direction, holding unemployment constant, we see only a weak positive relation between the number of vacancies and the outflow from unemployment.

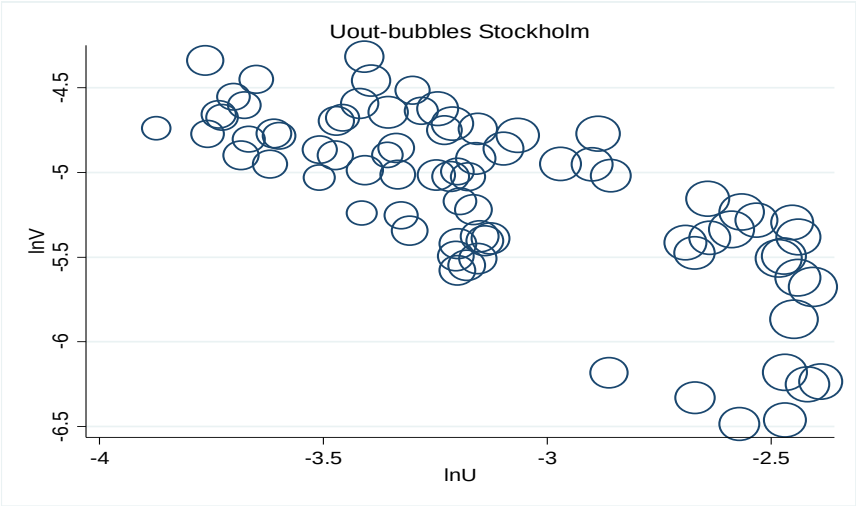
[17] Unfortunately, we have been unable to find more exogenous instruments. We tried to exploit the industry structure of different local labor markets, using input-output tables to construct exogenous shocks. Such an approach was used successfully by Carlsson, Eriksson and Gottfries (2013) for firm-level data. This approach was unsuccessful, however. Because of strong input-output linkages between different sectors, there turned out to be very little difference between the exogenous shocks calculated for different local labor markets.

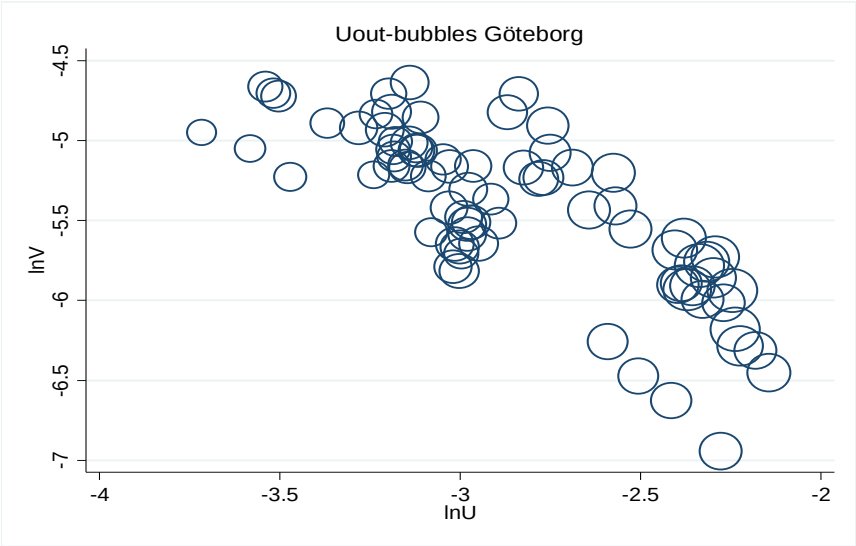
Figure 3. Outflow from Unemployment

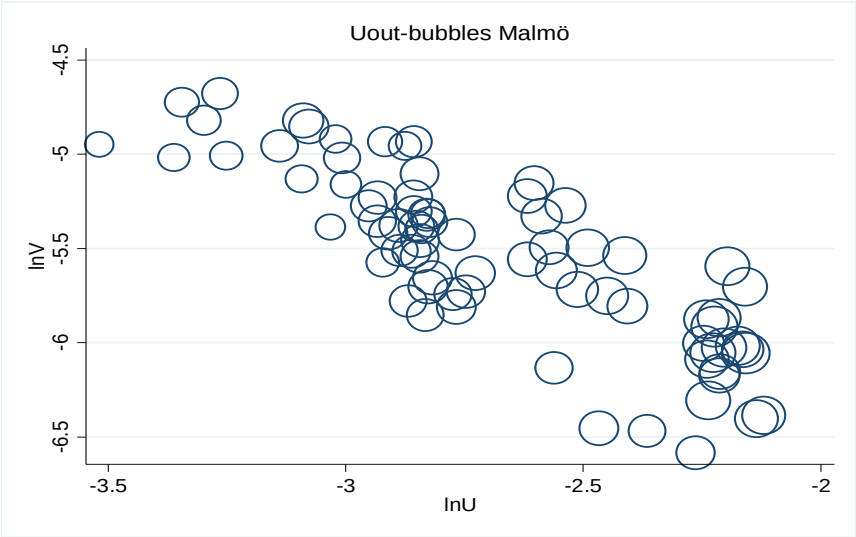
Note: Monthly register data from the Public Employment Service, seasonally adjusted.

Figure 4. Bubble Scatter Plots for Hiring from Unemployment 1992-2011

Larger bubble = larger outflow from unemployment







Note: Quarterly averages of monthly register data from the Public Employment Service, seasonally adjusted.

