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The Beveridge curve and labour market flows – a reinterpretation

Abstract

According to search-matching theory, the Beveridge curve slopes downward because vacancies are filled more quickly when unemployment is high. Using monthly panel data for local labour markets in Sweden we find no (or only weak) evidence that high unemployment makes it easier to fill vacancies. Instead, there are few vacancies when unemployment is high because there is a *low inflow* of new vacancies. We construct a simple model with on-the-job search and show that it is broadly consistent with the cyclical behaviour of stocks and flows in the labour market also without search frictions. In periods of high unemployment, fewer employed job seekers find new jobs and this leads to a smaller inflow of new vacancies.

JEL-Codes: E240, J230, J620, J630, J640.

Keywords: Beveridge curve, frictional unemployment, matching function, turnover, mismatch, vacancy chain.

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1. Introduction

Vacancies and unemployment coexist in the labour market. In good times, unemployment is low and there are many vacancies. In bad times, unemployment is high and there are few vacancies. This correlation which was noted by Beveridge (1944), is typically explained with the help of a matching function which relates hirings (*H*) to unemployment (*U*) and vacancies (*V*):[1]

$$H = \phi U^{\alpha} V^{1-\alpha}, \tag{1}$$

where $0 \leq \alpha \leq 1$ and where the coefficient ϕ reflects matching efficiency. The matching function is a reduced-form relationship and the underlying microeconomic mechanisms are usually not spelled out, but discussions of the matching process often refer to search and *imperfect information*. If vacancies and job seekers are trying to find each other in some space, more vacancies should make it easier for unemployed workers to find jobs, and high unemployment should make it easier to fill a vacancy. The Beveridge curve can be simply derived from the matching function by assuming that employed workers quit at a constant rate *s*, so that separations are equal to $s\left(L-U\right)$ where *L* is the labour force and *U* is unemployment. For unemployment to stay constant, hiring must be equal to separations and this gives an equilibrium relation between vacancies and unemployment:

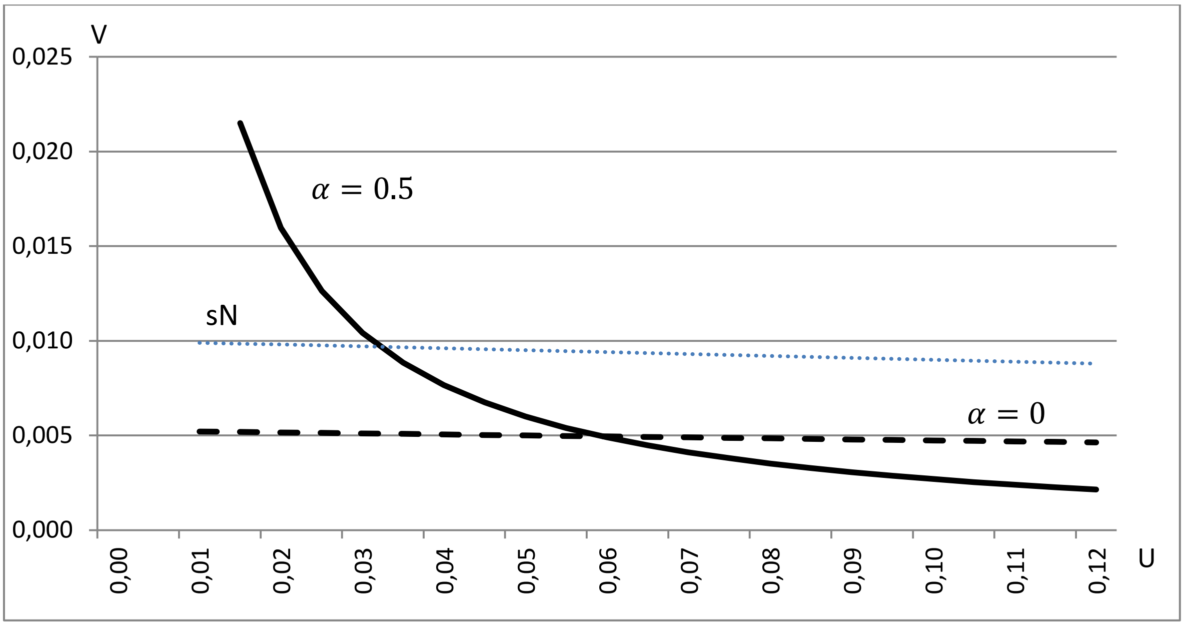
$$V = \left(\frac{s\left(L-U\right)}{\phi}\right)^{\frac{1}{1-\alpha}} U^{\frac{-\alpha}{1-\alpha}}. \tag{2}$$

This Beveridge Curve slopes downward for two reasons, which are captured by the two factors on the right-hand side. First, there is a mechanic effect as higher unemployment means lower employment and hence fewer workers leaving jobs that have to be filled or replaced in order for employment to stay constant; the *inflow* of new vacancies is smaller. Second, vacancies are filled quickly when unemployment is high, so a lower vacancy stock is needed to generate a given number of hires; the *duration* of a vacancy decreases.[2] The latter effect

[1] For surveys and recent contributions, see Petrongolo and Pissarides (2001), Yashiv (2007), Daly, Hobijn, Sahin and Valletta (2012), Håkanson (2014), Elsby, Michaels and Ratner (2015).
[2] Mortensen and Pissarides (1994) consider a model with endogenous job destruction. They write that "On the one hand, higher vacancies imply more job matchings, so unemployment needs to be lower for stationary matching rate. On the other hand, higher vacancies also imply more job destruction …" They find that the Beveridge curve may be upward-sloping if the latter effect dominates but assume that the former (matching) effect dominates, so the Beveridge curve slopes down.

arises only if there are search frictions $(\alpha > 0)$. If $\alpha = 0$, vacancies are filled at a rate that is independent of the labour market situation and the Beveridge curve becomes a line with a slight downward slope: $V = s(L-U)/\phi$ (see Figure 1).

Figure 1. Beveridge curve with exogenous separations with and without matching frictions



Note: All variables are measured relative to the labour force. The parameter s is set to 0.01 and ϕ is adjusted to keep vacancies at 0.5 percent when unemployment is 6 percent.

In this paper we ask a simple question: Is this interpretation of the Beveridge curve consistent with the correlations between stocks and flows of vacancies and unemployed workers that we observe in the labour market? To answer the question, we use monthly panel data from the Swedish Public Employment Service covering stocks and inflows and outflows of registered vacancies and unemployment in all 90 local labour markets in Sweden 1992:1-2011:12.

There is a clear Beveridge curve in the data and we start by examining “bubble plots” for aggregate data showing how de-registrations of vacancies and hiring from unemployment vary as we move along the Beveridge curve. Looking at de-registrations of vacancies we find that more vacancies are deregistered when there are many vacancies, but we see no evidence that more vacancies are deregistered when unemployment is high. In fact, inflows and de-registrations of vacancies are extremely well correlated with the vacancy stock, suggesting that vacancies are filled at a roughly constant rate. When it comes to hiring from unemployment, we see that more unemployed workers get jobs when there is high unemployment, but it is less clear whether more unemployed workers get hired when there is a large number of vacancies.

To investigate this further, we estimate two “matching functions” with de-registrations of vacancies and hiring of unemployed workers as dependent variables. The explanatory variables are the same in both equations: the stocks of unemployment and vacancies at the beginning of the month as well as to the inflows of new vacancies and newly registered unemployed workers during the month. In the panel estimation, we include fixed effects for local labour markets and time dummies to reduce the risk of spurious correlations due to unobserved aggregate shocks and long-term structural changes.

Estimation of matching functions confirms what we see in the graphs. More vacancies are filled when there are many vacancies and more unemployed workers get jobs when there are many unemployed workers looking for jobs, but the “cross effects” are weak. In most specifications, there is no evidence that higher unemployment leads to more vacancies being filled and vacancies have a statistically significant but surprisingly small effect on the job findings of unemployed workers. Thus we get very different results depending on what flow we have as dependent variable and the results are hard to reconcile with the predictions of the standard search-matching model. If information frictions were important, more agents on the other side of the market should increase the number of searchers finding suitable matches.

The results may come as a surprise to many readers, but a close look at the literature reveals that qualitatively similar results have been found in other studies when similar empirical strategies and data have been used (see Section 4). Also, our empirical results are in line with some recent empirical studies on micro and macro data. Carlsson, Eriksson and Gottfries (2013) and Stadin (2015) used firm-level data and found that higher unemployment does not make firms hire more workers. Christiano, Trabandt and Walentin et al. (2011) and Christiano, Eichenbaum and Trabandt (2016) estimated macro models where the recruitment cost per hired worker could potentially vary with the labour market situation, finding 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.

Our results lead to the question how to explain the Beveridge curve. If unemployment has no, or only a weak effect on the number of vacancies being de-registered, the matching function cannot be the main foundation for the Beveridge curve. In Section 5 we present a very simple model with on-the-job search as in Akerlof, Rose and Yellen (1988) and Eriksson and Gottfries (2005). Such a model can produce a Beveridge curve even if vacancies are filled at a constant rate. We show that a simply calibrated model of this type can generate correlations between stocks and flows that are broadly consistent with what we observe in the data. High unemployment is associated with a low vacancy stock, not because vacancies are filled more quickly but because fewer employed job searchers switch jobs when they have to compete with a large number of unemployed job applicants, leading to a *low inflow* of new vacancies. According to our estimates, this is the main mechanism behind the Beveridge curve.

As mentioned above, we find a statistically significant, but surprisingly weak effect of vacancies on hiring from unemployment – the estimated elasticity is around 0.1. We argue that this low elasticity may be due to three factors. First, unemployed workers may find jobs that have not been announced as vacancies. They may be recalled from temporary layoffs, become self-employed or find jobs abroad or in labour market programs. Second, variations in the number of vacancies that are due to variations in on-the-job search will not affect the job prospects of the unemployed. There is a simple intuition for this: when a job switcher leaves a job, a vacancy will be opened, but since he also fills a vacancy, the number of job openings available for *other* job seekers stays the same. A third factor may be mismatch: if labour demand increases in tight sections of the labour market where there are no (or very few) unemployed workers, this will lead to high turnover and long vacancy chains as firms try to replace quitting workers, but these vacancies will not help many unemployed job seekers to find jobs. To more directly document mismatch, we would need more detailed data on the composition of unemployment and vacancies than we have in this study.

We propose an alternative interpretation of the Beveridge curve, which is a well-established empirical correlation, as an *equilibrium relation* between vacancies and unemployment. Thus, we do not address the question what drives the movements along the Beveridge curve, nor do we investigate why the Beveridge curve has shifted on particular occasions. We disregard month-to-month transitional dynamics. The question is simply: Why are there typically few vacancies when unemployment is high and many vacancies when unemployment is low?

In Section 2, we present the data and we illustrate the relations between stocks and flows graphically. In Section 3 we report estimates of matching functions and in Section 4 we compare our results with the results in previous studies. In Section 5 we present an alternative model with search on the job but without search frictions and we show that it is broadly consistent with the correlations between stocks and flows that we see in the data. In Section 6 we use this model to interpret our estimates from Section 3 and Section 7 concludes.

2. A Look at the Data

We use register data from the Public Employment Service (Arbetsförmedlingen) for the period 1992:1-2011:12. After 2011 there was a large increase in vacancies while unemployment remained relatively stable. We view this as a structural break associated with a very large inflow of immigrants during this period and for this reason we exclude data after 2011 in the baseline estimation.[3] This development is discussed in appendix B where we also show that the estimates (which include time dummies) are fairly similar if we include the most recent period. Data are available at the municipality level and 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 relatively independent from the rest of the world with respect to labour demand and labour supply.[4]

Definitions

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 programs 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 number of workers who are newly registered as unemployed during the month and hires from unemployment, H_t^u, are measured as the number of workers who leave registered

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[3] Increased automation in the handling of vacancies via internet may also play a role.

[4] The 90 local labour markets are listed in Appendix A. Johansson and Persson (2000) reported that 80-90 percent of all hired workers came from the local labour market area where the firm was located. Survey data for vacancies and unemployment are not sufficiently large to allow panel estimation with fixed effects for local labour markets and time dummies.

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 (de-registrations) as the inflow of new vacancies over the month minus the change in the stock:

$$V_t^{out} = V_t^{in} - \left(V_t - V_{t\text{-}1}\right). \tag{3}$$

The main weakness of these data is that we do not know if vacancies that are withdrawn are actually 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. A recruitment survey, which is issued irregularly by the employer´s federation, shows that, on average, about 1/5 of all recruitment attempts fail, but this fraction has no clear cyclical pattern.[5]

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 flow from unemployment to jobs was slightly smaller, 0.92 percent of the labour force. The difference arises because 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.[6] Thus, the flows of workers and vacancies are of similar magnitudes but the stock of vacancies is more than ten times smaller than the stock of unemployed workers and the duration is correspondingly smaller (about 3 weeks).

