Vacancy Matching and Labor Market Conditions

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Abstract

This paper studies the probability of filling a vacancy, how it varies with the number of unemployed and the 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 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. One likely reason why unemployment has a small effect is that many vacancies are filled with workers coming directly from another job. Simulations of a theoretical model of employment at the firm level, 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. The simulations show that 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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1 Introduction

This paper investigates the probability of filling a vacancy and how it varies with the state of the labor market. First, I estimate how the probability of filling a vacancy varies with the number of unemployed and the number of vacancies in the local labor market. Then I use these estimates in a theoretical model to examine how variations in the probability of filling a vacancy affect firms' employment dynamics.

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.

Many authors have estimated matching functions, usually focusing on hiring of unemployed workers.[1] The use of the outflow from unemployment as the dependent variable is relevant if the purpose of the study is to understand the probability that an unemployed worker finds a job. This study differs because the focus is on how firms are affected by labor market conditions, and hence the outflow of vacancies is the most relevant measure of the number of matches. 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 of matches and the estimated effects differ.

To empirically study how the probability of filling a vacancy 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. The estimation results suggest that the number of vacancies in the local labor market has a significant, negative, and robust effect on the probability of filling a vacancy. The number of unemployed has a positive effect on the probability of filling a vacancy in some specifications, but the effect is not big and in some

[1]See Petrongolo and Pissarides (2001) for a survey of studies estimating matching functions. Examples of Swedish studies are Forslund & Johansson (2007), Aranki & Löf (2008), and Eriksson & Stadin (2012).

specifications it is zero. A smaller effect of the number of unemployed is expected since many vacancies are filled with employed workers searching on the job, for which I have no data. However, a zero effect is not expected and in the simulations I use the positive effect.

In order to say something about the effects of changes in labor market conditions on firms' employment decisions, 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, but 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 firm changes when there is a typical change in the number of vacancies or unemployed in the local labor market where the firm is located.

According to the simulations, shocks to the number of vacancies in the local labor market – and hence to the probability of filling a vacancy– have economically significant effects on the employment at the firm, 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.

Looking at aggregate monthly data for Sweden in 1970-2011, I find that the mean probability of filling a vacancy has been higher during recessions. According to simulations, a shock of the same size to the probability of filling a vacancy has a smaller impact on employment in recessions than it has in booms. Hence, matching frictions seem to be less important for employment in recessions. 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 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 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 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 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 roughly in the same direction.

Edin and Holmlund (1991) estimated matching functions using the outflow of vacancies in Sweden as a measure of matches, as in this paper. They used aggregate data for 1970-1988 and found a stronger positive effect of unemployment than I find in this paper. One reason may be that labor market conditions 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.

2 Empirical specification and data

2.1 Empirical specification

In this section, I derive the equation to be estimated. 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, and F_τ = inflow of vacancies. In the dataset I have F_t^m = inflow of vacancies during the month beginning at time *t*, V_t = stock of vacancies at the beginning of month *t*, and U_t = stock of unemployed at the beginning of month *t*. 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.

The matching function is usually specified as $M_\tau = \phi U_\tau^\alpha V_\tau^{(1-\alpha)}$, where the number of matches depends positively on unemployment (labor supply) and also positively on the number of vacancies (labor demand). In a more realistic specification, the job searchers should also include employed workers searching on the job. Therefore I specify the matching function as $X_\tau = \phi S_\tau^\alpha V_\tau^{(1-\alpha)}$, exhibiting constant returns to scale in all job searchers and the number of vacancies. The number of job searchers is the sum of unemployed and employed workers searching for jobs: $S_\tau = U_\tau + E_\tau$.[2] Loglinearizing the expression for S_τ around a steady state I can approximately write the log of the outflow of vacancies as $\ln X_\tau = \ln\phi + \alpha\left(\frac{U}{S}(\ln U_\tau - \ln U) + \frac{E}{S}(\ln E_\tau - \ln E) + \ln S\right) + (1-\alpha)\ln V_\tau$. The instantaneous probability of filling a vacancy is $Q_\tau = \frac{X_\tau}{V_\tau}$. Thus, the log of the probability of filling a vacancy is

$$\ln Q_\tau = \ln X_\tau - \ln V_\tau = \left(\ln\phi + \alpha\frac{E}{S}\ln E_\tau - \alpha\frac{U}{S}\ln U - \alpha\frac{E}{S}\ln E + \alpha\ln S\right) + \alpha\frac{U}{S}\ln U_\tau - \alpha\ln V_\tau =$$
$$\ln\phi_e + \alpha\frac{U}{S}\ln U_\tau - \alpha\ln V_\tau \qquad (1)$$

[2]A more complex specification could be $S = \mu_U U + \mu_E E$, where μ_U depend on the search intensity, abilities, choosiness etc. of the unemployed job searchers and μ_E is the corresponding parameter for employed job searchers. Firms seem to view employment status as a signal of productivity (see, e.g., Eriksson & Lagerström (2006)), which should have a positive effect on μ_E. Unemployed workers can somewhat compensate by spending more time searching and accepting less attractive job offers and hereby raising μ_U. The specification could also include those who are out of the labor force.

Since I do not have data for on-the-job search, I treat this variable as a constant (discussed below). I denote the constant including on-the-job search and the steady state terms $\ln\phi_e$.

Integrating over month *t*, I get

$$\int_t^{t+1} \ln Q_\tau d\tau = \int_t^{t+1} \ln\phi_e + \alpha\frac{U}{S}\int_t^{t+1} \ln U_\tau d\tau - \alpha\int_t^{t+1} \ln V_\tau d\tau \tag{2}$$

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:

$$\int_t^{t+1} \ln Q_\tau\, d\tau = \int_t^{t+1} \ln X_\tau d\tau - \int_t^{t+1} \ln V_\tau d\tau = \int_t^{t+1} \ln\left(F_\tau - \dot{V}_\tau\right) d\tau - \int_t^{t+1} \ln V_\tau d\tau$$
$$\approx \ln(F_t^m - (V_{t+1} - V_t)) - \frac{\ln V_t + \ln V_{t+1}}{2} \tag{3}$$

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

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

where *n* is an index for the local labor market, $\overline{\ln Q}_{n,t} = \ln\left(F_{n,t}^m + V_{n,t} - V_{n,t+1}\right) - \frac{\ln V_{n,t} + \ln V_{n,t+1}}{2}$,[3] $\overline{\ln U}_{n,t} = \frac{\ln U_{n,t} + \ln U_{n,t+1}}{2}$ 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., $\beta_U = \alpha\frac{U}{S} > 0$, and negatively on vacancies, such that $\beta_V = -\alpha < 0$. The coefficient for unemployed is expected to be smaller

[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 $\overline{\ln Q}_{n,t}$ to be missing, while a negative outflow causes only three missing values out of more than 20,000.

than the coefficient for vacancies and $\beta_U+|\beta_V| < 1$, since the unemployed workers' share of all job searchers is less than one. $\varepsilon_{n,t}$ 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. The equation is a sort of firm side matching function which can roughly be derived by dividing both sides of the underlying matching function by the stock of vacancies and then taking logs. It is worth to note here that the purpose of this paper is to estimate β_U and β_V, not α or ϕ.

If on-the-job search is procyclical, the omission of this variable will affect the coefficients β_U and β_V so that they will be closer to zero compared to the case when on-the-job search is constant.[4] When there are more vacancies opened at other firms, employed workers find it more rewarding to search for other jobs, and thus on-the-job search increases. Increased job search by employed workers has a positive effect on the probability of filling a vacancy, counteracting the negative congestion effect of more vacancies on the probability of filling a vacancy. As more workers are unemployed this will have a positive effect on the probability of filling a vacancy, but a decrease in on-the-job search will counteract this effect. Evidence of employer-to-employer flows being high and procyclical can be found in Bjelland, Fallick, Haltiwanger and McEntarfer (2011) and other studies. Evidence of on-the-job search in Sweden being procyclical in 1970-1982 can be found in Holmlund (1984). Thus procyclical on-the-job-search will probably reduce the estimated effects of the number of unemployed and vacancies on the probability of filling a vacancy.

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 new vacancies during the month. Many vacancies are never announced at the Public Employment Service,[5] even though it is mandatory to do so, but this

[4]If the estimates of β_U and β_V are closer to zero this means a too small estimated α and hence a too high elasticity of matches with respect to vacancies (1-α) and a too low elasticity with respect to the unemployed (α) in the underlying matching function.

[5]The 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.

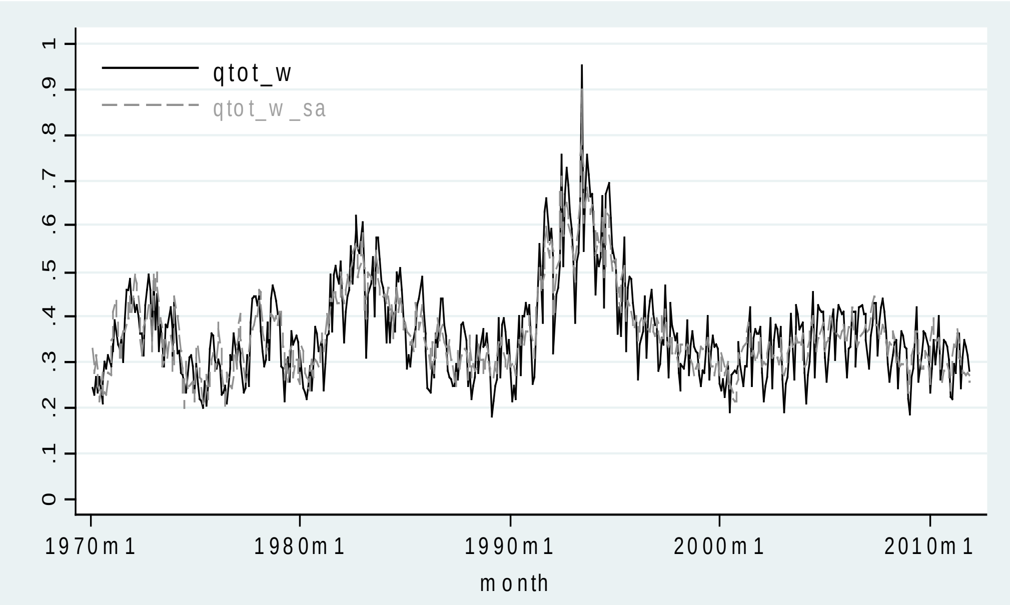
is the best measure of vacancies available for a longer time period. Unemployment is measured by the number of openly unemployed workers registered at the Public Employment Service in the beginning of the month. There is a strong incentive to register since this is required to qualify for unemployment benefits. Labor market program participants are not included since 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. They are constructed to be geographical areas that are as independent as possible from the rest of the world concerning labor demand and labor supply. 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.[6] 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 (1989), 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.

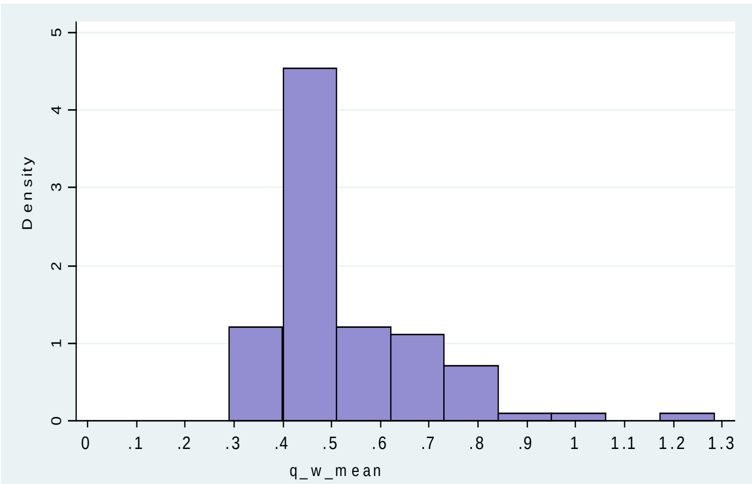
[6] I have received aggregate AMS data for 1970-1988 from Bertil Holmlund, earlier used in Edin and Holmlund (1991). Aggregate data for 1989-1991 as well as municipality data for 1992-2011 are directly from AF, 2012.