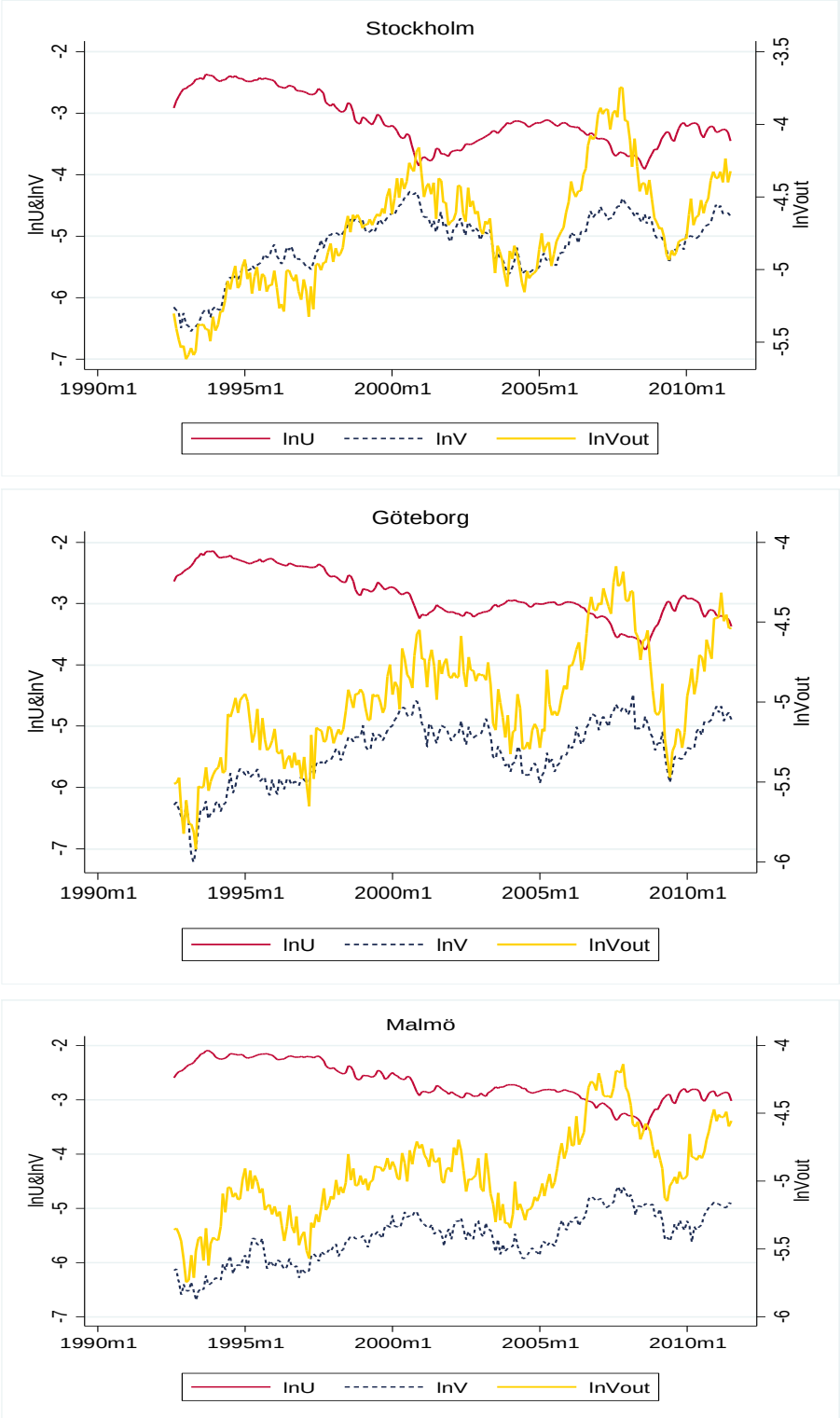
Figure 5 shows vacancies and unemployment for the three largest labour markets together with the outflow of vacancies. The outflow of vacancies is very closely correlated with the number of vacancies, but it is difficult to see whether the outflow of vacancies is related to unemployment.

In *Figure 6* we again have unemployment on the horizontal axis and vacancies on the vertical axis, but now the size of the bubbles reflects the outflow of vacancies. By comparing the sizes of the bubbles in the vertical direction, holding unemployment constant, we see that more vacancies are associated with a bigger outflow of vacancies. Comparing the sizes of the bubbles in the horizontal direction, holding vacancies constant, we see no obvious relation between unemployment and the outflow of vacancies.

Our graphical examination indicates strong “own effects” in the sense that high unemployment leads to a high outflow from unemployment and more vacancies lead to more vacancies being filled. The “cross effects” appear weak, however. Hiring from unemployment is only weakly related to the number of vacancies, and we see no clear relation between unemployment and the rate at which vacancies are filled.

Note, however, that this graphical examination exploited the time series variation in individual labour markets, so the results may be driven by common unobserved shocks and structural changes. By including time dummies in our panel estimation we can eliminate the effects of common shocks, and this should make the results more reliable. By IV estimation we can reduce the effects of measurement errors and simultaneity.