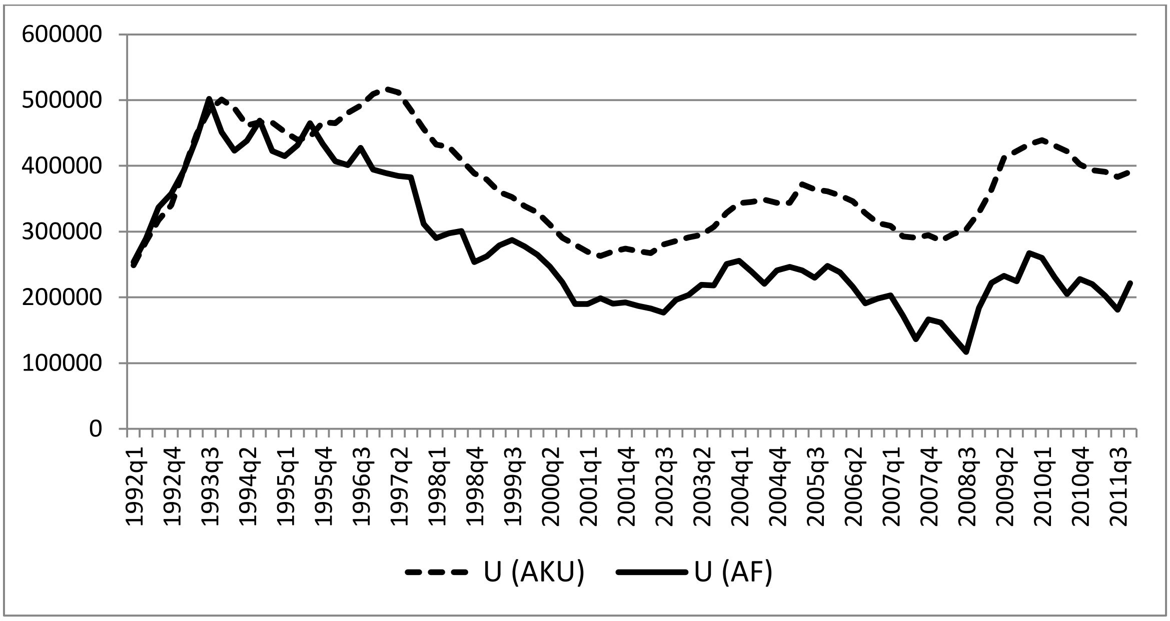
Not all unemployed workers are registered at the Public Employment Service. According to Aranki and Löf (2008), vacancies reported to the Public Employment Service corresponded to 30-45 percent of total hirings in the 1990s and 2000s. Thus, we should view our measures of unemployment and vacancies as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

[5] The fraction of failed recruitment attempts was on the same level in 2010, just after the financial crisis (19 %) as in the boom year 2007 (18 %). Source:"Rekryteringsenkäten" published by Svenskt Näringsliv.

[6] These are unweighted means across local labour markets. If we instead consider aggregate numbers, we find that unemployment was, on average, 6.18 percent, the monthly inflow into unemployment was 0.85 percent and hiring from unemployment was 0.65 percent of the labour force. Vacancies were 0.54 percent and the monthly inflow and outflow of vacancies were both 0.79 percent of the labour force.

An important question, then, is how representative registered unemployed workers are of the total population of unemployed workers. To get some idea, we can compare with data from the labour force survey. The survey data are too limited to do analysis on the local labour market level but we can compare aggregate time series. *Figure 2* shows that, for Sweden as a whole, unemployment registered at the Public Employment Service (AF) has fluctuated in a similar way as unemployment according to the labour force survey (AKU). However, the number of unemployed workers that are registered at the Public Employment Service has declined over time compared to the survey measure.[7]

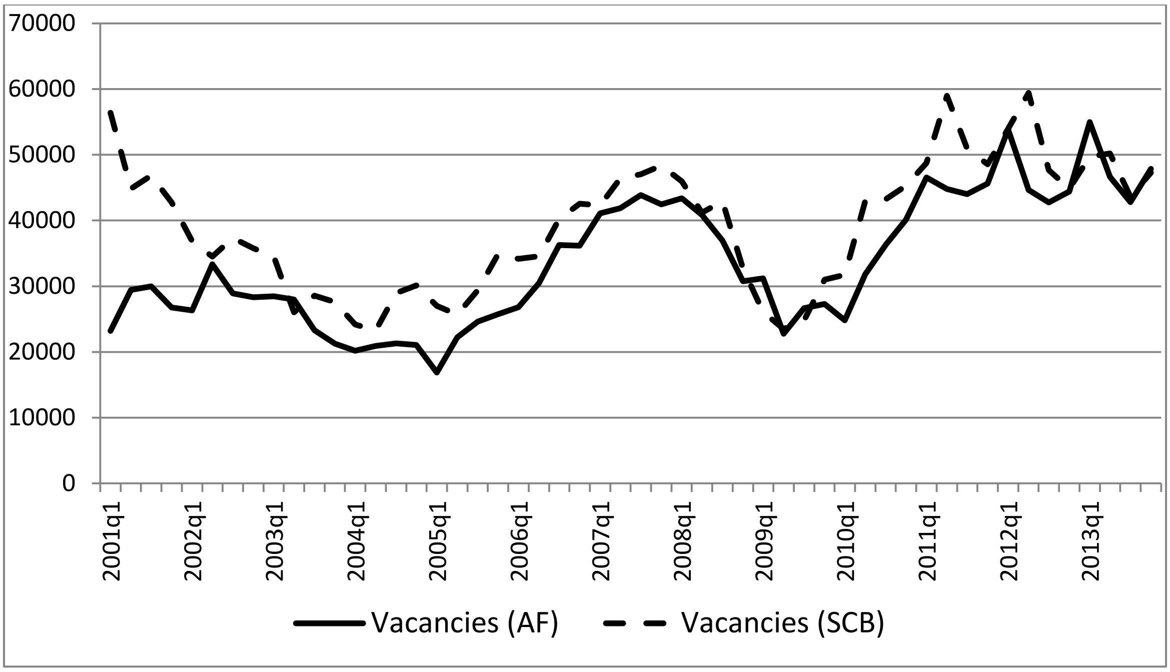
Figure 2. Alternative Measures of Unemployment



Note: The figure 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 series are seasonally adjusted.

7 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. There are several differences between these two measures of unemployment, which have 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. 191 100 persons were openly unemployed according to AF: $376\,700 - 133\,600 - 105\,500 + 34\,700 + 18\,700 \approx 191\,100$.

Figure 3. Alternative Measures of Vacancies



Note: The figure 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.

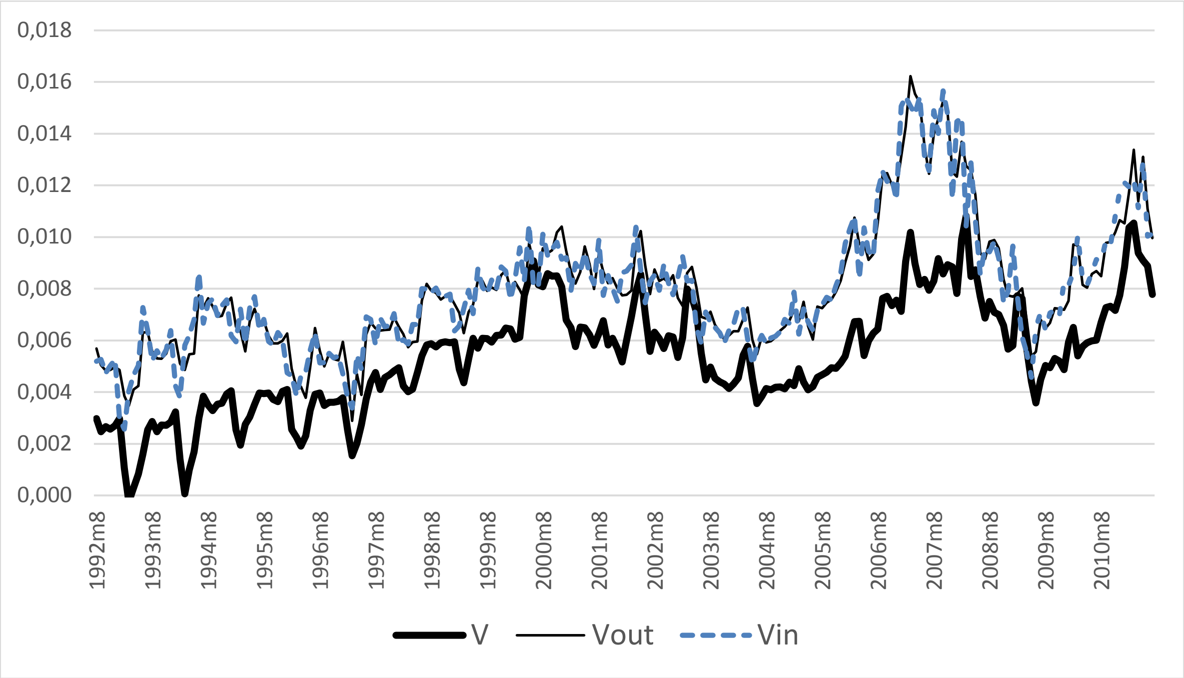
Figure 3 shows that aggregate vacancies registered at the Public Employment Service (AF) are closely correlated with available jobs according to a survey conducted by Statistics Sweden (SCB) that began in the year 2001 (except for the first year of the survey).

Thus we see that, at the aggregate level, the measures from the Public Employment Service correlate well with the survey measures. They appear to be sufficiently broad and representative to be useful for studying the relations between stocks and flows in the labour market. The long-term decline 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.

Flows of Vacancies and Hirings along the Beveridge Curve

Before we move to estimation we illustrate the data for the aggregate economy. *Figure 4* shows that the inflow and the outflow of vacancies are very similar and they are very closely correlated with the vacancy stock. Note also that the flows are larger than the stock because the duration of a vacancy is less than a month.

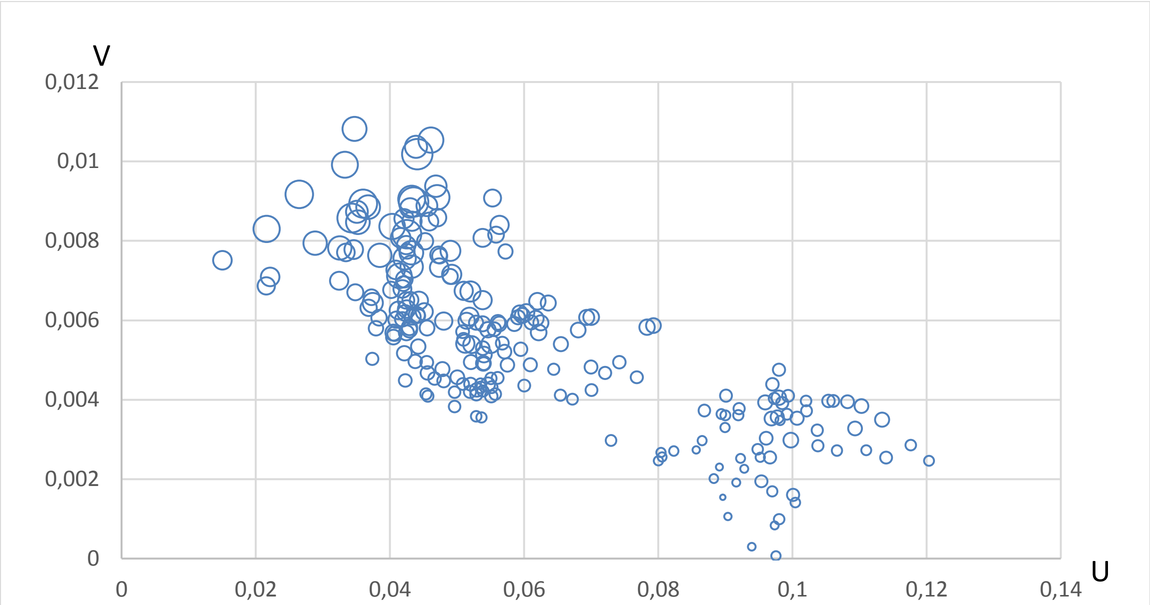
Figure 4. Inflow, Outflow and Stock of Vacancies



Note: All variables are measured relative to the labour force and seasonally adjusted. The seasonal adjustment produces some negative values.