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). 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, this 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 reported having received enough applications to hire someone. Edin and Holmlund (1991) referred to evidence indicating that the major part of the outflow of vacancies was associated with hiring; Farm (1989), for instance, found that only 10 percent of the posted vacancies were withdrawn because of failure to find a suitable worker.

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.

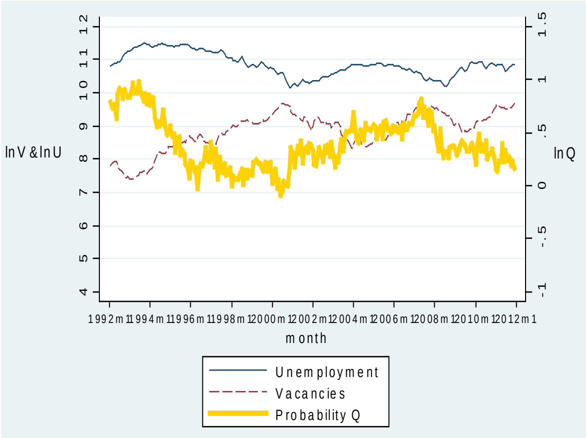
Figure 2 shows the distribution of the mean probabilities of filling a vacancy within a week for the local labor markets. The total unweighted mean of the means for the local labor markets in 1992-2011 is 0.52, which is higher than the corresponding probability of 0.38 for the aggregate data for Sweden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

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 Figure 3. 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.

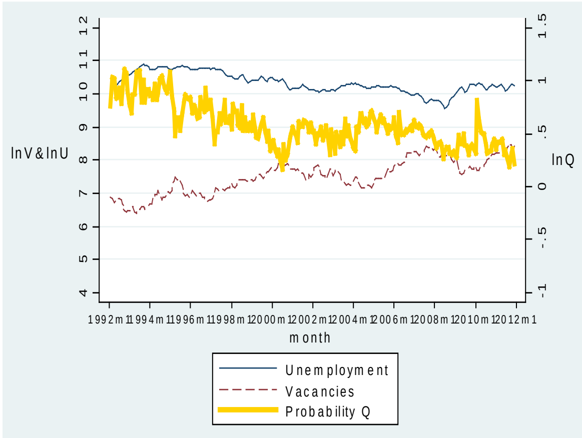
Figures 4 also show how the probability of filling a vacancy is related to vacancies and unemployment for Sweden's six largest local labor markets. The sizes of the bubbles reflect the probability of filling a vacancy. The probability of filling a vacancy visibly seems to increase in the vertical direction 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 the probability of filling a vacancy (Q) versus tightness $\left(\frac{V}{U}\right)$, the number of vacancies (V), and the number of unemployed (U), with none of the variables in logs, are shown in Figures A1 and A2 in the Appendix.

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

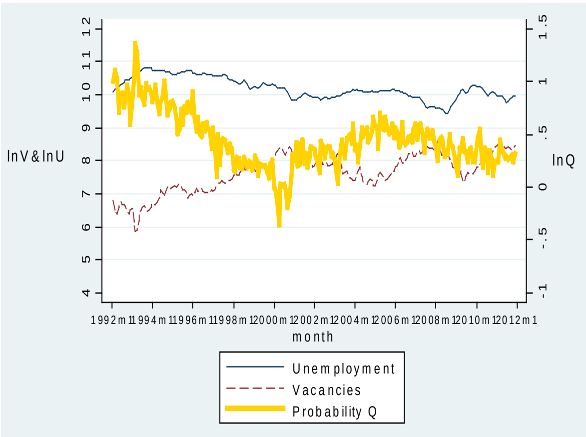
3a. Stockholm (llc 1)



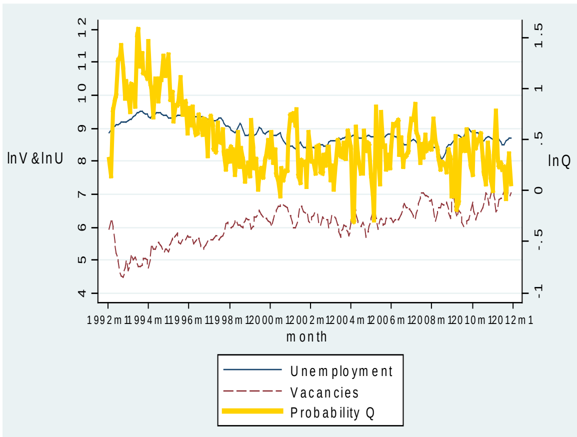
3b. Malmö (llc 25)



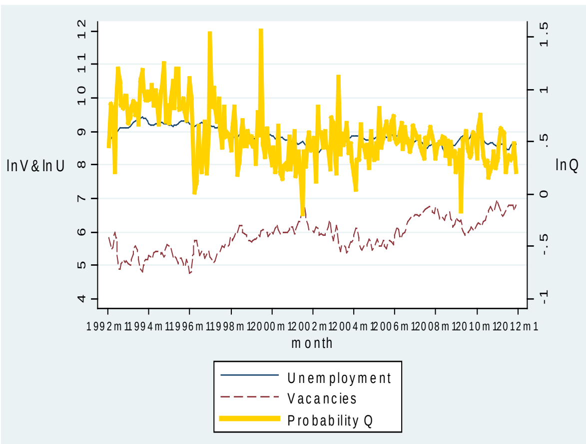
3c. Göteborg (Gothenburg, llc 32)



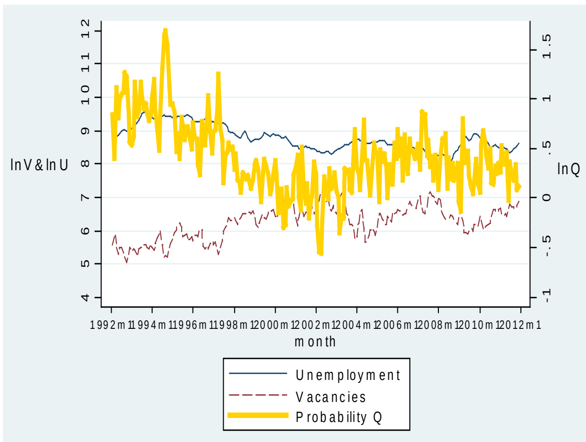
3d. Västerås (llc 49)



3e. Örebro (llc 47)



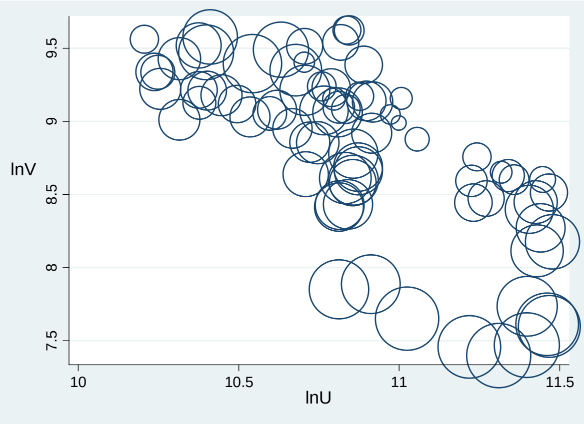
3f. Trollhättan (llc 34)



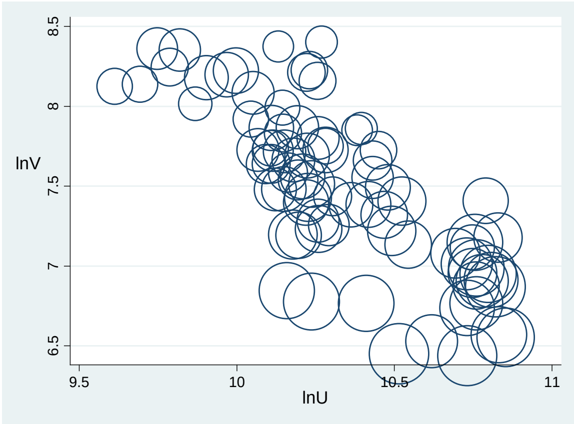
Note: All variables are in logs and seasonally adjusted for each local labor market using dummies for month. Data from AF (Swedish Public Employment Service) for 1992-2011.

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

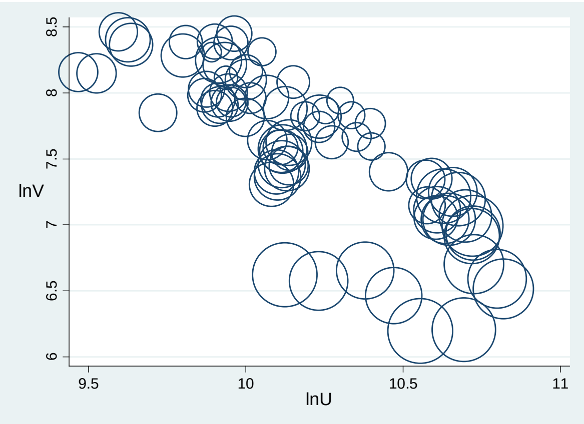
4a. Stockholm (llc 1)



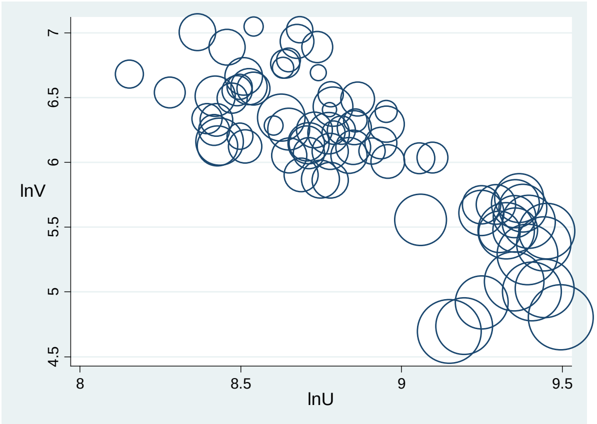
4b. Malmö (llc 25)



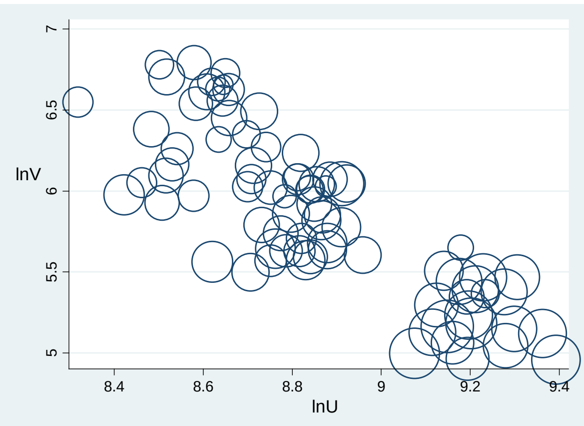
4c. Göteborg (Gothenburg, llc 32)



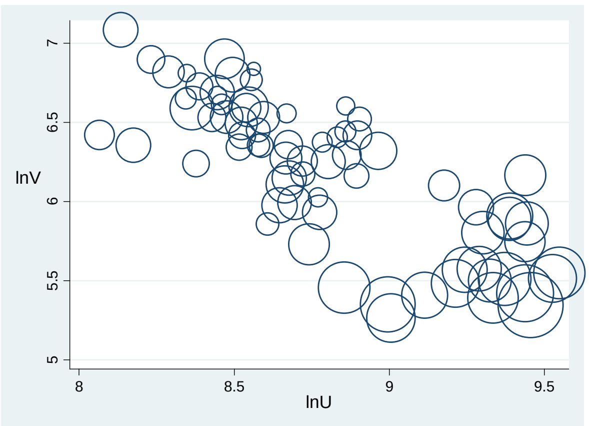
4d. Västerås (llc 49)



4e. Örebro (llc 47)



4f. Trollhättan (llc 34)



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

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, and of course by Statistics Sweden constructing the local labor markets with the purpose of making them as independent as possible.