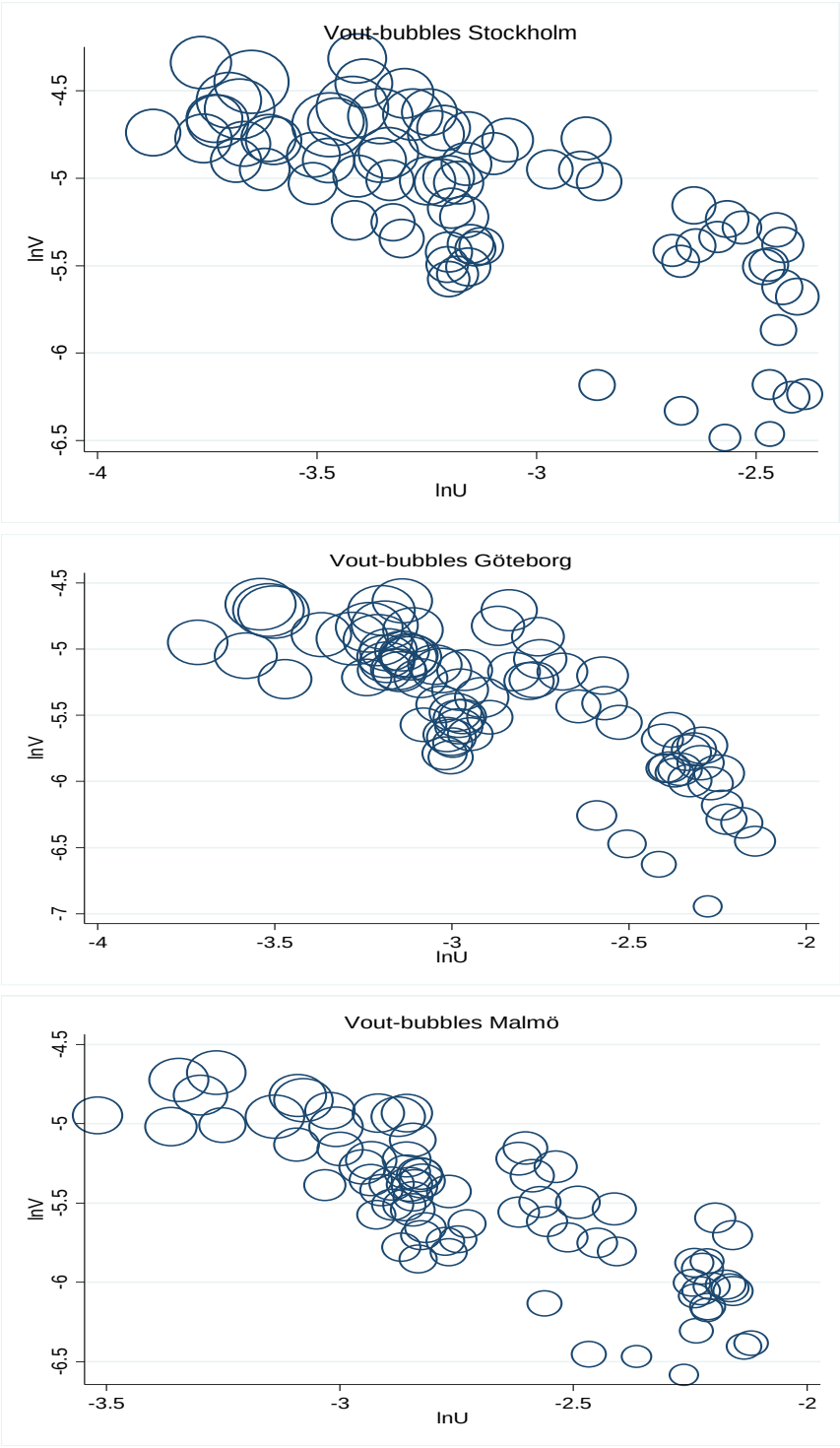
Figure 5. Outflow of Vacancies



Note: Monthly register data from the Public Employment Service, seasonally adjusted.

Figure 6. Bubble Scatter Plots for the Outflow of Vacancies 1992-2011

Larger bubble = larger outflow of vacancies



Note: Quarterly averages of monthly register data from the Public Employment Service, seasonally adjusted.

5. Results

Table 2 shows OLS and IV estimates of equations (4) and (5) with the outflow from unemployment and the outflow of vacancies as dependent variables.

Table 2. Determinants of Outflows of Unemployed Workers and Vacancies

	(1) lnUout OLS	(2) lnUout IV	(3) lnVout OLS	(4) lnVout IV
lnU	0.576***	0.585***	-0.012	0.103
	(0.023)	(0.053)	(0.022)	(0.071)
lnUin	0.000	0.207***	-0.016	-0.065
	(0.013)	(0.060)	(0.019)	(0.083)
lnV	0.009***	0.013*	0.415***	0.487***
	(0.003)	(0.007)	(0.009)	(0.018)
lnVin	0.038***	0.111**	0.462***	0.821***
	(0.005)	(0.043)	(0.013)	(0.065)
Observations	20,394	19,725	20,391	19,722
R-squared	0.853	0.845	0.799	0.731
Number of llm	90	90	90	90
Hansen (p-value)		0.220		0.973
Kleibergen-Paap (p-value)		0.000		0.000

Note: Robust standard errors (clustered on local labour market) in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Fixed effects for local labour markets, time dummies, local seasons and linear and quadratic local time trends are included in all specifications. Instruments for IV are five lags of inflows plus the stocks in t-6.

Unemployment Outflow Equation

According to the OLS estimates in column 1 of *Table 2*, unemployment and vacancies both have statistically significant effects on the outflow from unemployment, but the stock of unemployed workers has a quantitatively much larger effect than the effect of vacancies. There is no effect of the inflow of newly unemployed workers. In column 2 we account for measurement errors and simultaneity by instrumenting all the variables on the right hand side with five lags of the inflows and the stocks lagged six months. The test statistics show that this instrument set is both valid and relevant. One concern, which was raised above, is that

mismatch shocks may create a simultaneity problem that affects the coefficients for the stocks, but this does not appear to be an important problem; the coefficients for the stocks are roughly similar as we go from OLS to IV. The coefficients for the inflows increase, however, and become quantitatively important when we estimate by IV. One possible interpretation is that estimation by IV reduces the effects of measurement errors with respect to the inflows. As discussed above, estimation by IV should be a good way to address measurement errors.

In the IV estimation, the sum of the coefficients for the stock and inflow of unemployment is about 0.8, so a 10 percent increase in the stock and the inflow into unemployment will raise the outflow by approximately 8 percent. A ten percent increase in (new and old) vacancies increases hiring from unemployment by only 1.2 percent. The sum of the four coefficients in column 2 is 0.916 and we cannot reject constant returns to scale at conventional levels of significance. The signs of the effects are qualitatively in line with the implications of the matching function, but the effect of vacancies on the hiring of unemployed workers is surprisingly weak.

Vacancy Outflow Equation

Column 3 in *Table 2* shows the OLS estimate of equation (5) with the outflow of vacancies as the dependent variable. We see that the initial stock and the inflow of new vacancies both contribute to the outflow of vacancies, but neither the initial stock of unemployment nor the unemployment inflow have significant effects on the rate at which vacancies are filled.

The IV estimates are shown in Column 4, and again the test statistics show that the instruments are both valid and relevant. Compared to OLS, we find a much bigger effect of the vacancy inflow, while the effect of the vacancy stock is somewhat larger. As discussed above, this difference between OLS and IV could be due to measurement errors. Again, we see no effect of unemployment on the vacancy outflow.

The sum of the coefficients in column 4 is 1.308 and we can reject constant returns to scale statistically, so instead of congestion we find increasing returns to scale. One possible interpretation is that this reflects heterogeneity among vacancies. There may be some fairly constant sets of vacancies that are difficult to fill, while the vacancies that do fluctuate are filled at a faster rate.[18]

Robustness across Time and Space

In *Table 3* we investigate the robustness of the results for the unemployment outflow across time and space; all estimations are performed by IV, including local labour market fixed effects, time dummies, local seasons and local trends. Column 1 repeats our baseline estimate for the whole time period and all labour markets. In columns 2 and 3 we estimate the equation for two periods, 1992-1999 and 2000-2011. The coefficient estimates are similar to what we find for the whole period, but some coefficients are more uncertain and not statistically significantly different from zero. In columns 4-6 we divide the sample into small, medium and large labour markets, with one third of the labour markets placed in each category. The results are qualitatively roughly similar those for the whole sample, but some estimates are more uncertain.

In *Table 4* we investigate the robustness of the results for the vacancy outflow across time and space. The results are robust across time and space. In no case do we find any statistically significant effect of unemployment, but the coefficients for the stock and inflow of vacancies are stable showing significant, positive effects on the outflow of vacancies.

[18] There are a large number of job openings in tele-marketing where payment is often based on commission and firms may simply want to hire as many as possible.