Figure 5. De-registrations of Vacancies along the Beveridge Curve

Larger bubble = larger deregistrations of vacancies



Note: The period is 1992-2011. All variables are measured relative to the labour force and seasonally adjusted. The seasonal adjustment produces some negative values.

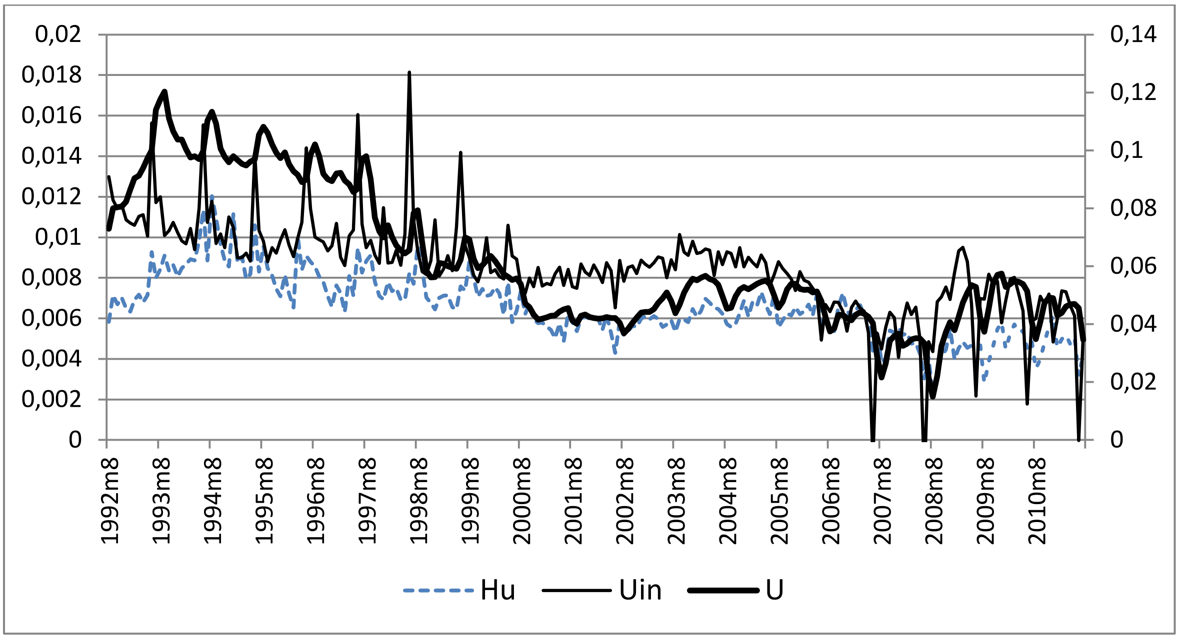
Figure 5 allows us to see how de-registrations of vacancies vary along the Beveridge Curve. Here we have unemployment on the horizontal axis and vacancies on the vertical axis and the size of the bubbles reflects outflows (de-registrations) of vacancies. If we compare the sizes of the bubbles in the vertical direction, holding unemployment constant, we can see that a larger stock of vacancies leads to more vacancies being deregistered. Comparing the sizes of the bubbles in the horizontal direction, holding vacancies constant, it is hard to see any relation between unemployment and the number of vacancies being deregistered. There is no sign that vacancies are filled more quickly when unemployment is high.[8]

Figure 6 shows that hiring from unemployment and the inflow into unemployment are both positively correlated with unemployment. In *Figure 7*, we again have unemployment on the horizontal axis and vacancies on the vertical axis, but now the size of the bubbles reflects hiring from unemployment. Comparing the bubbles in the horizontal direction, holding the stock of vacancies constant, we see clearly that hiring from unemployment is higher when unemployment is high. Of course, the probability of finding a job is lower when there are many unemployed workers competing for the jobs, but the number of unemployed job searchers is higher and the latter effect dominates. Comparing the sizes of the bubbles in the vertical direction, holding unemployment constant, we can perhaps see some evidence of a positive relation, between the number of vacancies and hiring from unemployment, but this relation is surprisingly weak.

Our graphical examination indicates strong “own effects” in the sense that more vacancies lead to more vacancies being filled and high unemployment leads to more hires from unemployment, but the “cross effects” appear surprisingly weak. However, we may worry that the picture is distorted because of common unobserved shocks and long-term structural changes. By including time dummies in our panel estimation we can eliminate the effects of common unobserved factors and this should make the results more reliable. By IV estimation we can reduce the effects of measurement errors and simultaneity.

[8] The reader may think that it would be more intuitive to present data on the probability of filling a vacancy but many vacancies are registered and deregistered in the same month and we cannot follow individual vacancies over time, so there is no obvious measure of this probability. This is why we consider flows rather than probabilities in the graphs and the empirical estimation.

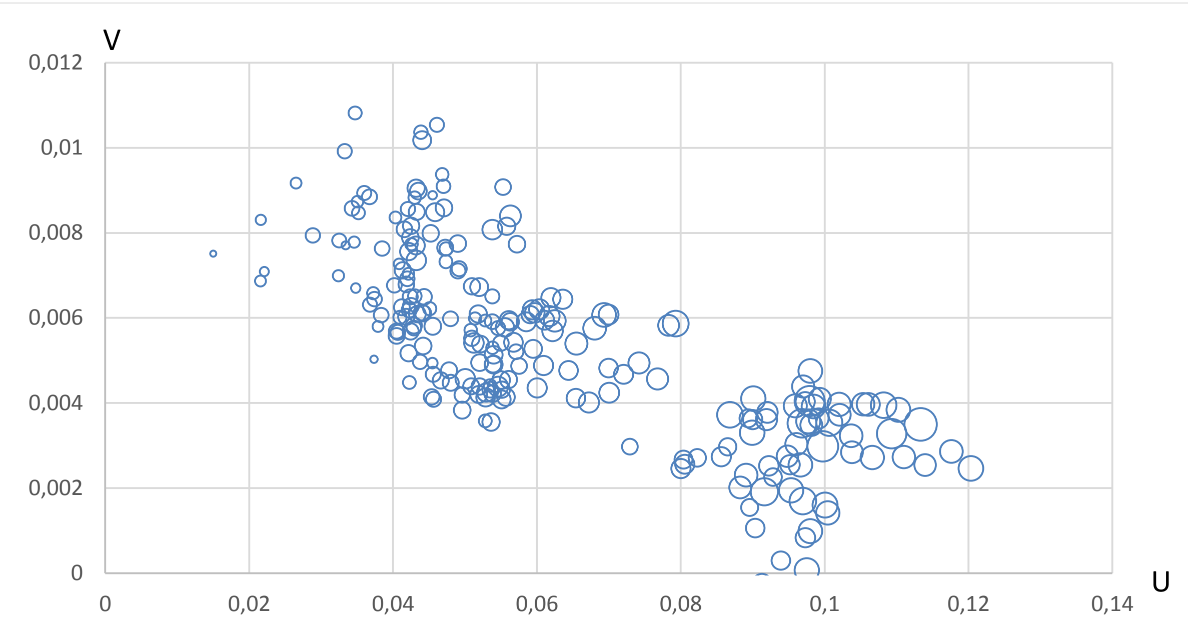
Figure 6. Inflow, Hiring from Unemployment and Stock of Unemployment



Note: All variables are measured relative to the labour force and seasonally adjusted. The seasonal adjustment produces some negative values. The scale for the flows is on the left axis and the scale for the stock is on the right axis.

Figure 7. Hiring from Unemployment along the Beveridge Curve

Larger bubble = larger hiring from unemployment



Note: The period is 1992-2011. All variables are measured relative to the labour force and seasonally adjusted. The seasonal adjustment produces some negative values.

3. Estimation of Matching Functions

In this section, we specify a matching function and we derive the equations 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 and U_t^{in} is the inflow during the month. E_t is unobserved and consists of two groups of job seekers: employed job seekers and those without jobs who are not registered as unemployed but still available for work. 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 have less time to be matched 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. The argument is that the new entrants 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.[9]

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

$$H_t = \phi_t \left(U_{t-1} + \lambda U_t^{in} + E_t \right)^{\alpha} \left(V_{t-1} + \theta V_t^{in} + \Omega_t \right)^{\beta} \qquad (4)$$

where H_t is the total number of hires and we assume that α and β are positive but smaller than unity. We do not impose constant returns to scale because we see no compelling reason to do so.[10] The variable ϕ_t represents variations in "matching efficiency," which may be due to variations in mismatch, incentives and the efficiency of the public employment service.

[9] Studies of stock-flow matching include Coles and Smith (1998), Gregg and Petrongolo (2005), Coles and Petrongolo (2008) and Ebrahimy and Shimer (2010).

[10] 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.

With this specification, the rate at which vacancies are filled is $Q_t = H_t / \left(V_{t-1} + \theta V_t^{in} + \Omega_t\right)$ and the number of registered vacancies that are filled during the month can be written as

$$V_t^{out} = Q_t \left(V_{t-1} + \theta V_t^{in}\right) = \left(U_{t-1} + \lambda U_t^{in}\right)^{\alpha} \left(V_{t-1} + \theta V_t^{in}\right)^{\beta} \eta_t \tag{5}$$

where the unobserved part is $\eta_t = \phi_t \left(1 + E_t / \left(U_{t-1} + \lambda U_t^{in}\right)\right)^{\alpha} \left(1 + \Omega_t / \left(V_{t-1} + \theta V_t^{in}\right)\right)^{\beta - 1}$.

Similarly, the job-finding rate for someone who is unemployed at the beginning of the period is $F_t^u = H_t / \left(U_{t-1} + \lambda U_t^{in} + E_t\right)$ and hiring from registered unemployment is

$$H_t^u = F_t^u \left(U_{t-1} + \lambda U_t^{in}\right) = \left(U_{t-1} + \lambda U_t^{in}\right)^{\alpha} \left(V_{t-1} + \theta V_t^{in}\right)^{\beta} \varepsilon_t \tag{6}$$

where the unobserved part is $\varepsilon_t = \phi_t \left(1 + E_t / \left(U_{t-1} + \lambda U_t^{in}\right)\right)^{\alpha - 1} \left(1 + \Omega_t / \left(V_{t-1} + \theta V_t^{in}\right)\right)^{\beta}$. To test the predictions of the model, we estimate log-linearized versions of these equations:

$$\ln \mathrm{V}_{\mathrm{t}}^{\mathrm{out}} = a_{11} \ln U_{t-1} + a_{12} \ln U_t^{in} + a_{13} \ln V_{t-1} + a_{14} \ln V_t^{in} + \ln \eta_t \tag{7}$$

$$\ln \mathrm{H}_{\mathrm{t}}^{\mathrm{u}} = a_{21} \ln U_{t-1} + a_{22} \ln U_t^{in} + a_{23} \ln V_{t-1} + a_{24} \ln V_t^{in} + \ln \varepsilon_t \tag{8}$$

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

Values without time indexes denote steady-state values. We chose to estimate a log-linear specification as baseline because it is the standard specification and it 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 parameters α and β could potentially be inferred from the estimates.[11] 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 difference depends on how the unobserved variables co-vary with registered unemployment and vacancies. If on-the job search is constant or decreases when unemployment increases, η_t is negatively correlated with U_{t-1} and U_t^{in}, so the sum of the estimates $a_{11} + a_{12}$ will be smaller than α. Intuitively, this is

[11] 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).

because higher unemployment crowds out other job searchers. We may still argue that we estimate the *net effect* of unemployment on the filling of vacancies, but we are unable to recover the coefficients of the underlying matching function. Similar biases arise with respect to the other coefficients.[12] Thus, pro-cyclical on-the-job search changes the interpretation of the coefficients, but we would still expect all coefficient estimates to be positive when we estimate equations (7) and (8).[13]

Estimation Method

To investigate how stocks and flows are related, we rely on differences in the variation over time across local labour markets. Thus, we include fixed effects for local labour markets and time dummies in our baseline specification. We include fixed effects because the matching process may differ between labour markets due to geography and industry structure.

We include time dummies in the estimation 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 would be driven mainly by the aggregate business cycle. Then, there would be a risk that the results were driven by some unobserved macroeconomic shocks that affected all local labour markets in a similar 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 macro shocks.

The second reason to include time dummies is that we have data for a long time period, and there have clearly been long-term structural changes in the labour market during this period. As discussed above, there has been a decline in the number of unemployed workers that are registered at the Public Employment Service compared to the survey measure of unemployment and firms' behaviour with respect to the posting of vacancies may also have

[12] Petrongolo and Pissarides (2001) discuss these biases. Whether search on the job is pro-cyclical is not clear. Elsby, Michaels and Ratner (2015) construct a measure of on the job search and find it to be slightly countercyclical.

