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Working Paper

Vacancy matching and labor market conditions

Working Paper, No. 2012:16

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Suggested Citation: Stadin, Karolina (2012) : Vacancy matching and labor market conditions, Working Paper, No. 2012:16, Uppsala University, Department of Economics, Uppsala, <https://nbn-resolving.de/urn:nbn:se:uu:diva-183881>

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Working Paper 2012:16

Vacancy Matching and Labor Market Conditions

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Working paper 2012:16
October 2012
ISSN 1653-6975

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Vacancy Matching and Labor Market Conditions

Karolina Stadin^{*}

October 29, 2012

Abstract

This paper studies the probability of filling a vacancy, how it varies with the number of unemployed and number of vacancies in the local labor market, and what impact it has on employment. A greater availability of unemployed workers should make it easier for a firm to fill a vacancy but more vacancies at other firms should make it more difficult, due to the congestion effect. I use monthly panel data for all local labor markets in Sweden from 1992-2011. The results suggest that unemployment has a weak positive effect on the probability of filling a vacancy, while the number of vacancies in the local labor market has a significant and robust negative effect. Simulations of a theoretical model, with parameters based on the estimation, show economically significant effects of shocks to the number of vacancies on employment dynamics, while shocks to the number of unemployed are not very important. Matching frictions are more important for employment during booms than during recessions.

Keywords: Vacancies, Unemployment, Matching, Labor demand, Employment dynamics, Business cycle

JEL classification: E24, E39, J23, J63, J64

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I am grateful for helpful comments from Nils Gottfries, Bertil Holmlund, Erik Mellander, and seminar participants at Uppsala University and the Swedish National Conference in Economics in Stockholm 2012.

1 Introduction

This paper investigates the probability of filling a vacancy and how it varies with the state of the labor market. According to search and matching theory, the state of the labor market affects the probability of filling a vacancy, which in turn affects the creation of new vacancies and hiring. The probability of filling a vacancy should depend positively on unemployment and negatively on the number of vacancies in the relevant labor market. It is easier to fill vacancies when there are more unemployed workers available, and it is more difficult when there is a congestion effect due to other firms opening vacancies. According to labor demand oriented models, on the other hand, the probability of filling a vacancy is independent of the state of the labor market. In these models there is excess supply of workers and no matching frictions and hence firms can always fill their vacancies. This paper has two purposes. The first is to estimate how the probability of filling a vacancy varies with labor market conditions. The second is to use a theoretical model to examine how variations in the probability of filling a vacancy affect employment dynamics.

To empirically study the probability of filling a vacancy over time and how it depends on the number of unemployed and the number of vacancies in the local labor market, I use monthly data for all local labor markets in Sweden in 1992-2011. I also look at the probability of filling a vacancy using aggregate monthly data for Sweden in 1970-2011.

In order to say something about the magnitude of the employment effect of changes in labor- and product-market conditions facing the firms, I simulate a model of employment dynamics. The theoretical model used is a search and matching model with imperfect competition in the product market from Carlsson, Eriksson, and Gottfries (2012). In the model, a firm's hiring decision is affected by vacancies and unemployment through their effect on the probability of filling a vacancy. Hiring also depends on product demand and real wage costs. Parameters used in the calibration are partly estimates obtained in this paper and partly parameters from other studies. Theoretical impulse responses resulting from shocks to the explanatory variables are simulated. This allows me to see how the employment of a typical firm changes when there is a change in the number of vacancies or unemployed in the local labor market where the firm is located.

The estimation results suggest that unemployment has a positive effect on the probability of filling a vacancy in some specifications, but the effect is not big and in some specifications it is zero. The number of vacancies in the local labor market, on the other hand, has a significant, negative, and robust effect on the probability of filling a vacancy. According to the simulations, shocks to the number of vacancies –and hence to the probability of filling a vacancy– have economically significant effects on employment, while shocks to the number of unemployed are not very important. The small simulated employment effect of a shock to the number of unemployed is partly due to the small estimated effect of unemployment on the probability of filling a vacancy, and partly due to the fact that these shocks in the data are typically much smaller than shocks to the number of vacancies.

In the data, I find that the mean probability of filling a vacancy has been higher during recessions than during booms. According to simulations with different mean values of the probability of filling a vacancy, shocks to the probability of filling a vacancy have a larger impact on employment in booms than in recessions. Hence, matching frictions seem to be more important in booms.

Michaillat (2012) has argued that the probability of filling a vacancy varies over the business cycle depending on labor market conditions, and that this has implications for the character of the unemployment. He has developed a search and matching model of unemployment with wage rigidity where total unemployment can be decomposed into a frictional part, caused by matching frictions, and a job rationing part which is the cyclical remainder. In good times, all unemployment is frictional. In recessions, when total unemployment is higher, the rationing part makes up the largest fraction of unemployment and the frictional unemployment actually decreases. When there is excess supply of labor, recruiting workers is easy and matching frictions contribute little to unemployment. My results support Michaillat's idea that matching frictions are less important in recessions.

In a closely related paper, Carlsson, Eriksson, and Gottfries (2012) analyzed the determinants of net employment change at the firm level. They used yearly data for Swedish manufacturing firms in the 1990s, which is a period including a deep and long recession. They found that product demand and real wages were important for employment, while the availability of unemployed workers was not. Vacancies in the local labor market had a

negative effect on employment in some specifications, indicating a congestion effect. The results in the present paper point in the same direction.

Many authors have estimated matching functions, focusing on hiring of unemployed workers.¹ Often the elasticity of matching with respect to unemployment is larger than the elasticity with respect to vacancies. This study differs because the outflow of vacancies is used to measure the number of matches. The use of the outflow from unemployment as the dependent variable is more relevant if the purpose of the study is to understand the probability of unemployed workers finding jobs. The purpose of this paper is to understand firms' hiring and employment dynamics, which makes the outflow of vacancies more relevant. In the simplest search and matching model, the outflow of unemployed and the outflow of vacancies are the same thing. This is because there are only two states – employed or unemployed – and employed workers do not search on the job. In a more realistic model, many vacancies are filled with people coming directly from other jobs or from out of the labor force. Because of this, the measures and the estimated effects differ.

Edin and Holmlund (1991) also estimated matching functions using the outflow of vacancies. They used data for Sweden in 1970-1988 and found a stronger positive effect of unemployment than I find in this paper. One reason may be that the labor market differed during the two periods.

The rest of the paper is organized as follows. In section 2, the empirical specification is derived and the data are presented. The results of the estimation are shown and discussed in section 3. In section 4, the theoretical employment dynamics are studied, using the estimates from section 3. Section 5 concludes the paper.

¹Some examples are Blanchard & Diamond (1990), Coles & Smith (1996), Boeri & Burda (1996), Forslund & Johansson (2007), Aranki & Löf (2008), and Eriksson & Stadin (2012).

2 Empirical specification and data

2.1 Empirical specification

In this section, I derive the equation to be estimated, including the definitions of the variables. A theoretical model in continuous time is used to derive discrete time approximations using the variables available in my dataset. Continuous time is denoted by τ and discrete time by t , where t denotes the beginning of the month. Definitions of variables used in the derivation are Q_τ = probability of filling a vacancy, X_τ = outflow of vacancies, F_τ = inflow of vacancies, F_t^m = inflow of vacancies during month beginning at time t (in dataset), V_t = stock of vacancies at the beginning of month t (in dataset), and U_t = stock of unemployed at the beginning of month t (in dataset).

I assume that each vacancy that disappears is a hire, so the instantaneous probability of filling a vacancy is $Q_\tau = \frac{X_\tau}{V_\tau}$. Taking logs, I get $\ln Q_\tau = \ln X_\tau - \ln V_\tau$. The matching function is $X_\tau = \phi U_\tau^{\alpha_U} V_\tau^{\alpha_V}$, which in logs can be written as $\ln X_\tau = \ln \phi + \alpha_U \ln U_\tau + \alpha_V \ln V_\tau$, where the outflow of vacancies (i.e., the hires/matches) depends positively on unemployment (labor supply) and also positively on the number of vacancies (labor demand). The outflow of vacancies is chosen as the measure of matches, since the focus is on the firms' hiring behavior, and also since a consistent probability measure is desirable, measuring the number of matched vacancies out of those registered in the data. Using the above stated definitions, the log probability of filling a vacancy is

$$\ln Q_\tau = \ln X_\tau - \ln V_\tau = \ln \phi + \alpha_U \ln U_\tau + \alpha_V \ln V_\tau - \ln V_\tau = \ln \phi + \alpha_U \ln U_\tau - (1 - \alpha_V) \ln V_\tau \quad (1)$$

Integrating over month t , I get

$$\int_t^{t+1} \ln Q_\tau d\tau = \int_t^{t+1} \ln \phi + \alpha_U \int_t^{t+1} \ln U_\tau d\tau - (1 - \alpha_V) \int_t^{t+1} \ln V_\tau d\tau \quad (2)$$

To estimate this equation (2), approximate measures of $\int_t^{t+1} \ln Q_\tau d\tau$, $\int_t^{t+1} \ln U_\tau d\tau$ and $\int_t^{t+1} \ln V_\tau d\tau$ are needed. For $\int_t^{t+1} \ln U_\tau d\tau$ and $\int_t^{t+1} \ln V_\tau d\tau$, I use the mean of the log stocks at the beginning of the current period and the beginning of the next period, i.e., $\int_t^{t+1} \ln U_\tau d\tau \approx \frac{\ln U_t + \ln U_{t+1}}{2}$ and $\int_t^{t+1} \ln V_\tau d\tau \approx \frac{\ln V_t + \ln V_{t+1}}{2}$.

To get an approximation for $\int_t^{t+1} \ln Q_\tau d\tau$, I use the fact that the change in the stock of vacancies is $\dot{V}_\tau = F_\tau - X_\tau$ and thus $X_\tau = F_\tau - \dot{V}_\tau$. A discrete time approximation can be derived as follows:

$$\begin{aligned} \int_t^{t+1} \ln Q_\tau d\tau &= \int_t^{t+1} \ln X_\tau d\tau - \int_t^{t+1} \ln V_\tau d\tau = \int_t^{t+1} \ln(F_\tau - \dot{V}_\tau) d\tau - \int_t^{t+1} \ln V_\tau d\tau \\ &\approx \ln(F_t^m - (V_{t+1} - V_t)) - \frac{\ln V_t + \ln V_{t+1}}{2} \end{aligned} \quad (3)$$

Thus, the empirical specification that will be used in this paper is

$$\overline{\ln Q}_{n,t} = \beta_n + \beta_U \overline{\ln U}_{n,t} + \beta_V \overline{\ln V}_{n,t} + \varepsilon_{n,t}, \quad (4)$$

where n is an index for the local labor market, $\overline{\ln Q}_{n,t} = \ln(F_{n,t}^m + V_{n,t} - V_{n,t+1}) - \frac{\ln V_{n,t} + \ln V_{n,t+1}}{2}$, $\overline{\ln U}_{n,t} = \frac{\ln U_{n,t} + \ln U_{n,t+1}}{2}$ and $\overline{\ln V}_{n,t} = \frac{\ln V_{n,t} + \ln V_{n,t+1}}{2}$. The probability of filling a vacancy should depend positively on unemployment, i.e., $\beta_U = \alpha_U > 0$, and negatively on vacancies, such that $\beta_V = -(1 - \alpha_V) < 0$. $\varepsilon_{n,t}$ is the error term for local labor market n in month t and represents stochastic shocks with an overall mean of zero. The constant β_n is a scale parameter including local specific fixed effects.

2.2 Data and estimation

Data

The equation derived in the previous section is estimated on monthly data from the Swedish Public Employment Service (AF) for the time period of 1992-2011. The data includes both the stock of vacancies registered at the Public Employment Service in the beginning of each month and the inflow of vacancies during the month. Many vacancies are never announced at the Public Employment Service, even though it is mandatory to do so, but this is the best measure of vacancies available for a longer time period.² Unemployment is a wide measure of the number of openly unemployed workers registered at the Public Employment Service in the beginning of the month. There is a strong incentive to register since this is required to qualify for unemployment benefits. Labor market program participants are not included since

²The share of vacancies reported to the Public Employment Service has been about 30-45% during in the 1990s and 2000s according to Aranki and Löf (2008). This is a problem if these vacancies are not representative of all vacancies.

they contribute to matching to a significantly lesser extent than openly unemployed workers, according to other studies, such as Forslund and Johansson (2007). The program participants will be included in the unemployment measure as a robustness check. The data from the Public Employment Service are measured at the municipality level and at a monthly frequency. I aggregate the data to get a dataset with variables for local labor markets. A local labor market consists of one or more municipalities and is constructed by Statistics Sweden based on commuting patterns. All the 90 local labor markets are listed in the Appendix.

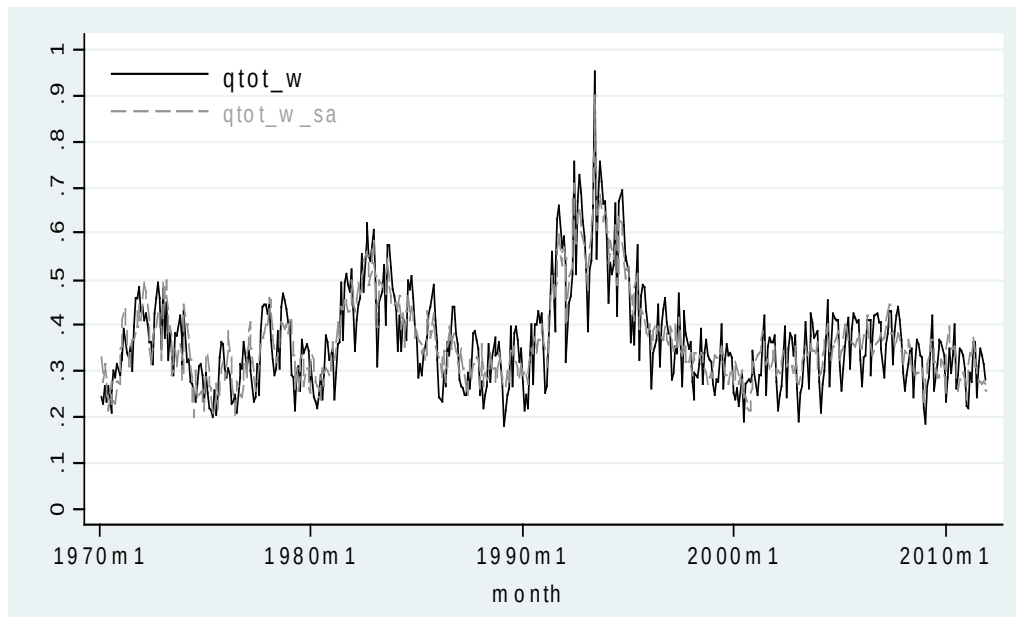
In Figure 1, I plot the monthly mean probability of filling a vacancy during a week in Sweden. Since I just need aggregate data series in this case, I can get data for a longer time period. I use data for 1970-2011 from the Swedish Public Employment Service.³ Almost the whole time, the probability of filling a vacancy within a week has been higher than 0.2 and lower than 0.8. The mean of this probability during this period is 0.37, which implies that a vacancy has usually been filled within slightly more than half a month (assuming that vacancies are filled when deregistered). This duration seems to be in line with earlier findings. Edin and Holmlund (1991) found that the average duration of registered vacancies varied in the range of two to four weeks in Sweden in 1970-1988. In Blanchard and Diamond (1990), the average duration of vacancies in the USA in 1968-1981 also varied between two and four weeks.

The probability of filling a vacancy has been higher during recessions. It was particularly high in the 1990s, when unemployment was very high and the number of vacancies was low. The probability of filling a vacancy within a week was around 60 percent in the recession of the early 1990s and around 30 percent in early 2000s.

Figure 2 shows the distribution of the mean probabilities of filling a vacancy within a week for the local labor markets. The total unweighted mean of the means for the local labor markets in 1992-2011 is 0.52, which is higher than the corresponding probability of 0.38 for the aggregate data for Sweden during the same period. In the aggregate data, large and tight local labor markets, such as Stockholm, have a large weight.

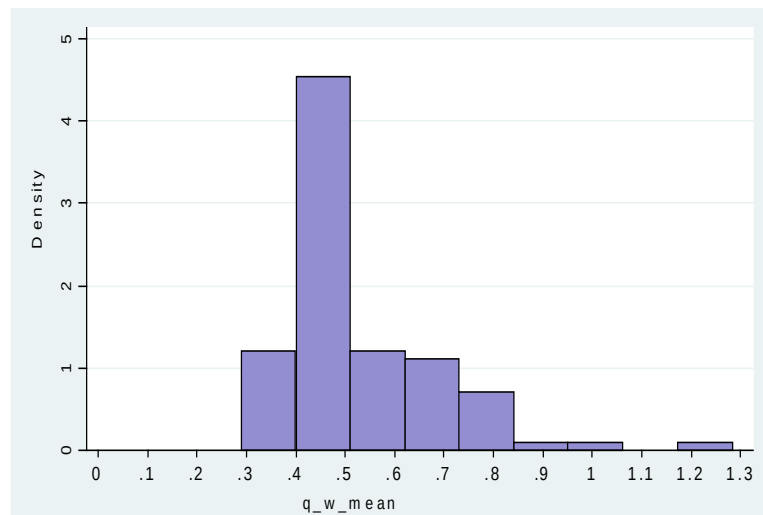
³I have received aggregate data for 1970-1988 from Bertil Holmlund, earlier used in Edin and Holmlund (1991). Aggregate data for 1989-1991 as well as municipality data for 1992-2011 are from AF, 2012.