Table 3. The Outflow from Unemployment: Robustness across Time and Space

Dep. variable: lnUout	(1)	(2)	(3)	(4)	(5)	(6)
Period	1992-2011	1992-1999	2000-2011	1992-2011	1992-2011	1992-2011
Labour markets	All	All	All	Small	Medium	Large
lnU	0.585***	0.844***	0.668***	0.718***	0.568***	0.483***
	(0.053)	(0.193)	(0.059)	(0.095)	(0.043)	(0.084)
lnUin	0.207***	0.242	0.123	0.061	0.205**	0.278***
	(0.060)	(0.243)	(0.084)	(0.104)	(0.100)	(0.097)
lnV	0.013*	0.022*	0.012**	0.009	0.022***	-0.003
	(0.007)	(0.011)	(0.005)	(0.012)	(0.008)	(0.013)
lnVin	0.111**	0.144	0.098	0.079	0.104	0.218***
	(0.043)	(0.090)	(0.066)	(0.056)	(0.069)	(0.063)
Observations	19,725	7,317	11,870	6,405	6,660	6,660
R-squared	0.845	0.859	0.826	0.801	0.870	0.921
Number of llm	90	90	90	30	30	30

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. IV-regressions. Instruments: five lags of inflows plus the stocks in t-6. Regressions include fixed effects for local labour markets, time dummies, local seasons and local trends.

Table 4. The Outflow of Vacancies: Robustness across Time and Space

Dep. variable: lnVout	(1)	(2)	(3)	(4)	(5)	(6)
Period	1992-2011	1992-1999	2000-2011	1992-2011	1992-2011	1992-2011
Labour markets	All	All	All	Small	Medium	Large
lnU	0.103	-0.238	-0.024	0.168	-0.022	0.150
	(0.071)	(0.216)	(0.075)	(0.143)	(0.098)	(0.122)
lnUin	-0.065	0.464	0.013	-0.078	0.016	-0.105
	(0.083)	(0.344)	(0.122)	(0.174)	(0.108)	(0.135)
lnV	0.487***	0.428***	0.536***	0.498***	0.479***	0.446***
	(0.018)	(0.030)	(0.018)	(0.026)	(0.026)	(0.045)
lnVin	0.821***	0.884***	0.578***	0.886***	0.610***	0.796***
	(0.065)	(0.119)	(0.115)	(0.075)	(0.123)	(0.142)
Observations	19,722	7,317	11,867	6,403	6,659	6,660
R-squared	0.731	0.779	0.791	0.665	0.791	0.854
Number of llm	90	90	90	30	30	30

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. IV-regressions. Instruments: five lags of inflows plus the stocks in t-6. Regressions include fixed effects for local labour markets, time dummies, local seasons and local trends.

These robustness checks show that our main results are not due to some specific shocks that happened in particular time periods or in specific labour markets. If we think of these regressions as estimates of "the matching function," two results are surprising. The first is that the number of vacancies has such a weak effect on the hiring of unemployed workers. The second is that unemployment has *no* effect on the outflow of vacancies. Both results are consistent with a model of persistent mismatch in the labour market but inconsistent with a standard matching function.

Our estimates tell us something important about vacancy data. There are many vacancies in a boom, but this is not because their durations increase; instead, it is because there is a large inflow of vacancies in boom periods.

One may argue that the latter result arises mechanically because firms routinely post vacancies for a fixed time and then collect applications and hire the best applicant. However, this is exactly how we would expect firms to behave if they expect to quickly attract a sufficient number of qualified applicants for most jobs that they announce.

Alternative Trends, Aggregate Data and Labour market Programs

Table 5 shows regressions where we leave out either the local trends or the time dummies. The "cross effects" become positive in some cases and negative in other cases, but they are generally weak. Without time dummies or without local trends, higher unemployment appears to have a positive effect on the outflow of vacancies. However, the effect is quite small and of limited economic significance. A one-standard-deviation change in both V and v^{in} has an effect on v^{out} that is almost 10 times larger than the effect of one standard deviation changes in both U and u^{in}.[19]

[19] Using the standard errors in the first row of Table 1 and the coefficients in the sixth column of Table 5, we get $0.133 \cdot 0.403 + 0.088 \cdot 0.308 = 0.081$ for unemployment and $0.453 \cdot 0.706 + 0.720 \cdot 0.505 = 0.683$ for vacancies.

Table 5. Leaving out Local Trends or Time Dummies

	(1) Baseline lnUout IV	(2) No trend lnUout IV	(3) No TD lnUout IV	(4) Baseline lnVout IV	(5) No trend lnVout IV	(6) No TD lnVout IV
lnU	0.585***	0.416***	0.811***	0.103	0.152***	0.133***
	(0.053)	(0.041)	(0.038)	(0.071)	(0.037)	(0.029)
lnU^{in}	0.207***	0.328***	0.083**	-0.065	-0.100*	0.088***
	(0.060)	(0.057)	(0.038)	(0.083)	(0.059)	(0.031)
lnV	0.013*	0.020***	-0.027**	0.487***	0.488***	0.453***
	(0.007)	(0.007)	(0.013)	(0.018)	(0.017)	(0.019)
lnV^{in}	0.111**	-0.012	0.462***	0.821***	0.727***	0.720***
	(0.043)	(0.025)	(0.048)	(0.065)	(0.034)	(0.041)
Time dummies	YES	YES	NO	YES	YES	NO
Local trends	YES	NO	YES	YES	NO	YES
Observations	19,725	19,725	19,725	19,722	19,722	19,722
R-squared	0.845	0.820	0.645	0.731	0.749	0.741
Number of llm	90	90	90	90	90	90

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. IV-regressions. Instruments: five lags of inflows plus the stocks in t-6. In baseline time dummies, local seasonal dummies, linear and quadratic local trends, and fixed effects for the local labour market are included.

Table 6. Estimation on Aggregate Data

	(1) lnUout OLS	(2) lnUout IV	(3) lnVout OLS	(4) lnVout IV
lnU	0.627***	0.748***	-0.055***	-0.070*
	(0.030)	(0.047)	(0.021)	(0.039)
lnUin	0.144***	0.198**	-0.111***	0.035
	(0.049)	(0.100)	(0.037)	(0.067)
lnV	-0.160***	-0.284***	0.137***	0.103***
	(0.026)	(0.041)	(0.020)	(0.027)
lnVin	0.485***	0.715***	0.761***	0.889***
	(0.035)	(0.067)	(0.027)	(0.040)
Observations	228	222	228	222
R-squared	0.964	0.956	0.985	0.981

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Seasonal dummies, linear and quadratic trends included. There is clear evidence of changes in the seasonal pattern and the public employment service has noted that summer jobs are announced earlier towards the end of the sample period. To account for this we include interaction terms between trends and season. (In the baseline panel estimation, common changes in seasonality are handled by the time dummies.)