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. I test for stationary and find that all variables are non-stationary in themselves but they are trend-stationary, and I hence should be able to use them in the estimation if I include the trends. However, 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 lnQ, lnU, and lnV. I test for cointegration between these variables and find that a cointegrating relation is most likely present. Thus, the trends are probably not necessary in the empirical specification. (For more information about these tests, see section III in the Appendix.)

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. Table A3 in the Appendix shows the variation left after removing the variation explained by the control variables. The variation left is not very small and should be enough to enable identification of the effects I am interested in.

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 number of unemployed workers goes down and the probability of filling a vacancy goes up. 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 problem.

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

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

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 and seasonal variation 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 1 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 strongly significant, 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.

3.2 Robustness

Estimation of the equation on aggregate data in Table 2, the effect of vacancies is slightly bigger than in the panel estimation in Table 1, and there is no positive effect of unemployment. When the estimation is done in differences, to allow for stochastic trends and not just deterministic, the positive effect of the number of unemployed also disappears while the vacancy effect is robust (see Table A4 in the Appendix). Several other robustness checks are conducted (see section V in the Appendix). Separate estimations for some important local labor markets are presented, local seasonal effects are introduced, labor market program participants are included in the unemployment measure, outliers are removed, both stocks and flows are included, a different definition of the local labor markets is used, and estimations are done on quarterly data and for different sub periods. The conclusion from these robustness checks is that vacancies have a robust negative effect on the probability of filling a vacancy, 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.

Table 1. 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***	0.162***	-0.006
	(0.031)	(0.044)	(0.043)
Vacancies $(\overline{\ln V}_{n,t})$	-0.266***	-0.266***	-0.287***
	(0.016)	(0.020)	(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 for local labor markets 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 2. 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	-0.147*	-0.062	-0.133
	(0.107)	(0.085)	(0.118)	(0.086)
Total Vacancies $(\overline{\ln V}_t)$	-0.429***	-0.363***	-0.420***	-0.346***
	(0.070)	(0.070)	(0.083)	(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.

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 in a standard matching function. 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 coefficients around 0.5 for both vacancies and unemployment (CRS) fits the data well (see, e.g., Blanchard & Diamond (1989)). Disaggregate studies have also found positive coefficients for both vacancies and unemployed, often quite similar to the aggregate estimates (see, e.g., Coles & Smith (1996) and Boeri & Burda (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 matches is defined as the number of unemployed workers who are deregistered by the Public Employment Service. In this paper, the number of matches is defined as the number of vacancies deregistered at the Public Employment Service, since I have the firms’ perspective. However, since the outflow from unemployment exists in my data, I can estimate a standard matching function using both measures. Using the outflow of unemployed, the coefficient for unemployed is about 0.6 and the coefficient for vacancies is only about 0.03 (see Table A11 in the Appendix). The measures are theoretically different and they also differ due to both measures being associated with different measurement problems. 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 get other jobs than those registered. Furthermore, on-the-job search is probably procyclical, which affect the estimated coefficients in different ways. Using the matches from unemployed as dependent variable, a regression of a matching function that omits on-the-job search will give a too high estimated coefficient for unemployment and a too low estimated coefficient for vacancies (formally derived in Petrongolo and Pissarides (2001)). If the matches are defined as the outflow of vacancies, it is the other way around. This will make both β_U and β_V too small (since β_V is one minus the too big coefficient in standard matching function in Table A11).

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. Doing the same estimation for my aggregate data 1992-2011, I found no positive 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 deep 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. (One speculation of why this could be the case, is that on-the-job search might have increased since the 1970s.) Yet another study using the outflow of vacancies as dependent variable, not for Sweden but for the Netherlands, is van Ours (1991). He estimated an aggregate matching function using the yearly vacancy flow from the Dutch public unemployment office in 1961-1987, and he found coefficients of about 0.6 for vacancies and about 0.4 for unemployment.

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, are 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 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. 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 pure 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.[7] 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 in the local labor market may be for the employment decisions of individual firms. This is analyzed by simulating impulse responses of shocks to a theoretical model in steady state. The theoretical model used, which is from Carlsson, Eriksson, and Gottfries (2012), is a model of firm level 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*,

[7]An exception would be the very special case when there are changes in on-the-job search totally outweighing the changes in the search by unemployed.

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 individual 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 advance in nation-wide branch-level union contracts.

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

Matching of unemployed workers and vacancies takes place in each local labor market every period. The probability of filling a vacancy is given by $\mathrm{Q_{n,t}} = \phi \mathrm{U_{n,t}^{\beta_U} V_{n,t}^{\beta_V}}$. 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 $\mathrm{V_{i,t}}$ vacancies and incurs real linear vacancy costs given by $\mathrm{c_V V_{i,t}}$. Hiring is $\mathrm{H_{i,t} = Q_{n,t} V_{i,t}}$ and the firm incurs quadratic hiring costs given by $\frac{\mathrm{c_H}}{2}\left(\frac{\mathrm{H_{i,t}}}{\mathrm{N_{i,t-1}}}\right)^2 \mathrm{N_{i,t-1}}$. 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.

$$\max E_t \left\{ \sum_{\tau=t}^{\infty} \beta^{\tau-t} \left(\frac{(P_{i,\tau}-W_{i,\tau})}{P_{i,\tau}^C} N_{i,\tau} - \frac{c_H}{2} \left(\frac{H_{i,\tau}}{N_{i,\tau-1}} \right)^2 N_{i,\tau-1} - c_V V_{i,\tau} \right) \right\} \tag{6}$$

s.t. $N_{i,\tau} = H_{i,\tau} + (1-\lambda) N_{i,\tau-1}$, $H_{i,\tau} = Q_{n,\tau} V_{i,\tau}$ and $N_{i,\tau} = \left(\frac{P_{i,\tau}}{P_{i,\tau}^C} \right)^{-\eta} D_{i,\tau}^{\sigma}$

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

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

From the Euler equation, one can see that the 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 are 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 3.

In line with the estimation results including time dummies but no local trends (in column 2, Table 1), I set β_U=0.16 and β_V=-0.27. If β_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 lnV and lnU are zero, I calibrate the constant such that $\ln\phi$ is equal to the mean of lnQ in the data.[8] 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 about two vacancies per month.

Table 3. Parameter values

β_U	0.16	elasticity of Q with respect to U, own estimate
β_V	-0.27	elasticity of Q with respect to V, own estimate
ϕ	1.9	constant in the Q function, own estimate
λ	0.01	monthly 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

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. I set $\lambda = 0.01$ to match this number. [9] 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, has almost no effect on 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

[8] $\text{mean}(\ln Q) = \ln\phi + \beta_U * \text{mean}(\ln U) + \beta_V * \text{mean}(\ln V)$, inserting values $0.62 \approx \ln\phi + 0 + 0$.

[9] Diagram in ”Kortperiodisk sysselsättningsstatistik 4:e kvartalet 2011”, AM 63 SM 1201, Statistics Sweden. Of course, lambda being exogenous is a simplification. Especially in a recession, layoffs arise because firms close down or have to shrink their workforce drastically. Thus, the value for lambda 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 lambda may be understated because of this. It is not clear if the measure is overall overstating or understating the value of lambda.

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. In Yashiv (2000), the estimated vacancy costs are not significantly different from zero, while convex adjustment costs are shown to be empirically relevant. Convex hiring costs have also recently found support in Blatter, Muehlemann and Schenker (2012). However, there doesn't seem to be consensus in the literature about the structure of recruitment costs. With no adjustment costs (c_H=0) and a very high price elasticity (high η), the model approaches a standard search and matching model.

The value of the linear vacancy costs parameter, c_V, is taken from Michaillat (2012). In his calibration, the recruiting cost in the benchmark model was 0.32 $=0.32\overline{W}$, where $\overline{W}$ was the steady state wage. This value is a midpoint between two estimates, based on data from two different U.S. data sources.[10] He also stated that his estimate was an average compared to others found in the literature.[11] 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 η =11 and σ=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). [12]

Carlsson and Smedsaas (2007) have estimated the markup for Swedish manufacturing firms to 17 percent, translating into η=7 (since the price markup over marginal cost is $\frac{\eta}{\eta-1}$). In Bowman (2003), the markup for the private U.S. economy as a whole was 4 percent (η=26),

[10]The two data sources are Job Openings and Labor Turnover Survey and PricewaterhouseCooper.
[11]Michaillat refers to 0.213 in Shimer (2005), 0.357 in Pissarides (2009) and 0.433 in Hall and Milgrom (2008).
[12]The 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 VI in the Appendix.

and for manufacturing 11 percent (η=10). Christiano, Eichenbaum, and Evans (2005) estimated a markup of 20 percent (η=6) for the U.S. I choose a markup of 10 percent (η=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.

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. 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 and 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).[13] The estimated AR(2) processes for the explanatory variables are presented in Table 4. 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.

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

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

Eriksson and Stadin (2012). I do not have these variables on the firm level, but the industry level should work as an approximation.

Table 4. AR(2) processes for vacancies, unemployment, product demand and real wage costs

Dependent: Current value of variable	(1) $\overline{\ln V}_{n,t}$	(2) $\overline{\ln U}_{n,t}$	(3) $\ln D_{j,t}$	(4) $\ln W^{r}_{j,t}$
First lag of variable	0.929***	1.471***	1.019***	0.461***
Second lag of variable	-0.303***	-0.548***	-0.079***	0.374***
Time trends	yes	yes	yes	yes
Seasonal effects	yes	yes	yes	yes
Std.Dev. of residual	0.335	0.053	0.007	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 and mining 1992-2008, all in logs and at monthly frequency. The standard errors are robust, clustered at local labor market or industry. Fixed effects for local labor markets or industry, local or industry specific linear and quadratic time trends and seasonal effects are included in all regressions.

Franco and Philippon (2007) used data for US firms and found that permanent changes in firm specific product demand and technology explain most of the firms' dynamics, but since these shocks seemed to be uncorrelated across firms, they were not important for aggregate dynamics. Transitory shocks, on the other hand, were found to be significantly correlated across firms, and accounted for most of the volatility in aggregate production and aggregate labor input. In this paper, the focus is on the effects of typical, macro-related, transitory shocks (around a trend) on the hiring behavior of a typical firm.

4.3 Simulation of impulse response functions

The simulations show the employment dynamics for an individual firm.[14] The effects of temporary but persistent shocks to the exogenous variables are simulated. Shocks to the explanatory variables are induced one at the time, and then the effects of each of these changes on the firm's hiring decision can be observed. The shocks are log deviations from

[14]The Matlab application Dynare is used, which makes an approximation of the model around steady state. A 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 employment dynamics.

steady state, which are referred to as approximate percentage changes.[15] I start with the baseline case, using the parameters listed in Table 3, 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 firm increases employment to avoid layoffs, i.e., to avoid employment decreases larger than the exogenous quitting rate. There are no vacancy costs associated with layoffs of workers, and the adjustment costs are probably different when hiring and when firing.[16] In the baseline simulation, however, there are no downward adjustments of employment that cannot be handled by simply not hiring.

Baseline simulation

Impulse response functions for the baseline case are presented in Figure 5. 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 of 0.86 percent in the number of employed at the firm. A typical shock consisting of a 5.3 percent increase in the number of unemployed in the local labor market induces a 1.5 percent increase in the probability of filling a vacancy and a maximum increase of 0.14 percent in the number of employed at the firm. It takes about two years for employment to return to steady state after a shock to the probability of filling a vacancy.