Figure 1. Aggregate probability of filling a vacancy within a week in Sweden 1970-2011



Note: $qtot_w = \frac{V_t + F_t^m - V_{t+1}}{4.3} \div \frac{V_t + V_{t+1}}{2}$ (no logarithms), where the vacancy measures are at monthly frequency and the outflow of vacancies is assumed to be constant during the month consisting of 4.3 weeks. This measures the monthly mean probability of filling a vacancy within a week during the month. Data series are from AMS/AF (PES). In 1970-1974, the stock of vacancies was measured in the middle of the month, which is why the monthly value is used instead of the mean stock in the computation for these years. The variation explained by month of the year is removed from the seasonally adjusted series (gray, dashed line), for which the standard deviation is 0.09 instead of the original 0.11. If many vacancies are closed without getting filled, my measure of the probability of filling vacancies is not very good. According to a survey conducted by AF in 2011, about 80 percent of the employers posting vacancies at AF reported having received enough applications to hire someone.

Figure 2. Histogram of the mean probabilities for the local labor markets 1992-2011



Note: The mean of the probability of filling a vacancy within a week for each local labor market, which is computed in the same way as for the whole of Sweden in Figure 1, then taking the mean. The outlier is Dorotea (llc 74) with $q_w_mean = 1.28$, the only value over 1. The reason for this high value is that during some months, a lot of vacancies were posted and then they were all deregistered before the end of the month. At the same time, the number of vacancies registered in the beginning and the end of the month was very low. Hence, I do not have a good approximation of the mean stock of vacancies in these cases and the probability of filling a vacancy is seriously overstated. However, excluding Dorotea changes the estimation results very little.

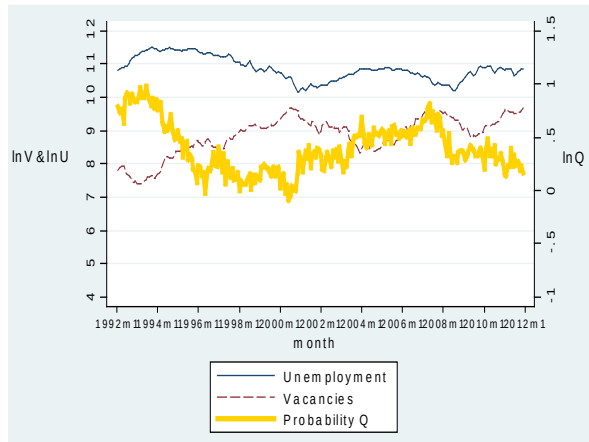
To give an idea about the main variables in the dataset and how they move together, I have plotted them together for Sweden's six largest local labor markets in Figures 3a-f. The variables are in logs, as in the estimation, and seasonally adjusted. The crude correlations seem to roughly be in line with what is expected from search and matching theory. The number of unemployed and the number of vacancies are negatively correlated. When the number of unemployed workers was higher and the number of vacancies fewer, the probability of filling a vacancy within the month was higher.

It is worth noting that what is referred to as a probability in this paper, is actually rather a rate of filling vacancies implied by a probability. The value of Q is higher than one if a vacancy is filled within less than a month, which is usually the case. This is why the log of Q varies around approximately 0.5 for the local labor markets in Figure 3. The measure of the log of the probability will be undefined if the measure of the outflow is zero or negative ($F_t^m - (V_{t+1} - V_t) \leq 0$) or if a stock of the vacancies is zero ($V_t = 0$ or $V_{t+1} = 0$). Zeros in the non-log series of the stock of vacancies for small local labor markets cause about one percent of the observations of $\ln \bar{Q}_{n,t}$ to be missing, while a negative outflow causes only three missing values out of more than 20,000. Missing values is not a problem in the unemployment measure.

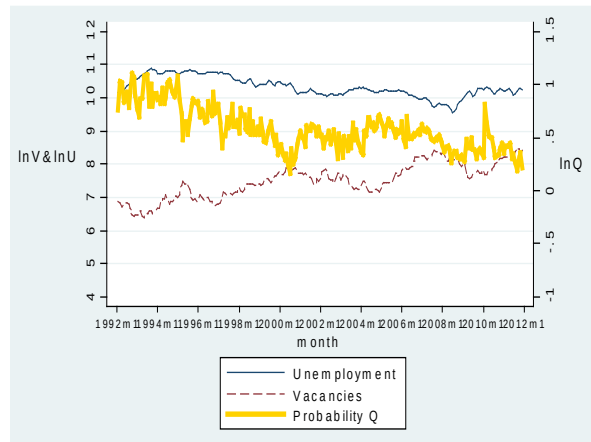
Figures 4a-f also show how the probability of filling a vacancy is related to vacancies and unemployment for Sweden's six largest local labor markets. The sizes of the bubbles reflect the probability of filling a vacancy. The probability of filling a vacancy visibly seems to increase in the vertical direction, when the number of vacancies falls. The relation to the number of unemployed in the horizontal direction is less clear, but the probability of filling a vacancy seems to have been smaller when unemployment was low. Scatter plots of Q versus $\frac{V}{U}$, V , and U (not in logs) are shown in Figures A1 and A2 in the Appendix.

Figure 3. Monthly data for unemployment ($\ln \bar{U}_{n,t}$), vacancies ($\ln \bar{V}_{n,t}$), and the probability of filling a vacancy ($\ln \bar{Q}_{n,t}$) for some large local labor markets in Sweden 1992-2011.

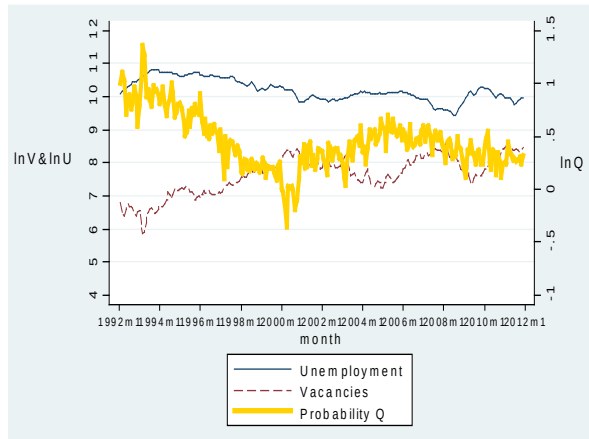
3a. Stockholm (llc 1)



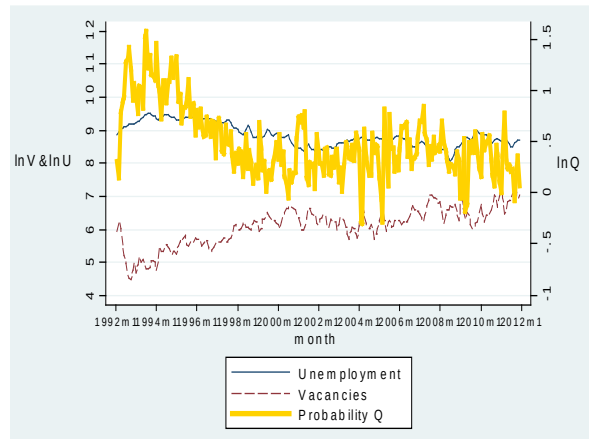
3b. Malmö (llc 25)



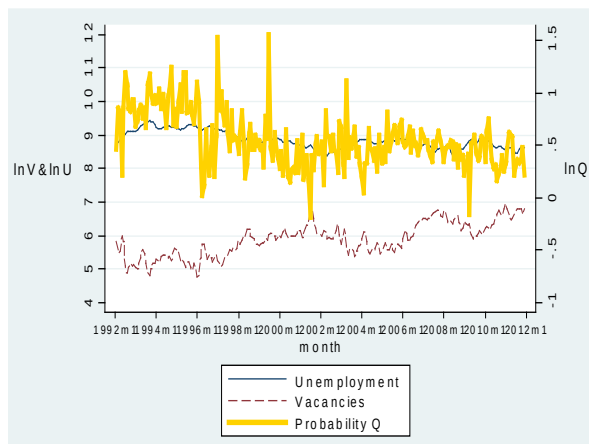
3c. Göteborg (Gothenburg, llc 32)



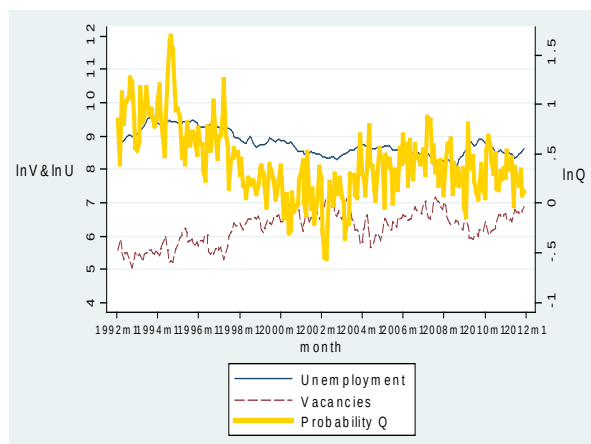
3d. Västerås (llc 49)



3e. Örebro (llc 47)



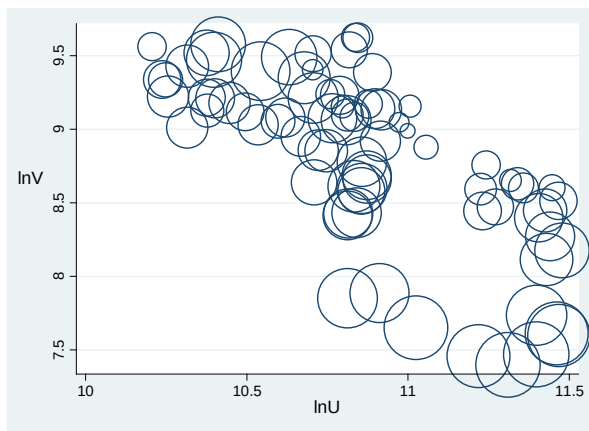
3f. Trollhättan (llc 34)



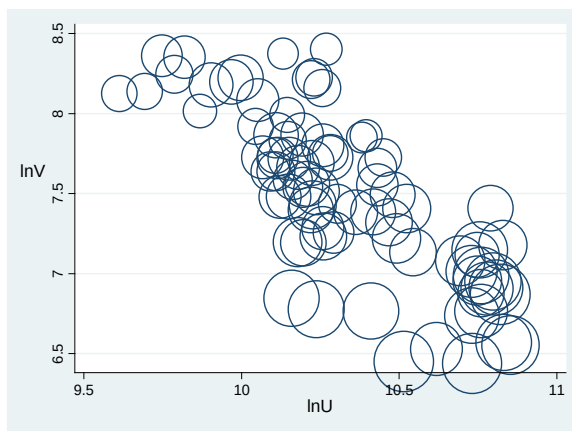
Note: All variables are in logs and seasonally adjusted for each local labor market using dummies for month. Data from AF (Swedish Public Employment Service) for 1992-2011.

Figure 4. Bubble scatter plots for some large local labor markets in Sweden 1992-2011, the larger probability of filling a vacancy the larger the bubble

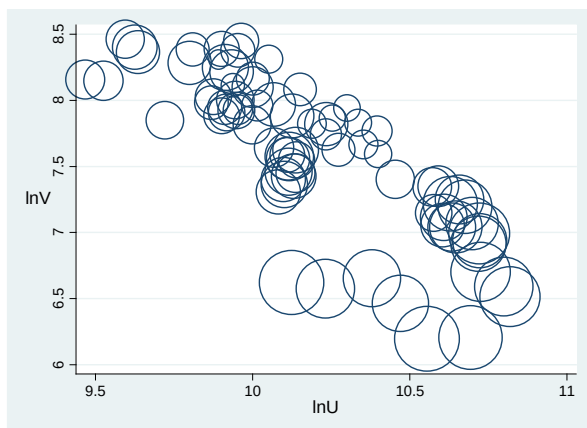
4a. Stockholm (llc 1)



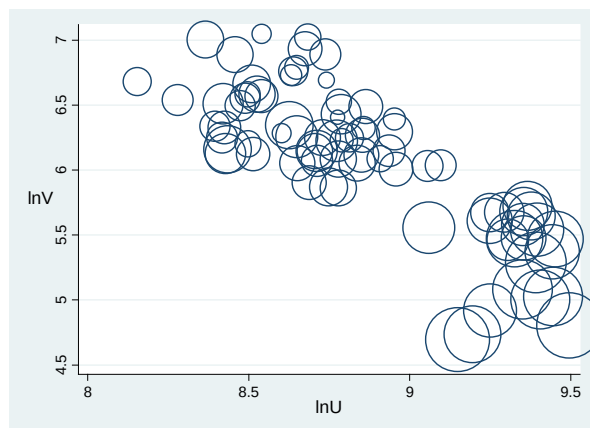
4b. Malmö (llc 25)



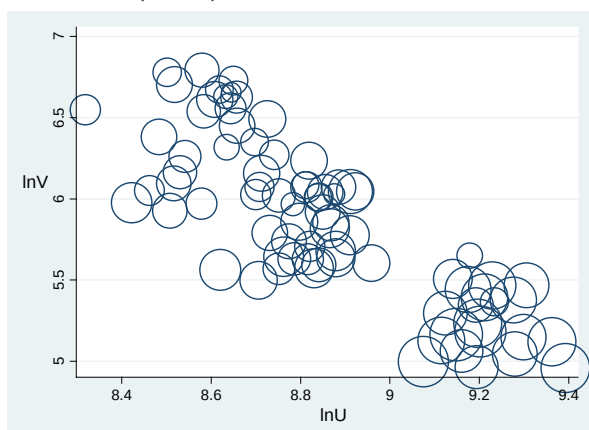
4c. Göteborg (Gothenburg, llc 32)



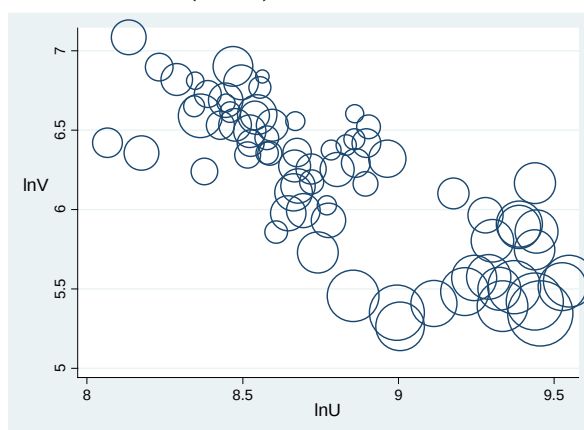
4d. Västerås (llc 49)



4e. Örebro (llc 47)



4f. Trollhättan (llc 34)



Note: All variables are in logs. Quarterly means of seasonally adjusted monthly values. Data from AF.

Estimation method

The estimation methods used are OLS and IV, with fixed effects and time dummies. The fixed effects are included to take into account different local labor markets having different mean levels of efficiency in matching vacancies with unemployed workers. Time dummies are included to diminish the risk of biased estimates due to unobserved aggregate shocks. They handle, e.g., changes in benefits and regulation that affect matching efficiency and change the variables at all local labor markets at a certain point in time. They also control for seasonal effects. In the analysis, all matching is assumed to take place within the local labor market where the worker lives and the firm is located, i.e., the local labor markets are treated as isolated. This assumption is supported by Johansson and Persson (2000), who reported that 80-90 percent of all hired workers came from the local labor market area where the firm is located.

Figure 3 shows that there are long run trends in the variables, with the unemployment and the probability of filling a vacancy being higher and vacancies being lower in the early 1990s. If the variables are non-stationary, I will have to take measures to handle this to avoid spurious regressions. It is a problem if unobserved factors influence the variables in a way that make them correlated in some other way than through the causal effect I am trying to estimate. To test for stationarity in the variables, I use a Fisher-type unit root test with the null hypothesis of all panels containing a unit root, i.e., the time series for each local labor market being non-stationary. The Hadri LM test for the null hypothesis of all panels being stationary cannot be used if there are missing values, which is the case in my dataset. However, after interpolation over missing values, the test can be performed. The test results suggest that none of the variables are stationary, especially not the unemployment variable. Tests on variables with the common variation removed show that the non stationarity is not taken care of by the time dummies. Time dummies can control for a common trend, but if the trends are different in different local labor markets, local trends might have to be included in the estimation. If local linear and quadratic time trends are controlled for, tests suggest that the detrended variables are stationary (p-values are presented in Table A1 in the Appendix). Thus all variables seem to be trend-stationary, and I should be able to use them in the estimation if I include the trends. For aggregated variables, Dickey Fuller tests result in the same conclusion.

If the variables are non-stationary, the equation may still be correctly specified if there is a cointegrating relation. If a linear combination of non-stationary variables is stationary, the non-stationarity of the variables will not bias the estimated coefficients. Theory suggests a long run linear relation between the three variables $\ln Q$, $\ln U$, and $\ln V$. Since Westerlund ECM panel cointegration test requires continuous time series, the variables are interpolated over missing values before the test is performed. The test strongly indicates that there exists a cointegrating relation between $\overline{\ln Q}_{n,t}$, $\overline{\ln U}_{n,t}$, and $\overline{\ln V}_{n,t}$ (see Table A2 in the Appendix). Furthermore, Johansen and Engle-Granger tests suggest that there exists an integrating relation between the aggregated series $\overline{\ln Q}_t$, $\overline{\ln U}_t$, and $\overline{\ln V}_t$. A cointegrating relation is most likely present, and thus the trends are probably not necessary in the empirical specification.

To identify the effects of vacancies and unemployment on the probability of filling a vacancy, I rely on variation in unemployment and vacancies across local labor markets and over time. I have found that 52 percent of the variation in vacancies and 84 percent of the variation in unemployment is common. After removing the common variation, using time dummies and fixed effects, the remaining variation in the log variables is a standard deviation of 0.51 for vacancies and 0.17 for unemployment. The local time trends do not remove much more of the variation, see Table 1. The variation left should be enough to enable identification of the effects I am interested in.

Table 1. Variation remaining in variables after removing fixed effects, common time effects and local time trends

	(1)	(2)	(3)
Unemployment ($\overline{\ln U}_{n,t}$)	0.413	0.166	0.121
Vacancies ($\overline{\ln V}_{n,t}$)	0.732	0.505	0.473
Fixed effects	yes	yes	yes
Time dummies	no	yes	yes
Local time trends	no	no	yes

Note: Standard deviations of residuals of regressions with the mean log stock of unemployment or vacancies explained by fixed effects, time dummies, and local time trends (linear and quadratic). There is essentially no correlation between the remaining variation in $\overline{\ln U}_{n,t}$ and $\overline{\ln V}_{n,t}$ when controlling for common variation in column 2 and 3 (−0.03).