Table 6 shows estimates on aggregate data for the same period. Looking at the IV results, the initial stock of vacancies appears to have a negative effect on the outflow from unemployment, which is difficult to understand, but the sum of the effects of the stock and inflow of vacancies on the unemployment outflow is positive. Again, the effect of unemployment on the outflow of vacancies is quite close to zero.

As noted above, there have been structural changes over this long time period, and we therefore view the panel estimates with time dummies as the most convincing estimates.

On average, 3.9 percent of the labour force participated in labour market programs during this period. As an alternative specification, we include job searchers who participated in labour market programs in the unemployment measure; the results are very similar (see *Table A2* in the Appendix).

6. Comparison with Previous Empirical Results

No/Weak Effect of Unemployment on the Outflow of Vacancies

Our most striking result is that unemployment does not affect the rate at which vacancies are filled – or it has a weak effect. Comparing to previous empirical results, we find it most interesting to compare with studies which use similar methodology, i.e. panel studies where the dependent variable is the filling of vacancies, constant returns to scale are not imposed and the regressions include time dummies and fixed effects for the local or regional labour market.[20] Taking a close look at the literature, we find that some results that are similar to ours have, in fact, been reported before.

Anderson and Burgess (2000) use a quarterly panel of four US states, and the dependent variable is new hires according to register data. In most of their estimates, they do not include seasonal dummies. When they include time effects (which pick up seasonality) the coefficient for the log of unemployment is 0.19, but it is far from statistically significant. Furthermore, they find a zero effect of unemployment on hires from non-employment (Table 2, columns 4 and 5 in their paper).

Kangasharju, Pehkonen and Pekkala (2005) use a panel very similar to ours, with monthly data for Finland and filled vacancies as the dependent variable. Similar to our study, they include both initial stocks and inflows as explanatory variables, and they include year dummies, seasonal dummies and fixed effects. In fact, they find very similar results to ours, reporting that "…matches are mainly driven by the demand side of the labour market … the elasticity with respect to the stock of old vacancies is 0.3 and with respect to new vacancies 0.6. The corresponding effect from the supply side (job seekers) is only around 0.1." With a

[20] As discussed above, studies on aggregate data can easily generate spurious results, and pure cross section estimates such as Coles and Smith (1996) answer very different questions about how the size and density of the labor market affects the matching process.

translog specification they find a somewhat bigger role for the supply side, but it is still the demand side that dominates.[21]

Borowczyk-Martins, Jolivet and Postel-Vinay (2013) estimate matching functions on JOLTS data using all additions to the payroll as the dependent variable. In their baseline estimate, they impose CRS so that the explanatory variable is tightness. When they relax CRS, their OLS estimate gives a *negative* effect of unemployment on the number of matches (-0.280). They also perform GMM estimation, finding an effect of unemployment that is positive but far from statistically significant.

For Sweden, Edin and Holmlund (1991) estimated aggregate matching functions with the outflow of vacancies as the dependent variable and initial stocks and a trend as explanatory variables, finding coefficients of 0.23 for unemployment and 0.56 for vacancies. One reason for the difference may be that they have data for the period 1970-1988, when unemployment was much lower, while our sample begins with the crisis in the 1990s and there is slackness in the labour market for large parts of the sample period. Finding workers should be more of a problem when unemployment is low (Michaillat 2012). Running the same regression (with only initial stocks) on aggregate data for the period 1992-2011, we obtain coefficients of -0.05 for the initial stock of unemployment (not significant) and 0.64 for the initial stock of vacancies.

Small Effect of Vacancies on Hiring from Unemployment

With hiring from unemployment as the dependent variable, we found positive coefficients for unemployment and vacancies but the latter effect was surprisingly weak. It is interesting to relate our results to the recent studies of stock-flow matching by Gregg and Petrongolo (2005)

[21] There are typos in their Table 2. Hynninen (2005) estimates matching functions on monthly panel data for local labor markets in Finland using the outflow of vacancies as the dependent variable. A key difference is that she does not include the inflows on the right hand side and, for this reason, the estimates are not directly comparable. As seen from our estimates, the inflows help very much to explain the outflows, especially for vacancies.

and Coles and Petrongolo (2008). A key point they make is that the vacancies and job seekers "at risk" are weighted sums of the initial stocks and the inflows and they also note that, because of the high turnover of vacancies, the initial stock of vacancies is a poor proxy for the vacancies "at risk". In fact, they find that the inflow of vacancies is a more important determinant of hiring from unemployment than the vacancy stock. This is also what we find when we estimate by IV. According to our IV estimate in *Table 2*, column 2, a one-standard-deviation increase in the vacancy inflow leads to a 5.6 percent increase in hiring from unemployment $\left(0.111 \cdot 0.505 = 0.056\right)$ while a one standard deviation increase in the initial vacancy stock leads to a 0.9 percent increase in hiring from unemployment $\left(0.013 \cdot 0.706 = 0.009\right)$.[22]

In a study of aggregate data for Sweden, Forslund and Johansson (2007) used the hiring of registered job seekers as the dependent variable. Measuring vacancies as the initial stock plus half the inflow, they found a coefficient of approximately 0.2 for vacancies, which is a bit higher than what we find. When estimating a stock-flow matching model they find, like Coles and Petrongolo (2008) and the present study, and that the inflow of new vacancies is more important for the hiring of job searchers than the initial vacancy stock.

Aranki and Löf (2008) estimated panel regressions very similar to ours for the outflow from unemployment. The main difference is that they use administrative provinces (län) rather than local labour markets as units of analysis. Their results are very similar to ours, with small effects of vacancies on the outflow from unemployment. They do not analyse the outflow of vacancies.

[22] Here we use the standard deviation from *Table 1* after fixed effects and local seasons.

We conclude that although our results may come as a surprise to many readers, similar results can, in fact, be found scattered in the literature.

7. Alternative Functional Forms

The mismatch model does not imply a log-linear relation between stocks, inflows and outflows. On the contrary, equation (14) will be linear if there are enough job-searchers to fill all vacancies. Thus, it may be interesting to consider alternative functional forms.

A Linear Specification

Table 7 shows estimates of linear regressions where the variables are not logged. According to the IV estimates in column 2, an increase in the stock of unemployment of 100 workers leads to 6 hires from unemployment, while an inflow of 100 workers into unemployment during the month leads to 42 workers being hired; the difference may be due to composition effects.