[13] For unemployment to have no effect on the rate at which vacancies are filled, an increase in unemployment would have to be fully countered by a decrease in on-the-job search, and this is unlikely. 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 remains unchanged.

changed. By including time dummies, we can account for changes in rules and behaviour – provided that these changes had similar effects across local labour markets.[14]

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. To further account for long-term structural changes, we include linear and quadratic time trends which are specific for each labour market. *Table 1* shows that substantial variation remains in the explanatory variables after removing fixed effects for local labour markets, common time effects, and local seasons and trends.

We estimate equations (7) and (8) by ordinary least squares (OLS) and instrumental variable estimation (IV). In the IV estimation, we use five lags of the inflows and the stocks six months earlier as instruments. By instrumenting, we can alleviate two problems. First, there may be purely random variation in the fractions of unemployed workers and vacancies that register with the employment service. This is a measurement error that may lead to biased estimates. 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 leading to a decline in ϕ_t. This means that hiring from unemployment decreases and the stock of unemployment increases over time. Thus, persistent mismatch shocks imply reverse causation that will lead us to underestimate the effect of unemployment on hiring. To address these problems, we use lagged inflows and stocks as instruments because they should be more exogenous with respect to the matching process in a given period than recent stocks and current inflows.

Results

Table 2 shows OLS and IV estimates of equations (7) and (8) with de-registrations of vacancies and hiring from unemployment as dependent variables. All variables are measured relative to the labour force.

[14] 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 register of the Public Employment Service, and this appears to have increased the share of job postings that are registered. iv) Vacant summer jobs are posted earlier in the year in the latter part of the sample period.

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.

Table 2. Determinants of Outflows of Unemployed Workers and Vacancies

	(1)	(2)	(3)	(4)
Dependent variable	$\ln V_t^{out}$	$\ln V_t^{out}$	$\ln H_t^{u}$	$\ln H_t^{u}$
Estimation	OLS	IV	OLS	IV
$\ln U_{t-1}$	-0.012	0.103	0.576***	0.585***
	(0.022)	(0.071)	(0.023)	(0.053)
$\ln U_t^{in}$	-0.016	-0.065	0.000	0.207***
	(0.019)	(0.083)	(0.013)	(0.060)
$\ln V_{t-1}$	0.415***	0.487***	0.009***	0.013*
	(0.009)	(0.018)	(0.003)	(0.007)
$\ln V_t^{in}$	0.462***	0.821***	0.038***	0.111**
	(0.013)	(0.065)	(0.005)	(0.043)
Observations	20,391	19,722	20,394	19,725
R-squared	0.799	0.731	0.853	0.845
Number of llm	90	90	90	90
Hansen (p-value)		0.973		0.220
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. All variables are measured relative to the labour force in the local labour market.

Column 1 in *Table 2* shows the OLS estimate of equation (7) 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 any significant effects on the number of vacancies being filled.

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. 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 and simultaneity. Again, we see no effect of unemployment on de-registrations of vacancies. The sum of the four coefficients in column 2 is 1.346, so instead of congestion we find increasing returns to scale.[15]

Columns 3 and 4 in *Table 2* show estimates of equation (8) with hiring from unemployment as the dependent variable. According to the OLS estimates in column 3, unemployment and vacancies both have statistically significant effects on hiring from unemployment, but unemployment has a quantitatively much larger effect than vacancies have. The IV estimates are shown in column 4, and again the test statistics show that the instruments are both valid and relevant. As expected, the coefficients for the stocks increase as we go from OLS to IV, but the differences are small. The concern, which was raised above, that persistent mismatch shocks (shocks to ϕ_t) create a simultaneity problem does not appear to be an important problem. The coefficients for the inflows increase 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.

In the IV estimation, the sum of the coefficients for the stock and inflow into unemployment is 0.792, so a 1 percent increase in the stock and the inflow into unemployment will raise hiring from unemployment by 0.79 percent. A 1 percent increase in (new and old) vacancies increases hiring from unemployment by only 0.12 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. Thus, the signs of the effects are qualitatively in line with the implications of the

[15] We can statistically reject constant 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.

matching function, but the effect of vacancies on the hiring of unemployed workers is surprisingly weak.

Robustness across Time and Space

In *Table 3* we investigate the robustness of the results for the vacancy 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 and in columns 4-6 we divide the sample into small, medium and large labour markets based on their mean employment level, with one third of the labour markets placed in each category. The results are robust across time and space. In no case do we find any statistically significant effect of unemployment on deregistration of vacancies.

In *Table 4* we investigate the robustness of the results for the unemployment outflow across time and space. 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.

These robustness checks show that our results are not due to some specific shocks that happened in particular time periods or in specific labour markets.

Alternative Trends, Aggregate Data and Labour market Programs

Table 5 shows estimations 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 some positive effect on de-registrations of vacancies, but 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 8 times larger than the effect of one standard deviation changes in both U and U^{in}.[16]

[16] Using the standard errors in the first row of Table 1 and the coefficients in the third 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 3. De-registrations of Vacancies: Robustness across Time and Space

	(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
$\ln U_{t-1}$	0.103	-0.238	-0.024	0.168	-0.022	0.150
	(0.071)	(0.216)	(0.075)	(0.143)	(0.098)	(0.122)
$\ln U_t^{in}$	-0.065	0.464	0.013	-0.078	0.016	-0.105
	(0.083)	(0.344)	(0.122)	(0.174)	(0.108)	(0.135)
$\ln V_{t-1}$	0.487***	0.428***	0.536***	0.498***	0.479***	0.446***
	(0.018)	(0.030)	(0.018)	(0.026)	(0.026)	(0.045)
$\ln V_t^{in}$	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: Dependent variable is $\ln V_t^{out}$. 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. All variables are measured relative to the labour force in the local labour market.

Table 4. Hiring from Unemployment: Robustness across Time and Space

	(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
$\ln U_{t-1}$	0.585***	0.844***	0.668***	0.718***	0.568***	0.483***
	(0.053)	(0.193)	(0.059)	(0.095)	(0.043)	(0.084)
$\ln U_t^{in}$	0.207***	0.242	0.123	0.061	0.205**	0.278***
	(0.060)	(0.243)	(0.084)	(0.104)	(0.100)	(0.097)
$\ln V_{t-1}$	0.013*	0.022*	0.012**	0.009	0.022***	-0.003
	(0.007)	(0.011)	(0.005)	(0.012)	(0.008)	(0.013)
$\ln V_t^{in}$	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: Dependent variable is $\ln H_t^u$ 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. All variables are measured relative to the labour force in the local labour market.

Table 5. Leaving out Local Trends or Time Dummies

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	$\ln V_t^{out}$	$\ln V_t^{out}$	$\ln V_t^{out}$	$\ln H_t^{u}$	$\ln H_t^{u}$	$\ln H_t^{u}$
Estimation	Baseline IV	No trends IV	No t. d. IV	Baseline IV	No trends IV	No t. d. IV
$\ln U_{t-1}$	0.103	0.152***	0.133***	0.585***	0.416***	0.811***
	(0.071)	(0.037)	(0.029)	(0.053)	(0.041)	(0.038)
$\ln U_t^{in}$	-0.065	-0.100*	0.088***	0.207***	0.328***	0.083**
	(0.083)	(0.059)	(0.031)	(0.060)	(0.057)	(0.038)
$\ln V_{t-1}$	0.487***	0.488***	0.453***	0.013*	0.020***	-0.027**
	(0.018)	(0.017)	(0.019)	(0.007)	(0.007)	(0.013)
$\ln V_t^{in}$	0.821***	0.727***	0.720***	0.111**	-0.012	0.462***
	(0.065)	(0.034)	(0.041)	(0.043)	(0.025)	(0.048)
Time dummies	YES	YES	NO	YES	YES	NO
Local trends	YES	NO	YES	YES	NO	YES
Observations	19,722	19,722	19,722	19,725	19,725	19,725
R-squared	0.731	0.749	0.741	0.845	0.820	0.645
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. All variables are measured relative to the labour force in the local labour market.

Table 6 shows estimates on aggregate data for the same period. In columns 1 and 2, the effect of unemployment on the outflow of vacancies is negative but quite close to zero. In columns 3 and 4, the initial vacancy stock appears to have a negative effect on hires from unemployment, but the sum of the effects of the stock and inflow of vacancies is positive. The Hansen test indicates lack of validity of the instruments. As noted above, there have been structural changes over this long time period, and we therefore view the panel estimates with time dummies as much more convincing estimates.

Table 6. Estimation on Aggregate Data

	(1)	(2)	(3)	(4)
Dependent variable	$\ln V_t^{out}$	$\ln V_t^{out}$	$\ln H_t^{u}$	$\ln H_t^{u}$
Estimation	OLS	IV	OLS	IV
$\ln U_{t-1}$	-0.055***	-0.071*	0.627***	0.748***
	(0.021)	(0.039)	(0.030)	(0.047)
$\ln U_t^{in}$	-0.111***	0.035	0.144***	0.198**
	(0.037)	(0.067)	(0.049)	(0.100)
$\ln V_{t-1}$	0.137***	0.103***	-0.160***	-0.284***
	(0.020)	(0.027)	(0.026)	(0.041)
$\ln V_t^{in}$	0.761***	0.889***	0.485***	0.715***
	(0.027)	(0.040)	(0.035)	(0.067)
Observations	228	222	228	222
R-squared	0.985	0.981	0.964	0.956
Hansen (p-value)		0.000		0.066
Kleibergen-Paap (p-value)		0.000		0.000

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.) Instruments for IV are five lags of inflows plus the stocks in t-6. All variables are measured relative to the labour force in the local labour market.

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 Appendix A).

To sum up, we find two surprising results. First, there is no (or only weak) evidence that high unemployment speeds up the rate at which vacancies are filled. Second, vacancies have a surprisingly small effect on the hiring of unemployed workers. These results are hard to reconcile with the predictions of standard search-matching model. If information frictions are important, more agents on the other side of the market should increase the probability that a searcher finds a suitable match.

4. Comparison with Previous Empirical Results

Comparing to previous empirical results, we find it most interesting to compare with studies which use similar methodology, i.e. panel studies where constant returns to scale are not imposed and the regressions include time dummies and fixed effects for local or regional labour markets.[17] Taking a close look at the literature, we find that results that are similar to ours have, in fact, been reported before.

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 small effect). 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 (see 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

[17] As discussed above, studies on aggregate data can lead to spurious results because of macro shocks and pure cross section estimates such as Coles and Smith (1996) answer very different questions about how the size and density of the labour market affects the matching process.

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 translog specification they find a somewhat bigger role for the supply side, but it is still the demand side that dominates.[18]

Borowczyk-Martins, Jolivet and Postel-Vinay (2013) estimate matching functions using JOLTS data. They measure the job finding rate by all additions to the payroll divided by unemployment. In their baseline estimation, they impose constant returns to scale so that the explanatory variable is tightness, which means that the effects of unemployment and vacancies are restricted to be equal in magnitude but with opposite signs. When they relax constant returns to scale, their OLS estimate gives a *negative* effect of unemployment on the number of matches. They also perform GMM estimation, finding a positive effect of unemployment on hiring, but the estimated effect is far from statistically significant.[19]

Using firm-level data Carlsson, Eriksson and Gottfries (2013) and Stadin (2015) found that higher unemployment does not make firms hire more workers.

Edin and Holmlund (1991) estimated matching functions on aggregate data for Sweden with the outflow of vacancies as the dependent variable and initial stocks and a trend as explanatory variables. They found 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 very low, while our sample begins with the crisis years 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.

[18] There are typos in their Table 2. Hynninen (2005) estimates matching functions on monthly panel data for local labour 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, vacancies have very short durations and the inflows help very much to explain the outflows.

[19] Relaxing CRS they write the matching function as $m = a + \eta v + \delta u$. The OLS estimate of δ is -0.282 $1-1.118-0.164$ and the GMM estimate is 0.381; see page 449 in the paper.

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) and Coles and Petrongolo (2008), which have inspired our specification. 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 that 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 and 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 $(0.111 \cdot 0.505 = 0.056)$ while a one standard deviation increase in the initial vacancy stock leads to a 0.9 percent increase in hiring from unemployment $(0.013 \cdot 0.706 = 0.009)$.[20]

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 found, 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 similar to ours, with small effects of vacancies on the outflow from unemployment.

