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The Beveridge Curve, Matching, and Labour Market Flows: A Reinterpretation

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ABSTRACT

A standard theory of the Beveridge curve is based on the matching function: when unemployment is high, vacancies are filled quickly, so fewer vacancies are needed to balance the inflow into unemployment. Estimating matching functions on panel data, we find no (or very weak) evidence that vacancies are filled quickly when unemployment is high. A model with on-the-job search can explain the Beveridge curve when vacancies are filled at a constant rate: when unemployment is high, unemployed job seekers fill a larger share of the vacancies, so fewer vacancies are needed to balance the inflow into unemployment.

JEL Classification: E24, J63, J64

1 | Introduction

Beveridge [1] found a negative relation between unemployment and vacancies, and this relation, the Beveridge curve, has been observed in many countries. In theoretical models, points on the Beveridge curve are seen as equilibrium points where the flow into unemployment equals the flow out of unemployment, while movements along the Beveridge curve are driven by productivity and other shocks to labour demand. In order to understand the Beveridge curve, we need to understand how the flows into and out of unemployment are related to the observed levels of vacancies and unemployment.

Most analyses of the Beveridge curve are based on variants of the search-matching model of Pissarides [2, 3] and Mortensen and Pissarides [4].[1] In the simplest version of this model, employed workers enter into unemployment at an exogenous rate s, so the flow into unemployment is $s(L-U)$, where L is the labour force and U is unemployment, and the flow out of unemployment is determined by a matching function with constant returns to scale $H^u/V = \phi(U/V)^\alpha$, where H^u denotes hiring from unemployment and V denotes vacancies. A positive value of α means that higher unemployment leads to more hires for given vacancies. If we set the inflow into unemployment equal to the outflow from unemployment, we get an equilibrium relation between unemployment and vacancies:

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

The slope of this Beveridge Curve depends on the value of α. If α is zero the Beveridge curve in (1) becomes an almost flat line.[2] If α is positive, vacancies are filled quickly when unemployment is high, so that fewer vacancies are needed to generate hires from unemployment that balance the inflow into unemployment. This implies a downward-sloping Beveridge curve as seen in Figure 1.[3]

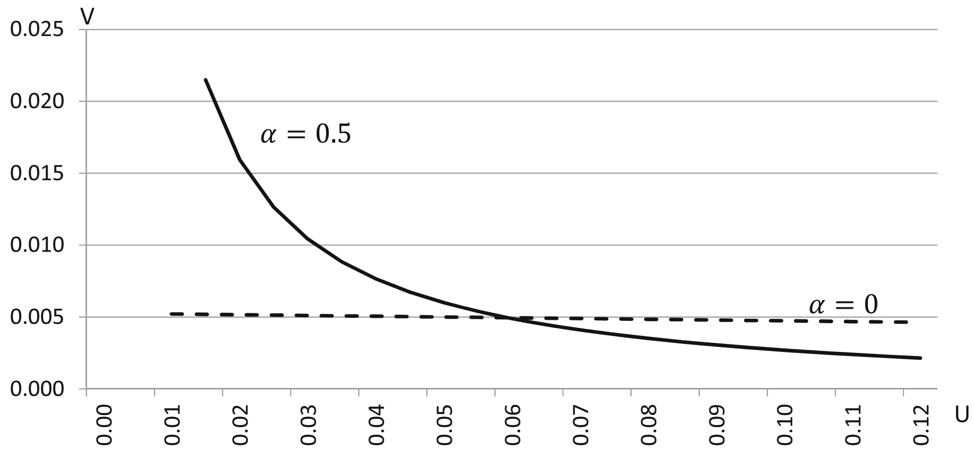

FIGURE 1 | Beveridge curve: Exogenous separations and no on-the-job search. Equation (1). Vacancies and unemployment are measured relative to the labour force. The parameter s is set to 0.01 and ϕ adjusted to keep vacancies at 0.5% when unemployment is 6%.

However, as we will show in Section 2, most of the cyclical variation of the observed stock of vacancies is explained by the *inflow* of new vacancies, and a similar observation can be made for Germany; see Supplementary Appendix A. There are few vacancies in bad times, but it is not primarily because vacancies are filled quickly—it is because there is a low inflow of new vacancies in periods of high unemployment.