A Wald test strongly indicates that the residuals are heteroskedastic. A Wooldridge test indicates autocorrelation when not including the time dummies, but not when the time dummies are included (with or without local time trends). However, regressing the residual from specifications including time dummies on its first and second lags gives significant coefficients. Thus, serial correlation might still be present though not detected by the test. To make the estimated standard errors of the coefficients robust to arbitrary heteroskedasticity and arbitrary intragroup autocorrelation, they are clustered at the local labor markets.

Another issue is simultaneity due to the construction of the vacancy and unemployment measures. The matching function describes a process that takes place continuously, and the use of discrete time data to estimate matching functions introduces temporal aggregation problems. Unemployment and vacancies are reduced by matches, which biases the estimated coefficients. Suppose, for example, that there is a local shock to matching efficiency. If the matching becomes more efficient, the probability of filling a vacancy goes up and the number of unemployed workers goes down. This has nothing to do with the causal effect that I wish to estimate, i.e., the expected positive effect of the available number of unemployed on the probability of filling a vacancy. The effect of unemployment would be biased downwards. The lagged stocks are good instruments for the current if there is no serial correlation in the residual. Since I have found no strong evidence of autocorrelation, I instrument the mean stocks with the initial stocks for each period (which in the data are measures on the last day of the previous month). The instruments might not be ideal, since some autocorrelation may be present, but should at least diminish the simultaneity problem.

I come to the conclusion that I should estimate the following equation with fixed effects, clustered standard errors, and the mean stocks instrumented with the initial stocks:

$$\overline{\ln Q}_{n,t} = \beta_n + \beta_U \overline{\ln U}_{n,t} + \beta_V \overline{\ln V}_{n,t} + \text{time dummies} + (\text{local trends}) + \varepsilon_{n,t} \quad (5)$$

The specification including all control variables should have the smallest risk of spurious correlation. I also show the results without some or all control variables. The estimation with neither time dummies nor local time trends gives an idea about the crude correlations, but there is a considerable risk that some unobserved macro shocks affect the estimates. The results including time dummies but no local time trends are more interesting. Since there

seems to be a cointegrating relation between the variables, the trends are probably not necessary.

3 Results

3.1 Main results

Table 2 shows the results of estimations with and without time dummies and local time trends. The estimated coefficient for vacancies is between -0.27 and -0.29, and thus robust to changes in the specification. For unemployment, there seems to be a positive effect, but it is not robust. With neither time dummies nor local trends included in the estimation, the coefficient for unemployment is positive, quite big (0.38), and significant. However, this is not a reliable result because there is a considerable risk of spurious correlation. With time dummies but no local trends as controls, the estimated coefficient for unemployment is still positive and significant, but smaller: 0.16. The estimation results for the specification with all controls shows no significant effect of unemployment on the probability of filling a vacancy.

An alternative way of doing the estimation is to do it in differences. This specification allows for stochastic trends, not just deterministic. The results of this estimation are shown in Table 3. The estimated coefficients for vacancies are quite similar in Table 2 and in Table 3, only slightly bigger in the difference estimations. The main difference is that in Table 3, there is no positive effect of unemployment in any specification (in the case of no control variables, the effect is even negative). Estimation of the equation on aggregate data also gives estimates of the effect of vacancies slightly bigger than those in Table 2, and no positive effect of unemployment. This is the case with and without instrumentation of the mean stocks of unemployment and vacancies, and with and without time trends. See Table 4.

Separate IV estimations for some important local labor markets are presented in Table 5. Time trends are included in all regressions. The results are roughly in line with those including time trends in Table 2 and Table 3, except for an unexpected significantly negative coefficient for unemployment for Stockholm and Göteborg (Gothenburg). When excluding the time trends (not in table), these negative effects are still present.

Table 2. Explaining the probability of filling a vacancy, levels, IV

Dependent: $\overline{\ln Q}_{n,t}$	(1)	(2)	(3)
Unemployment ($\overline{\ln U}_{n,t}$)	0.379*** (0.031)	0.162*** (0.044)	-0.006 (0.043)
Vacancies ($\overline{\ln V}_{n,t}$)	-0.266*** (0.016)	-0.266*** (0.020)	-0.287*** (0.020)
Time dummies	no	yes	yes
Local time trends	no	no	yes
Observations	21,270	21,270	21,270
R-squared (within)	0.343	0.499	0.548
Number of llc	90	90	90

Note: Robust standard errors are in parentheses, clustered at the local labor markets. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively. Monthly data for all local labor markets in Sweden in 1992-2011 from AF (PES). All variables are in logs. Fixed effects are included in all regressions (“xivtreg2, fe” in Stata). IV estimations where the mean log stocks of the number of unemployed and vacancies ($\overline{\ln U}_{n,t}$ and $\overline{\ln V}_{n,t}$) are instrumented with initial log stocks. The p-value for the F-statistic is 0.0000 for all regressions, and all equations are exactly defined by relevant instruments (according to Kleibergen-Paap LM and Wald tests). The local time trends are both linear and quadratic.

Table 3. Explaining the probability of filling a vacancy, differences, IV

Dependent: $D. \overline{\ln Q}_{n,t}$	(1)	(2)	(3)
Unemployment ($D. \overline{\ln U}_{n,t}$)	-0.880*** (0.090)	-0.049 (0.160)	-0.053 (0.157)
Vacancies ($D. \overline{\ln V}_{n,t}$)	-0.363*** (0.023)	-0.325*** (0.024)	-0.326*** (0.024)
Time dummies	no	yes	yes
Local time trends	no	no	yes
Observations	21,080	21,080	21,080
R-squared (within)	0.135	0.270	0.270
Number of llc	90	90	90

Note: Robust standard errors are in parentheses, clustered at the local labor markets. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively. Monthly data for all local labor markets in Sweden in 1992-2011. All variables are in logs. Fixed effects are included in all regressions. IV estimations where the differences of the mean log stocks of unemployment and vacancies are instrumented with lags of the initial stocks of unemployed and vacancies. The local time trends are only linear after the differentiation (no quadratic trends).

Table 4. Explaining the aggregate probability of filling a vacancy in Sweden

Dependent: $\overline{\ln Q}_t$	(1)	(2)	(3)	(4)
Total Unemployment ($\overline{\ln U}_t$)	-0.073 (0.107)	-0.147* (0.085)	-0.062 (0.118)	-0.133 (0.086)
Total Vacancies ($\overline{\ln V}_t$)	-0.429*** (0.070)	-0.363*** (0.070)	-0.420*** (0.083)	-0.346*** (0.075)
Time trends	no	yes	no	yes
Seasonal dummies	yes	yes	yes	yes
Estimation method	OLS	OLS	IV	IV
Observations	239	239	239	239
R-squared			0.750	0.804

Note: Robust standard errors are in parentheses. ***, **, and * denote significance at the 1, 5 and 10 percent levels, respectively. Monthly data for Sweden in 1992-2011. All variables are in logs. In IV regressions in column 3-4, the mean stocks are instrumented with initial stocks. A linear and a quadratic trend are included in columns 2 and 4. Seasonal dummies are included in all regressions, since the seasonal variation is not controlled for by time dummies (time dummies and fixed effects are not included since there is no panel dimension). Excluding the seasonal dummies has little effect on the estimated coefficients.

Table 5. Explaining the probability of filling a vacancy, separate IV regressions

Dependent: $\overline{\ln Q}_t$	(1) Stockholm	(2) Malmö	(3) Göteborg	(4) Västerås	(5) Örebro	(6) Trollhättan
Unemployment	-0.286*** (0.063)	-0.055 (0.062)	-0.213** (0.104)	0.011 (0.121)	0.108 (0.144)	0.158 (0.097)
Vacancies	-0.453*** (0.054)	-0.214*** (0.078)	-0.392*** (0.082)	-0.344*** (0.067)	-0.172** (0.070)	-0.264*** (0.085)
Time trends	yes	yes	yes	yes	yes	yes
Seasons	yes	yes	yes	yes	yes	yes
Observations	239	239	239	239	239	239
R-squared	0.674	0.773	0.740	0.741	0.570	0.750

Note: Robust standard errors are in parentheses. ***, **, and * denote significance at the 1, 5 and 10 percent levels, respectively. Monthly data for the six largest local labor markets in Sweden in 1992-2011. All variables are in logs. IV estimations where the mean log stocks of the number of unemployed and vacancies are instrumented with initial log stocks. Linear and quadratic trends and seasonal dummies are included in all regressions. (Time dummies are not included since there is no panel dimension.)

3.2 Robustness

The seasonal pattern is probably not the same in all local labor markets. However, using local seasons, instead of just the common seasonal effects captured by the time dummies, doesn't change the results much. See Table A3 in the Appendix, where I have also included the case of no time dummies but local seasonal effects together with local linear and quadratic time trends. When I have all these controls, the time dummies might be redundant and removing a lot of the variation, especially in the unemployment variable. The coefficient for vacancies in this case is -0.31 and the coefficient for the number of unemployed is 0.05 and significantly different from zero.

In the measure of unemployed that I have used so far, labor market program participants are not included, only the openly unemployed. The results when including these program participants do not differ much from those in Table 2 (see Table A4 in the Appendix). The positive coefficients for unemployment with no local trends included are actually slightly bigger when the program participants are included in the unemployment measure.

Timing issues, such as a delay between an unemployed person finding a job and being deregistered, could influence the results. Estimations using data aggregated to quarterly frequency should diminish these problems. In fact, they change the results only modestly. The effect of the number of unemployed is slightly stronger in the specifications not including local time trends, compared to the corresponding monthly effect (see Table A5 in the Appendix).

To make sure that there are not a few extreme local labor markets driving the results, I try to drop local labor markets that have possible outliers or very high variation in the variables. The definition here is of course a bit arbitrary, but I decide to remove the 10 percent of the local labor markets with the highest variation relative to the mean in the unemployment variable, the 10 percent of the local labor markets with the highest variation relative to the mean in the vacancy variable, and also the 10 percent of the local labor markets with the highest mean probability of filling a vacancy (there are no low outliers according to Figure 2). Taken together, there are 22 local labor markets removed, which is slightly more than one fourth of all local labor markets. The results are quite similar to those for all local labor markets in Table 2, which can be seen in Table A6 in the Appendix.

Under stock-flow matching theory, inefficient matching is mainly due to mismatch. There are no workers suitable for the vacancies that remain in the end of a period, and vice versa, there are no suitable jobs for the remaining stock of unemployed. The firms are trying to match the stock of vacancies remaining from the last period with the inflow of new unemployed workers during the period, and the unemployed workers remaining in the end of a period are trying to match with the inflow of new vacancies during the next period. Two recent Swedish studies found support for a stock-flow specification when using the outflow from unemployment as the dependent variable: Forslund and Johansson (2007) and Aranki and L f (2008). To see if both inflows and initial stocks matter for the probability of filling a vacancy in my dataset, I include measures of both as explanatory variables in the estimations presented in Table A7 in the Appendix. As before, I find that the initial stock of vacancies has a negative effect, and the initial stock of unemployed has a positive or no effect. The results surrounding the inflows are not as expected and not robust. The inflow of unemployed has an unexpected negative effect when including both time dummies and local time trends, and no effect when including time dummies but no local trends. The inflow of vacancies during the month has no significant effect, or a positive effect. These results are hard to interpret. In any case, they don't seem to support stock-flow matching and a change in the specification.

To sum up, vacancies have a robust negative effect on the probability of filling a vacancy (with a coefficient around -0.3), while the positive effect of unemployment is rather small and not robust. This result could actually be expected when looking at the bubbles in Figure 4.

3.3 Comparison to other studies

The dependent variable in this study is the probability of filling a vacancy and not the number of matches/hires. Still, what I estimate can be seen as a matching function. The implied elasticity of matching with respect to vacancies is about 0.7, and the implied elasticity of matching with respect to unemployment is 0.16 or 0. These estimated elasticities differ from those in many other studies. According to Petrongolo and Pissarides (2001), most studies estimating aggregate matching functions have found that a log-linear specification with constant returns to scale ($\alpha_U = \alpha_V = 0.5$) fits the data well (see, e.g., Blanchard & Diamond (1990)). Disaggregate studies have also found positive coefficients for both vacancies and

unemployment, but often less than constant returns to scale (see, e.g., Boeri & Burda (1996) and Coles & Smith (1996)).

A study of the aggregate matching function in Sweden was made by Forslund and Johansson (2007), and both Aranki and Löf (2008) and Eriksson and Stadin (2012) have estimated matching functions on monthly Swedish panel data. All these studies found significant effects of both vacancies and the number of unemployed, although with a coefficient for vacancies far below 0.5. In these studies, however, the number of matches is not defined the same way as in this paper. There number of hires is defined as the number of unemployed workers who are deregistered by the Public Employment Service because they have found a job. In this paper, the number of matches is defined as the outflow of vacancies, since I have the firms' perspective. The most important reasons why the measures differ are probably that vacancies are often filled with employed workers who are switching jobs rather than with unemployed workers, and that unemployed workers sometimes get other jobs than those registered at the Public Employment Service.

One may argue that a correct specification should include all job searchers, not only the unemployed. Unfortunately, there are no time series data available of on-the-job search. If on-the-job search is procyclical, the omission of this variable probably biases the estimated effects towards zero compared to the correct specification. When there are fewer vacancies opened at other firms in a recession, employed workers find it less rewarding to search for other jobs, and thus on-the-job searching decreases. The decreased job search by employed workers has a negative effect on the probability of filling a vacancy at the same time as more workers become unemployed (positive effect), and also at the same time as the congestion effect between firms searching for workers decreases (positive effect).

Another study using the outflow of vacancies as a measure of matches was made by Edin and Holmlund (1991). They estimated aggregate matching functions for Sweden on monthly data for 1970-1988. The stocks of vacancies and unemployed were measured the previous month. The coefficient for vacancies in their estimation, with a time trend included, was 0.56, and the coefficient for unemployment was 0.23. I have replicated this result using their data. They motivated the use of the outflow of vacancies as a measure of hiring by referring to available evidence indicating that the major part of the outflow of vacancies was associated with

hirings. Farm (1989), for instance, found that only 10 percent of the posted vacancies were withdrawn because of failure to find a suitable worker. As an alternative measure of hires, Edin and Holmlund used a series of survey-based data on new hires in manufacturing, for which they found quite similar results. In my aggregate estimation (Table 4), I found no effect of the number of unemployed. The reason for the difference in results is unclear, but it is worth to note that unemployment increased dramatically during the financial crises in the early 1990s and that it has remained on a higher level ever since. Thus, it is possible that the Swedish labor market functioned differently in the sample period of 1992-2011 than it did in 1970-1988.

In this study, I find less than constant return to scale, but this is also the case in many other studies estimating matching functions. The largest difference between the results in this paper and the results in the matching literature is that in many cases I find no significant effect of unemployment. A different dependent variable is probably the most important reason for the differences in results, but different time periods also matter and perhaps also the control variables. A significantly negative effect of vacancies and no effect of the number of unemployed, however, is in line with what was found in Carlsson, Eriksson, and Gottfries (2012). In their study, the dependent variable was the firm level employment changes in Sweden in the 1990s (a period of crises) and they included additional explanatory variables (product demand and wages) together with vacancies and unemployment.

3.4 Theoretical implications of estimation results

What are the theoretical implications of these results? In a search and matching model of the labor market, tightness $\left(\frac{V}{U}\right)$ should have a direct effect on the probability of filling a vacancy. There are other models of the labor market, where the number of unemployed is not expected to affect hiring. According to efficiency wage and bargaining theories there is excess supply in the labor market due to wages being above the clearing level. In these theories, firms have no problems filling all the vacancies they want to, since the supply of unemployed is always enough and there are no matching frictions. According to these demand-oriented theories, neither the number of unemployed nor the number of vacancies should have a significant effect on the probability of filling a vacancy. I find a strong negative effect of vacancies, indicating a congestion effect, which is not consistent with the labor demand models. Neither is the positive effect of the number of unemployed which is present in some specifications. A

negative effect of the number of vacancies and at the same time no effect of the number of unemployed is not consistent with any of the models. In the simulations, I use the result with a positive effect of the number of unemployed together with the negative effect of the number of vacancies, consistent with search and matching theory.

4 Employment dynamics

In this section I use the estimates from the previous section to try to evaluate how important variations in unemployment and vacancies at the local labor market may be for the employment decisions of individual firms. One common way of doing this kind of analysis is simulating impulse responses of shocks to a theoretical model in steady state. This is also what I do in this paper. The theoretical model used, which is from Carlsson, Eriksson, and Gottfries (2012), is a model of employment that includes search frictions, linear vacancy costs, convex hiring costs, and monopolistic competition in the product market. The model is based on the standard search and matching model (cf. Pissarides (2000)) with the main differences being that the product market is characterized by imperfect competition and that firms hire more than one worker. The model has been applied to data by Carlsson, Eriksson, and Gottfries (2012) and Eriksson and Stadin (2012). In these studies there is empirical support for all the supply- and demand-factors in the model being determinants of hiring.

4.1 The theoretical model

The national labor market consists of a number of local labor markets and all matching is assumed to take place within these local labor markets. In each local labor market, indexed n , there is a large number of firms, indexed i . The firms sell their products in different product markets and they face different competitors' prices, denoted $P_{i,t}^C$. The nominal wages ($W_{i,t}$) are assumed to be exogenous to the firm. A conventional search and matching model with the wage in each period endogenously determined by Nash bargaining between firms and workers, induces too much volatility in wages compared to what can be observed in the data (see, e.g., Shimer (2005)). The exaggerated procyclical movement in wages dampens the cyclical movement in firms' incentives to hire. According to Yashiv (2007), there is agreement that wage behavior is not well explained by this model. Some wage stickiness has been found to better match U.S. data in, for instance, Gertler and Trigari (2009) and Christiano, Eichenbaum, and Evans (2005). The best way to model the wages is probably

somewhere between totally exogenous and totally endogenous. However, the effect of wages is not a main focus of this paper and therefore I stick with the exogenous wages as in Carlsson, Eriksson, and Gottfries (2012). This assumption is made to keep the model simple, but can also be justified by arguing that wages in Sweden are to a large extent set in nation-wide branch-level union contracts.