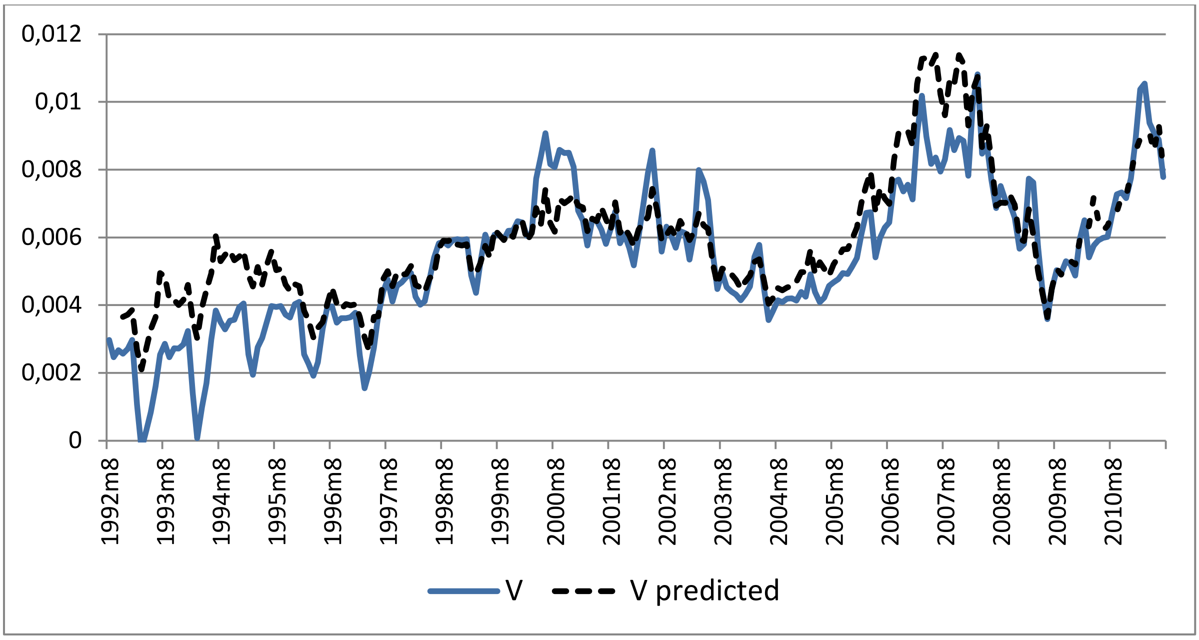
We conclude that although our results may come as a surprise to some readers, similar results can be found scattered in the literature.

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

5. A Model of Competition between Employed and Unemployed Job Seekers

The estimates in Section 3 tell us something important about vacancy data. High unemployment has no, or only a weak effect on the number of vacancies that are de-registered. There are many vacancies in a boom, not because vacancy durations increase but because there is a *large inflow* of new vacancies when the labour market is tight. To document this in another way, we estimated the following regression on the panel data: $V_t^{out} = \beta_1 V_t^{in} + \beta_2 V_{t-1}$, where the variables are not in logs. *Figure 8* shows that using this equation we can explain most of the variation in the aggregate vacancy stock.

Figure 8. Vacancy Stock: Actual and Predicted by Inflows



Note: Estimating $V_t^{out} = \beta_1 V_t^{in} + \beta_2 V_{t-1}$ by IV with fixed effects, time dummies, local seasons and trends we obtained the estimates $\hat{\beta}_1 = 0.460 \ (0.154)$ and $\hat{\beta}_2 = 0.705 \ (0.048)$. The predicted stock is generated as $V_t^{\text{Predicted}} = (1-0.460)\cdot V_t^{in} + (1-0.705)\cdot V_{t-1} = 0.540 \cdot V_t^{in} + 0.295 \cdot V_{t-1} = 0.540 \cdot \left(V_t^{in} + 0.295 \cdot V_{t-1}^{in} + 0.295^2 V_{t-2}^{in}\right)$ where we neglect inflows before t-2. Vacancies are measured relative to the labour force and seasonally adjusted.

So how can we explain the Beveridge curve? In this section we argue that the Beveridge curve slopes downward, not because vacancies are filled more quickly when there is high unemployment, but because fewer employed workers switch jobs when there is more competition for jobs, leading to a *smaller inflow* of new vacancies. To make this argument concrete, we construct a very simple model with on-the-job search.[21] We show that a model with on-the-job search and small (or no) search frictions can generate a Beveridge curve and that it is broadly consistent with the observed cyclicality of the labour market flows.

The model is similar to those of Akerlof, Rose and Yellen (1988) and Eriksson and Gottfries (2005). We do not model labour demand. Our aim is to derive some *equilibrium relations* between unemployment, vacancies and the labour market flows that we can observe in these data. We make the following assumptions:

- At the end of a month, workers can be in three states: employed in "regular jobs", N_t, employed in "alternative jobs" X_t, or they can be non-employed job seekers, S_t.
- The stock S_t includes both those who are registered as unemployed and the effective number of other non-employed job-seekers, i.e. workers who are potentially available for work but, for some reason, do not count as unemployed. We assume that a fraction λ of the non-employed job seekers are registered as unemployed: $U_t = \lambda S_t$. We make the distinction between S_t and U_t because we know that many workers are hired from non-employment without having first been registered as unemployed.
- Job seekers consist of those who were not employed at the beginning of the period, S_{t-1}, and employed job seekers, $(s_t + z_t) N_{t-1}$. Hiring in the regular labour market is determined by a matching function with constant returns to scale: $H_t = \phi\left(S_{t-1} + \left(s_t + z_t\right) N_{t-1}\right)^{\alpha} V_{t-1}^{1-\alpha}$.
- Each month, a share z_t of the previously employed workers search on the job and *switch jobs if they find a new job* – otherwise they stay in their old job. The variable z_t is taken as exogenous and we do not model the reasons why some workers want to

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

switch jobs.[22] The number z_t reflects not only the number of employed workers trying to switch jobs but also their search intensity and their willingness and ability to compete for jobs. This means that if employed workers tend to have skills that are more attractive to employers compared to unemployed workers, this will be reflected in a higher z_t.[23]

- Each month, a share s_t of the previously employed workers *must leave their jobs* for exogenous reasons which may have to do with the job, the worker, or the match. These workers apply for a new job and switch directly to the new job if they find one. If they do not find a job, they join the pool of non-employed job seekers.[24]
- Each month, a fraction χ of the non-employed job searchers find *alternative jobs* which have not been announced as vacancies. The stock of workers in alternative jobs is denoted X_t. Workers in alternative jobs do not search and these jobs end at a rate θ in which case the worker returns to job search. The flow to "alternative" jobs is included in order to account for the fact that, in periods when there were almost no registered vacancies, 6-7 percent of the unemployed still reported that they found jobs. Workers may find jobs abroad, become self-employed, or join a labour market programs that provide some form of employment. Temporary layoffs may also contribute to this flow. If, instead of one worker being unemployed over a period, there are several workers who alternate on temporary layoffs, we will see flows in and out of unemployment without any vacancies being registered.
- Each month, a fraction δ of the non-employed job searchers enter into a pool Λ_t of *latent job seekers* who do not seek jobs and a fraction μ of these workers return to job search. These flows are included in order to account for the fact that some unemployed workers leave unemployment without finding jobs. Workers may interrupt their search in order to study or go abroad or they may become discouraged and temporarily abandon job search.

[22] Job-ladder models provide micro-foundations for workers wanting to switch jobs. However, Akerlof, Rose and Yellen (1988) emphasize that many job-switchers do not increase their wages by switching jobs, so non-pecuniary rewards must also be important for turnover.

[23] Consider a model where job seekers apply for all job openings and an employer hires the applicant who is most productive in the specific position that he needs to fill. The productivity of a particular worker in a specific position is the sum of his inherent ability and a stochastic component. In the long run equilibrium of that model, the pool of unemployed workers will on average have less inherent ability than the pool of employed workers.

[24] We can think of some of these workers as retiring and being replaced by new entrants who behave the same way. We do not explicitly include retirement and new entrants because these flows are small relative to the other flows. Including them would complicate the equations without changing the conclusions.

With these assumptions, the job-finding rate for a worker searching on the job is

$$F_t = \frac{H_t}{S_{t-1} + (s_t + z_t) N_{t-1}} \tag{9}$$

and the job finding rate for a non-employed job searcher is $F_t + \chi$.[25] To keep the model simple, we assume that turnover is sufficiently large so that all adjustments of employment can be made via hiring. This means that total separations from jobs are $(s_t + z_t F_t) N_{t-1}$ and the stocks evolve according to the following equations:

$$\Delta N_t = H_t - (s_t + z_t F_t) N_{t-1} \tag{10}$$

$$\Delta S_t = (1 - F_t) s_t N_{t-1} + \theta X_{t-1} + \mu \Lambda_{t-1} - (F_t + \chi + \delta) S_{t-1} \tag{11}$$

$$\Delta X_t = \chi S_{t-1} - \theta X_{t-1} \tag{12}$$

$$\Delta \Lambda_t = \delta S_{t-1} - \mu \Lambda_{t-1}. \tag{13}$$

We now examine the implications of this simple model for how vacancies, the job-finding rate, and the flows in and out of unemployment vary with the state of the labour market.

The Beveridge Curve

Using (9) to substitute for the job finding rate in (10) and using $U_t = \lambda S_t$ we get

$$H_t = \left(1 + \frac{z_t N_{t-1}}{U_{t-1} / \lambda + s_t N_{t-1}} \right) \left(\Delta N_t + s_t N_{t-1} \right). \tag{14}$$

If $z_t > 0$, the multiplier before the parenthesis is larger than unity. This means that if 10 workers quit for exogenous reasons, this leads to more than 10 workers being hired. This is due to the fact that a new vacancy is created when a worker is hired directly from another job, leading to a *vacancy chain,* which will continue until a non-employed worker is hired (Akerlof, Rose and Yellen, 1988). This chain will be longer the more important on-the-job search is compared to search by the non-employed. If $z_t = 0$, there is no vacancy-chain effect,

[25] Note that z_t is measured in efficiency units; we do not assume that unemployed workers have a higher chance of finding a job than employed job seekers.

so the multiplier is one. If many of the hires come directly from other jobs, the vacancy chains can be very long.[26]

Since we are not interested in transitional dynamics, we consider a situation when all variables are constant.[27] Using (14) to substitute for hiring in the matching function, we get an equation for the Beveridge curve:[28]

$$\frac{V}{N}=\frac{1}{N}\left(\frac{H/\phi}{\left(U/\lambda+\left(s+z\right)N\right)^{\alpha}}\right)^{\frac{1}{1-\alpha}}=\frac{U/N+\lambda\left(s+z\right)}{\lambda}\left(\frac{\lambda s/\phi}{U/N+\lambda s}\right)^{\frac{1}{1-\alpha}}. \qquad (15)$$

This equation should be seen as an *equilibrium relation* between unemployment and vacancies for given *s* and *z*. If we assume that $z=0$, we get a similar equation for the Beveridge curve as the one presented in the introduction.[29] If, in line with our estimates, we instead set $\alpha=0$ we get the following Beveridge curve:[30]

$$\frac{V}{N}=\frac{s}{\phi}\left[1+\frac{\lambda z}{U/\mathrm{N}+\lambda s}\right]. \qquad (16)$$

If there is close to full employment, almost all workers who want to switch jobs do that and vacancies are close to $\left(s+z\right)N/\phi.$ As unemployment increases, vacancy chains become shorter and the vacancy stock approaches sN/ϕ. If $z>0$ we have a downward-sloping non-linear Beveridge curve also without search frictions. High search on the job (*s* and *z*) shifts up the Beveridge curve and the fraction of potential job-switchers, *z*, is a key determinant of the slope of the Beveridge curve. Note that *z* is measured in efficiency units so if workers searching on the job have a greater advantage in job search compared to the non-employed job seekers, this will increase the level and slope of the Beveridge curve.

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26 Our interpretation of the multiplier in equation (14) as a vacancy-chain effect is based on the notion that a firm’s demand for workers is independent of how many of its workers that quit. This interpretation is consistent with micro-evidence in Carlsson, Eriksson and Gottfries (2013) and Stadin (2015) that firms´ demand for workers depends on product demand and wages but is not directly affected by the state of the labour market.

27 Mortensen-Pissarides (1994) use the same approach.

28 We express the Beveridge curve in terms of the ratios *V/N* and *U/N* because this makes the equation simpler but it we equally well write it in terms of *V* and *U*.

29 The equation is not exactly the same because we assume that those who leave their jobs can apply for jobs in the same period.

30 This equation is essentially the same as equation (9) in Akerlof, Rose and Yellen (1988) but we have modified the model in several ways to include the labour market flows that we can observe in our data.