Consistent with this observation, several researchers have found estimates of α close to zero when they estimated matching functions with the outflow of vacancies as the dependent variable. At the same time, researchers who estimate matching functions with hires from unemployment as the dependent variable typically find estimates of α around 0.6 (see Section III for a review of earlier results). Why do these estimates differ so much and what do they imply for the Beveridge curve?

In this paper, we first reconfirm these diverging results using monthly panel data from the Swedish Public Employment Service. Then we construct an alternative model with on-the-job search, estimate its parameters and show that this alternative model is broadly consistent with the Beveridge curve and the cyclicality of the flows into and out of unemployment. We argue that the negative correlation between unemployment and vacancies arises primarily because unemployed job seekers fill a larger share of the vacancies when unemployment is high; hence fewer vacancies are needed to balance the inflow into unemployment. With high unemployment, fewer employed workers find new jobs, leading to low turnover and a low inflow of new vacancies.

In order to document the diverging results of matching function estimation, we estimate two standard log-linear equations on panel data, one with hiring of unemployed workers as the dependent variable and one with de-registrations of vacancies as the dependent variable. The explanatory variables are the same in the two equations: the observed stocks of unfilled vacancies and unemployed workers at the beginning of the month and the inflows during the month. We find that unemployment and vacancies both increase the hiring of unemployed workers, but vacancies have a relatively small effect. With de-registrations of vacancies as the dependent variable, we find (in most specifications) no evidence that high unemployment speeds up the matching of vacancies. At the same time, there is clearly a Beveridge curve in these data.

TABLE 1 | Sources of hires and measures of job openings.

Shares of hires, recruitment survey 2006	
From another employer	0.33
Internal recruitment	0.13
From outside labour force	0.28
From unemployment	0.26
Job openings relative to labour force 2001	
Vacancies, PES	0.0061
New vacancies per month, PES	0.0087
Job openings, survey	0.0151
Unmanned vacancies, survey	0.0073
Hires per month, survey	0.0285

Note: Data for recruitments comes from the Recruitment Survey which is made occasionally by the Swedish Labour Force Survey (AKU). PES: data from the Public Employment Service. Job openings and unmanned vacancies are from survey data (Kortsiktig Vakansstatistik). A job opening means that the firm has initiated the recruitment process, while an unmanned vacancy means that the job can be started immediately. Hires are from short-term employment statistics (Kortsiktig Sysselsättningsstatistik).

To understand these diverging results, we must note that filling a vacancy is not the same thing as hiring an unemployed worker. Two key differences can be seen in Table 1. First, there are job seekers who are not registered as unemployed. Survey evidence indicates that hires directly from other jobs and hires of new entrants to the labour force are of similar magnitudes as hires from unemployment. Hires from unemployment constitute only 30% of all external hires.[4] Second, there are job openings which are not registered as vacancies. Informal contacts are often used for recruitment. Survey data indicates that in 2001, monthly hires were three times as large as the inflow of vacancies to the Public Employment Service and more than four times as large as the vacancy stock. In fact, hires from unemployment are *countercyclical* while de-registrations of vacancies are *procyclical* in Sweden and several other countries (see Section 2) so it is not surprising that we get different results depending on what variable we have as the dependent variable in the matching function.

Conditional on identifying assumptions, log-linear matching functions may capture *causal effects* of the initial stocks and the inflows on the outflows. However, in the presence of unobserved job applicants and unobserved job openings, such estimates will give us biased estimates of the parameters of the underlying matching technology that connects all relevant job applicants with all relevant job openings. This insight is not new: Broersma and Van Ours [5] and Petrongolo and Pissarides [6] analyse the biases that arise when there is search on the job. The study by Sunde [7] is most closely related to the present one because he estimates matching functions allowing for unobserved job seekers as well as unobserved job openings. However, he does not formulate a theoretical model to explain his results, nor does he investigate the implications of his results for the Beveridge curve.

In order to explain our estimation results and the Beveridge curve, we construct an extended matching model where we allow for a constant fraction of employed workers searching on the job and general lags in the hiring process. Also, we assume that unemployed workers are less able to compete for registered vacancies compared to employed job seekers and that a fixed amount of hiring occurs via informal contacts, without any vacancies being registered. To match the data, we also model a countercyclical inflow into unemployment as explained in Section 6. We estimate the model parameters and compare them to available evidence from other sources.