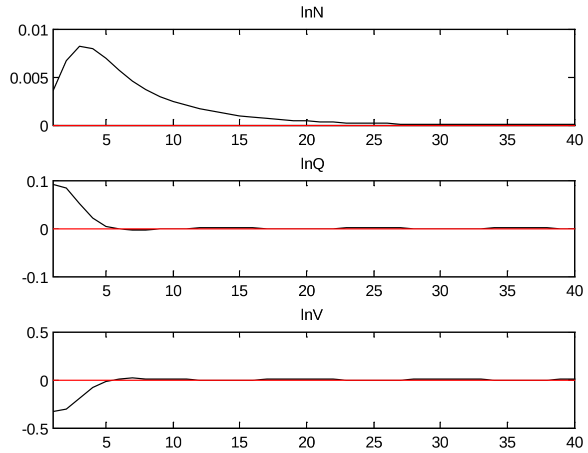
Figure 5 also shows that a 0.7 percent positive shock to product demand has a maximum response of 0.35 percent increase in employment, and a 1.2 percent negative shock to the real wage costs has a maximum response of 2.7 percent higher employment. It takes more than three years for employment to return to steady state after a shock to product demand or real wage costs.

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

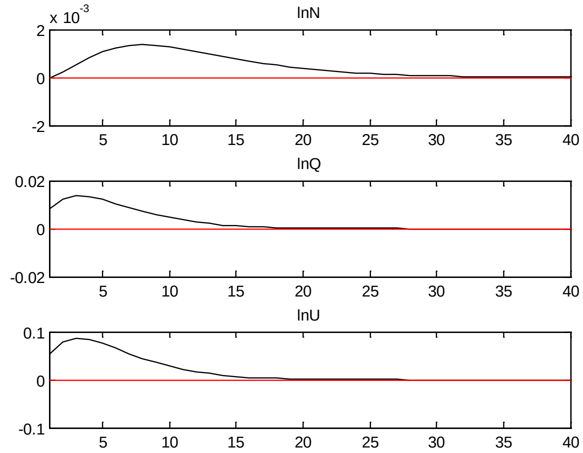
[16] According to Kramarz and Abowd (2003) and Kramarz and Michaud (2010), French firms adjust employment primarily through changes in hiring, since hiring costs are much lower than separation costs. In the U.S. it is the other way around. Kramarz and Abowd believed that institutions in other European 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.

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

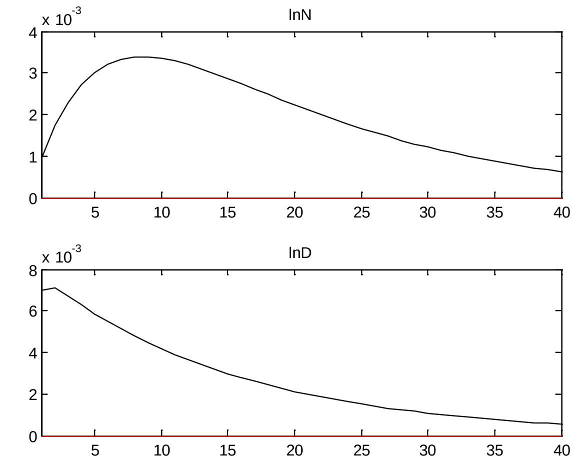
5a. Shock to the number of vacancies



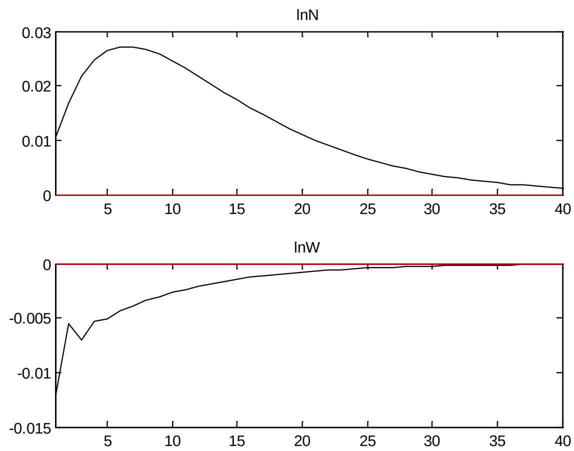
5b. Shock to the number of unemployed



5c. Shock to product demand



5d. Shock to the 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. The development of the exogenous variables over time is given by the data, see Table 4. Parameter values are listed in Table 3.

Approximate maximum employment responses at the typical firm in Figures 5a-d:

	a. V-shock (-34%)	b. U-shock (+5%)	c. D-shock (+0.7%)	d. W-shock (-1.2%)
N max response	0.9 %	0.1 %	0.4 %	2.7 %

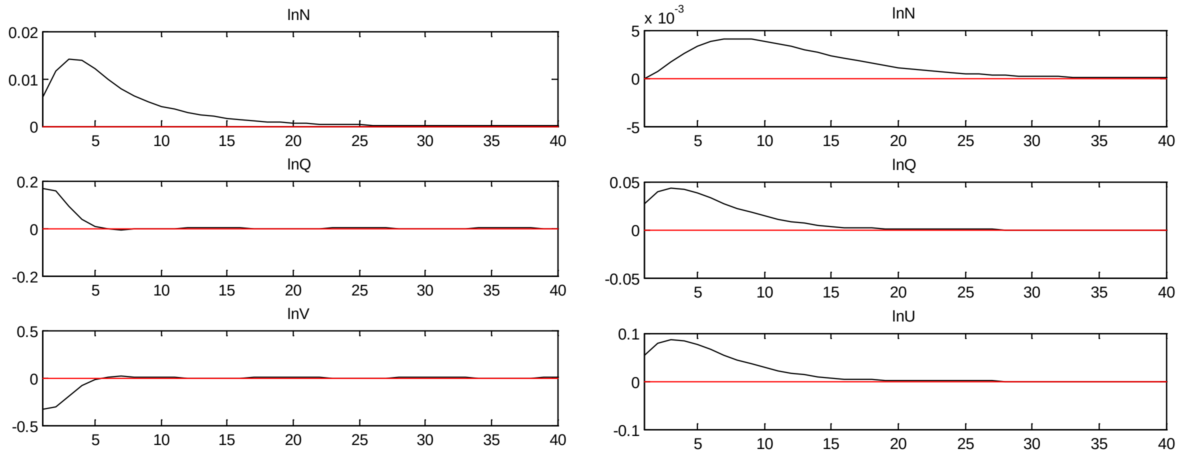
Figure A3 in the Appendix shows the impulse responses when a one-percent shock is induced to all variables, still using the baseline parameter values. This is to ease the interpretation of the effects, making them like elasticities. The maximum response in employment to a one-percent shock is 0.03 percent when the shock is to vacancies, 0.03 percent as well when the shock is to unemployment, 0.5 when the shock is to product demand, and 2.3 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 effect of unemployment on the probability of filling a vacancy.

Special cases simulations –changes in steady state parameters

How important are my estimates of β_U and β_V? In Figure 6, $\beta_U = 0.5$ and $\beta_V = -0.5$, i.e., equal weights and constant returns to scale in the standard matching function, which is parameter values used in other studies such as Gertler and Trigari (2009). The employment effects of shocks to the number of vacancies and the number of unemployed in the local labor market where the firm is located become bigger. 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.

Figure 6. Effects of shocks to vacancies and unemployment, standard CRS

6a. Shock to vacancies, $\beta_U = 0.5$ & $\beta_V = -0.5$ 6b. Shock to unemployment, $\beta_U = 0.5$ & $\beta_V = -0.5$



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 in Table 3, with the exception that $\beta_U = 0.5$ & $\beta_V = -0.5$, i.e. constant returns to scale in the standard matching function (with no on-the-job search).

Changing the parameter values for the convex hiring costs, the linear vacancy costs, and the degree of competition in the product market (see section VII in the Appendix), I come to the conclusion that the convex adjustment costs seem to be important for the sizes of the employment effects, particularly in combination with the degree of competition in the product market. With no convex hiring costs and very high competition in the product market (see Figure A7 in the Appendix), the model approaches a standard search and matching model. With no costs associated with adjusting the number of employees (except for the linear vacancy costs) and at the same time high competition from other firms, the firm's responses to temporary shocks are fast and very strong. The other special cases studied do not involve such dramatic changes in employment.

Simulations at different stages of the business cycle

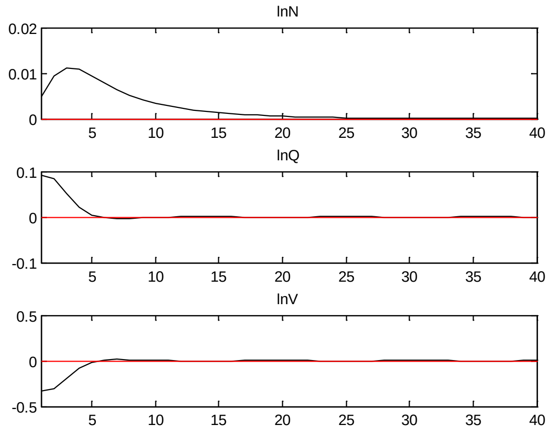
How do the employment effects of changes in the probability of filling a vacancy vary with the state of the labor market? Figure 7 shows impulse responses during a boom, which is a period assumed to be long enough for firms to adjust. In a boom, the labor market is tight and the mean probability of filling a vacancy is lower than in the baseline case. 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, which means $Q^{ss}=1.3$. Setting Q^{ss} to this number (not changing parameter values), I find that the 9 percent increase in the probability of filling a vacancy due to a typical 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 8 shows the corresponding results for a recession. In a recession, the labor market is slack, i.e., there are many unemployed in relation to the number of vacancies and the mean probability of filling a vacancy is higher than in the baseline case. I set $Q^{ss}=2.5$, since the log of the probability of filling a vacancy during the years of the recession in the mid-1990s was about 0.9. In this case, the 9 percent increase in the probability of filling a vacancy due to a typical 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 increase in employment of 0.1 percent. When the probability of filling a vacancy is already at a high level, the duration of vacancies is short and the costs associated with vacancies are small. A typical shock to these costs of small importance is also of small importance.[17]

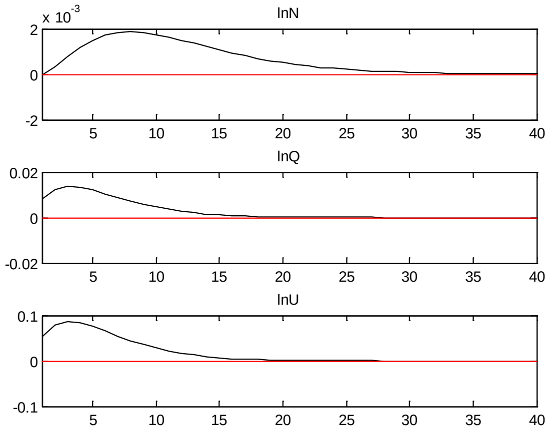
[17]To better understand this result, look at the term $-\frac{cv}{Q_{n,t}}$ in the Euler equation (7). When $Q_{n,t}$ is big, $\frac{cv}{Q_{n,t}}$ is small.