The Job-finding Rate

Using (14) to substitute for H_t in (9) we get the job-finding rate for a non-employed job seeker:

$$F^u = \frac{sN + \Delta N}{U/\lambda + sN} + \chi . \tag{17}$$

Note that, for a given level and growth in employment, the job-finding rate is independent of z_t. The intuition is simple: a worker who switches jobs leaves a job vacant, but she also fills a vacancy, so the total number of vacancies available for other job searchers remains unchanged. Thus we see that although the fraction of potential job switchers, z_t, is a key determinant of the number of vacancies, it does not affect the job-finding rate or hiring from unemployment. As we will discuss in the next section, variations in z_t may be one reason why we find such a weak relation between vacancies and the rate at which unemployed workers find jobs.

Hiring from Unemployment

Hiring from unemployment is

$$H^u = F^u U = \frac{U}{U/\lambda + sN} sN + \chi U . \tag{18}$$

Hiring from unemployment is high when unemployment is high, for two reasons. First, the unemployed constitute a *larger fraction* of the job seekers when unemployment is high and second, unemployed workers find jobs in alternative ways, e.g. in labour market programs.

The Flow into Unemployment

We also want to check whether the model is consistent with the observed cyclical movements of the inflow into unemployment. Considering again an equilibrium situation when all variables are constant, $\lambda\theta X = \chi U$ and $\lambda\mu\Lambda = \delta \mathrm{U}$, so the flow into unemployment is

$$u^{in} = \lambda sN\left(1-F\right) + \lambda\theta X + \lambda\mu\Lambda = \lambda sN\left(1-F\right) + \left(\chi+\delta\right)U. \tag{19}$$

The inflow into unemployment is high when unemployment is high, for two reasons. First, a larger fraction of those who must leave their jobs end up in unemployment because they are unable to secure a job before they leave. Second, more workers return to unemployment from periods in alternative jobs and interruptions in their job seeking.[31]

Can a Calibrated Model Explain the Cyclical Patterns?

Since we do not have time series data for on-the-job search, it is hard to estimate the structural parameters of the model by conventional econometric methods. We therefore chose to calibrate a simple version of the model based on means and external information. We disregard transitional dynamics and consider an equilibrium situation when employment is constant and we treat s and z as constant parameters. The level of unemployment is used as indicator of the state of the labour market and the question we ask is whether the model can reproduce the correlations between unemployment, vacancies and labour market flows that we observe in aggregate data.

In the aggregate data, average unemployment was 6.18 percent, the inflow into unemployment was 0.85 percent and average hiring from unemployment was 0.65 percent of the labour force. In terms of our model, this means that the probability that an unemployed worker interrupted his job seeking and became a latent job seeker was 3.2 percent $\left(\delta = \left(0.0085 - 0.0065\right)/0.0618 = 0.032\right)$ and the job finding rate for the unemployed was 10.5 percent: $F + \chi = 0.0065/0.0618 = 0.105$.

As concerns the fraction of the unemployed finding jobs which have not been announced as vacancies, χ, we have no direct evidence that allows us to pin down this parameter. We chose to set it to 6.9 percent which is the lowest job finding rate in the sample period. This job finding rate was observed in a period with very few vacancies. This implies $F = 0.105 - 0.069 = 0.036$ when all observed variables were at their means. As concerns the number of workers in alternative jobs, the exact number is not important for the calibration. To simplify notation we assume that the alternative jobs are jobs, which are not included in the statistics.[32] Normalizing the labour force to one we then have $N = 1 - 0.0618 = 0.938$ when unemployment is at the mean.

[31] That the flow from employment to unemployment and the flow from unemployment to employment both increase in recessions has been noted by Blanchard-Diamond (1990) and other studies.

[32] As noted above, the flow to alternative jobs may represent workers finding jobs abroad or "sharing" the unemployment in the form of temporary layoffs. When all variables are constant $X/U = \chi/(\lambda\theta)$. If we set this ratio to e. g. 0.3 this has a very small effect on the graphs presented below.

According to a recruitment survey made by the Swedish Labour Force Survey (AKU), 33 percent of all workers recruited came directly from another employer and 13 percent were internally recruited, meaning that 46 percent came directly from another job, while another 28 percent had been outside the labour force and only 26 percent came directly from unemployment.[33] We use these numbers as measures of the *effective* number of job applicants from the different groups. Thus we set $\lambda = 26/(26+28) = 0.48$ and $(s+z)N/U = 46/26$ which gives $s+z = (46/26)0.0618/0.938 = 0.117$. To find *s* we set the inflow into unemployment to its mean value, 0.0085, which implies $s = 0.005$ and thus $z = 0.112$.[34]

In line with the baseline calibration we set $\alpha = 0$, so there are no search frictions, but we also consider values $\alpha = 0.1$ and $\alpha = 0.2$. As concerns ϕ, one possibility is to set it equal to the ratio between the means of de-registrations of vacancies and the stock: $\phi = 0.00794/0.00539 = 1.47$.[35] However, our measure of vacancies does not include all vacancies in the economy so we instead set it so that registered vacancies are at their mean level when unemployment is at its mean, which implies $\phi = 1.58$.

To evaluate the model, we solve for vacancies, the job-finding rate, hiring from unemployment and the inflow into unemployment when the labour force and employment are constant. We then plot these variables against unemployment and compare to the data. Thus we compare situations when unemployment is high and low, disregarding transitional dynamics.

Figure 9 shows that a model with $\alpha = 0$ generates a Beveridge curve that is broadly consistent with the data. If we increase α to 0.1 or 0.2, this increases the slope of the Beveridge curve but the effect is relatively small. If we set $\alpha = 0.4$ we get a somewhat better fit of the Beveridge curve for aggregate data but this value is not consistent with our estimates.

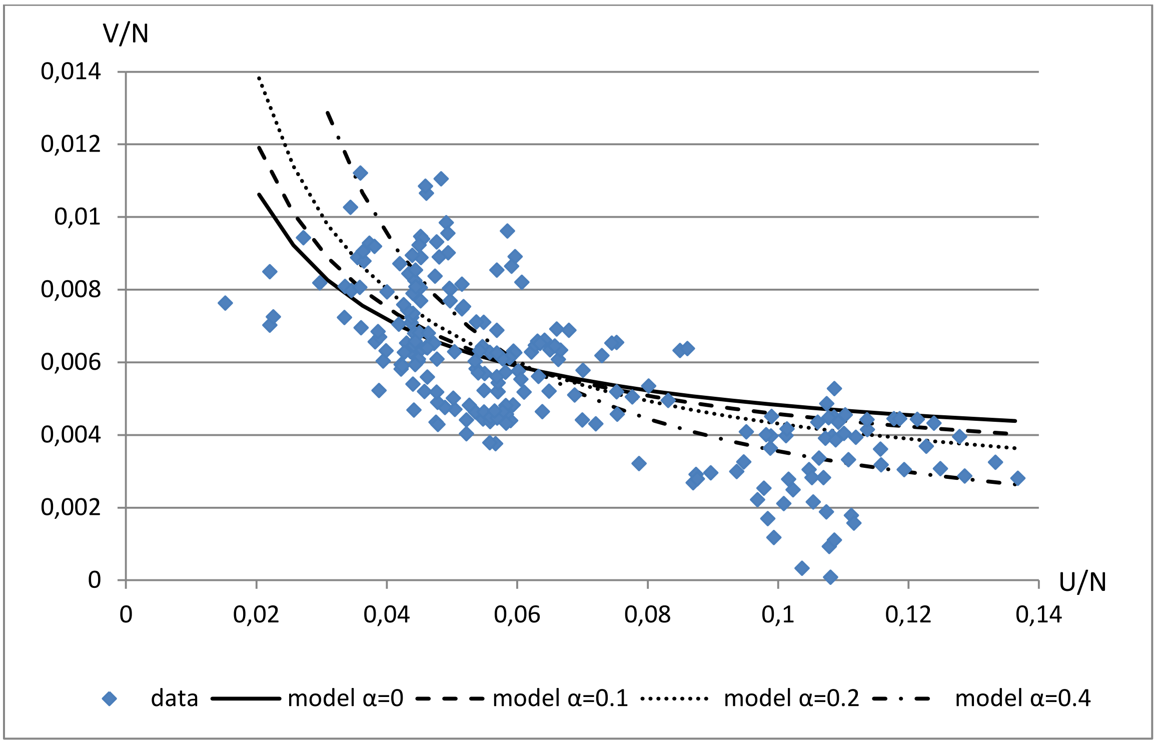
Figures 10-12 show that the model is broadly consistent with the observed cyclical fluctuations in the job finding rate, the inflow into unemployment and hiring from unemployment.

[33] These numbers are from the 2006 survey but the numbers are similar for the other years when this survey was carried out. According to Fallick and Fleischman (2004), employer-to-employer transitions comprise around 1/3 of all hires in the U. S.

[34] $u^{in} == \lambda sN(1-F) + (\chi + \delta)U = 0.48 \cdot s \cdot 0.938 \cdot (1-0.036) + (0.032+0.069) \cdot 0.0618 = 0.0085$ implies $s = 0.005$.

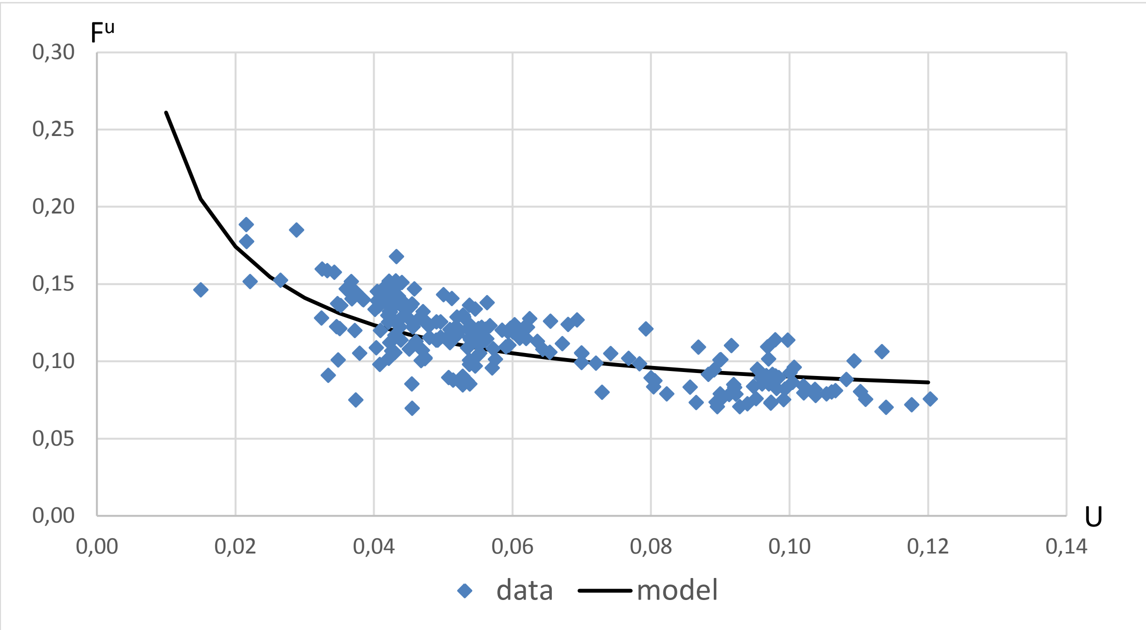
[35] The interpretation of this number is that a vacancy that is open for one month generates 1.47 hires.

Figure 9. Beveridge Curve: Model and Data



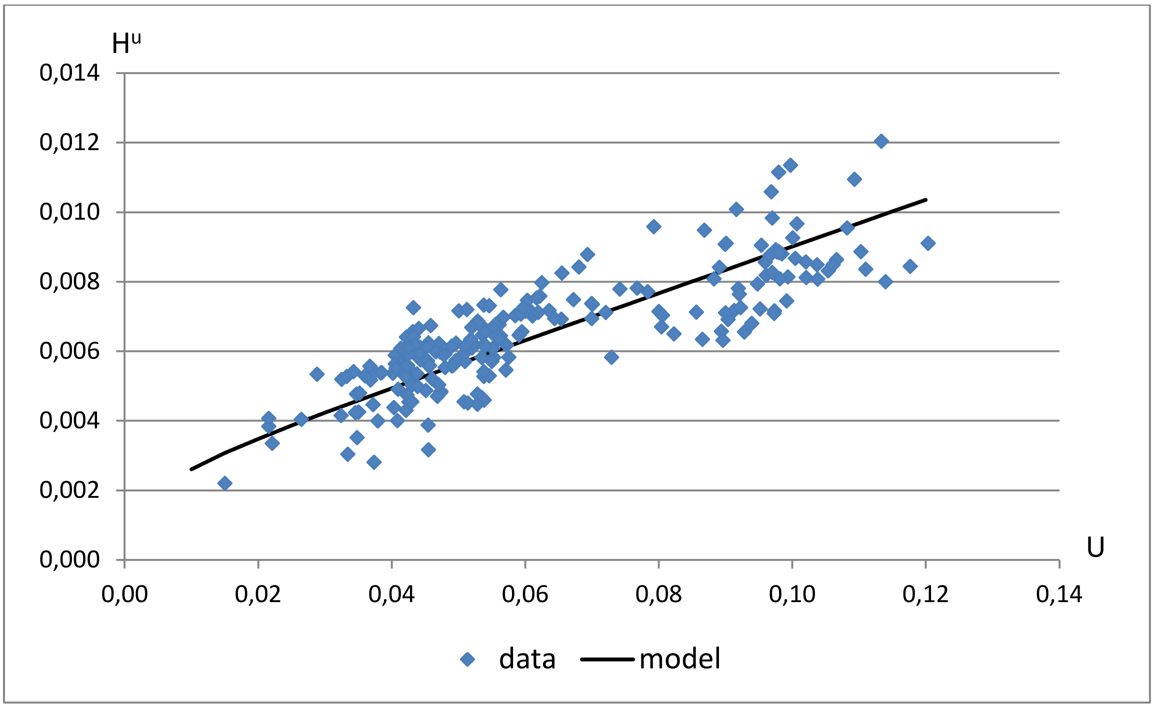
Note: Vacancies and unemployment are measured relative to employment and seasonally adjusted. The seasonal adjustment produces some negative values.