Then we investigate the implications of our model for the Beveridge curve. Following Mortensen and Pissarides [4], Elsby, Michaels and Ratner [8] and many others, we disregard transitional dynamics and think of a point on the Beveridge curve as a combination of vacancies and unemployment that makes the flow into unemployment equal to the flow out of unemployment. We find that our alternative model can explain the Beveridge curve reasonably well and that it is broadly consistent with the cyclicality of the flows that we can see in the data. De-registrations of vacancies and the job finding rate are procyclical but the flows into and out of unemployment and hires relative to vacancies are countercyclical.

As we discuss in Section 3, some previous studies have already documented a weak effect of unemployment on the de-registration of vacancies. Compared to the previous literature, we make three contributions. First, we investigate the relation between *stocks and flows* of vacancies and unemployment carefully, using a large monthly panel dataset with more than 20,000 observations. Register data have often been used to document the Beveridge curve, and a great advantage of register data—compared to most survey data—is that we have not only stocks at the beginning of the month, but also inflows and outflows of vacancies and unemployed workers during the month. Also, panel data allow us to investigate the robustness of the results across different time periods and across large and small labour markets.

Second, we point out that a weak effect of unemployment on the matching of vacancies has important implications for the interpretation of the Beveridge curve that we see in the data from the Public Employment Service. The Beveridge curve slopes down, not primarily because high unemployment reduces vacancy durations, but because there is a low inflow of vacancies in periods of high unemployment.

Third, we show that a model with on-the-job search can generate a reasonable Beveridge curve when vacancies are filled at a constant rate ($\alpha = 0$). Akerlof, Rose and Yellen [9] pointed out that a model of this kind can generate a Beveridge curve but we extend their model with hiring via contacts, mismatch and a countercyclical inflow into unemployment. We estimate the corresponding parameters and we evaluate *quantitatively* how well this type of model can explain the Beveridge curve.

Two closely related studies are Fujita and Ramey [10] and Fujita and Nakajima [11]. They show that on-the-job search helps to explain the variability and pro-cyclicality of vacancies. However, they set α to 0.5 and 0.7 so that unemployment has a big effect on the matching of vacancies. We go further, arguing that α is close to zero, so that this effect plays a small role in the explanation of the Beveridge curve. Some related studies are discussed in Section 8.

We illustrate the relations between stocks and flows graphically in Section 2, and estimates of standard log-linear matching functions are reported in Section 3. In Sections 4 and 5, we extend the matching framework to allow for heterogeneity, on-the-job search, mismatch, and hiring via contacts. A model of the countercyclical inflow into unemployment is estimated in Section 6. In Section 7, we derive the alternative Beveridge curve, and we suggest an interpretation in terms of vacancy chains. In Section 8, we examine how well our model can explain the Beveridge curve and the flows into and out of unemployment. Section 9 concludes.

2 | A Look at the Data

For our baseline estimation, we use register data from the Swedish Public Employment Service for the period 1992:8–2011:6. After 2011 there was a structural break associated with a very large inflow of immigrants and for this reason, we exclude data after 2011.[5] Data are available at the municipality level and we aggregate the data to obtain a dataset with variables for local labour markets, which consist of one or more municipalities. Local labour markets have been constructed by Statistics Sweden based on commuting patterns so as to be geographical areas that are relatively independent from the rest of the world with respect to labour demand and supply.[6]

2.1 | Definitions

The stock of unemployment U_t is measured as the number of openly unemployed workers that are registered at the Public Employment Service at the beginning of the month. There is a strong incentive to register because doing so is required to qualify for unemployment benefits.[7] The inflow into unemployment U_t^{in} is measured as the number of workers who are newly registered as unemployed during the month and hires