One hundred more registered vacancies will, at most, lead to 4 more unemployed workers being hired. Such a small effect may be surprising, but recruitment statistics from the labour force survey (AKU) can shed some light on this. In 2006, 33 percent of those recruited came directly from a job at another employer, and 13 percent were internally recruited while 28 percent had not been in the labour force. Only 26 percent came from unemployment and if around 60 percent of those were registered as unemployed at the public employment service (see Figure 2) this would mean that registered unemployed workers filled approximately 16 percent of the vacancies. This is still substantially more than 4, however.

Table 7. Determinants of Outflows of Unemployed Workers and Vacancies: Linear Specification

	(1) Uout OLS	(2) Uout IV	(3) Vout OLS	(4) Vout IV
U	0.074***	0.064***	-0.001	-0.002
	(0.005)	(0.012)	(0.004)	(0.012)
Uin	0.049***	0.418***	0.002	0.074
	(0.018)	(0.094)	(0.018)	(0.101)
V	0.005	0.032***	0.659***	0.705***
	(0.004)	(0.009)	(0.032)	(0.048)
Vin	0.037***	-0.015	0.416***	0.460***
	(0.007)	(0.088)	(0.027)	(0.154)
Observations	20,394	19,725	20,391	19,722
R-squared	0.816	0.792	0.781	0.775
Number of llm	90	90	90	90

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Instruments: five lags of inflows plus the stocks in t-6. Regressions include fixed effects for local labour markets, time dummies, local seasons and local linear and quadratic time trends.

Column 4 in *Table 7* shows that 71 percent of an increase in the stock of vacancies and 46 percent of an increase in the vacancy inflow are filled within the month. The coefficient for the inflow is roughly half the coefficient for the stock, which is what you would expect if vacancies were filled at a constant rate determined by mechanical delays in hiring. As in the log-linear specification, we find no effect of unemployment on the vacancy outflow.

Complementarity and Congestion

Both models imply congestion on the worker side because unemployed job seekers compete with other unemployed job seekers for a limited number of jobs, but if unemployed workers compete mainly with other types of job searchers, this congestion effect may be weak. The standard search model implies congestion on the firm side as vacancies compete with other vacancies. Stock-flow matching implies a non-linear model where the stock of unemployed

workers matches primarily with the inflow of vacancies and vice versa. To investigate if there are important nonlinear effects, we estimate a linear-quadratic specification.

Table 8 shows the results after adding second order terms to the regression equation. This specification can be seen as a second order approximation to a general functional form. The equations are estimated on deviations from local labour market means, and we estimate by OLS because we find it hard to construct instruments for all the second order terms. The first four lines show the first order effects, which are very similar to what we found in the linear specification in *Table 7*.

The next four lines of coefficients are coefficients for cross terms between U and u^{in} on the one hand and V and v^{in} on the other hand. These coefficients should be positive if unemployed and vacancies complement each other in the matching process. In fact, all but one of these coefficients are positive, and three are statistically significant. The significant positive coefficient for $U_{t-1} \cdot v_t^{in}$ indicates complementarity in line with stock-flow matching, where the stock of unemployed workers matches primarily with the inflow of new vacancies (see, e.g., Coles and Petrongolo 2008, page 1134).

The last six lines of coefficients for cross effects are expected to be negative if there is congestion. In fact, few effects are significantly different from zero, but significant negative coefficients for $\left(U_{t-1}\right)^2$ and $\left(v_{t-1}^{in}\right)^2$ indicate some congestion on both sides of the market.

In summary, some second order effects are statistically significant and those that are significant make economic sense. The economic magnitudes of the second order effects are small, however. This is shown in *Table 9*, where we consider the effects on the different terms in the equation if all explanatory variables increase simultaneously by one standard deviation. If the initial unemployment stock increases by one standard deviation (2.95 percent of the

labour force) the outflow from unemployment increases by 0.214 percent of the labour force.[23] If the initial vacancy stock increases by one standard deviation (0.34 percent of the labour force) the outflow of vacancies increases by 0.224 percent of the labour force.[24] Compared to these effects, the second order cross effects are an order of magnitude smaller. The biggest second order effect is the effect of $u^{in} \cdot v^{in}$ on v^{out}, which is 0.035 percent of the labour force.

Allowing for of second order effects does not change our conclusions. Instead, these results strengthen our conclusion that vacancies and unemployment are largely separate from each other. Normal variations in the number of vacancies have small effects on the outflow from unemployment, and variations in unemployment have no or very weak effects on the outflow of vacancies.

[23] Effect of a one s.d. shock to U_{t-1} on u_t^{out} is $0.082 \cdot 0.0295 - 0.317 \cdot 0.0295^2 = 0.00242 - 0.00028 = 0.00214$.

[24] Effect of a one s.d. shock to V_{t-1} on v_t^{out} is $0.658 \cdot 0.0034 - 0.273 \cdot 0.0034^2 = 0.00224 - 0.00000 = 0.00224$.

Table 8. Determinants of Outflows of Unemployed Workers and Vacancies: Linear-Quadratic Specification

	(1) Uout OLS	(2) Vout OLS
U	0.082***	0.002
	(0.006)	(0.003)
Uin	0.053**	0.005
	(0.025)	(0.017)
V	0.014*	0.658***
	(0.007)	(0.037)
Vin	0.053***	0.479***
	(0.009)	(0.020)
U*V	0.326	-0.586
	(0.260)	(0.769)
U*Vin	0.738***	1.470***
	(0.205)	(0.486)
Uin *V	0.425	1.387
	(1.702)	(3.081)
Uin*Vin	2.116	13.387***
	(1.297)	(2.128)
U*U	-0.317***	0.007
	(0.052)	(0.036)
Uin*Uin	1.317	0.062
	(0.850)	(0.722)
U*Uin	-0.196	0.167
	(0.411)	(0.331)
V*V	-0.001	-0.273
	(0.091)	(0.658)
V*Vin	0.193	-0.812
	(0.197)	(1.486)
Vin*Vin	-0.466*	-1.662***
	(0.237)	(0.535)
Observations	20,394	20,391
R-squared	0.811	0.787
Number of llm	90	90

Note: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. OLS regressions including cross terms for demeaned variables (local labour market means). Regressions include fixed effects for local labour market, time dummies, local seasons and local linear and quadratic time trends.