Figure 10. Job Finding Rate for Unemployed: Model and Data



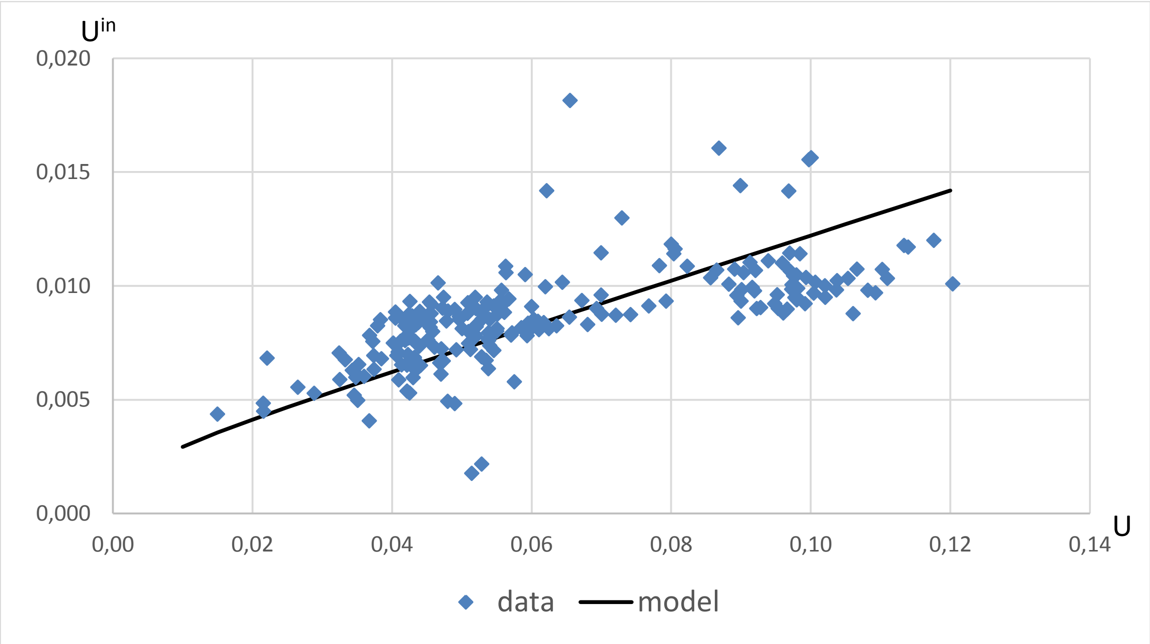
Note: Data are seasonally adjusted. U is measured relative to the labour force.

Figure 11. Hiring from Unemployment: Model and Data



Note: All variables are measured relative to the labour force and seasonally adjusted.

Figure 12. Inflow into Unemployment: Model and Data



Note: All variables are measured relative to the labour force and seasonally adjusted..

To summarize, there are many vacancies in a boom, but this is not primarily because it takes longer to fill them. Instead, long vacancy chains lead to a large inflow of new vacancies when there are few unemployed workers competing for the jobs. The chance of finding a job is low when unemployment is high, but hiring from unemployment is still high because the unemployed constitute a large fraction of the job seekers and because unemployed workers find jobs that have not been announced as vacancies. In bad times, there is a relatively large inflow into unemployment because workers who must leave their jobs are less likely to go directly to another job and because there are more workers returning from interruptions in job seeking and from temporary jobs.

Estimation of the Beveridge curve

Another way to investigate the validity of the model is to estimate the equation for the Beveridge curve. Setting $\alpha = 0$ and assuming that s, λ, z and N are constant we have the following equilibrium relation between unemployment and vacancies

$$\frac{V}{N} = a_0 + \frac{a_1}{U / \mathrm{N} + a_2}. \qquad (20)$$

Our calibration implies $a_0 = s / \phi = 0.003$, $a_1 = s\lambda z / \phi = 0.0002$ and $a_2 = \lambda s = 0.0024$. When we estimate this function, the constant a_0 is mopped up by the fixed effects. Note also that a_2 is very small relative to *U/N* (with an average of 0.0618) so for reasonable values, it has a very marginal effect on the Beveridge curve. This means that it is poorly identified and we therefore set it to 0.0024 in line with the calibration. Thus we can only estimate a_1.
Estimating a_1 with fixed effects and time dummies we obtained an estimate of 0.00026 (with t-value 1.94) which is in line with the calibrated value of 0.0002.

6. Understanding "Matching Function" Estimates

Finally, we use the model to interpret our estimates of matching functions.

Vacancy Flows

When we estimated matching functions, we found no or very weak evidence that vacancies are filled more quickly when unemployment is high. This result can be explained if firms normally have a number of qualified applicants for a job opening. Then, firms will simply post the vacancy for a while, collect the applications and chose the best applicant. Of course, it takes time and effort to recruit workers, but this time appears to be independent of the level of unemployment. A longer list of applicants will not lead to more workers being hired.

One may object that there are subsections of the labour market where there is a shortage workers and where firms have difficulties filling their vacancies. But in such markets, there is hardly any unemployment. We could allow for this in the model by assuming that the labour market is divided into sub-markets and that there are barriers that prevent workers from moving between sub-markets. Thus, suppose that there is excess supply of workers in most labour markets and they function as described above, but there are also some tight labour markets with full employment and more vacancies than workers willing to switch jobs. In the tight labour markets, all workers who want to switch jobs do that, so turnover is $(s+z)N$ and some vacancies remain unfilled. Then, higher unemployment (in other sections of the labour market) will not help to fill those vacancies, nor will an increase in vacancies in the tight labour markets help the unemployed to find jobs.

Hiring from Unemployment

The IV-estimate in *Table 2* implies that if U_{t-1} and U_t^{in} both increase 1 percent, hiring from unemployment increases 0.79 percent. To understand how this can be consistent with a model where vacancies are filled at a constant rate, it is important to realize two things: i) unemployed workers find jobs in other ways than by applying for vacancies and ii) unemployed workers constitute a clear minority of all job applicants. Considering a static equilibrium where $N = L - U$ we can write hiring from unemployment as

$$H^u = \left[\frac{\phi V}{U/\lambda + (s+z)(L-U)} + \chi \right] U \ . \tag{21}$$

To see how hiring from unemployment depends on the unemployment stock for a given number of vacancies, we calculate the elasticity with respect to U_t:

$$\frac{dH^u}{dU}\frac{U}{H^u}=1-\frac{\left(H^u-\chi U\right)\left(1/\lambda-s-z\right)}{U/\lambda+\left(s+z\right)\left(L-U\right)}\cdot\frac{U}{H^u}=1-\frac{H^u-\chi U}{H^u}\cdot\frac{U+S-\left(s+z\right)U}{U+S+\left(s+z\right)N}$$

$$=1-\frac{0.0065-0.069\cdot 0.0618}{0.0065}\cdot\frac{0.0618/0.48-0.117\cdot 0.0618}{0.0618/0.48+0.117\cdot 0.938}=1-0.34\cdot 0.51=0.83. \tag{22}$$

This number is not far from the sum of the coefficients for U_{t-1} and U_t^{in} in *Table 2*, which is 0.79. To understand this, consider first the case when unemployed workers cannot find alternative jobs: $\chi=0.$ Then the elasticity depends on how large a fraction of effective job search the unemployed workers represent. If there was no search on the job the elasticity would be zero: there would not be more unemployed workers hired because there were more applicants for the jobs. But since unemployed workers constitute a clear minority of the effective pool of job searchers, the unemployed “crowd out” the job switchers and fill a *larger fraction* of the vacancies when there are more unemployed workers seeking jobs. If, in addition, unemployed workers can find alternative jobs $(\chi>0)$ this further increases the elasticity.

Let us finally consider the effect of an increase in vacancies on hiring from unemployment. Using our calibrated model, we can calculate the elasticity of H^u with respect to *V* as

$$\frac{dH^u}{dV}\frac{V}{H^u}=\frac{\phi V}{U/\lambda+\left(s+z\right)\left(L-U\right)}\frac{U}{H^u}=1-\frac{\chi U}{H^u}=1-\frac{0.069\cdot 0.0618}{0.0065}=0.34 \tag{23}$$

This elasticity is well below unity because a substantial fraction of unemployed workers find jobs, which have not been advertised as vacancies. Still, this theoretical elasticity is substantially higher than the IV-estimate in *Table 2*, which implies that if V_{t-1} and V_t^{in} both increase 1 percent, hiring from unemployment increases only 0.12 percent. Why do we find this discrepancy between the theoretical prediction and the estimated coefficient?

Our model can help us to understand this. Note that the coefficient calculated in (23) is the effect of an increase in *V* on H^u *holding U, s and z constant*. But according to the model, an increase in vacancies for given unemployment may be caused by three possible shocks: i) there may be an increase in search on-the-job search (z), ii) there may be more exogenous separations (s), or iii) firms' desired employment growth may increase so they open more vacancies (ΔN). The last two of these shocks will lead to increased hiring of unemployed workers, but an increase in z will not increase the probability that an unemployed worker finds a job (see equation (17)). As explained above, such a shock will not only increase vacancies, but also the number of workers competing for the jobs, leaving the job opportunities for the unemployed workers unchanged. Thus, the relation between vacancies and hiring from unemployment depends on *why* vacancies vary. In practice, variations in V for given U are driven by variations in all the three factors mentioned above, so based on our calibrated model, we should expect the estimated coefficient to be somewhere between 0.34 and zero.

Mismatch is another factor that may help to explain a weak effect of vacancies on hiring from unemployment. In our model, mismatch is partly captured by z_t which will be higher if employed job seekers have a better skill composition than unemployed job seekers. But as discussed above, a more elaborate model could treat the labour market as divided into sub-markets, where some markets have full employment and more vacancies than workers willing to switch jobs. If labour demand increases in such markets, there will be more vacancies created, but these vacancies will not help the unemployed to find jobs. Quantitative modelling of mismatch is beyond the scope of this paper, however.

7. Conclusions

A common explanation of the Beveridge curve is that it reflects information frictions, which can be represented by a matching function. But when we estimate matching functions on monthly panel data for local labour markets, we find no or very weak evidence that unemployment speeds up the rate at which vacancies are filled and the number of vacancies appears to have a surprisingly weak effect on hiring from unemployment. These results are hard to reconcile with the standard search-matching framework.

One possible reaction to these results is that they may be due to measurement errors because registered unemployment and vacancies are imperfect measures of all job seekers and vacancies in the economy. But on the aggregate level, our measures correlate well with survey measures of unemployment and vacancies, so they seem to pick up economically meaningful variation. The advantage of the register data is that we have a large amount of data so that we can estimate matching functions with fixed effects and time dummies, reducing the risk of spurious correlations.

Our finding that higher unemployment does not have much effect on the rate at which vacancies are filled leads us to question the importance of search frictions. With search frictions, more unemployed workers should increase the probability that the firm finds a good match. We offer an alternative interpretation of the results, emphasising excess supply in the labour market and competition between employed and unemployed job seekers. Most of the time, firms have a que of applicants for a job opening and vacancies are filled quickly, independent of the level of unemployment. Furthermore, filling a job is not the same thing as hiring an unemployed worker. Half the recruited workers come directly from other jobs and job switches give rise to new vacancies. As unemployment falls, more workers are hired directly from other jobs, leading to more vacancies being created. There are many vacancies in a boom, not because they take longer to fill, but because there is a large inflow of new vacancies when turnover is high.