Production takes place with the CRS technology $Y_{i,t} = N_{i,t}$. All firms sell their products in monopolistic competitive markets. The demand for a firm's output is $Y_{i,t} = \left(\frac{P_{i,t}}{P_{i,t}^C}\right)^{-\eta} D_{i,t}^\sigma$, where $P_{i,t}$ is the firm's price, $D_{i,t}$ is a firm specific demand-shifter, $\sigma > 0$ and $\eta > 1$. There is no price rigidity – the firms adjust their prices to make $Y_{i,t} = D_{i,t}$.

Matching of unemployed workers and vacancies takes place in each local labor market every period. The matching process between vacancies and unemployed workers is described by a matching function: $M_{n,t} = \phi U_{n,t}^{\alpha_U} V_{n,t}^{\alpha_V}$. The probability of filling a vacancy is thus given by $Q_{n,t} = \frac{M_{n,t}}{V_{n,t}} = \phi U_{n,t}^{\alpha_U} V_{n,t}^{\alpha_V - 1}$. A fraction λ of the previously employed workers quit their jobs for exogenous reasons each period. This fraction is assumed to be sufficiently large for firms to be able to adjust the number of employees sufficiently downwards by hiring fewer workers, i.e., layoffs are not necessary. At the start of each period, firms choose the number of vacancies to open. Firm i opens $V_{i,t}$ vacancies and incurs real linear vacancy costs given by $c_V V_{i,t}$. Hiring is $H_{i,t} = Q_{n,t} V_{i,t}$ and the firm incurs quadratic hiring costs given by $\frac{c_H}{2} \left(\frac{H_{i,t}}{N_{i,t-1}}\right)^2 N_{i,t-1}$. Convex hiring costs implies a smooth adjustment of the firms' labor force over time. The hiring costs include costs for training, reorganization, etc., while the vacancy costs include costs for advertisement, recruiters, etc.

Firm i chooses the number of vacancies to open by solving the profit maximization problem.

$$\begin{aligned} \max E_t \left\{ \sum_{\tau=t}^{\infty} \beta^{\tau-t} \left(\frac{(P_{i,\tau} - W_{i,\tau})}{P_{i,\tau}^C} N_{i,\tau} - \frac{c_H}{2} \left(\frac{H_{i,\tau}}{N_{i,\tau-1}} \right)^2 N_{i,\tau-1} - c_V V_{i,\tau} \right) \right\} \\ \text{s.t. } N_{i,\tau} = H_{i,\tau} + (1 - \lambda) N_{i,\tau-1}, \quad H_{i,\tau} = Q_{n,\tau} V_{i,\tau} \text{ and } N_{i,\tau} = \left(\frac{P_{i,\tau}}{P_{i,\tau}^C} \right)^{-\eta} D_{i,\tau}^\sigma \end{aligned} \quad (6)$$

Inserting the constraints and maximizing with respect to $N_{i,t}$ yields the Euler equation (7).

$$E_t \left\{ \begin{aligned} & \frac{\eta - 1}{\eta} \left(\frac{D_{i,t}^\sigma}{N_{i,t}} \right)^{\frac{1}{\eta}} - \frac{W_{i,t}}{P_{i,t}^C} - c_H (N_{i,t} - (1 - \lambda)N_{i,t-1}) N_{i,t-1}^{-1} - \frac{c_V}{Q_{n,t}} \\ & + \beta c_H (N_{i,t+1} - (1 - \lambda)N_{i,t}) (1 - \lambda) N_{i,t}^{-1} + \beta \frac{c_H}{2} (N_{i,t+1} - (1 - \lambda)N_{i,t})^2 N_{i,t}^{-2} \\ & + \beta (1 - \lambda) \frac{c_V}{Q_{n,t+1}} = 0 \end{aligned} \right\} \quad (7)$$

From the Euler equation, one can see that the typical firm will hire more workers if the probability of finding a worker in the current period ($Q_{n,t}$) is higher, if the expected probability of finding a worker in the next period ($Q_{n,t+1}$) is lower, if the demand for the firm's products ($D_{i,t}$) is higher or if the real wage costs $\left(\frac{W_{i,t}}{P_{i,t}^C}\right)$ are lower. This is the equation I will use in the theoretical simulations.

4.2 Calibration

The model is simulated around a steady state, where the levels of the exogenous variables are all normalized to 1, and hence the logs of the variables are all 0. I look at changes from the mean values in steady state, not at the levels of these variables. The period length is one month. The parameter values used in my calibration are listed in Table 6.

Table 6. Parameter values

α_U	0.16	in matching function, own estimate
α_V	0.73	in matching function, own estimate
ϕ	1.9	in matching function, own estimate
λ	0.01	exogenous separation rate
c_V	0.32	parameter in linear vacancy costs
c_H	2.6	parameter in quadratic hiring costs
η	11	elasticity of production with respect to the price
σ	1	elasticity of production with respect to demand
β	0.997	monthly discount rate

In line with the estimation results including time dummies but no local trends (in column 2, Table 2), I set $\alpha_U=0.16$ and $\alpha_V=0.73$. If α_U would be set in line with the results for the estimation including the local time trends, it would simply mean shutting down the effect of

the number of unemployed. Since the model is simulated around a steady state where $\ln V$ and $\ln U$ are zero, I calibrate the constant of the matching function such that $\ln \phi$ is equal to the mean of $\ln Q$ in the data.⁴ This gives $0.62 \approx \ln \phi$ and hence $\phi \approx 1.9$, i.e., $Q^{ss} = 1.9$ which means that vacancies are filled at the rate of approximately two vacancies per month.

The parameter λ is the rate at which employed workers quit their jobs for exogenous reasons in the model. According to Statistics Sweden, around 3 percent or slightly more of the permanently employed workers in the private sector left their jobs each quarter in 1990-2011, indicating a monthly separation rate of about 1 percent.⁵ I set $\lambda = 0.01$ to match this number. Of course, λ being exogenous is a simplification. Especially in a recession, layoffs arise because firms close down or have to shrink their work force drastically. Thus, the value for λ that I use is probably an overstatement, since it includes some layoffs that are not exogenous but depend on the state of the labor market. Another issue is that temporary employees are not included in the measure, so λ may be understated because of this. It is not clear if the measure is overall overstating or understating the value of λ . The value 0.01 is smaller than the separation rate of 0.038 for the U.S. in Michaillat (2012) and the monthly value that can be derived from quarterly value for the U.S. in Shimer (2005): $0.1/3 \approx 0.033$. A lower separation rate for Sweden than for the U.S. is expected, but it is not clear how much lower. Yashiv (2000) set λ to 0.017 per month for Israel. Setting $\lambda = 0.02$, more in line with Yashiv, doesn't affect my results.

The cost of recruiting a worker consists of two parts. The linear vacancy costs make up one part that is higher the longer the duration of the vacancy. The other part is the quadratic hiring costs, which are independent of the probability of filling a vacancy. If the vacancy cost parameter c_v is set to zero, employment is not at all affected by shocks to vacancies and unemployment. If the hiring cost parameter c_h is set to zero, on the other hand, the employment effects of all shocks become stronger, and employment returns faster to steady state.⁶ With no adjustment costs ($c_h=0$) and a very high price elasticity (high η), the model approaches a standard search and matching model.

⁴ $\text{mean}(\ln Q) = \ln \phi + \alpha_U * \text{mean}(\ln U) - (1 - \alpha_V) * \text{mean}(\ln V)$, inserting values $0.62 \approx \ln \phi + 0 - 0$.

⁵Diagram in "Kortperiodisk sysselsättningsstatistik 4:e kvartalet 2011", AM 63 SM 1201, Statistics Sweden.

⁶In Yashiv (2000), the estimated vacancy costs are actually not significantly different from zero, while convex adjustment costs are shown to be empirically relevant. Convex hiring costs have recently also found support in

The value of the linear vacancy costs, c_v , is taken from Michaillat (2012). In his calibration, the recruiting cost in the benchmark model is $0.32 = 0.32\bar{W}$, where $\bar{W}$ is the steady state wage. This value is a midpoint between two estimates, based on data from two different U.S. data sources.⁷ He also states that his estimate is average compared to others found in the literature.⁸ I have seen no estimates of the vacancy cost for Sweden. The steady state wage in my calibration is one, and hence I calibrate c_v as 0.32. This might overstate the linear vacancy costs, since some costs that should be included in the quadratic hiring costs might be included in this measure.

The value of the parameter in the quadratic hiring costs is derived from the estimation of the Euler equation in Carlsson, Eriksson, and Gottfries (2012). Setting $\eta = 11$ and $\sigma = 1$, I can use their estimated coefficient for the product demand variable to derive a monthly value of 2.6. I haven't seen any other study exactly estimating the parameter c_H . Due to this uncertainty, I also examine the cases where there are no hiring costs ($c_H = 0$), and where there are markedly higher hiring costs ($c_H = 13$).⁹

Carlsson and Smedsaas (2007) have estimated the markup for Swedish manufacturing firms to 17 percent, translating into $\eta = 7$.¹⁰ In Bowman (2003), the markup for the private U.S. economy as a whole was 4 percent ($\eta = 26$), and for manufacturing 11 percent ($\eta = 10$). Christiano, Eichenbaum, and Evans (2005) estimated a markup of 20 percent ($\eta = 6$) for the U.S. I choose a markup of 10 percent ($\eta = 11$), which is about a midpoint of the above-mentioned estimates. Moreover, a steady-state markup of 10 percent is a customary value in the literature (according to Krause, Lopez-Salido, and Lubik (2008)). The other parameter in the monopolistic demand function, σ , is set to 1 to make the interpretation easy. For a given price, a 1 percent increase in demand leads to a 1 percent increase in production.

Blatter, Muehleman and Schenker (2012). However, there doesn't seem to be consensus in the literature about the structure of recruitment costs.

⁷The two data sources are Job Openings and Labor Turnover Survey and PricewaterhouseCooper.

⁸Michaillat refers to 0.213 in Shimer (2005), 0.357 in Pissarides (2009) and 0.433 in Hall and Milgrom (2008).

⁹The value 13 is also derived from Carlsson, Eriksson, and Gottfries (2012), using their low value of η . For more information about the derivations of $c_H = 2.6$ & $c_H = 13$, see section V in the Appendix.

¹⁰Since the price markup over marginal cost is $\frac{\eta}{\eta-1}$.

The discount rate is the same as in Gertler and Trigari (2009), $\beta = 0.99^{1/3} \approx 0.997$, i.e., a monthly interest rate of 0.3 percent, which is close to the 0.4 percent in Yashiv (2000) and the values in most other studies.

Vacancies, unemployment, product demand and real wage costs are exogenous in the theoretical model, but estimates of how these variables move over time are needed to simulate the model. Second order autoregressive processes are estimated, controlling for local linear time trends and seasonal effects. The aim is to identify unexpected variations that the firms haven't already taken into account in earlier employment decisions. Neither the trend nor the seasonal variation should come as a surprise to the firms. AR(2) is chosen to keep it simple but still catch more of the dynamics than with AR(1).¹¹ The estimated AR(2) processes for the explanatory variables are presented in Table 7. The standard deviations of the residuals are the estimates that will be used as initial exogenous shocks to the variables. The coefficients for the lags provide information about how the variables will move over time until they return to steady state after the initial shock. The shocks should be of reasonable magnitude and persistence and are interpreted as standard unpredictable changes in economic conditions according to the data.

Table 7. AR(2) processes for vacancies, unemployment, product demand and real wage costs

Dependent: Current value of variable	(1) $\ln \bar{V}_{n,t}$	(2) $\ln \bar{U}_{n,t}$	(3) $\ln D_{j,t}$	(4) $\ln W_{j,t}^r$
First lag of variable	0.929***	1.471***	1.042***	0.461***
Second lag of variable	-0.303***	-0.548***	-0.113***	0.373***
Time trends	yes	yes	yes	yes
Seasonal effects	yes	yes	yes	yes
Std.Dev. of residual	0.335	0.053	0.006	0.012
R-squared (within)	0.803	0.985	0.997	0.996

Note: All AR(2) coefficients are significant at the 1 percent level, denoted ***. Unemployment and vacancy data are for all local labor markets (n) in Sweden in 1992-2011, the product demand for all industries (j) in Sweden in 1992-2008, and the real wage costs for all industries in manufacturing 1992-2008, all in logs and at monthly frequency. The standard errors are robust, clustered at llc or industry. Fixed effects, linear and quadratic time trends, and seasonal effects (local or industry specific) are included in all regressions.

¹¹Using AR(3) or AR(1) instead of an AR(2) in the simulations changes the employment dynamics very little.

The variables representing product demand and real wage costs are constructed on the industry level using data from Statistics Sweden and the OECD. Product demand is an index including both domestic and foreign demand, weighted together by the export shares. The real wage cost is the nominal wage deflated by a competitor price consisting of domestic and international product prices. A more detailed description of these variables can be found in Eriksson and Stadin (2012). I do not have these variables on the firm level, but the industry level should work as an approximation.

4.3 Simulation of impulse response functions

The simulations show employment dynamics for what is assumed to be a typical firm. I use the Matlab application Dynare, which makes an approximation of the model around steady state, to make simulations of the effects of temporary but persistent shocks to the variables.¹² Shocks to the explanatory variables are induced one at the time, and then the response in the firm's hiring decision can be observed. The shocks are log deviations, which I refer to as approximate percentage changes.¹³ I start with the baseline case, using the parameters listed in Table 6, then I do some sensitivity analysis, changing some parameter values, and finally I look at two different states of the labor market: a boom and a recession.

The employment effects are symmetrical when simulating the responses to positive and negative shocks of the same size. In the model, all employment adjustments are assumed to take place through changes in hiring. I focus on situations when the typical firm increases employment to avoid layoffs, i.e., to avoid employment decreases larger than the exogenous quitting rate. In the baseline simulation, there are no downward adjustments of employment that cannot be handled by simply not hiring, so this is not a big issue. Nevertheless, layoffs would be necessary in some special cases with extreme values of parameters. There are no vacancy costs associated with layoffs of workers, and the adjustment costs are probably different when hiring and when firing. According to Kramarz and Abowd (2003) and Kramarz and Michaud (2010), French firms adjust employment primarily through changes in hiring, since hiring costs are much lower than separation costs. In the U.S. it is the other way

¹²A second order approximation is default in Dynare, and this is what is used in this simulation. Using a first order approximation (linearization) or a third order yields almost identical results.

¹³The relatively big shock of 0.34 log deviation in the vacancy variable is actually not very well approximated by 34 percent. When $\ln V$ goes from 0 to 0.34, V goes from 1 to 1.4, i.e., a 40 percent increase.

around. Kramarz and Abowd believed that institutions in other European countries, such as Sweden, are typically more similar to those in France than those in the U.S. This supports the assumption that firms adjust the number of employed by changing hiring. It also implies that I cannot do very reliable simulations of large, negative employment responses, but this is not important for the conclusions in this paper.

Baseline simulation

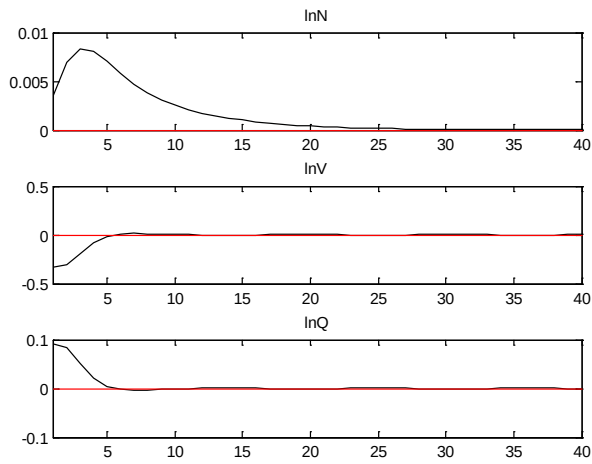
Impulse response functions for the baseline case are presented in Figures 5a-d. A typical shock consisting of a decrease of 33.5 percent in the number of vacancies in the local labor market where the firm is located induces a 9 percent increase in the probability of filling a vacancy and a maximum increase in employment of 0.86 percent. A typical shock consisting of a 5.3 percent increase in the number of unemployed induces a 1.5 percent increase in the probability of filling a vacancy and a maximum increase in employment of 0.14 percent. A 0.6 percent positive shock to product demand has a maximum response of 0.35 percent increase in employment. A 1.2 percent negative shock to the real wage costs has a maximum response of 1.4 percent higher employment. It takes about two years for employment to return to steady state after a shock.

A variance decomposition shows the fraction of the variance of employment that each type of shock would explain if the shocks would happen during each period for a large number of periods, not just one type of shock occurring once. Shocks to the number of vacancies would explain 26.2 percent, shocks to the number of unemployed 1.3 percent, shocks to product demand 8.2 percent, and shocks to the real wage costs 64.3 percent of the variation in employment. The big effect of the real wage is due to the high elasticity of demand.

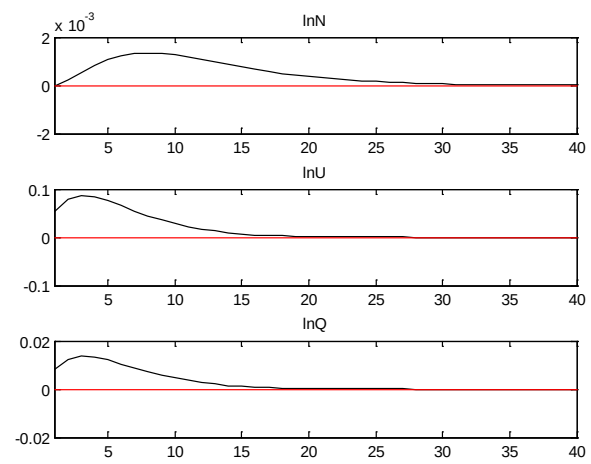
Figure A3 in the Appendix shows the impulse responses when a one-percent shock is induced to all variables, still using the baseline parameter values. This is to ease the interpretation of the effects, making them like elasticities. The maximum response in employment to a one-percent shock is 0.03 percent when the shock is to vacancies, 0.03 percent as well when the shock is to unemployment, 0.59 when the shock is to product demand, and 1.15 percent when the shock is to real wage costs. The unemployment shock is more persistent than the vacancy shock and rises after the initial one percent, which apparently offsets the smaller coefficient for unemployment in the matching function.