Table 9. Linear-Quadratic Specification: Effects of one standard deviation shocks

Outflow from unemployment

Coefficients for linear and second order terms

	U	Uin	V	Vin
Linear term	0.082	0.053	0.014	0.053
U	-0.317	-0.196	0.326	0.738
Uin		1.317	0.425	2.116
V			-0.001	0.193
Vin				-0.466

Linear and nonlinear effects of one standard deviation shocks

	U	Uin	V	Vin	s.d
Linear term	**0.00242**	0.00026	0.00005	0.00028	
U	-0.00028	-0.00003	0.00003	0.00012	0.0295
Uin		0.00003	0.00001	0.00005	0.0049
V			0.00000	0.00000	0.0034
Vin				-0.00001	0.0053
s.d.	0.0295	0.0049	0.0034	0.0053	

Outflow of vacancies

Coefficients for linear and second order terms

	U	Uin	V	Vin
Linear term	0.002	0.005	0.658	0.479
U	0.007	0.167	-0.586	1.47
Uin		0.062	1.387	13.387
V			-0.273	-0.812
Vin				-1.662

Linear and nonlinear effects of one standard deviation shocks

	U	Uin	V	Vin	s.d
Linear term	0.00006	0.00002	**0.00224**	**0.00254**	
U	0.00001	0.00002	-0.00006	0.00023	0.0295
Uin		0.00000	0.00002	0.00035	0.0049
V			0.00000	-0.00001	0.0034
Vin				-0.00005	0.0053
s.d.	0.0295	0.0049	0.0034	0.0053	

8. Conclusions

Estimating matching functions on monthly panel data for local labour markets, we obtain very different results if we use hiring of unemployed workers as the dependent variable compared to when we use the outflow of vacancies as the dependent variable. The number of vacancies has a surprisingly weak effect on hiring from unemployment, and unemployment has no (or a weak) effect on the rate at which vacancies are filled. It is almost as if vacancies and unemployed workers were in different universes!

One interpretation of these results is that they may be due to measurement errors because registered unemployed workers and vacancies are very imperfect measures of all job seekers and vacancies in the economy. However, we address measurement errors by doing IV estimation and our test statistics show that our instruments are both valid and relevant. On the aggregate level, our measures correlate well with survey measures of unemployment and vacancies. Thus, we seem to pick up economically meaningful variation.

Instead, our interpretation is that the results reflect persistent mismatch in the labour market. Vacancies in sections of the labour market where there is no or little unemployment will not help unemployed workers to get jobs and longer queues for jobs in sections of the labour market where there is high unemployment will not speed up hiring.

A key to understanding our results is to understand that, contrary to the simplest search-matching model, filling a job is not the same thing as hiring an unemployed worker. Much of the time, jobs are filled with workers who already had a job, and mismatch across different sections of the labour market means that the filling of vacancies is only weakly related to the hiring of unemployed workers. When there is high demand in sections of the labour market with little unemployment, there will be many vacancies and high turnover in those markets,

but this does not make it easier for unemployed workers to find jobs, nor does high unemployment make it easier to fill those vacancies.[25]

That unemployment is mainly due to mismatch does not mean that it is independent of macroeconomic conditions. On the contrary, higher demand across all sections of the labour market will imply lower unemployment in sections of the labour market with unemployment and many vacancies and high turnover in sections of the labour market with full employment, so aggregate demand-side shocks generate a Beveridge curve. Additionally, as emphasized by Shimer (2007), mismatch models are consistent with pro-cyclical job-to-job transitions and countercyclical separations into unemployment because it is easier for job switchers to find jobs when there are many vacancies and fewer unemployed workers that they have to compete with.[26]

The extent to which unemployment is due to imperfect information, heterogeneity and mismatch is relevant for policy because different diagnoses lead to different policy recommendations. If the main problem is imperfect information, helping unemployed workers in their job searches and increasing the incentives to search should be efficient measures of combatting unemployment. If unemployment is mainly due to mismatch between workers' skills and the demands of the labour market, making unemployed workers search harder may not, by itself, have a large effect on unemployment. Instead, our analysis points to education

[25] For the US, Bjelland, Fallick, Haltiwanger and McEntarfer (2011) emphasize the importance of employer-to-employer flows.

[26] In the simple model presented here, we do not have a countercyclical inflow into unemployment, but it could be included. The number of workers quitting in the A-markets is $(1-\lambda)s_t^A N_{t-1}^A$ and we assumed that those workers constituted the inflow into unemployment (u_t^{in}). But, suppose that a fraction κF^A of those workers never register as unemployed because they got a job immediately or they were unemployed for a very short time. Then, the registered inflow into unemployment will be $u_t^{in} = (1-\lambda)s_t^A N_{t-1}^A (1-\kappa F^A)$ which will be countercyclical provided that the procyclicality of F^A dominates that of N_{t-1}^A. We did not include this in the model because it would make the equations very nonlinear and prevent derivation of a simple expression for hiring from unemployment.

and retraining as key factors on the supply side, while wage formation should play an important role on the demand side.

References

Anderson, Patricia M. and Simon M. Burgess, 2000, Empirical Matching Functions: Estimation and Interpretation Using State-Level Data, *Review of Economics and Statistics*, vol. 82, pp. 93-102.

Aranki, Ted and Mårten Löf, 2008, Matchningsprocessen på den svenska arbetsmarknaden: En regional analys (in Swedish), *Penning- och valutapolitik* vol. 1/2008, pp.48-58.

Bjelland, Melissa, Bruce Fallick, John Haltiwanger, and Erica McEntarfer, 2011, Employer-to-Employer Flows in the United States: Estimates Using Linked Employer-Employee Data, *Journal of Business & Economic Statistics*, vol. 29, pp. 493-505.

Borowczyk-Martins, Daniel, Grégory Jolivet and Fabien Postel-Vinay, 2013, Accounting for Endogeneity in Matching function Estimation, *Review of Economic Dynamics*, vol. 16, pp. 440-451.

Blanchard, Olivier J. and Peter Diamond, 1989, The Beveridge Curve, *Brookings Papers on Economic Activity*, 1989, pp. 1-76.

Carlsson, Mikael, Eriksson, Stefan, and Gottfries, Nils, 2013, Product Market Imperfections and Employment Dynamics, *Oxford Economic Papers*, vol. 65, pp. 447-470.

Coles, Melvyn G. and Eric Smith, 1998, Marketplaces Matching, *International Economic Review*, 39, pp. 239-597.

Coles, Melvyn G. and Barbara Petrongolo, 2008, A Test Between Stock-flow Matching and the Random Matching Approach, *International Economic Review*, vol. 49, pp. 1113-1141.

Daly, Mary C., Bart Hoijn, Aysegul Sahin and Robert G. Valletta, A Search and matching Approach to Labor markets: Did the Natural Rate of Unemployment Rise?, *Journal of Economic Perspectives*, vol. 26, pp. 3-26.

Davis, S., J. Faberman and J. Haltiwanger, 2013, The Establishment-Level Behavior of Vacancies and Hiring, *The Quarterly Journal of Economics*, vol. 128, pp. 581-622.