Figure 7. Employment effects of shocks to Q, around a low Q in a boom

7a. Shock to vacancies, Q^{ss}=1.3



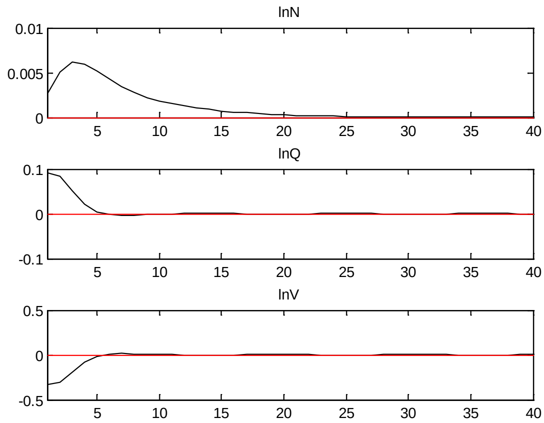
7b. Shock to unemployment, Q^{ss}=1.3



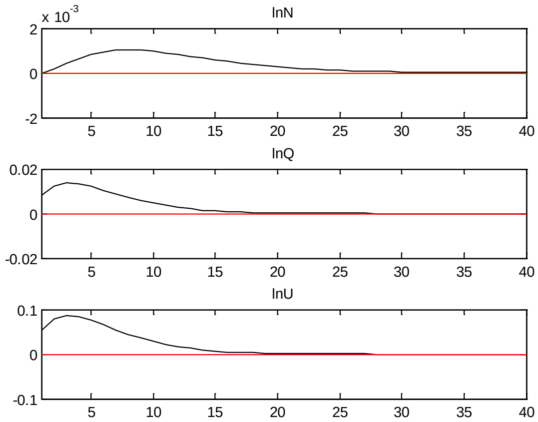
Note: Impulse response functions in a tight labor market with Q^{ss}=1.3 (everything else as in baseline). On the y-axis is log deviation from steady state and on the x-axis the number of months. N=number of employees at the firm, Q=probability of filling a vacancy, V=number of vacancies in the relevant labor market, and U=number of unemployed. The initial shocks to unemployment and vacancies, the development of these variables over time, and the steady state level of the probability of filling a vacancy are all exogenously given by the data.

Figure 8. Employment effects of shocks to Q, around a high Q in a recession

8a. Shock to vacancies, Q^{ss}=2.5



8b. Shock to unemployment, Q^{ss}=2.5



Note: Impulse response functions in a slack labor market with Q^{ss}=2.5 (everything else as in baseline). On the y-axis is log deviation from steady state and on the x-axis the number of months. N=number of employees at the firm, Q=probability of filling a vacancy, V=number of vacancies in the relevant labor market, and U=number of unemployed. The initial shocks to unemployment and vacancies, the development of these variables over time, and the steady state level of the probability of filling a vacancy are all exogenously given by the data.

Shocks to the number of vacancies and unemployed are more important to employment in a tight, booming labor market than in a slack labor market. 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, I find that the employment effect of a typical shock to the number of unemployed is not very important in any state of the labor market.

These simulations show how a firm responds to changes in labor market conditions at different mean levels of the probability of filling a vacancy, without modeling the reason for the different levels. Tightness could vary because of shifts in aggregate labor demand due to changing product demand or changing wage costs in relation to the productivity, affecting unemployment. The simulations can also be seen as impulse responses for different local labor markets with different tightness.[18]

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 standard search and matching theory, both should matter, and according to a pure labor demand model without frictions, none of the variables should matter. In the simulations, I focus on the case with a positive effect of the number unemployed.

The results in this paper differ from many earlier studies which used hires from unemployed as a measure of the matches. I start from the firms' perspective and use the outflow of vacancies to measure matches. A smaller estimated effect of the number of unemployed on the outflow of vacancies compared to the effect on the outflow of unemployed is expected since vacancies are often filled with employed workers moving between jobs rather than unemployed workers. The small estimated effect of the number of unemployed on the probability of filling a vacancy suggests that the employed job searchers (and those out of the labor force) make up a big share of all job searchers. Perhaps it also implies that it is hard for unemployed workers to compete with employed workers searching on the job, since

[18] They could also be simulations for different labor markets with different matching efficiency (ϕ: search intensity, occupational mismatch between unemployed and vacancies etc.). A different Q^{ss} caused by a change in matching efficiency affect the employment responses of the firm in the same way as when this specific Q^{ss} is caused by changes in V^{ss} and U^{ss}.

unemployed workers are less productive, or assumed to be less productive by the employers. Furthermore, procyclical on-the-job search as an omitted variable will decrease the coefficient for unemployment when the dependent variable is the outflow of vacancies, and increase the coefficient when the dependent variable is the outflow of unemployed. In the future, when the necessary data will hopefully be available, it would be interesting to use a wider measure of labor supply including all job searchers, and preferably also the intensity of their search and their productivity.

When it is easier to recruit workers, this should have a positive effect on hiring. According to the numerical simulations of the theoretical model of firm level employment from Carlsson, Eriksson and Gottfries (2012), this is also the case. I this model, employment at a firm is explained by product demand, real wage costs, and the probability of filling a vacancy. A change in the probability of filling a vacancy caused by a typical shock to the number of vacancies in the local labor market has an economically significant effect on the employment dynamics. 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 of significant importance (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. The small effect of temporary shocks to the number of unemployed doesn’t mean that the level of labor supply is unimportant for the aggregate level of employment in the long run. A permanent increase in supply is expected to create its own demand in the long run, if there are no structural changes.[19]

The mean probability of filling a vacancy in Sweden has been higher during recessions. According to theoretical simulations with different mean levels of the probability of filling a vacancy from the data, the same change in this probability is more important to employment during a boom than during a recession. Thus, matching frictions seem to be more important for employment in booms than in recessions, as suggested by Michaillat (2012).

[19]Examples of such structural changes are changes in conditions for starting up and running firms, including communications, tax system, and regulations regarding minimum wages, affecting labor demand, or changes in the unemployment insurance, retirement schemes, or school system, affecting labor supply.

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Appendix

I. Local labor markets

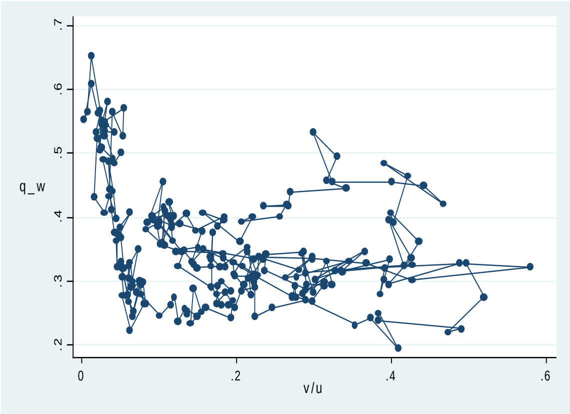
1	Stockholm	31	Bengtsfors	61	Bollnäs
2	Nyköping-Oxelösund	32	Göteborg (Gothenburg)	62	Hudiksvall
3	Katrineholm	33	Strömstad	63	Ånge
4	Eskilstuna	34	Trollhättan	64	Härnösand
5	Linköping	35	Borås	65	Sundsvall
6	Norrköping	36	Lidköping-Götene	66	Kramfors
7	Gislaved	37	Skövde	67	Sollefteå
8	Jönköping	38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

Note: The definitions of the local 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). I have also run the main regressions using the 109 local labor markets of the year 1993 version, which has little effect on the results.

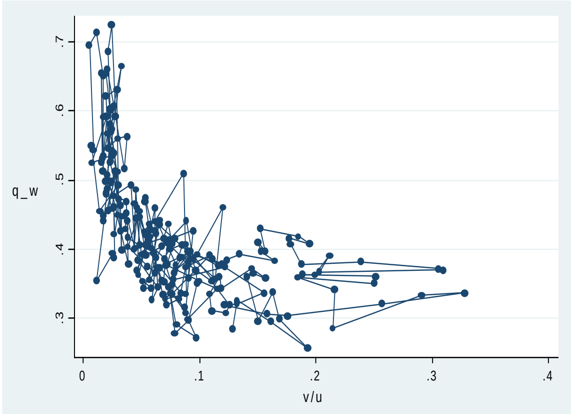
II. Extra plots of variables

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.

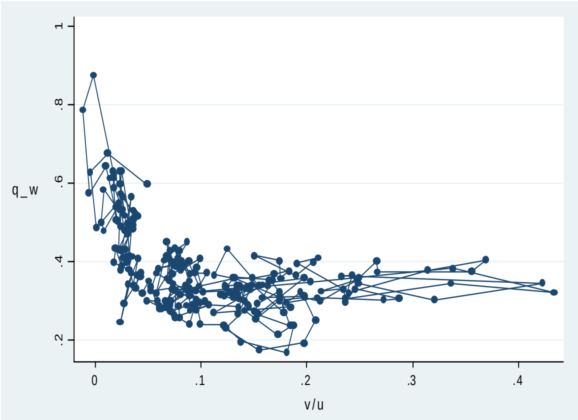
A1a. Stockholm (llc 1)



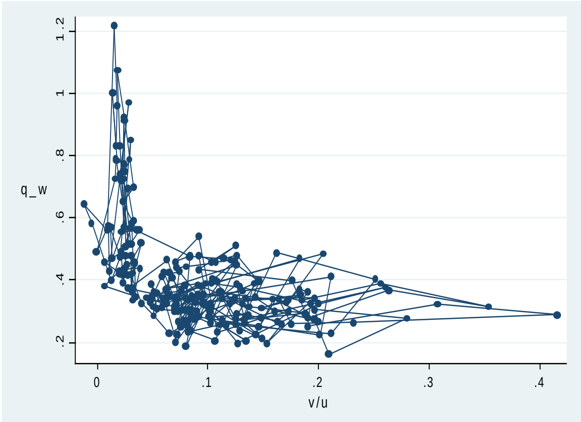
A1b. Malmö (llc 25)



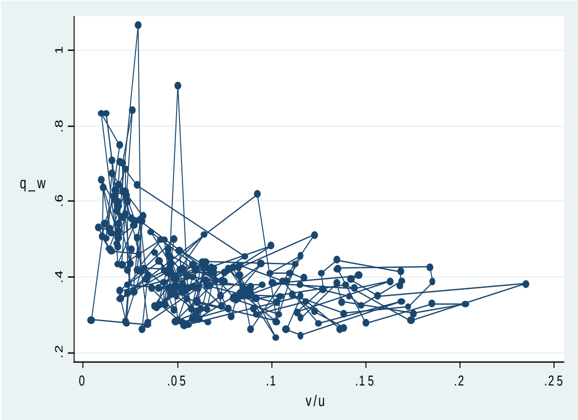
A1c. Göteborg (Gothenburg, llc 32)



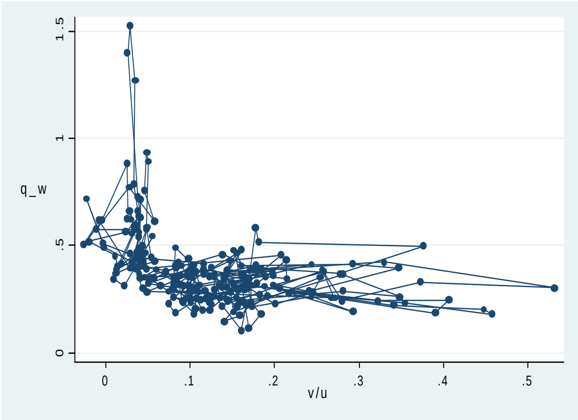
A1d. Västerås (llc 49)



A1e. Örebro (llc 47)



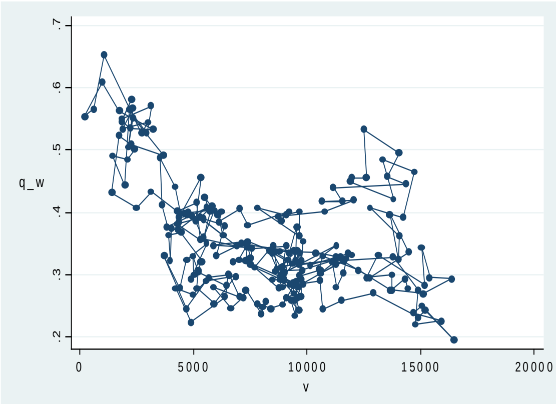
A1f. Trollhättan (llc 34)



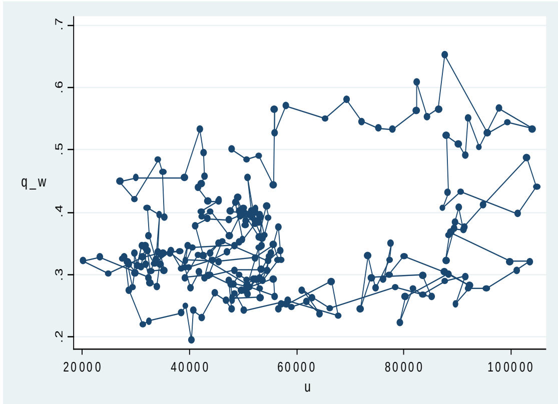
Note: Variables are seasonally adjusted and not in logs. Stocks of the number of unemployed and vacancies are measured in the very beginning of the month. q_w is the mean probability of filling a vacancy within a week during the month. Monthly data from AF (PES) for the six largest local labor markets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