Figure 5. Employment effects of exogenous changes in variables, baseline case

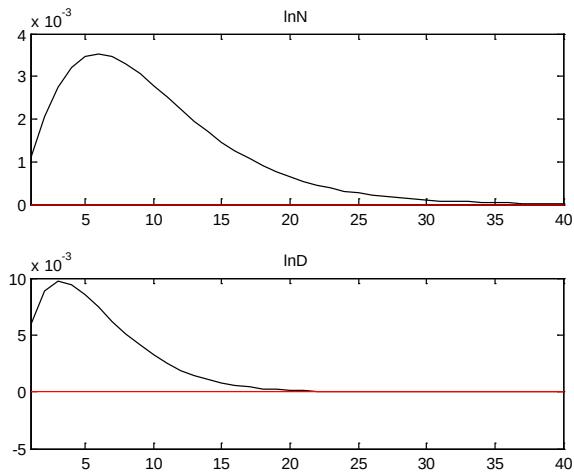
5a. Shock to the number of vacancies



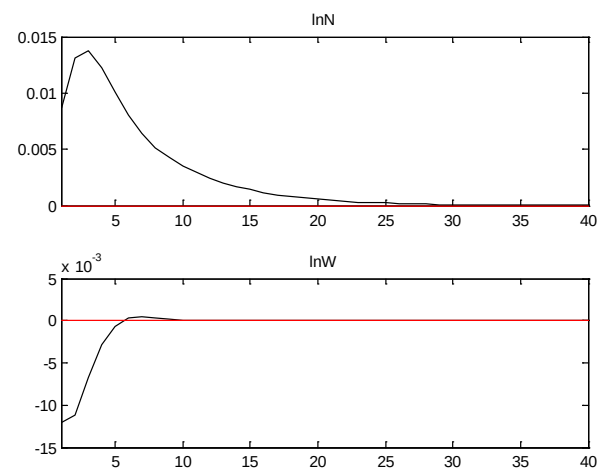
5b. Shock to the number of unemployed



5c. Shock to product demand



5d. Shock to real wage costs



Note: Theoretical impulse response functions simulated with Dynare. The graphs show the return to steady state after an exogenous shock. On the y-axis is log deviation from steady state and on the x-axis is the number of months. Parameter values are listed in Table 6.

Approximate maximum employment responses in Figures 5a-d:

	a. V-shock (-33.5%)	b. U-shock (+5.3%)	c. D-shock (+0.6%)	d. W-shock (-1.2%)
N max response	0.9 %	0.1 %	0.4 %	1.4 %

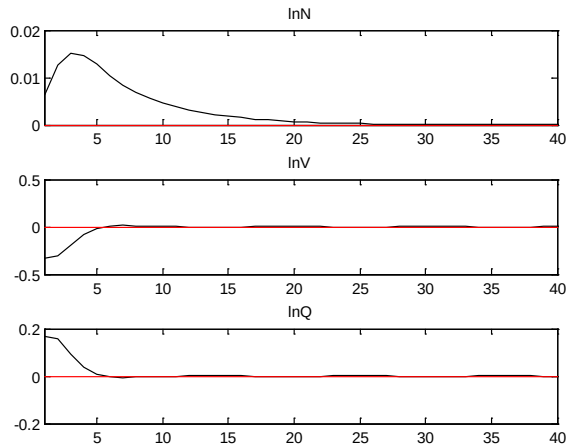
Special cases simulations –changes in steady state parameters

How important are my estimates of α_U and α_V ? If I set $\alpha_U = \alpha_V = 0.5$, i.e., equal weights and constant returns to scale in the matching function, the effects of shocks to the number of vacancies and the number of unemployed are larger.¹⁴ As can be seen in Figure 6, a 33.5 percent negative shock to the number of vacancies induces a maximum increase in employment of 1.5 percent (0.86 in baseline). A positive shock to the number of unemployed of 5.3 percent induces an increase in employment of maximum 0.45 percent (0.14 in baseline). The effects of shocks to product demand and real wage costs are the same as in the baseline case.

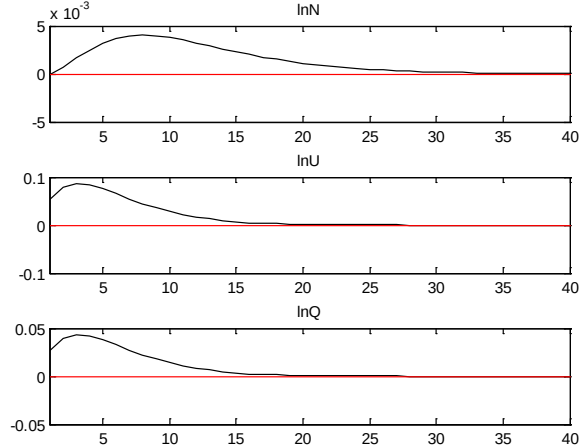
The relative importance of shocks to the number of vacancies and number of unemployed becomes noticeably larger. In the variance decomposition, shocks to vacancies explain 51.3 percent (26.2 in baseline), shocks to unemployment 7.3 percent (1.3 in baseline), shocks to product demand 4.7 percent, and shocks to real wage costs 36.7 percent of the variation in employment.

Figure 6. Effects of shocks to vacancies and unemployment, CRS, $\alpha_U = \alpha_V = 0.5$

6a. Shock to the number of vacancies, CRS



6b. Shock to the number of unemployed, CRS



Note: Theoretical impulse response functions. On the y-axis is log deviation from steady state and on the x-axis is the number of months. Parameter values in Table 6, with the exception that $\alpha_U = \alpha_V = 0.5$, i.e., constant returns to scale in the matching function and larger effects of both vacancies and unemployment than in baseline.

¹⁴The negative effect of V on Q is raised from 0.27 to 0.5 and the positive effect of U is raised from 0.16 to 0.5. $\alpha_U = \alpha_V = 0.5$ is used in other studies, such as Gertler and Trigari (2009).

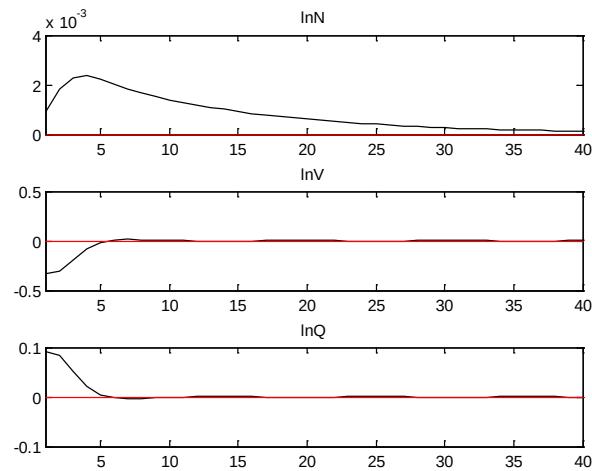
If the vacancy costs are set too low, the effect of a shock to the probability of filling a vacancy will be understated. When I set $c_v=0.5$, which is slightly higher than the highest value I have seen in the literature,¹⁵ the effects of a shock to vacancies and to unemployment become slightly bigger than in the baseline case. The typical shock to vacancies induces a maximum employment response of 1.3 percent, and the typical shock to unemployment an employment response of maximum 0.2 percent (see Figure A4 in the Appendix). The duration of a vacancy is always quite short, so even a rather large percent change in the probability of filling a vacancy induces only a few days of change in duration. Hence, the vacancy cost per unit of time has to be very high for drastic changes in employment due to typical changes in the probability of filling a vacancy. However, in the variance decomposition, the relative importance of shocks to vacancies becomes noticeably larger than in the baseline case. The relative importance of shocks to the number of unemployed is also increased but still small (for the exact numbers of the variance decomposition, see Table 8).

Since there is a good deal of uncertainty regarding the value of the parameter of the quadratic hiring costs, I do simulations setting it to a much higher value than in the baseline case and also setting the parameter to zero. Employment effects when $c_h=13$, are presented in Figure 7. The effects of all shocks are significantly smaller than in baseline. A 33.5 percent negative shock to vacancies induces a maximum increase in employment of 0.24 percent. A 5.3 percent positive shock to the number of unemployed gives a maximum increase in employment of only 0.05 percent. A 0.6 percent positive shock to product demand, gives a 0.14 percent maximum increase in employment. A 1.2 percent negative shock to the real wage costs has a response of maximum 0.36 percent higher employment. With high adjustment costs, firms don't do much employment adjustment in response to a temporary shock to any variable, and it takes a long time for employment to return to the initial level after a temporary shock. The return to steady state takes more than three years after a shock to any of the variables. The relative importance of the variables in the variance decomposition is quite similar to the baseline case.

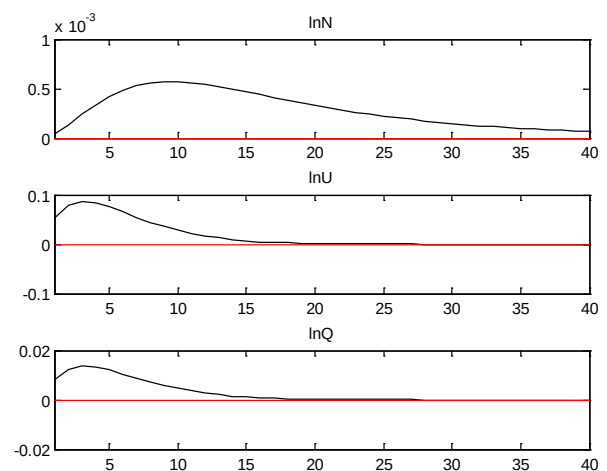
¹⁵ $c_v=0.433$ is the largest parameter value mentioned in Michaillat (2012).

Figure 7. Employment effects of exogenous changes in variables, high adjustment costs

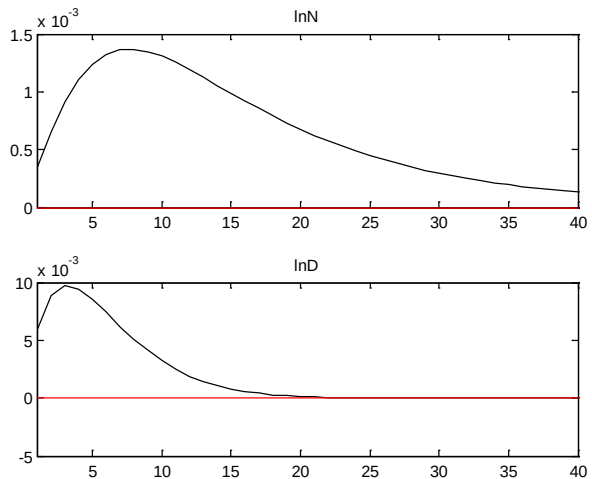
7a. Shock to vacancies, $c_H=13$



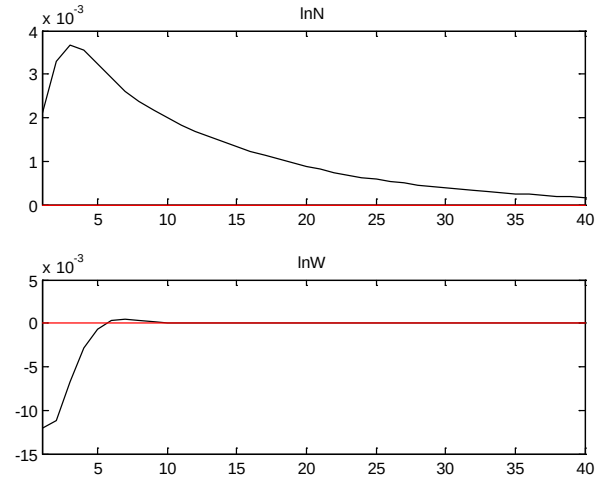
7b. Shock to unemployment, $c_H=13$



7c. Shock to product demand, $c_H=13$



7d. Shock to real wage costs, $c_H=13$



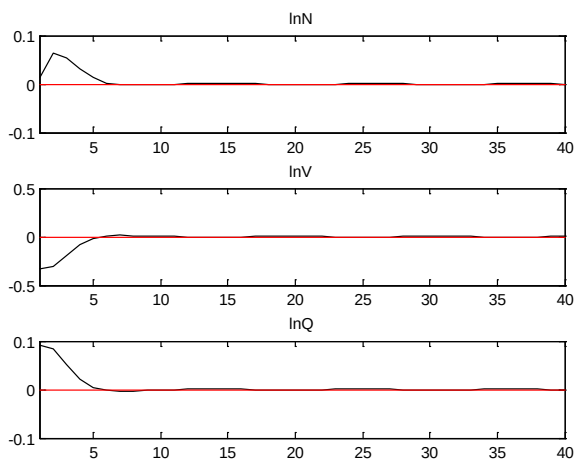
Note: Theoretical impulse response functions. On the y-axis is log deviation from steady state and on the x-axis is the number of months. Parameter values are listed in Table 6, with the exception that $c_H=13$.

If I shut down the quadratic hiring costs by setting $c_H=0$, the responses in employment become much stronger and employment doesn't deviate from steady state longer than the shocked variable. Impulse responses with $c_H=0$ are shown in Figure 8. A 33.5 percent negative shock to vacancies now induces a big maximum increase in employment of approximately 6 percent. A positive shock to the number of unemployed of 5.3 percent gives a maximum increase in employment of 0.3 percent after an initial drop. The initial drop in employment is caused by the fact that the probability of filling a vacancy over the next few months is expected to be even higher, in combination with no adjustment costs. If filling a vacancy during the next period is expected to be easier, the firm will hire fewer workers during the current period (see Euler equation). With no adjustment costs, employment

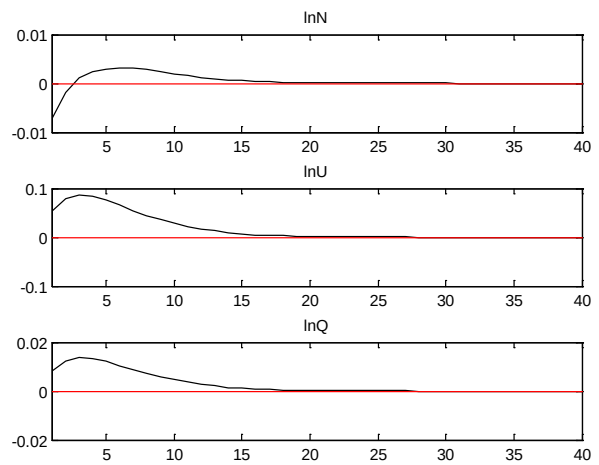
changes one to one with product demand. A 0.6 percent positive shock to product demand gives an initial rise in employment of 0.6 percent, which increases to maximum 1 percent. A 1.2 percent negative shock to the real wage costs has a strong response of a maximum 13 percent higher employment. Shocks to wages dominate in the variance decomposition, explaining about 80 percent of the variation in employment, while the relative importance of all the other shocks is smaller than in the baseline case.

Figure 8. Employment effects of exogenous changes in variables, no adjustment costs

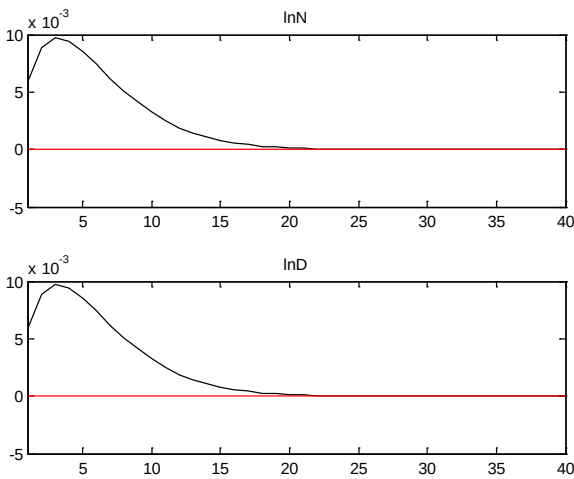
8a. Shock to vacancies, $c_H=0$



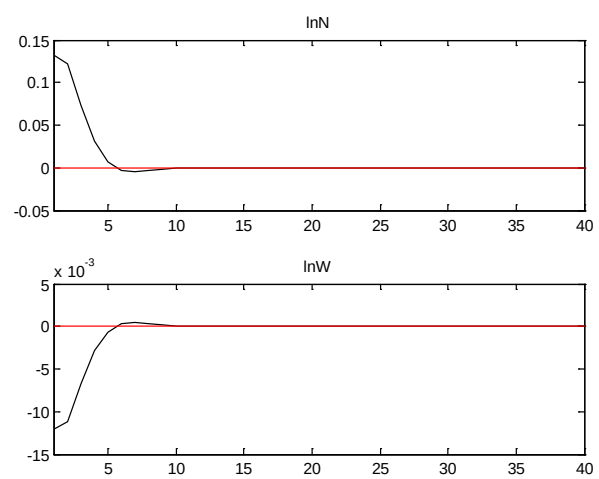
8b. Shock to unemployment, $c_H=0$



8c. Shock to product demand, $c_H=0$



8d. Shock to real wage costs, $c_H=0$



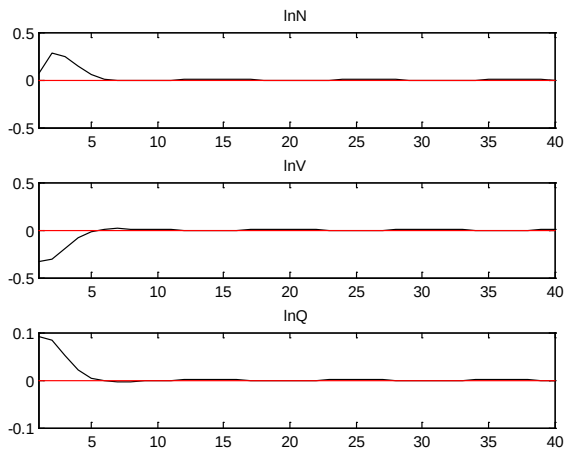
Note: Theoretical impulse response functions. On the y-axis is log deviation from steady state and on the x-axis is the number of months. Parameter values are listed in Table 6, with the exception that $c_H=0$.