Edin, Per-Anders and Bertil Holmlund, 1991, Unemployment, Vacancies and Labor Market Programmes: Swedish Evidence, Ch. 10 in *Mismatch and Labour Mobility*, edited by F. P. Schioppa, Cambridge University Press.

Elsby, Michael W. L., Ryan Michaels and David Ratner, 2015, The Beveridge Curve: A Survey, *Journal of Economic Literature*, vol. 53, pp. 571-630.

Forslund, Anders and Kerstin Johansson, 2007, Random and Stock-Flow Models of Labour Market Matching – Swedish Evidence, IFAU Working Paper 2007:11.

Gregg, Paul, and Barbara Petrongolo, 2005, Stock-flow Matching and the Performance of the Labor Market, *European Economic Review*, vol. 49, pp. 1987-2011.

Hynninen, Sanna-Mari, 2005, Matching Across Space: Evidence from Finland, *Labour*, 19, pp. 749-765.

Johansson, Mats and Lars Olof Persson, 2000, *Regionalpolitiska utredningen* (in Swedish), SOU 2000:36, Fritzes, Stockholm.

Kangasharju, Aki, Jaakko Pehkonen and Sari Pekkala, 2005, Returns to Scale in a Matching Model: Evidence from Disaggregated Panel data, *Applied Economics*, vol. 37, pp. 115-118.

Lagos, Ricardo, 2000, An Alternative Approach to Search Frictions, *Journal of Political Economy*, 108, pp. 851-73.

Michaillat, Pascal, 2012, Do Matching Frictions Explain Unemployment? Not in Bad Times, *American Economic Review*, vol. 102, pp. 1721-1750.

Michaillat, Pascal and Emmanuel Saez, 2015, "Aggregate Demand, Idle Time, and Unemployment", *Quarterly Journal of Economics*, vol. 130, pp. 507-569.

Petrongolo, Barbara and Christopher A. Pissarides, 2001, Looking into the Black Box: A Survey of the Matching Function, *Journal of Economic Literature*, vol. 39, pp. 390-431.

Petrongolo, Barbara and Christopher A. Pissarides, 2006, Scale Effects in Markets with Search, *Economic Journal*, vol. 116, pp. 21-44.

Pissarides, Christopher A. (2000), *Equilibrium unemployment theory*, MIT Press, Cambridge MA.

Shimer, Robert, 2005, The Cyclical Behavior of Equilibrium Unemployment and Vacancies, *The American Economic Review*, vol. 95, 25-49.

Shimer, Robert, 2007, “Mismatch”, *The American Economic Review*, 97, pp. 1074-1101.

Stadin, Karolina, 2014, *Employment Dynamics*, Ph D thesis, Uppsala University.

Stadin, Karolina, 2015, Firms´ Employment Dynamics and the State of the Labour Market, manuscript, Uppsala University, and IFAU WP 2015.

Statistics Sweden, 2016, Jämförande Studie AKU och AF 2015, Arbetsmarknad och Utbildning Bakgrundsfakta 2016:2

Yashiv, Eran, 2007, Labor Search and Matching in Macroeconomics, *European Economic Review*, vol. 51, pp. 1859-1895.

Appendix

Table A1. Local labour markets

1	Stockholm	31	Bengtsfors	61	Bollnäs
2	Nyköping-Oxelösund	32	Göteborg (Gothenburg)	62	Hudiksvall
3	Katrineholm	33	Strömstad	63	Ånge
4	Eskilstuna	34	Trollhättan	64	Härnösand
5	Linköping	35	Borås	65	Sundsvall
6	Norrköping	36	Lidköping-Götene	66	Kramfors
7	Gislaved	37	Skövde	67	Sollefteå
8	Jönköping	38	Torsby	68	Örnsköldsvik
9	Värnamo	39	Årjäng	69	Strömsund
10	Vetlanda	40	Karlstad	70	Härjedalen
11	Tranås	41	Filipstad	71	Östersund
12	Älmhult	42	Hagfors	72	Storuman
13	Markaryd	43	Arvika	73	Sorsele
14	Växjö	44	Säffle	74	Dorotea
15	Ljungby	45	Laxå	75	Vilhelmina
16	Hultsfred	46	Hällefors	76	Åsele
17	Emmaboda	47	Örebro	77	Umeå
18	Kalmar	48	Karlskoga	78	Lycksele
19	Oskarshamn	49	Västerås	79	Skellefteå
20	Västervik	50	Fagersta	80	Arvidsjaur
21	Vimmerby	51	Vansbro	81	Arjeplog
22	Gotland	52	Malung	82	Jokkmokk
23	Olofström	53	Mora	83	Överkalix
24	Karlskrona	54	Falun-Borlänge	84	Kalix
25	Malmö	55	Avesta	85	Övertorneå
26	Kristianstad	56	Ludvika	86	Pajala
27	Simrishamn-Tomelilla	57	Hofors	87	Gällivare
28	Halmstad	58	Ljusdal	88	Luleå
29	Falkenberg	59	Gävle	89	Haparanda
30	Varberg	60	Söderhamn	90	Kiruna

Note: The definitions of the local labour markets from Statistics Sweden have changed over the years because of changes in commuting patterns. In this study, the year 2000 version is used because it is approximately in the middle of the sample period (1992-2011).

Table A2. Including Participants in Labour Market Programs in Unemployment

	(1) lnUPout OLS	(2) lnUPout IV	(3) lnVout OLS	(4) lnVout IV
lnUP	0.631***	0.720***	-0.007	0.096
	(0.027)	(0.048)	(0.030)	(0.062)
lnUPin	-0.004	0.129**	-0.022	-0.045
	(0.012)	(0.053)	(0.019)	(0.065)
lnV	0.011***	0.010	0.415***	0.488***
	(0.003)	(0.007)	(0.009)	(0.018)
lnVin	0.039***	0.150***	0.462***	0.811***
	(0.004)	(0.040)	(0.013)	(0.062)
Observations	20,394	19,725	20,391	19,722
R-squared	0.860	0.847	0.799	0.735
Number of llm	90	90	90	90

Note: Robust standard errors (clustered on local labour market) in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Fixed effects for local labour markets, time dummies, local seasons and linear and quadratic local time trends are included in all specifications. Instruments for IV are five lags of inflows plus the stocks in t-6. The difference compared to the main specification (Table 2) is that the unemployment measure (UP) includes participants in labour market programs (sökande i program med aktivitetsstöd). The mean of UP was 11.1 percent of the labour force while the mean of U was 7.2 percent of the labour force.