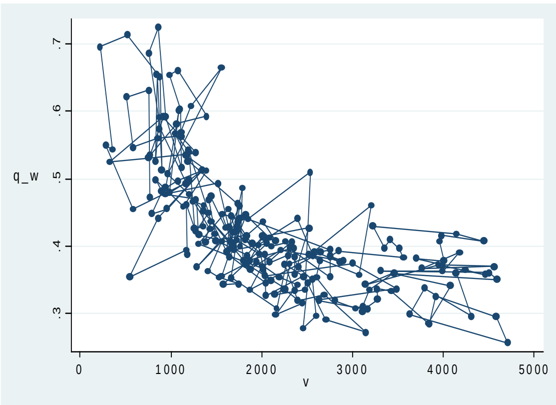
A2a. Stockholm (llc 1) – Q vs. V



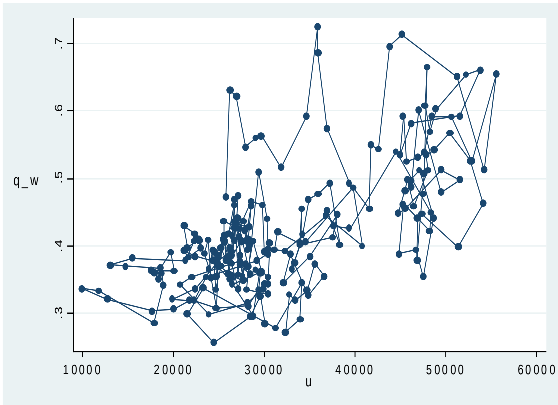
A2b. Stockholm (llc 1) – Q vs. U



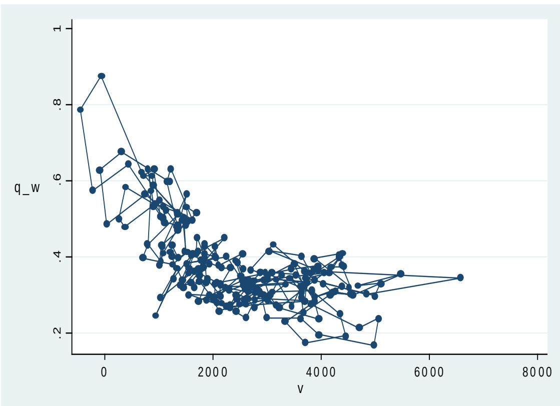
A2c. Malmö (llc 25) – Q vs. V



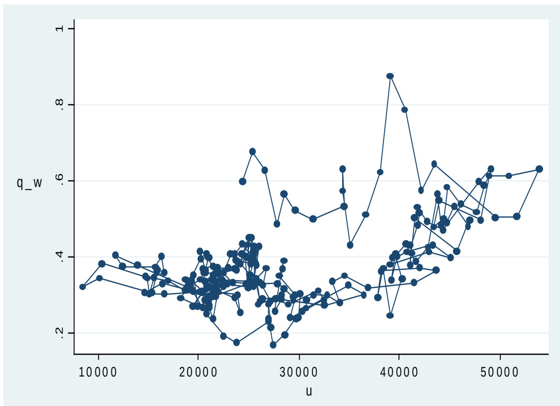
A2d. Malmö (llc 25) – Q vs. U



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

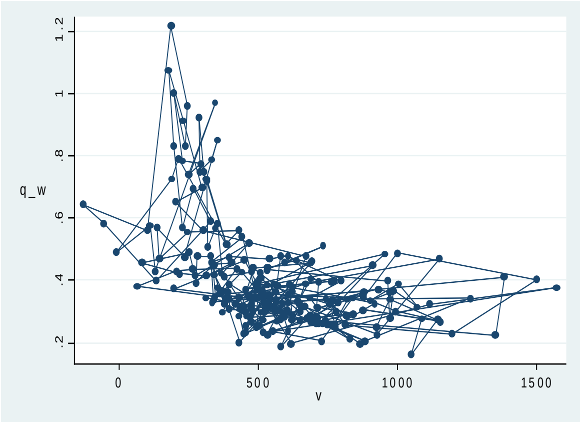


A2f. Göteborg (Gothenburg, llc 32) – Q vs. U

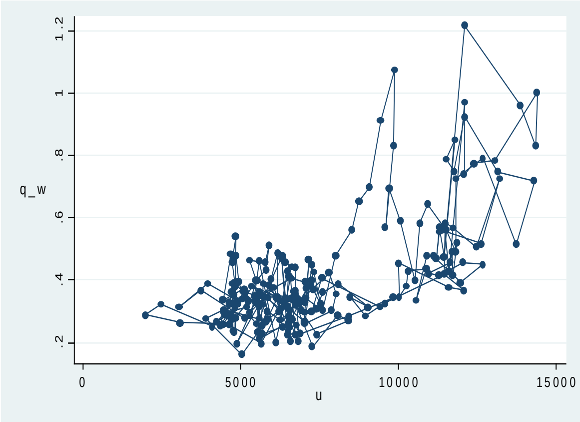


Note: Variables are seasonally adjusted and not in logs. Stocks of the number of unemployed and vacancies are measured in the very beginning of the month. q_w is the mean probability of filling a vacancy within a week during the month. Monthly data from AF for the largest local labor markets in Sweden,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

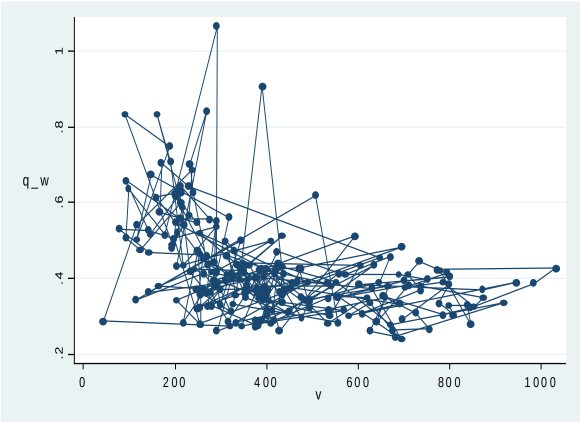
A2g. Västerås (llc 49) – Q vs. V



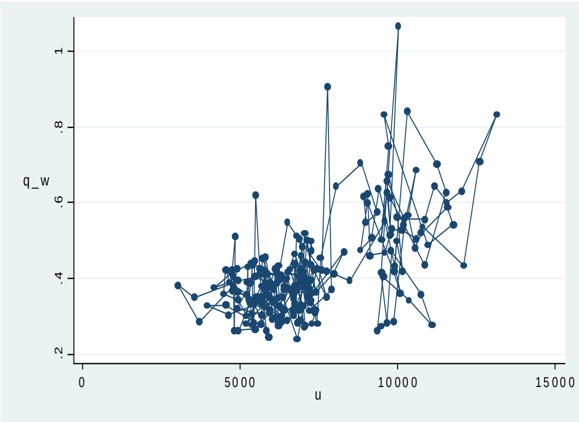
A2h. Västerås (llc 49) – Q vs. U



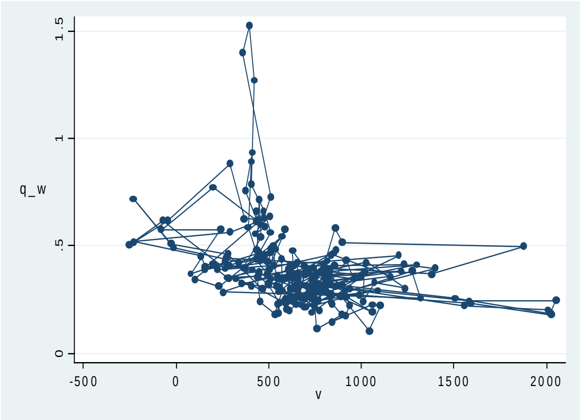
A2i. Örebro (llc 47) – Q vs. V



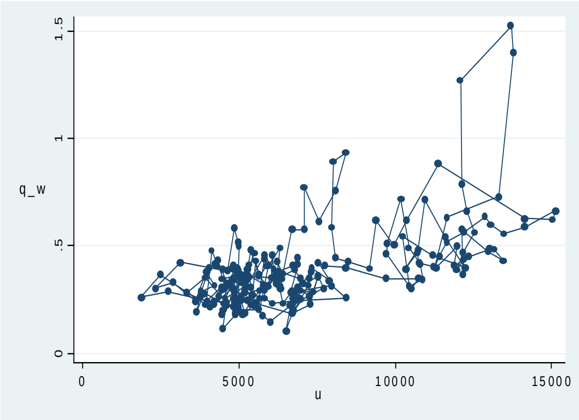
A2j. Örebro (llc 47) – Q vs. U



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

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).
All variables seem to be trend-stationary according to these tests. For aggregated variables, Dickey Fuller tests result in the same conclusion.

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. The variables have been linearly interpolated over missing values, since the tests do not allow for missing values. 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 1992m2-20011m12). 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 1992m1-20011m12, used as the initial value for the following month in the estimation dataset). The tests indicate that there exists a cointegrating relation in the panel. For aggregated variables, Johansen and Engle-Granger tests result in the same conclusion.

IV. Variation in the unemployment and vacancies

Table A3. Variation remaining in variables after removing fixed effects, common time effects and local time trends

	(1)	(2)	(3)
Unemployment $\left(\overline{\ln U}_{n,t}\right)$	0.413	0.166	0.121
Vacancies $\left(\overline{\ln V}_{n,t}\right)$	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). Other regressions show that 52 percent of the variation in vacancies and 84 percent of the variation in unemployment is common to for all local labor markets.

V. Extra tables of estimation results, robustness

Table A4. Explaining the probability of filling a vacancy, differences, IV

Dependent: $D.\overline{\ln Q}_{n,t}$	(1)	(2)	(3)
Unemployment $\left(D.\overline{\ln U}_{n,t}\right)$	-0.880***	-0.049	-0.053
	(0.090)	(0.160)	(0.157)
Vacancies $\left(D.\overline{\ln V}_{n,t}\right)$	-0.363***	-0.325***	-0.326***
	(0.023)	(0.024)	(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 for local labor markets 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 A5. 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***	-0.055	-0.213**	0.011	0.108	0.158
	(0.063)	(0.062)	(0.104)	(0.121)	(0.144)	(0.097)
Vacancies	-0.453***	-0.214***	-0.392***	-0.344***	-0.172**	-0.264***
	(0.054)	(0.078)	(0.082)	(0.067)	(0.070)	(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. When excluding the time trends (not in table), the negative effects of the number of unemployed are still present.

Table A6. Explaining the probability of filling a vacancy, IV, local seasonal effects

Dependent: $\overline{\ln Q}_{n,t}$	(1)	(2)	(3)	(4)
Unemployment $\left(\overline{\ln U}_{n,t}\right)$	0.387***	0.148***	-0.062	0.054**
	(0.034)	(0.048)	(0.040)	(0.026)
Vacancies$\left(\overline{\ln V}_{n,t}\right)$	-0.328***	-0.287***	-0.318***	-0.310***
	(0.019)	(0.021)	(0.019)	(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 for local labor markets and local seasonal effects are included in all regressions. The local trends are both linear and quadratic.