What happens to the employment effects if the hiring costs are set to zero and the price elasticity is set very high, such that the model approaches a standard search and matching model with perfect competition in the product market? A parameter value of $\eta=50$ in Figure 9

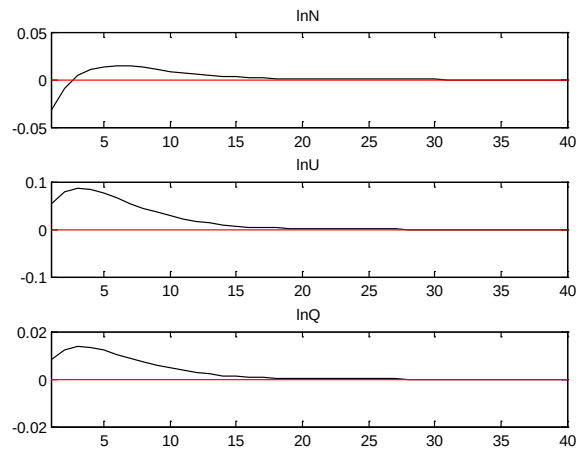
implies a markup of only 2 percent over marginal cost. A typical negative shock to vacancies of 33.5 percent now induces an unrealistic increase in employment of approximately 30 percent. A positive shock to unemployment of 5.3 percent raises employment to a maximum 1.2 percent above the steady state level after an initial decrease. The employment effect of a 1.2 percent negative shock to wages is huge, 60 percent higher employment, and the effect of a shock to product demand is still one to one. The real wage costs explain more than 80 percent of the variation in employment in the variance decomposition.

Figure 9. Employment effects, no adjustment costs and high competition

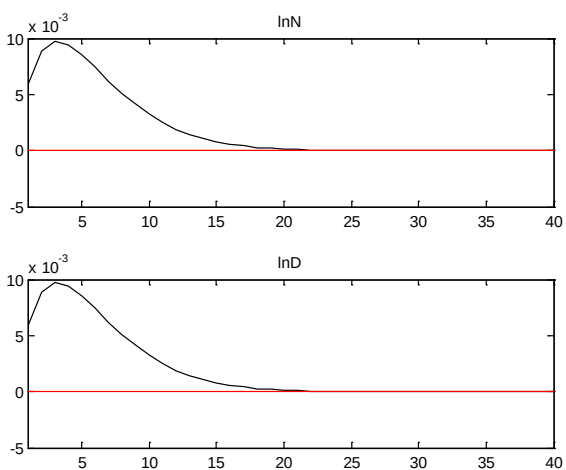
9a. Shock to vacancies, $c_H=0$ & $\eta=50$



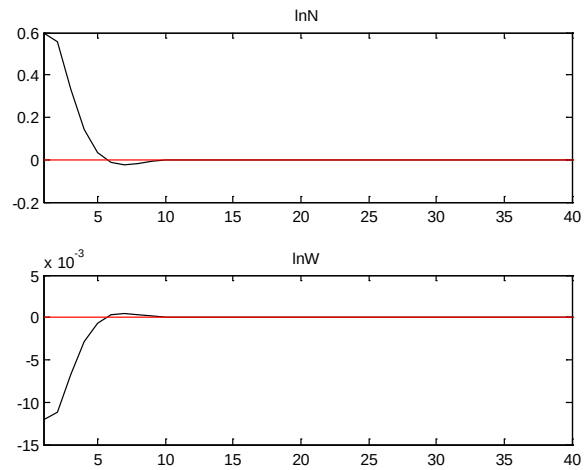
9b. Shock to unemployment, $c_H=0$ & $\eta=50$



9c. Shock to product demand, $c_H=0$ & $\eta=50$



9d. Shock to real wage costs, $c_H=0$ & $\eta=50$



Note: Theoretical impulse response functions. On the y-axis is log deviation from steady state and on the x-axis is the number of months. Parameter values are listed in Table 6, with the exceptions that $c_H=0$ & $\eta=50$.

In a standard search and matching model with perfect competition, the real wage and the product demand don't show explicitly in the hiring equation. In a perfect competition economy, the firm would go bankrupt if it would set wages and prices only slightly higher

than its competitors. With no costs associated with adjusting the number of employees (except for the linear vacancy costs), the firms' response to temporary shocks will be fast and strong. The precise sizes of the effects should not be taken too seriously in such an unrealistic environment and so far from steady state, but the results are qualitatively expected.

The adjustment costs seem to be important for the sizes of the employment effects, especially in combination with high competition in the product market. Only setting the competition parameter very high ($\eta=50$), keeping the baseline adjustment costs, changes the employment effects less drastically than when only setting the adjustments costs to zero, and far less dramatically than when combining the two. The employment effects of changes in the probability of filling a vacancy and real wage costs are slightly bigger and the employment effect of a shock to product demand is smaller when the competition is higher. Setting the vacancy cost high ($c_v=0.5$) and at the same time removing the adjustment costs, doesn't change the employment responses very much compared to only removing the adjustment costs. The effects of shocks to the probability of filling a vacancy are slightly bigger when the vacancy costs are higher (see the Appendix, Figures A5 and A6).

Table 8 shows the variance decompositions of all the cases that have been presented so far. Shocks to the number of vacancies and unemployed are relatively more important to the variation in employment when their effects on the probability of filling a vacancy are larger, when the vacancy costs are higher, or when the competition in the product market is higher.

Table 8. Variance decompositions of the variation in employment, baseline and special cases

		shocks to V	shocks to U	shocks to D	shocks to W
1)	baseline	26.21 %	1.30 %	8.17 %	64.3 %
2)	$\alpha_U=\alpha_V=0.5$	51.34 %	7.25 %	4.67 %	36.74 %
3)	$c_v=0.5$	45.81 %	2.27 %	5.86 %	46.06 %
4)	$c_H=13$	25.94 %	2.63 %	13.80 %	57.63 %
5)	$c_H=0$	17.91 %	0.25 %	1.10 %	80.74 %
6)	$\eta=50$	29.82 %	2.92 %	0.75 %	66.51 %
7)	$c_H=0$ & $c_v=0.5$	34.65 %	0.49 %	0.88 %	63.98 %
8)	$c_H=0$ & $\eta=50$	18.10 %	0.26 %	0.05 %	81.59 %

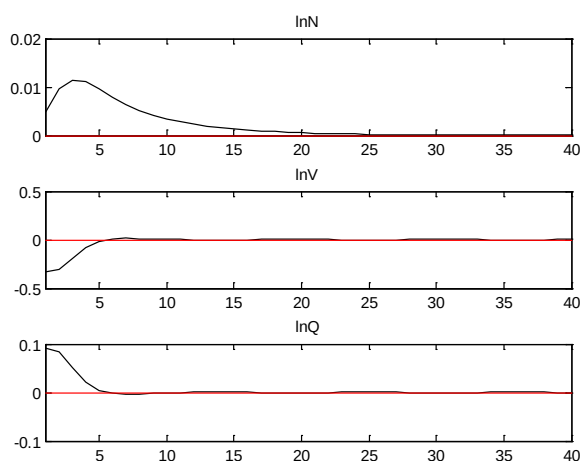
Note: Variance decompositions showing the fraction of the variance of employment (N) at a typical firm that each type of shock would explain if all the shocks would happen repeatedly during a large number of periods. The shocks are standard unpredictable changes in the total number of vacancies (V), in the number of unemployed (U), in the product demand (D), and in the real wage costs (W) according to Swedish data. Shocks to vacancies and unemployment affect employment via the probability of filling a vacancy (Q).

Simulations at different stages of the business cycle

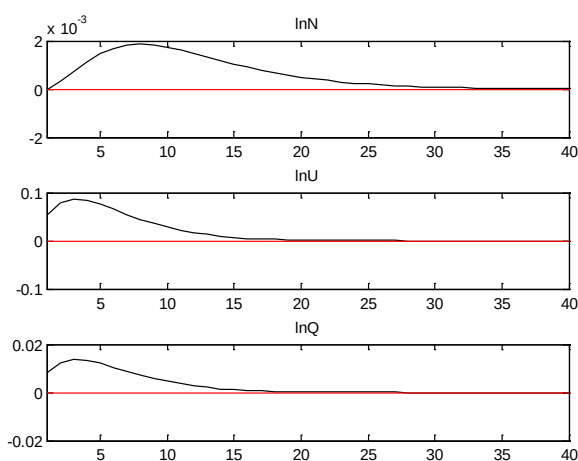
How do the employment effects of changes in the probability of filling a vacancy vary with the state of the labor market? Figure 10 shows impulse responses during a boom, which is a period long enough for firms to adjust. In a boom, the mean probability of filling a vacancy is lower than in the baseline case. I set the parameter ϕ to 1.3 to match the fact that, in my data, the log of the probability of filling a vacancy has a mean of about 0.3 during the years of the boom in the early 2000s. The 9 percent increase in the probability of filling a vacancy due to a typical negative shock to vacancies induces a maximum increase in employment of 1.2 percent. The 1.5 percent increase in the probability of filling a vacancy due to a typical positive shock to the number of unemployed induces an increase in employment of 0.2 percent.

Figure 10. Employment effects of shocks to Q , around a low Q in a boom

10a. Shock to vacancies, $Q^{ss}=1.3$



10b. Shock to unemployment, $Q^{ss}=1.3$

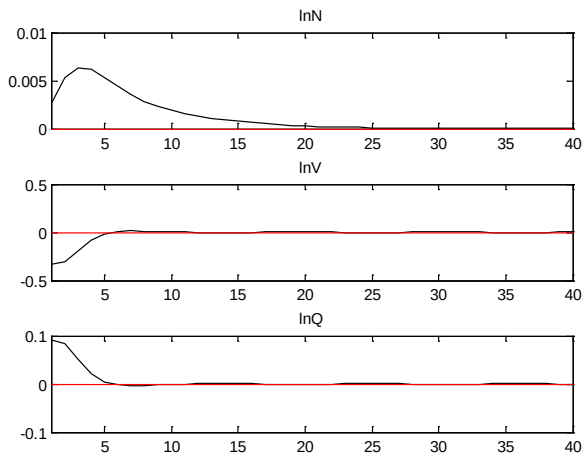


Note: Theoretical impulse response functions. On the y-axis is log deviation from steady state and on the x-axis is the number of months. Parameter values are listed in Table 6, with the exception that $\phi = Q^{ss} = 1.3$.

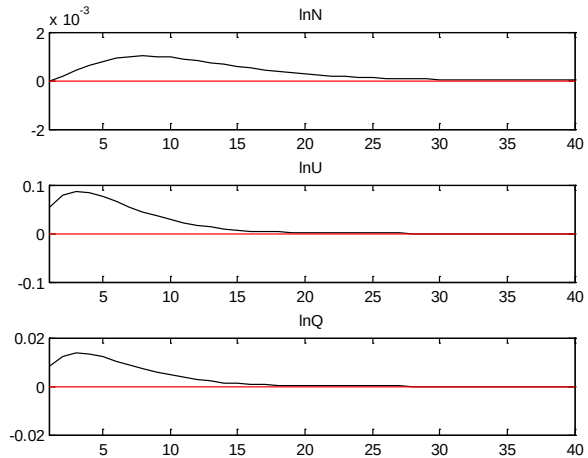
Figure 11 shows the corresponding results for a recession. The mean probability of filling a vacancy is higher than in the baseline case. The parameter ϕ is set to 2.5, since the log of the probability of filling a vacancy during the recession of the mid 1990s was about 0.9. The 9 percent increase in the probability of filling a vacancy due to a typical negative shock to vacancies induces a maximum increase in employment of 0.5 percent. The 1.5 percent increase in the probability of filling a vacancy due to a typical positive shock to the number of unemployed induces a maximum rise in employment of 0.1 percent.

Figure 11. Employment effects of shocks to Q , around a high Q in a recession

11a. Shock to vacancies, $Q^{ss}=2.5$



11b. Shock to unemployment, $Q^{ss}=2.5$



Note: Theoretical impulse response functions. On the y-axis is log deviation from steady state and on the x-axis is the number of months. Parameter values are listed in Table 6, with the exception that $\phi = Q^{ss} = 2.5$.

Shocks to the number of vacancies and unemployed are more important to employment in a boom than in a recession. These results support Michaillat's idea that matching frictions are less important to unemployment during recessions, when the probability of filling a vacancy is high. Still, the employment effect of a typical shock to the number of unemployed is not very important in any state of the labor market.

The simulations in Figures 10 and 11 can also be seen as simulating impulse responses around steady state in different local labor markets with different tightness $\left(\frac{V}{U}\right)$ or matching efficiency (ϕ). In a tight labor market, where the number of unemployed is low in relation to the number of vacancies, the mean probability of filling a vacancy is lower. This is also the case in a labor market with low matching efficiency caused by, e.g., low search intensity of unemployed workers or occupational mismatch between vacancies and unemployed. The employment effect of a lower or higher mean level of the probability of filling a vacancy can be applied for different reasons for this being the case. In the simulations in Figures 10 and 11, it is technically $\ln\phi$ that determines $\ln Q^{ss}$, since $\ln U$ and $\ln V$ are set to zero in steady state. I have also done simulations changing the steady state levels of $\ln V$ and $\ln U$ according to the data, and the results are very similar.

5 Conclusions

The number of unemployed in the local labor market has a rather small positive effect on the probability of filling a vacancy. The effect is not robust, and in some specifications there is no effect at all. The number of vacancies, on the other hand, has a significant, negative, and robust effect on the probability of filling a vacancy. Thus, I find fairly strong evidence of a congestion effect which affects employers posting vacancies. An effect of vacancies but not of unemployment is not consistent with any theory of the labor market. According to search and matching theory, both should matter, and according to efficiency wage and bargaining theories, none of the variables should matter. In the simulations, I focus on the case with a positive effect of the number unemployed.

Most other studies have used hires from unemployed as a measure of the matches, while I start from the firms' perspective and use the outflow of vacancies. The measures differ mainly because vacancies are often filled with employed workers moving between jobs rather than unemployed workers, and unemployed workers can get other jobs than those vacancies registered at the Public Employment Service (AF). The results in this paper differ from many earlier findings because of a different measure of the dependent variable (and also due to other factors, such as different time periods).

When it is easier to recruit workers, this should have a positive effect on hiring. According to the numerical simulations of a theoretical model, this is also the case. A change in the probability of filling a vacancy caused by a typical shock to the number of vacancies has an economically significant effect on the employment dynamics of a typical firm. The maximum employment effect is not huge but almost one percent in the baseline specification. A change in the probability of filling a vacancy caused by a typical shock to the number of unemployed also has an effect on employment, but it is too small to be very important (max 0.1 percent in baseline). This is because of the quite small estimated effect of unemployment on the probability of filling a vacancy, and also because shocks to the number of unemployed in the data are typically much smaller than shocks to vacancies. In the variance decomposition, shocks to the number of unemployed are relatively unimportant for explaining the variation in employment, compared to shocks to real wage costs, vacancies, and product demand.

The small effect on employment dynamics of temporary shocks to the number of unemployed doesn't mean that the level of labor supply is unimportant for the level of employment in the very long run. A permanent rise in supply, if there are no structural changes,¹⁶ is always expected to create its own demand in the long run.

According to theoretical simulations with different mean levels of the probability of filling a vacancy, corresponding to different phases of the business cycle in the data, changes in this probability are more important to employment during booms than in recessions. Thus, matching frictions seem to be more important for employment in a boom than in a recession.

¹⁶Relevant structural changes could be things like conditions for starting up and running firms, including communications, tax system, and regulations regarding minimum wages, affecting labor demand, or changes in employment insurance, retirement schemes, or the school system, affecting labor supply.

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Appendix

I. Local labor markets

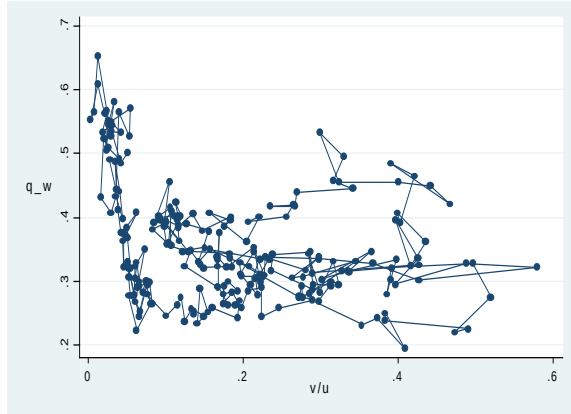
1	Stockholm	31	Bengtsfors	61	Bollnäs
2	Nyköping-Oxelösund	32	Göteborg (Gothenburg)	62	Hudiksvall
3	Katrineholm	33	Strömstad	63	Ånge
4	Eskilstuna	34	Trollhättan	64	Härnösand
5	Linköping	35	Borås	65	Sundsvall
6	Norrköping	36	Lidköping-Götene	66	Kramfors
7	Gislaved	37	Skövde	67	Sollefteå
8	Jönköping	38	Torsby	68	Örnsköldsvik
9	Värnamo	39	Ärjäng	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 labor markets from Statistics Sweden have changed over the years because of changes in commuting patterns. In this study, the year 2000 version is used, since it is about in the middle of the sample period (1992-2011).