How we interpret the Beveridge curve is important for policy. If the main matching problem has to do with information, giving unemployed workers assistance and incentives to search more intensively should be an efficient way to reduce unemployment. If many of the unemployed find it hard to compete for the jobs, skill mismatch between workers and jobs may be the central problem. The harder it is for unemployed workers to compete with employed workers for jobs (higher z in the model) the more vacancies will there be for a given level of unemployment.

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Appendix A

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) $\ln V_t^{out}$ OLS	(2) $\ln V_t^{out}$ IV	(3) $\ln H_t^{up}$ OLS	(4) $\ln H_t^{up}$ IV
$\ln UP_{t-1}$	-0.007	0.096	0.631***	0.720***
	(0.030)	(0.062)	(0.027)	(0.048)
$\ln UP_t^{in}$	-0.022	-0.045	-0.004	0.129**
	(0.019)	(0.065)	(0.012)	(0.053)
$\ln V_{t-1}$	0.415***	0.488***	0.011***	0.010
	(0.009)	(0.018)	(0.003)	(0.007)
$\ln V_t^{in}$	0.462***	0.811***	0.039***	0.150***
	(0.013)	(0.062)	(0.004)	(0.040)
Observations	20,391	19,722	20,394	19,725
R-squared	0.799	0.735	0.860	0.847
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.

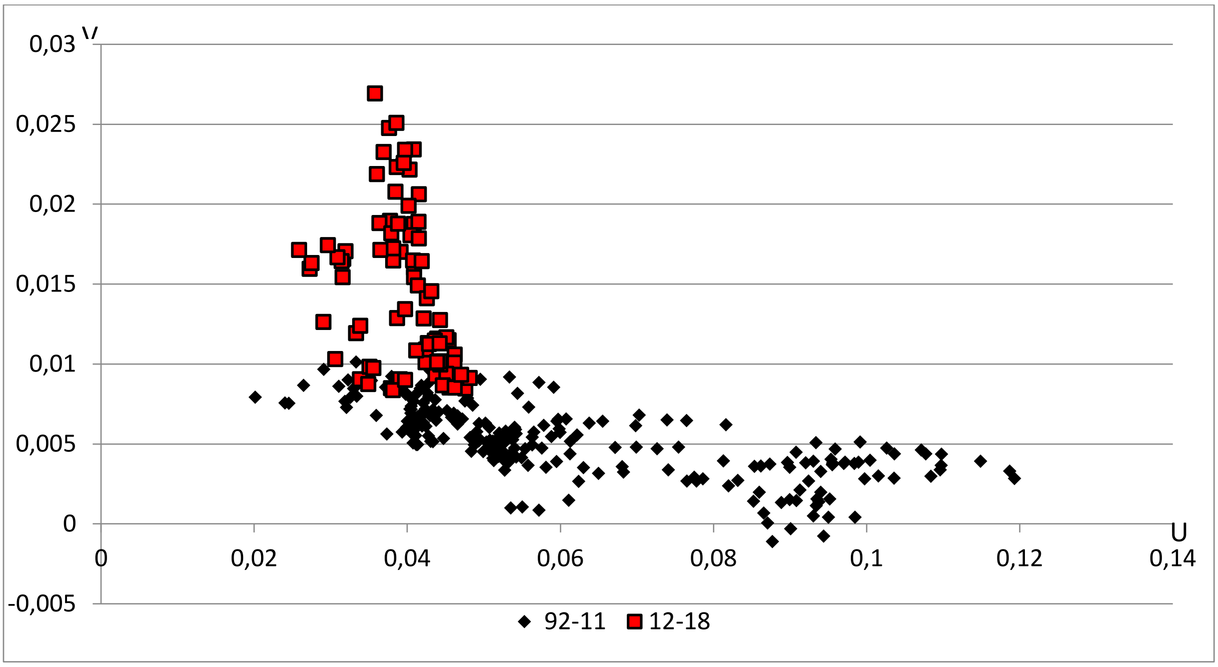
Appendix B

Estimates for the period 1992-2018

The aim of this study is to understand the co-variation of unemployment, vacancies and labour market flows in normal times. We exclude the period after 2011 because of a major structural change associated with a very large inflow of immigrants in recent years. The fraction of the registered unemployed who were born outside Europe increased from 20 percent in January 2011 to 49 percent in May 2018. *Figure B1* shows that there was a very large increase in vacancies after 2011 while unemployment remained relatively stable. We view this as a sign of growing demand for labour combined with an increase in mismatch (an increase in *z* in our model) that lead to a large upward shift in the Beveridge curve. We view the immigration as a structural shock that may distort our estimates and for this reason, we focused on estimations for the period 1992-2011 in the main analysis.[36]

However, one may argue that common structural shocks may be handled with time dummies. In this appendix we show the estimates for the whole period.[37] The baseline estimates in Table B2 are similar to those in Table 2 but we find a somewhat larger effect of unemployment on $\ln V_t^{out}$. The coefficient is 0.152 instead of 0.102 and it is significant on the 5 percent level.[38] However, as shown in *Figure 9*, setting $\alpha = 0.2$ instead of zero has a relatively small effect on the Beveridge curve.

Figure B1. Vacancies and unemployment 1992-2018



[36] Another factor is that digitalization may have increased the propensity to register vacancies.
[37] The estimations are not exactly the same, since we after 2011 don't have access to the monthly local labour force. The fact that the measures of vacancies and unemployment are not divided by the labour force should not have a big impact, however, since we include local fixed affect and local time trends.
[38] Note that the coefficient for $\ln U_t^{in}$ is also more negative.

Table B1. Standard Deviations of Explanatory Variables

Variation removed:	$\ln U$	$\ln V$	$\ln U^{in}$	$\ln V^{in}$
Fixed effects for llm, local seasons	0.421	0.844	0.366	0.587
Fixed effects for llm, local seasons, time dummies	0.187	0.552	0.227	0.457
Fixed effects for llm, local seasons, time dummies, linear and quadratic local time trends	0.128	0.523	0.196	0.410

Note: Monthly panel data from PES (AF) 1992-2018. Stocks are measured on the last day of the previous month.

Table B2. Determinants of Outflows of Unemployed Workers and Vacancies

	(1)	(2)	(3)	(4)
Dependent variable	$\ln V^{out}$	$\ln V^{out}$	$\ln H^{u}$	$\ln H^{u}$
Estimation	OLS	IV	OLS	IV
$\ln U_{t-1}$	-0.014	0.152**	0.527***	0.414***
	(0.018)	(0.066)	(0.024)	(0.049)
$\ln U_t^{in}$	-0.012	-0.085	0.007	0.325***
	(0.014)	(0.069)	(0.010)	(0.054)
$\ln V_{t-1}$	0.426***	0.500***	0.007**	0.015*
	(0.008)	(0.015)	(0.003)	(0.009)
$\ln V_t^{in}$	0.439***	0.715***	0.034***	0.069**
	(0.012)	(0.048)	(0.004)	(0.035)
Observations	28,929	28,239	28,932	28,242
R-squared	0.835	0.802	0.869	0.856
Number of llm	90	90	90	90
Hansen (p-value)		0.019		0.720
Kleibergen-Paap (p-value)		0.000		0.000

Note: Monthly panel data from PES (AF) in 1992-2018. 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.

Table B3. De-registrations of Vacancies: Robustness across Time and Space

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Period	1992-2018	1992-1999	2000-2009	2010-2018	1992-2018	1992-2018	1992-2018
Labour markets	All	All	All	All	Small	Medium	Large
$\ln U_{t-1}$	0.152**	-0.219	-0.089	-0.032	0.198	0.050	0.213**
	(0.066)	(0.177)	(0.091)	(0.087)	(0.150)	(0.054)	(0.104)
$\ln U_t^{in}$	-0.085	0.480	0.095	0.118	-0.091	-0.050	-0.066
	(0.069)	(0.303)	(0.132)	(0.265)	(0.147)	(0.088)	(0.108)
$\ln V_{t-1}$	0.500***	0.422***	0.545***	0.595***	0.518***	0.477***	0.452***
	(0.015)	(0.028)	(0.017)	(0.019)	(0.020)	(0.022)	(0.038)
$\ln V_t^{in}$	0.715***	0.865***	0.479***	0.422*	0.768***	0.582***	0.725***
	(0.048)	(0.113)	(0.133)	(0.223)	(0.061)	(0.077)	(0.110)
Observations	28,239	7,845	10,176	9,146	9,221	9,508	9,510
R-squared	0.802	0.784	0.807	0.846	0.710	0.834	0.917
Number of llm	90	90	90	90	30	30	30

Note: Monthly panel data from PES (AF) in 1992-2018. Dependent variable is $\ln V^{out.}$ 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 B4. Hiring from Unemployment: Robustness across Time and Space

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Period	1992-2011	1992-1999	2000-2009	2010-2018	1992-2018	1992-2018	1992-2018
Labour markets	All	All	All	All	Small	Medium	Large
$\ln U_{t-1}$	0.414***	0.853***	0.661***	-0.032	0.198	0.379***	0.451***
	(0.049)	(0.191)	(0.070)	(0.087)	(0.150)	(0.048)	(0.090)
$\ln U_t^{in}$	0.325***	0.177	0.137*	0.118	-0.091	0.221***	0.329***
	(0.054)	(0.228)	(0.082)	(0.265)	(0.147)	(0.077)	(0.088)
$\ln V_{t-1}$	0.015*	0.021	0.011*	0.595***	0.518***	0.022**	-0.008
	(0.009)	(0.013)	(0.006)	(0.019)	(0.020)	(0.009)	(0.011)
$\ln V_t^{in}$	0.069**	0.165*	0.131*	0.422*	0.768***	-0.027	0.220***
	(0.035)	(0.092)	(0.077)	(0.223)	(0.061)	(0.049)	(0.062)
Observations	28,242	7,845	10,179	9,146	9,221	9,510	9,510
R-squared	0.856	0.858	0.829	0.846	0.710	0.893	0.926
Number of llm	90	90	90	90	30	30	30

Note: Monthly panel data from PES (AF) in 1992-2018. Dependent variable is $\ln H^u$. 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 B5. Leaving out Local Trends or Time Dummies

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	$\ln V^{out}$	$\ln V^{out}$	$\ln V^{out}$	$\ln H^{u}$	$\ln H^{u}$	$\ln H^{u}$
Estimation	baseline IV	no lt IV	no td IV	baseline IV	no lt IV	no td IV
$\ln U_{t-1}$	0.152**	0.130***	0.154***	0.414***	0.307***	0.675***
	(0.066)	(0.034)	(0.025)	(0.049)	(0.037)	(0.026)
$\ln U_t^{in}$	-0.085	-0.110**	0.001	0.325***	0.368***	0.239***
	(0.069)	(0.054)	(0.027)	(0.054)	(0.048)	(0.032)
$\ln V_{t-1}$	0.500***	0.501***	0.469***	0.015*	0.018**	-0.043***
	(0.015)	(0.014)	(0.016)	(0.009)	(0.008)	(0.014)
$\ln V_t^{in}$	0.715***	0.664***	0.600***	0.069**	0.038	0.401***
	(0.048)	(0.027)	(0.034)	(0.035)	(0.023)	(0.049)
Time dummies	yes	yes	no	yes	yes	no
Local trends	yes	no	yes	yes	no	yes
Observations	28,239	28,239	28,239	28,242	28,242	28,242
R-squared	0.802	0.804	0.803	0.856	0.836	0.733
Number of llm	90	90	90	90	90	90

Note: Monthly panel data from PES (AF) in1992-2018. 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 B6. Estimation on Aggregate Data

	(1)	(2)	(3)	(4)
Dependent variable	$\ln V^{out}$	$\ln V^{out}$	$\ln H^{u}$	$\ln H^{u}$
Estimation	OLS	IV	OLS	IV
$\ln U_{t-1}$	-0.043**	-0.056**	0.568***	0.697***
	(0.020)	(0.027)	(0.030)	(0.035)
$\ln U_t^{in}$	-0.094***	0.026	0.148***	0.307***
	(0.030)	(0.061)	(0.039)	(0.085)
$\ln V_{t-1}$	0.150***	0.069***	-0.103***	-0.177***
	(0.016)	(0.023)	(0.022)	(0.034)
$\ln V_t^{in}$	0.752***	0.917***	0.399***	0.612***
	(0.024)	(0.041)	(0.033)	(0.065)
Observations	323	317	323	317
R-squared	0.992	0.991	0.962	0.959
Hansen (p-value)		0.000		0.202
Kleibergen-Paap (p-value)		0.000		0.000

Note: Monthly data from PES (AF) in 1992-2018. 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.) Instruments for IV are five lags of inflows plus the stocks in t-6.