Table A7. Explaining the probability of filling a vacancy, levels, IV, including program participants in the unemployment measure

Dependent: $\overline{\ln Q}_{n,t}$	(1)	(2)	(3)
Unemployment $(\overline{\ln U}_{n,t})$	0.444***	0.207***	-0.009
	(0.038)	(0.057)	(0.067)
Vacancies $(\overline{\ln V}_{n,t})$	-0.270***	-0.266***	-0.287***
	(0.016)	(0.020)	(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. Though the program participants search less intense than the openly unemployed, which should have a negative effect on the coefficient for the number of unemployed, the effect dominating is apparently the positive effect stemming from the increase in the share of the job searchers included (one can think of $\beta_U = \alpha \frac{\mu_U U}{S}$, where search intensity is included in μ_U).

Table A8. Explaining the probability of filling a vacancy, IV, quarterly data

Dependent: $\overline{\ln Q}_{n,t}$	(1)	(2)	(3)
Unemployment $(\overline{\ln U}_{n,t})$	0.492***	0.189***	0.023
	(0.039)	(0.055)	(0.050)
Vacancies$(\overline{\ln V}_{n,t})$	-0.141***	-0.249***	-0.290***
	(0.029)	(0.033)	(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. 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.

Table A9. Explaining the probability of filling a vacancy, levels, IV, local labor markets with extreme variable values removed

Dependent: $\overline{\ln Q}_{n,t}$	(1)	(2)	(3)
Unemployment $(\overline{\ln U}_{n,t})$	0.317***	0.114***	0.002
	(0.034)	(0.040)	(0.052)
Vacancies $(\overline{\ln V}_{n,t})$	-0.282***	-0.272***	-0.285***
	(0.018)	(0.023)	(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 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, 60, 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 10 percent with the highest variation relative to the mean in vacancies, and/or the 10 percent with the highest mean probability of filling a vacancy (there are no low outliers according to Figure 2).

Table A10. Explaining the probability of filling a vacancy, stocks and inflows

Dependent: $\overline{\ln Q}_{n,t}$	(1)	(2)	(3)
lnUin	0.229***	-0.033	-0.082***
	(0.016)	(0.028)	(0.022)
lnVin	0.128***	0.100***	0.031
	(0.022)	(0.025)	(0.024)
lnUstock_t	0.336***	0.156***	0.012
	(0.025)	(0.038)	(0.040)
lnVstock_t	-0.213***	-0.187***	-0.183***
	(0.014)	(0.015)	(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 for local labor markets are included in all regressions. The local trends are both linear and quadratic. 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. The results surrounding the inflows are not as expected and not robust.

More robustness results:

Using an older definition of the local labor markets with 109 local labor (1993 version) markets instead of 90 (2000 version) has no important impact on the results. The effect of the number of unemployed is slightly smaller. The main regressions have also been done for some different sub periods. There is always a significant negative effect of the number of vacancies, but there is sometimes no significant unemployment effect, especially not during the 2000s.

Table A11. Estimating matching functions

A11.a. The outflow of unemployed as dependent variable

Dependent: $\ln Uout_{n,t}$	(1)	(2)	(3)
Unemployment $(\overline{\ln U_{n,t}})$	0.657***	0.583***	0.696***
	(0.012)	(0.028)	(0.039)
Vacancies $(\overline{\ln V_{n,t}})$	0.110***	0.033***	0.033***
	(0.008)	(0.007)	(0.008)
Time dummies	no	yes	yes
Local time trends	no	no	yes
Observations	21,273	21,273	21,273
R-squared (within)	0.230	0.722	0.735
Number of llc	90	90	90

A11.b. The outflow of vacancies as dependent variable

Dependent: $\ln Vout_{n,t}$	(1)	(2)	(3)
Unemployment $(\overline{\ln U_{n,t}})$	0.379***	0.162***	-0.006
	(0.031)	(0.044)	(0.043)
Vacancies $(\overline{\ln V_{n,t}})$	0.734***	0.734***	0.713***
	(0.016)	(0.020)	(0.020)
Time dummies	no	yes	yes
Local time trends	no	no	yes
Observations	21,270	21,270	21,270
R-squared (within)	0.295	0.462	0.515
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 for local labor markets are included in all regressions. 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 (lags). The local time trends are both linear and quadratic.

VI. 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 η =11 and σ=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 $1*(11-1)/(0.38*11^2) \approx 0.22$, and hence the monthly value as 0.22*12≈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*12≈13. However, this is consistent with η=2.6, which is improbably small, implying a markup of over 60 percent in the product market. This is why c_H =13 is not used as baseline value but as a special case.

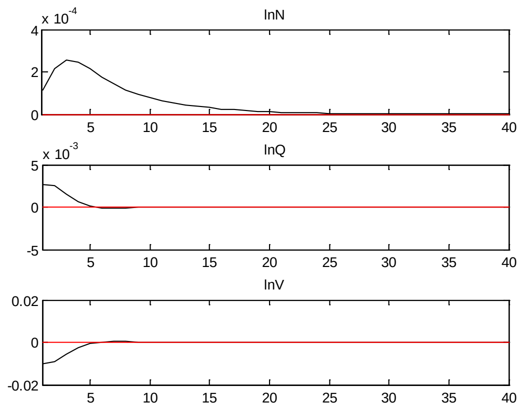
The relation between the yearly and monthly value can be derived as follows:
Approximately setting $H^y = 12H^m$ (constant hiring during the year) and $N_t = N_{t-1}$ (constant N, i.e., few hires in relation to a large number of employed at the firm), the yearly costs are $\sum_{t=1}^{t=12}\frac{c_H^m}{2}\left(\frac{N_t-(1-\lambda)N_{t-1}}{N_{t-1}}\right)^2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

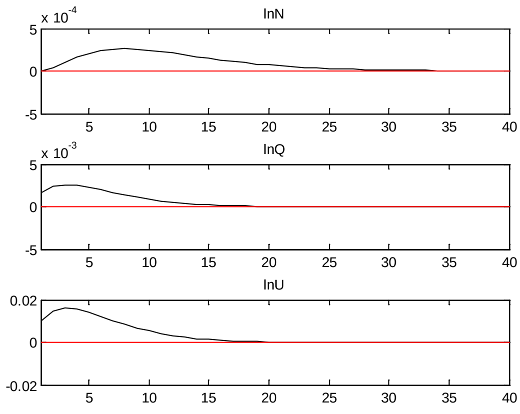
VII. Extra figures of simulations

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

A3a. Shock to the number of vacancies

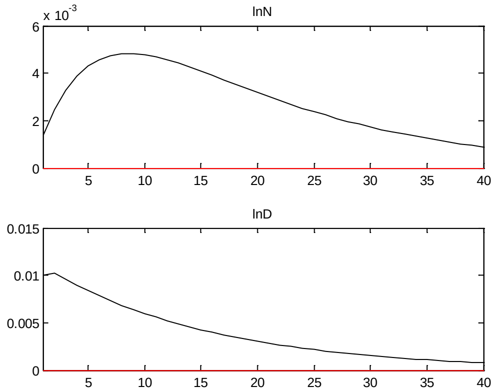


A3b. Shock to the number of unemployed

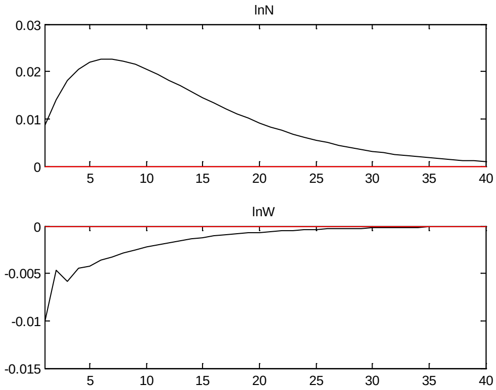


Note: Theoretical impulse response functions simulated with Dynare. The graphs show the return to steady state after a one percent exogenous shock. On the y-axis is log deviation from steady state and on the x-axis is the number of months. Parameter values are listed in Table 3.

A3c. Shock to product demand



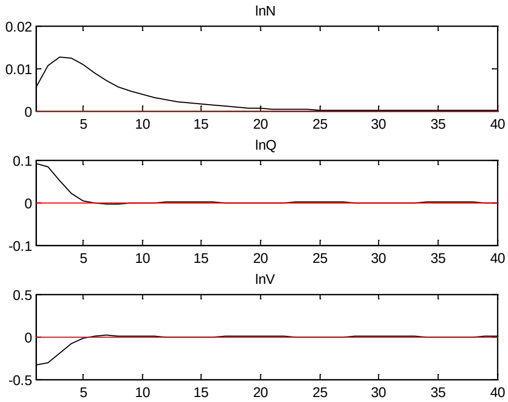
A3d. Shock to real wage costs



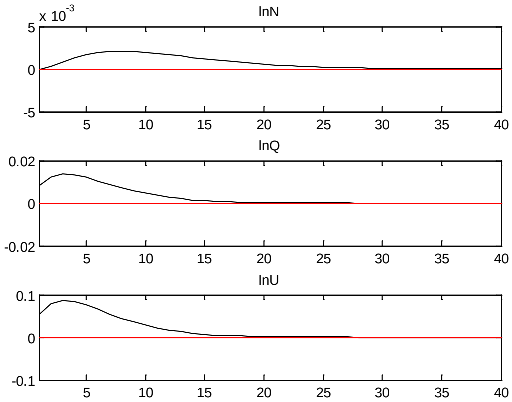
Note: Theoretical impulse response functions. The graphs show the return to steady state after a one percent exogenous shock. Parameter values are listed in Table 3.

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

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



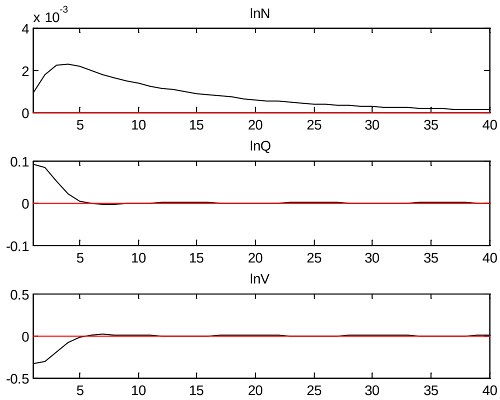
A4b. Shock to the number of unemployed, c_V=0.5



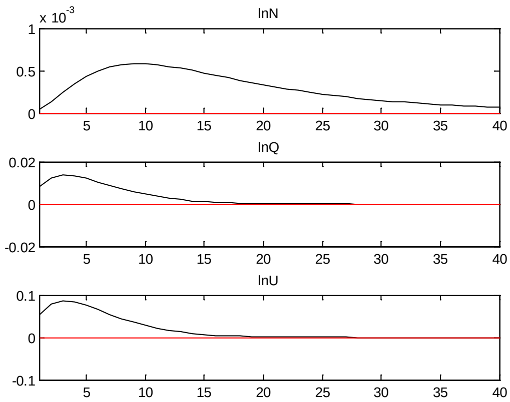
Note: Theoretical impulse response functions. On the y-axis is log deviation from steady state and on the x-axis is the number of months. Parameter values are listed in Table 3, with the exception that c_V=0.5. If the vacancy costs are set too low, the effect of a shock to the probability of filling a vacancy will be understated. c_V=0.5 is slightly higher than the largest parameter value from the literature mentioned in Michaillat (2012). The duration of a vacancy is always quite short, why the vacancy cost per unit of time would have to be very high for drastic changes in employment due to typical changes in the probability of filling a vacancy.