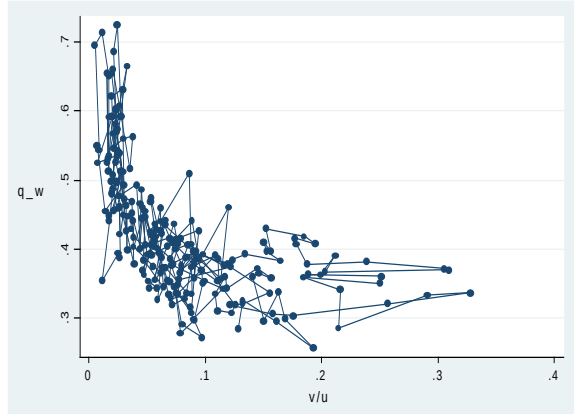
II. Extra plots of variables

Figure A1. Scatter plots of the probability of filling a vacancy (Q , y-axis) versus tightness (V/U , x-axis) for some important local labor markets.

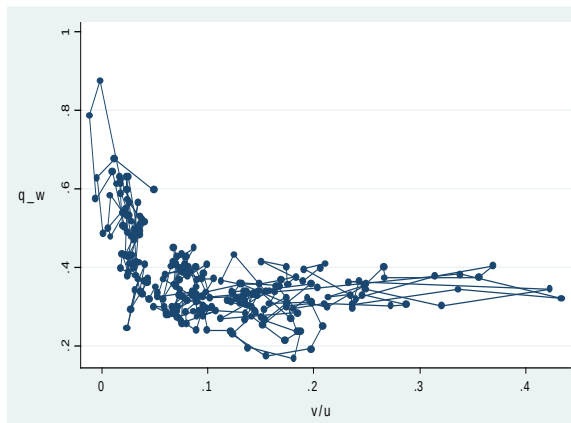
A1a. Stockholm (llc 1)



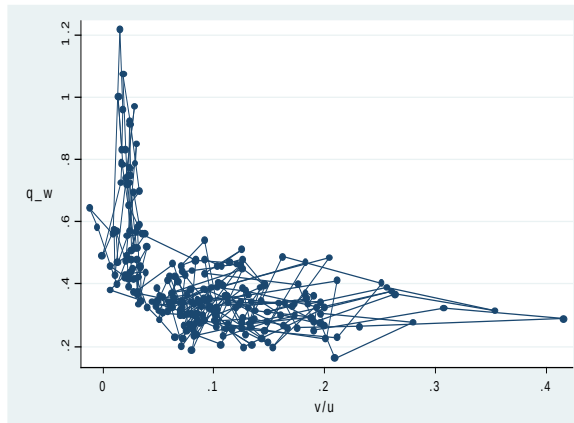
A1b. Malmö (llc 25)



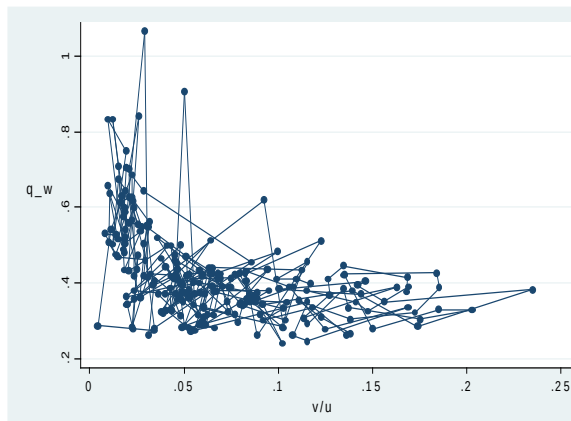
A1c. Göteborg (Gothenburg, llc 32)



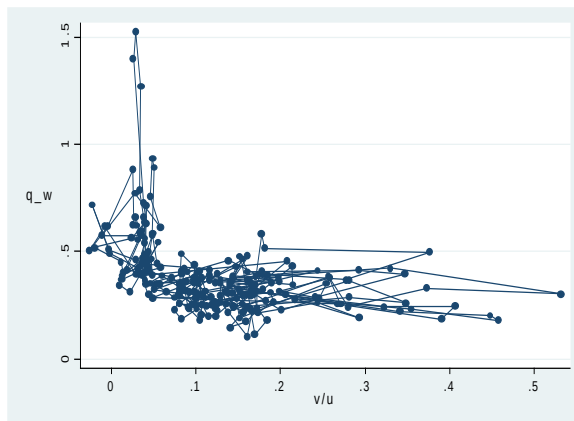
A1d. Västerås (llc 49)



A1e. Örebro (llc 47)



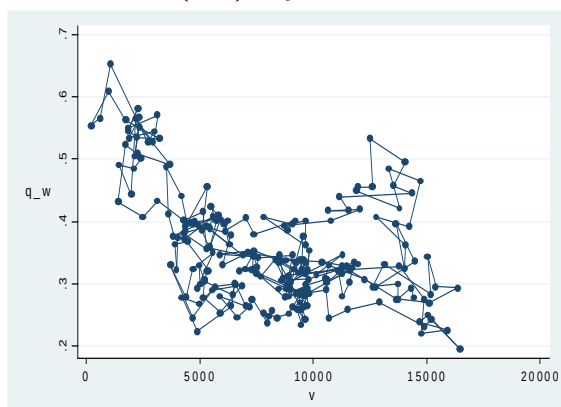
A1f. Trollhättan (llc 34)



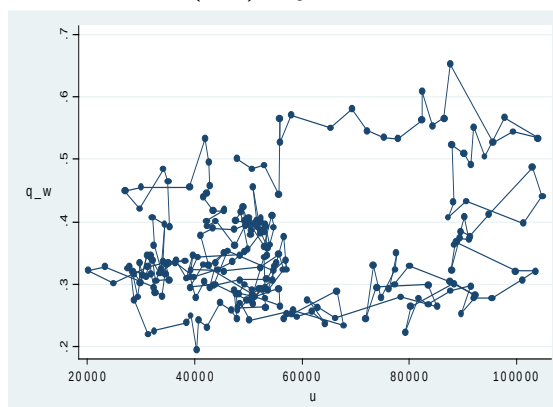
Note: Variables are seasonally adjusted and not in logs. Stocks of the number of unemployed and vacancies are measured in the very beginning of the month. q_w is the mean probability of filling a vacancy within a week during the month. Monthly data from AF for the six largest local labor markets in Sweden 1992-2011.

Figure A2. Scatter plots of the probability of filling a vacancy versus the number of vacancies and the number of unemployed for some important local labor markets in Sweden.

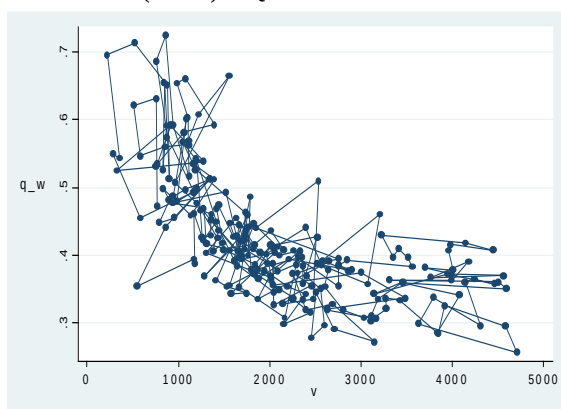
A2a. Stockholm (llc 1) – Q vs. V



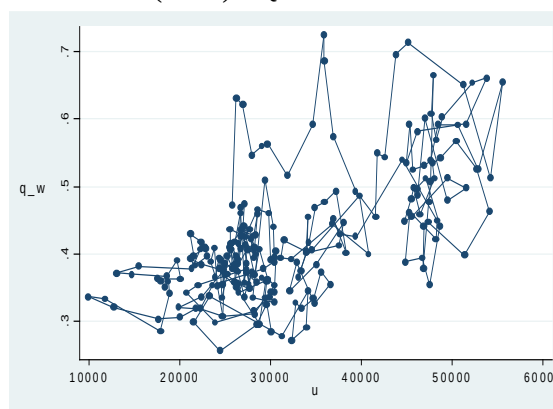
A2b. Stockholm (llc 1) – Q vs. U



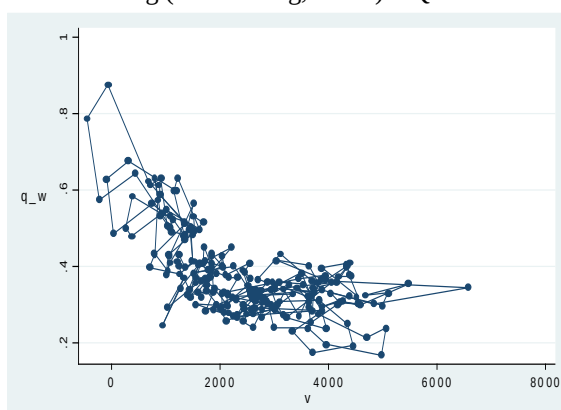
A2c. Malmö (llc 25) – Q vs. V



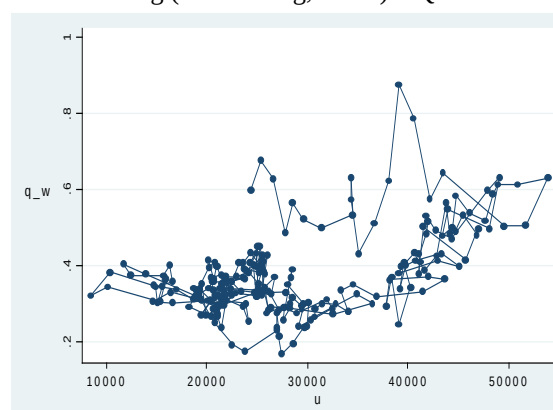
A2d. Malmö (llc 25) – Q vs. U



A2e. Göteborg (Gothenburg, llc 32) – Q vs. V

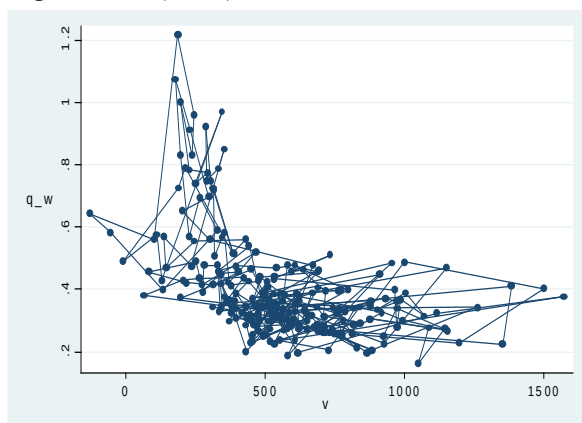


A2f. Göteborg (Gothenburg, llc 32) – Q vs. U

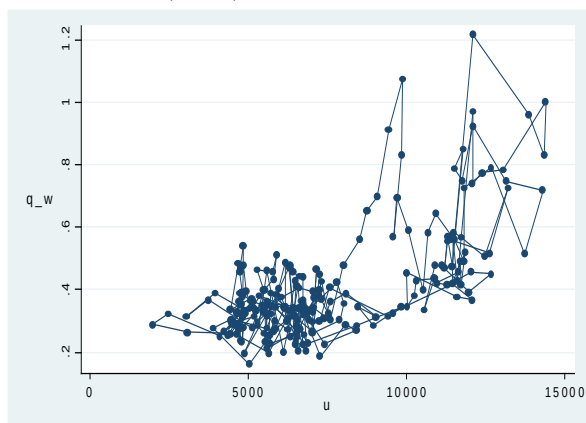


Note: Variables are seasonally adjusted and not in logs. Stocks of the number of unemployed and vacancies are measured in the very beginning of the month. q_w is the mean probability of filling a vacancy within a week during the month. Monthly data from AF for the largest local labor markets in Sweden, 1992-2011.

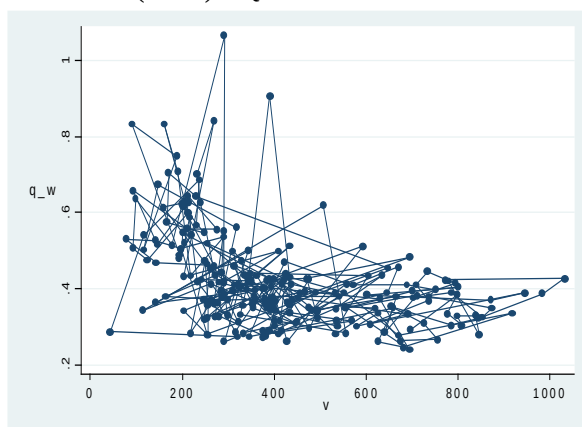
A2g. Västerås (llc 49) – Q vs. V



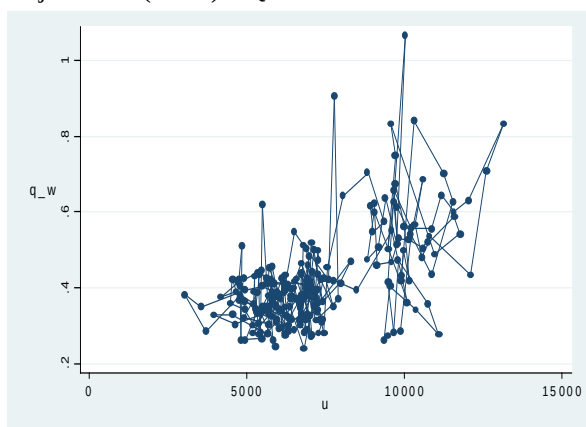
A2h. Västerås (llc 49) – Q vs. U



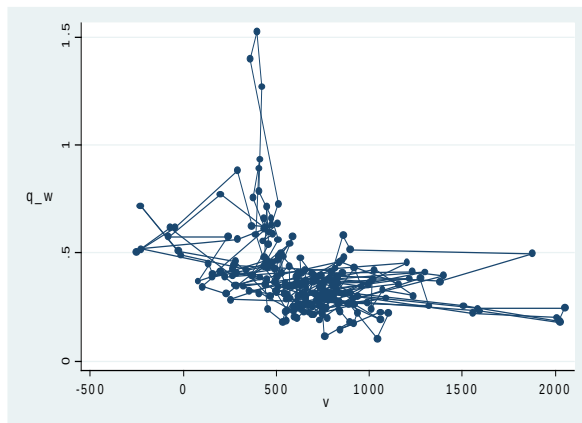
A2i. Örebro (llc 47) – Q vs. V



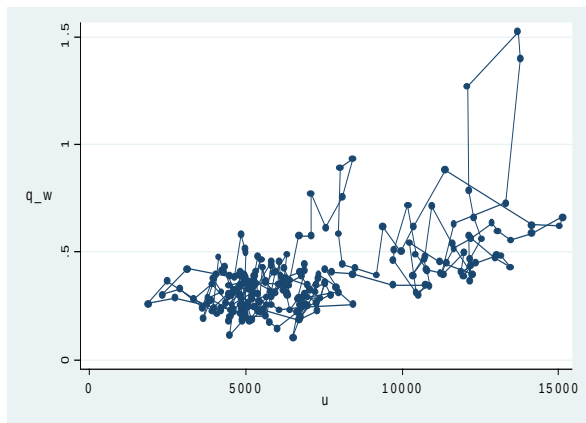
A2j. Örebro (llc 47) – Q vs. U



A2k. Trollhättan (llc 34) – Q vs. V



A2l. Trollhättan (llc 34) – Q vs. U



Note: Variables are seasonally adjusted and not in logs. Stocks of the number of unemployed and vacancies are measured in the very beginning of the month. q_w is the mean probability of filling a vacancy within a week during the month. Monthly data from AF for the largest local labor markets in Sweden, 1992-2011.

III. Tests for stationarity and cointegration in panel

Table A1. Tests for stationarity in $\overline{\ln Q}_{n,t}$, $\overline{\ln U}_{n,t}$ and $\overline{\ln V}_{n,t}$, table of p-values

	Fisher test H_0 : all panels contain a unit root					Hadri LM test H_0 : all panels are stationary				
$\overline{\ln Q}_{n,t}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.999	1
$\overline{\ln U}_{n,t}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.995	1
$\overline{\ln V}_{n,t}$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.444	1	1
time dummies	no	yes	no	no	yes	no	yes	no	no	yes
local trends t	no	no	yes	yes	yes	no	no	yes	yes	yes
local trends t^2	no	no	no	yes	yes	no	no	no	yes	yes

Note: Table showing p-values for the panel variables with and without variation explained by time dummies and local time trends removed (a “yes” indicating that the variation has been removed). Twelve lags specified in all tests. The Fischer test contains four p-values and the Hadri LM test one. To perform the Hadri LM test, the variables are first linearly interpolated over missing values. The Fisher test conducts Dickey-Fuller unit-root tests for each panel individually, and then combines the p-values from these tests to produce the overall test statistic for the variable studied. For more information about the Fisher test, see Choi (2001), and for the Hadri LM test, see Hadri (2000).

Table A2. Westerlund ECM panel tests for cointegration between $\overline{\ln Q}_{n,t}$, $\overline{\ln U}_{n,t}$ and $\overline{\ln V}_{n,t}$.

H_0 : no cointegration

Statistic	Value	Z-value	p-value
G_t	-2.764	-12.518	0.000
G_a	-43.075	-64.626	0.000
P_t	-24.057	-11.415	0.000
P_a	-43.985	-80.300	0.000

Note: No constant is included in the test (including a constant doesn’t change the p-values). The average AIC selected lag length is 9.2 and the average AIC selected lead length is 6.3. The Stata command xtwest implements the four panel cointegration tests developed by Westerlund (2007). The underlying idea is to test for the absence of cointegration by determining whether the individual panel members are error correcting. The G_a and G_t test statistics start from a weighted average of the individually estimated coefficients and their t-ratio’s, respectively. The P_a and P_t test statistics pool information over all the cross-sectional units. Missing values are not allowed. Hence, the variables have been linearly interpolated over missing values before the tests are performed. No value is missing for $\overline{\ln U}_{n,t}$, 237 values are missing for $\overline{\ln V}_{n,t}$, and 240 values are missing for $\overline{\ln Q}_{n,t}$ (during the period 1992m2-2001m12). The missing values are mainly due to a number of zeroes for some small local labor markets in the no-log series for the stock of vacancies. For the underlying non-log series there are no missing values, but there are 6 zeroes for the inflow of vacancies and 125 zeroes for the stock of vacancies (where stocks are measured on the last day of the month 1992m1-2001m12, used as the beginning of month value for the following month in the estimation dataset).

IV. Extra tables of estimation results, robustness

Table A3. Explaining the probability of filling a vacancy, IV, local seasonal effects

Dependent: $\ln \bar{Q}_{n,t}$	(1)	(2)	(3)	(4)
Unemployment ($\ln \bar{U}_{n,t}$)	0.387*** (0.034)	0.148*** (0.048)	-0.062 (0.040)	0.054** (0.026)
Vacancies ($\ln \bar{V}_{n,t}$)	-0.328*** (0.019)	-0.287*** (0.021)	-0.318*** (0.019)	-0.310*** (0.017)
Time dummies	no	yes	yes	no
Local time trends	no	no	yes	yes
Local seasons	yes	yes	yes	yes
Observations	21,270	21,270	21,270	21,270
R-squared (within)	0.510	0.562	0.613	0.577
Number of llc	90	90	90	90

Note: Robust standard errors are in parentheses, clustered at the local labor markets. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively. Monthly data for all local labor markets in Sweden, 1992-2011. All variables are in logs. IV estimations where the mean log stocks of unemployment and vacancies are instrumented with initial stocks. Fixed effects and local seasonal effects are included in all regressions. The local trends are both linear and quadratic.

Table A4. Explaining the probability of filling a vacancy, levels, IV, including program participants in the unemployment measure

Dependent: $\ln \bar{Q}_{n,t}$	(1)	(2)	(3)
Unemployment ($\ln \bar{U}_{n,t}$)	0.444*** (0.038)	0.207*** (0.057)	-0.009 (0.067)
Vacancies ($\ln \bar{V}_{n,t}$)	-0.270*** (0.016)	-0.266*** (0.020)	-0.287*** (0.020)
Time dummies	no	yes	yes
Local time trends	no	no	yes
Program participants	yes	yes	yes
Observations	21,270	21,270	21,270
R-squared (within)	0.341	0.498	0.548
Number of llc	90	90	90

Note: Robust standard errors are in parentheses, clustered at the local labor markets. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively. Monthly data for all local labor markets in Sweden, 1992-2011. All variables are in logs. IV estimations where the mean log stocks of unemployment and vacancies are instrumented with initial stocks. Fixed effects are included in all regressions. The local trends are both linear and quadratic. The unemployment measure includes the number of openly unemployed plus labor market program participants.

Table A5. Explaining the probability of filling a vacancy, IV, quarterly data

Dependent: $\ln \bar{Q}_{n,t}$	(1)	(2)	(3)
Unemployment ($\ln \bar{U}_{n,t}$)	0.492*** (0.039)	0.189*** (0.055)	0.023 (0.050)
Vacancies ($\ln \bar{V}_{n,t}$)	-0.141*** (0.029)	-0.249*** (0.033)	-0.290*** (0.034)
Time dummies	no	yes	yes
Local time trends	no	no	yes
Observations	7,057	7,057	7,057
R-squared (within)	0.387	0.594	0.677
Number of llc	90	90	90

Note: Robust standard errors are in parentheses, clustered at the local labor markets. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively. Quarterly data for all local labor markets in Sweden, 1992-2011. All variables are in logs. IV estimations where the mean log stocks of unemployment and vacancies are instrumented with initial stocks. Fixed effects are included in all regressions. The local trends are both linear and quadratic.

Table A6. Explaining the probability of filling a vacancy, levels, IV, local labor markets with extreme variable values removed

Dependent: $\ln \bar{Q}_{n,t}$	(1)	(2)	(3)
Unemployment ($\ln \bar{U}_{n,t}$)	0.317*** (0.034)	0.114*** (0.040)	0.002 (0.052)
Vacancies ($\ln \bar{V}_{n,t}$)	-0.282*** (0.018)	-0.272*** (0.023)	-0.285*** (0.025)
Time dummies	no	yes	yes
Local time trends	no	no	yes
Observations	16,171	16,171	16,171
R-squared	0.368	0.536	0.579
Number of llc	68	68	68

Note: Robust (clustered) standard errors are in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively. IV estimations where the mean of log stocks of unemployment and vacancies are instrumented with initial stocks. Fixed effects are included in all regressions. The local trends are both linear and quadratic. Monthly data for all local labor markets in Sweden in 1992-2011, except for llc 10, 11, 16, 17, 21, 33, 39, 45, 46, 51, 57, 58, 61, 72, 74, 76, 84, 85, 86, 89, and 90. These 22 excluded local labor markets belong to the 10 percent with the highest variation relative to the mean in unemployment, the corresponding 10 percent regarding vacancies, and/or the 10 percent with the highest mean probability of filling a vacancy.

Table A7. Explaining the probability of filling a vacancy, stocks and inflows

Dependent: $\ln \bar{Q}_{n,t}$	(1)	(2)	(3)
lnUin	0.229*** (0.016)	-0.033 (0.028)	-0.082*** (0.022)
lnVin	0.128*** (0.022)	0.100*** (0.025)	0.031 (0.024)
lnUstock_t	0.336*** (0.025)	0.156*** (0.038)	0.012 (0.040)
lnVstock_t	-0.213*** (0.014)	-0.187*** (0.015)	-0.183*** (0.014)
Time dummies	no	yes	yes
Local time trends	no	no	yes
Observations	21,269	21,269	21,269
R-squared (within)	0.233	0.398	0.433
Number of llc	90	90	90

Note: Robust standard errors are in parentheses, clustered at the local labor markets. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively. Monthly data for all local labor markets in Sweden, 1992-2011. All variables are in logs. Inflows of unemployed and vacancies during the month and stocks in the very beginning of the month. Fixed effects are included in all regressions. The local trends are both linear and quadratic.

V. Derivation of the quadratic hiring costs parameter

The value of the parameter in the quadratic hiring costs is derived from the estimation of the Euler equation in Carlsson, Eriksson, and Gottfries (2012). Setting $\eta = 11$ and $\sigma = 1$, I can use their estimated coefficient for the product demand variable to derive a monthly value of 2.6. I use $\gamma_d = \frac{\sigma(\eta-1)}{c_H \eta^2}$ and calculate c_H per year as $1 \cdot (11-1) / (0.38 \cdot 11^2) \approx 0.22$, and hence the monthly value as $0.22 \cdot 12 \approx 2.6$ in the baseline case.

Carlsson, Eriksson, and Gottfries themselves reported a yearly value of 1.1 for c_H , indicating a monthly value of $1.1 \cdot 12 \approx 13$. However, this is consistent with $\eta = 2.6$, which is improbably small, implying a markup of over 60 percent in the product market. This is why I don't use $c_H = 13$ as baseline value but as a special case.

The relation between the yearly and monthly value can be derived as follows:

Approximately setting $H^y = 12H^m$ (constant hiring during the year) and $N_t = N_{t-1}$ (constant N , i.e., few hires in relation to a large number of employed at the firm), the yearly costs are $\sum_{t=1}^{t=12} \frac{c_H^m}{2} \left(\frac{N_t - (1-\lambda)N_{t-1}}{N_{t-1}} \right)^2 \approx$

$$12 \frac{c_H^m}{2} \left(\frac{H^m}{N} \right)^2 = 12 \frac{c_H^m}{2} \left(\frac{H^y}{12N} \right)^2 = \frac{1}{12} \frac{c_H^m}{2} \left(\frac{H^y}{N} \right)^2, \text{ and } \frac{1}{12} \frac{c_H^m}{2} \left(\frac{H^y}{N} \right)^2 = \frac{c_H^y}{2} \left(\frac{H^y}{N} \right)^2 \rightarrow c_H^m = 12c_H^y.$$

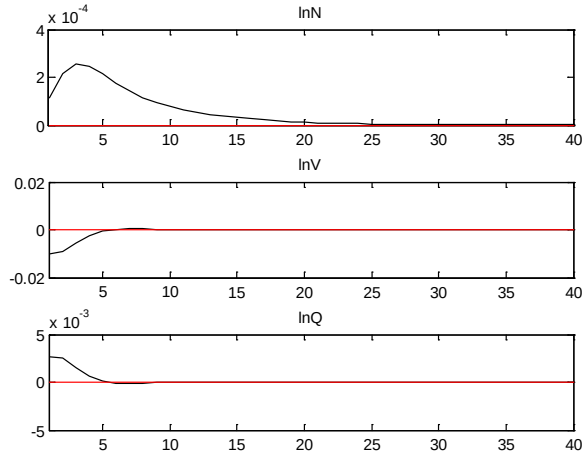
If c_H^m is 12 times bigger than c_H^y , there is about 12 times less adjustment per month than per year.

I have found no other estimates of the parameter c_H . Two examples of studies of hiring costs are Kramarz and Abowd (2003) and Kramarz and Michaud (2010). They estimated the costs of hiring and separation in France, but they did not take into account all the aspects included in the hiring costs in this paper, such as training costs. Also, their coefficients are in French francs and not directly applicable to the value of c_H .

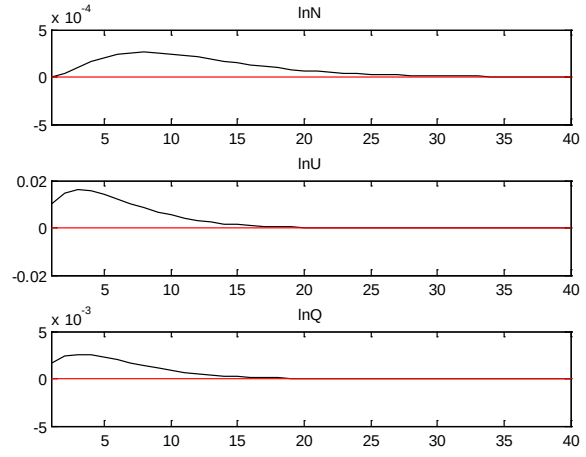
VI. Extra figures of simulations

Figure A3. Employment effects of one percent exogenous changes in variables

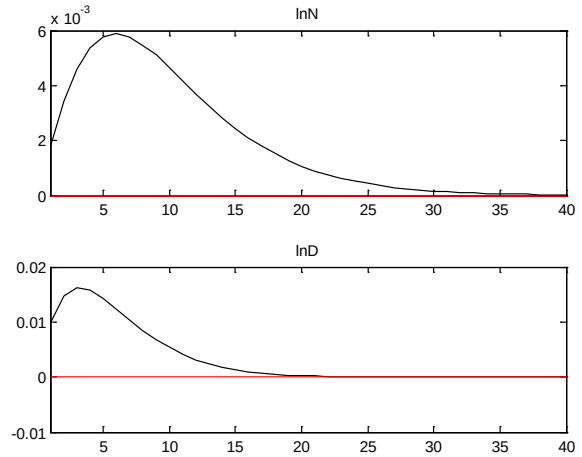
A3a. Shock to the number of vacancies



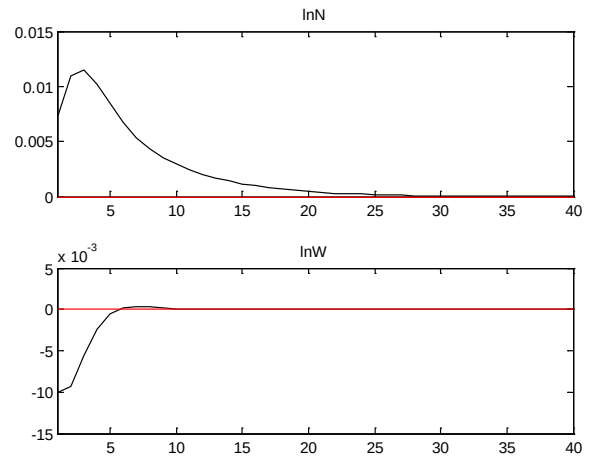
A3b. Shock to the number of unemployed



A3c. Shock to product demand



A3d. Shock to real wage costs



Note: Theoretical impulse response functions simulated with Dynare. The graphs show the return to steady state after a one percent exogenous shock. On the y-axis is log deviation from steady state and on the x-axis is the number of months. Parameter values are listed in Table 6.

Approximate initial employment effects resulting from a 1 percent shock.

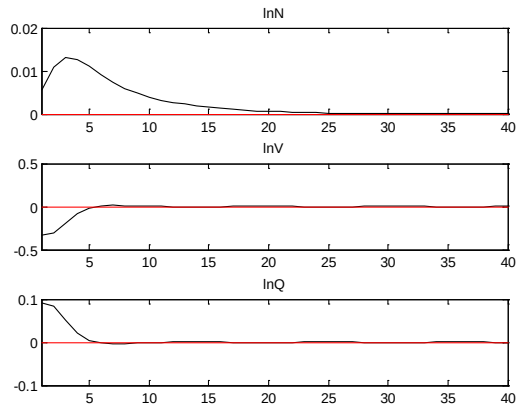
V: 0.01%, U: 0.00%, D: 0.2%, W: 0.7%

Approximate maximal employment effects resulting from a 1 percent shock.

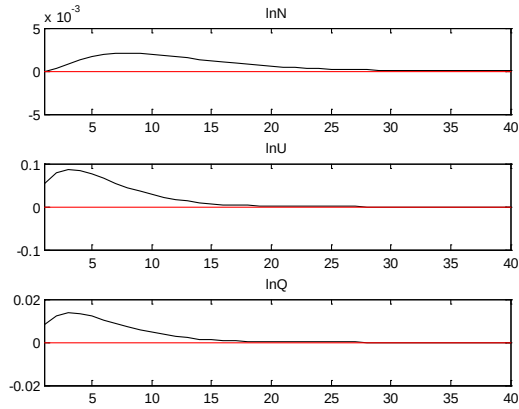
V: 0.03%, U: 0.03%, D: 0.6%, W: 1.2%

Figure A4. Employment effects of shocks to vacancies and unemployment, high vacancy costs

A4a. Shock to the number of vacancies, $c_V=0.5$



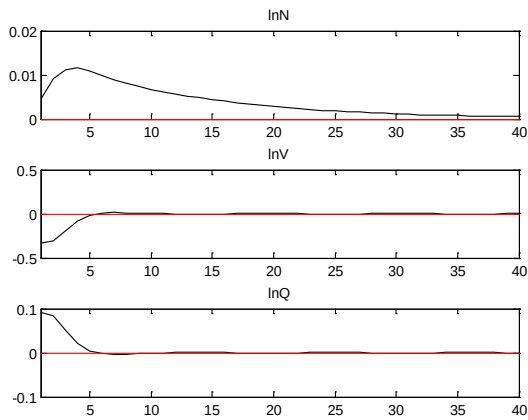
A4b. Shock to the number of unemployed, $c_V=0.5$



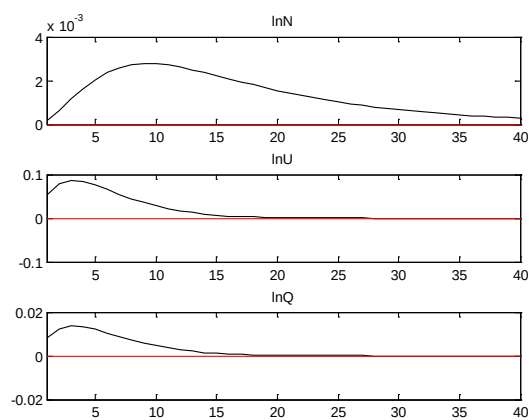
Note: Theoretical impulse response functions. On the y-axis is log deviation from steady state and on the x-axis is the number of months. Parameter values are listed in Table 6, with the exception that $c_V=0.5$.

Figure A5. Employment effects, high competition in the product market

A5a. Shock to vacancies, $\eta=50$



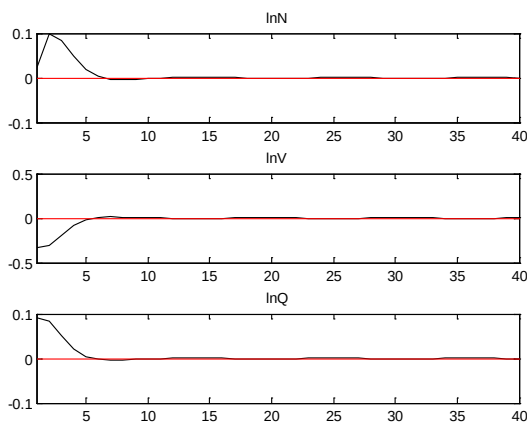
A5b. Shock to unemployment, $\eta=50$



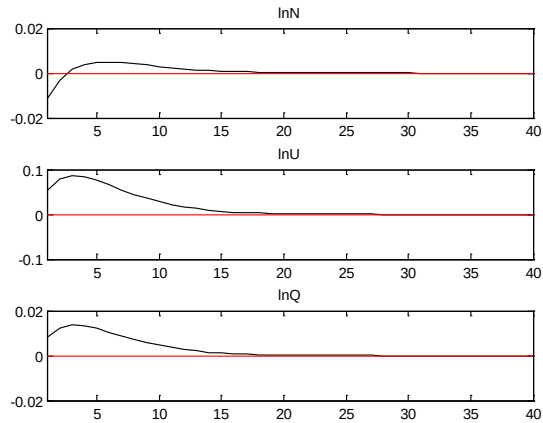
Note: Theoretical impulse response functions. On the y-axis is log deviation from steady state and on the x-axis is the number of months. Parameter values are listed in Table 6, with the exception that $\eta=50$.

Figure A6. Employment effects, no quadratic hiring costs and high linear vacancy costs

A6a. Shock to vacancies, $c_H=0$ & $c_V=0.5$



A6b. Shock to unemployment, $c_H=0$ & $c_V=0.5$



Note: Theoretical impulse response functions. On the y-axis is log deviation from steady state and on the x-axis is the number of months. Parameter values are listed in Table 6, with the exceptions that $c_H=0$ & $c_V=0.5$.

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