Figure A5. Employment effects of changes in exogenous variables, high adjustment costs

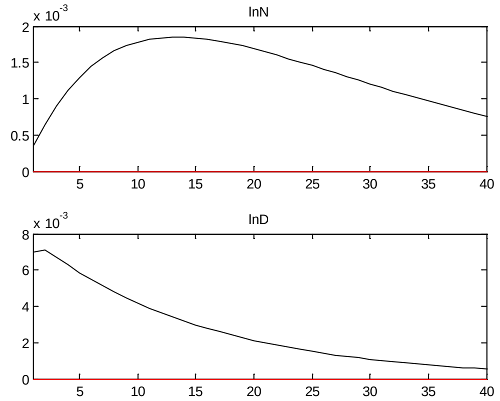
A5a. Shock to vacancies, c_H=13



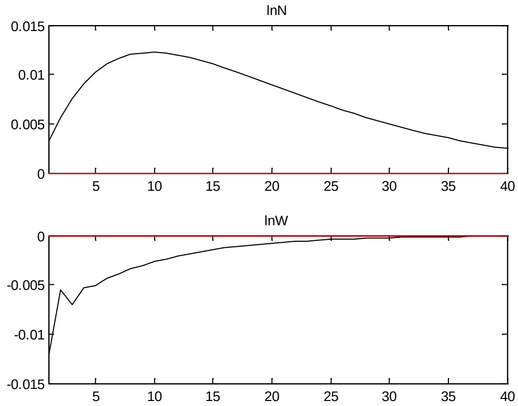
A5b. Shock to unemployment, c_H=13



A5c. Shock to product demand, c_H=13



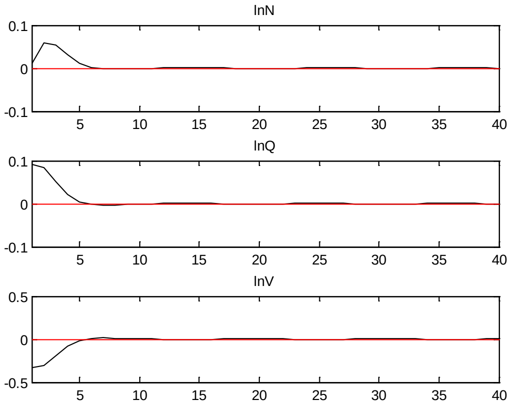
A5d. Shock to real wage costs, c_H=13



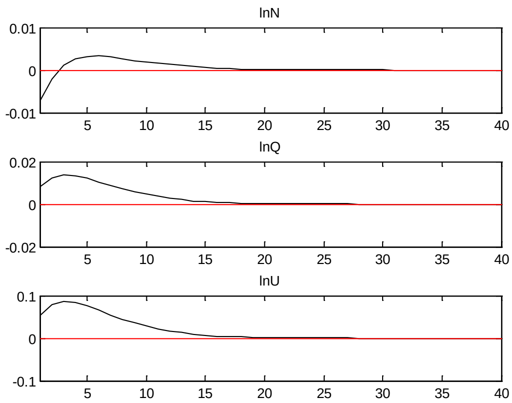
Note: Theoretical impulse response functions. On the y-axis is log deviation from steady state and on the x-axis is the number of months. Parameter values are listed in Table 3, with the exception that c_H=13.

Figure A6. Employment effects of changes in exogenous variables, no adjustment costs

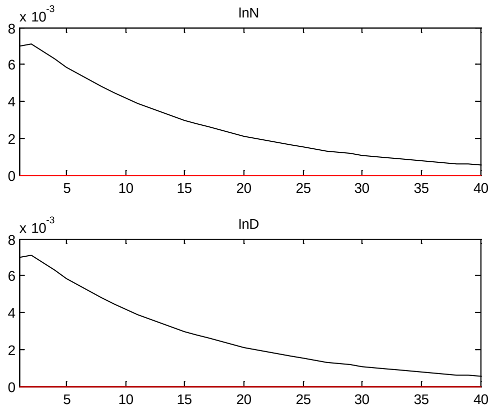
A6a. Shock to vacancies, c_H=0



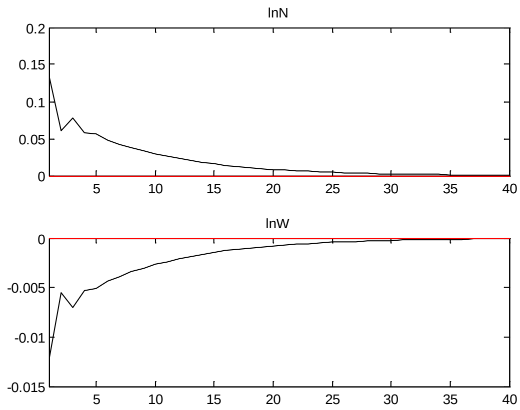
A6b. Shock to unemployment, c_H=0



A6c. Shock to product demand, c_H=0



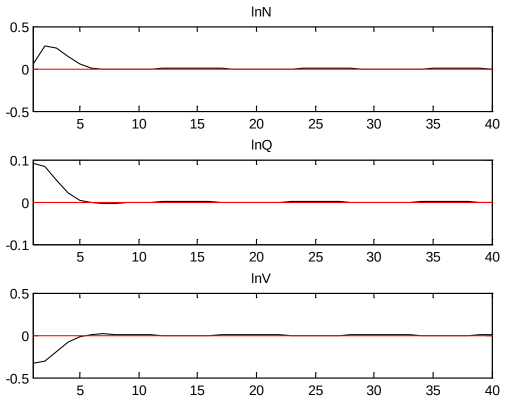
A6d. Shock to real wage costs, c_H=0



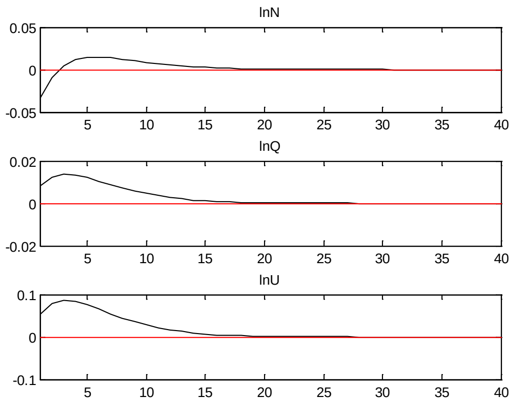
Note: Theoretical impulse response functions. On the y-axis is log deviation from steady state and on the x-axis is the number of months. Parameter values are listed in Table 3, with the exception that c_H=0. The initial drop in employment in Figure A6b is caused by the fact that the probability of filling 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 wait and hire fewer workers during the current period (see Euler equation).

Figure A7. Employment effects, no adjustment costs and very high competition

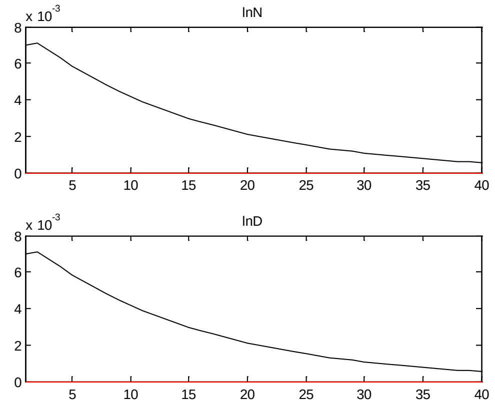
A7a. Shock to vacancies, c_H=0 & η=50



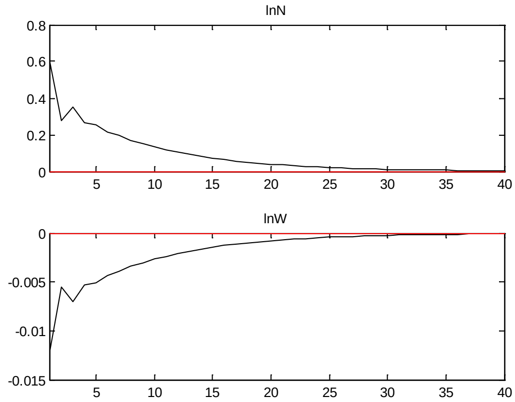
A7b. Shock to unemployment, c_H=0 & η=50



A7c. Shock to product demand, c_H=0 & η=50



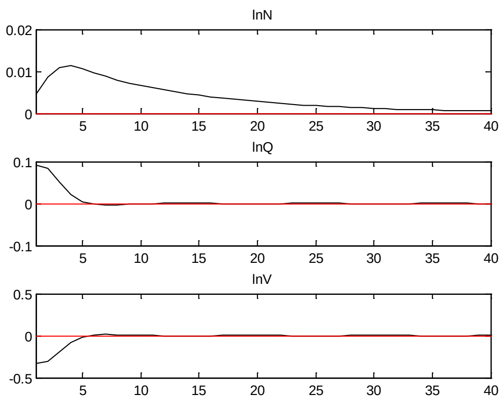
A7d. Shock to real wage costs, c_H=0 & η=50



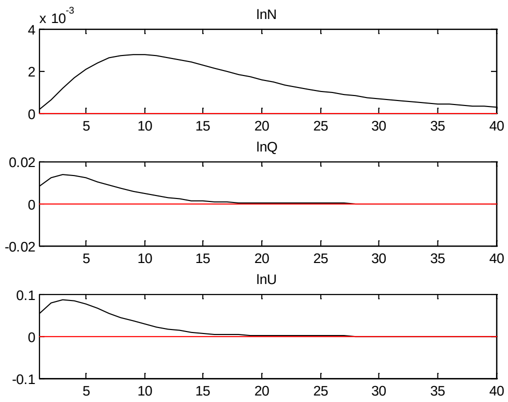
Note: Theoretical impulse response functions. On the y-axis is log deviation from steady state and on the x-axis is the number of months. Parameter values are listed in Table 3, with the exceptions that c_H=0 and η=50, i.e. no convex adjustment costs and very high competition in the product market such that the model approaches a standard search and matching model.

Figure A8. Employment effects, high competition in the product market

A8a. Shock to vacancies, η=50



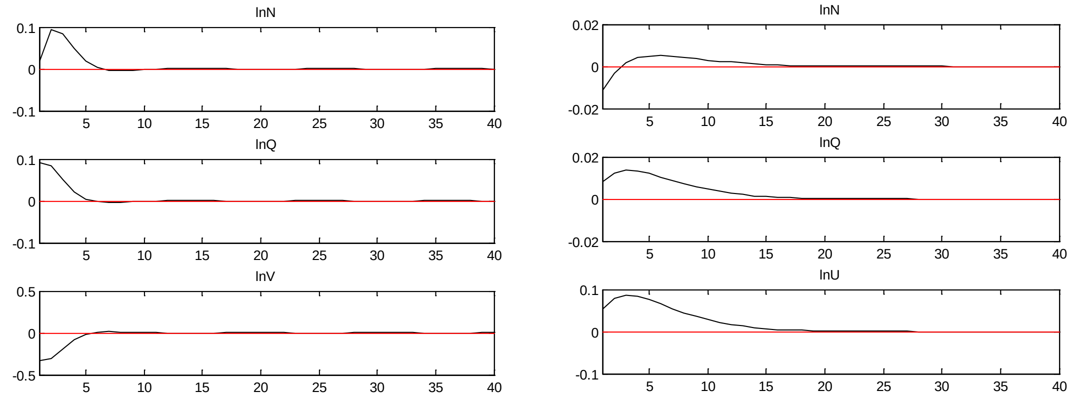
A8b. Shock to unemployment, η=50



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 3, with the exception that η=50.

Figure A9. Employment effects, no quadratic hiring costs and high linear vacancy costs

A9a. Shock to vacancies, c_H=0 & c_V=0.5 A9b. 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 3, with the exceptions that c_H=0 & c_V=0.5.

Table A12. 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	3.72 %	0.18 %	2.02 %	94.07 %
2)	β_U = 0.5 & β_V = -0.5	11.54 %	1.63 %	1.83 %	85.01 %
3)	c_V=0.5	8.61 %	0.43 %	1.92 %	89.04 %
4)	c_H=13	1.63 %	0.16 %	2.91 %	95.29 %
5)	c_H =0	16.18 %	0.23 %	0.86 %	82.74 %
6)	η=50	1.75 %	0.17 %	0.14 %	97.94 %
7)	c_H=0 & c_V=0.5	31.94 %	0.45 %	0.69 %	66.91 %
8)	c_H=0 & η=50	16.31 %	0.23 %	0.04 %	83.42 %

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.
In baseline 1), shocks to the number of unemployed explain 5 percent of the variation in the probability of filling a vacancy (while 95 percent is explained by the shocks to the number of vacancies). In 2), this share is 14 percent.