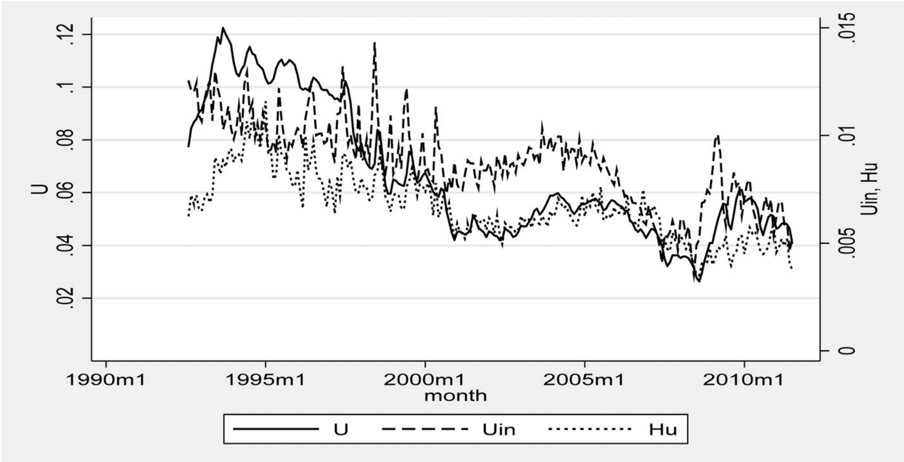

FIGURE 2 | Inflow, hiring from unemployment and the stock of unemployment. Unemployment: Full line. Inflow into unemployment: – – –. Hires from unemployment: · · ·. The scale for the stock is on the left axis and the scale for the flows is on the right axis. Aggregate data for Sweden from the Public Employment Service. All variables are measured relative to the labour force and seasonally adjusted.

from unemployment H_t^u are measured as the number of workers who leave registered unemployment, reporting to the employment service that they found jobs. V_t is the stock of vacancies registered at the Public Employment Service at the beginning of the month, and V_t^{in} is the inflow of new vacancies during the month.

We measure the outflow of vacancies (de-registrations) as the inflow of new vacancies over the month minus the change of the stock: $V_t^{\text{out}} = V_t^{\text{in}} - \left(V_{t+1} - V_t\right)$. A weakness of these data (and most other vacancy data) is that we do not know if the vacancies that are deregistered are actually filled. Firms may abandon their recruitment efforts without actually hiring a worker and if the fraction of firms that does this varies in a systematic way, we may draw incorrect conclusions. A recruitment survey, issued irregularly by the employer federation, shows that, on average, about 1/5 of all recruitment attempts fail, but this fraction does not appear to have a cyclical pattern.[8]

We measure stocks and flows relative to the labour force in the local labour market area.[9] In our sample, unemployment was, on average, 7.2% of the labour force, the average monthly inflow into unemployment was 0.97% of the labour force and the average flow from unemployment to jobs was slightly smaller, 0.92% of the labour force. The difference arises because some workers deregister without reporting that they found a job. Vacancies corresponded to 0.53% of the labour force, and the average monthly inflows and outflows of vacancies both corresponded to 0.82% of the labour force.[10] Thus, the flows of workers and vacancies are of similar magnitudes but the number of vacancies is 14 times smaller than the number of unemployed workers and the expected duration of a vacancy is correspondingly smaller (less than 3 weeks).

Aggregate data from the Public Employment Service correlate well with data from the labour force survey; see Supplementary Appendix A. However, there has been a trend decline in the number of workers that are registered at the Public Employment Service compared to the survey measure. This makes it important to account for underlying trends and structural changes in the estimation, and we do this by including local time trends and/or time dummies in the panel estimation.

2.2 | Stocks, Flows and the Beveridge Curve

Before we move to estimation, we illustrate the data for the aggregate economy. Figure 2 shows that the inflow into unemployment and hiring from unemployment are both positively correlated with unemployment. Countercyclical flows into and out of unemployment are consistent with the findings of Blanchard and Diamond [12] and Fujita and Ramey [10, 13] for the U.S., Burda and Wyplosz [14] for some European countries, and Fontaine [15] for France. Elsby et al. [16] show countercyclical inflows and outflows in half the countries for which they have data.[11]

Figure 3 illustrates a three-dimensional relationship between unemployment, vacancies, and hires from unemployment. Each bubble represents a month. Unemployment is measured on the horizontal axis and vacancies on the vertical axis, and the sizes of the bubbles reflect hires from unemployment. The downward slope shows that there is a Beveridge curve in these data. Comparing the bubbles in the horizontal direction, we see that hires from unemployment increase with unemployment for given vacancies. Comparing vertically, we can see a weak positive relation between vacancies and hires from unemployment for a given level of unemployment. As predicted by the matching function, unemployment and vacancies appear to have positive effects on hires from unemployment, but the effect of vacancies appears to be weak.

Figure 4 shows that the vacancy stock is very closely correlated with the vacancy inflow. The inflow is larger than the stock, so the average duration of a vacancy is less than a month, consistent with the findings of Barron et al. [17]. The outflow lags the inflow, but this lag is barely visible because of the very short duration of the vacancies.

Figure 5 shows how de-registrations of vacancies vary along the Beveridge curve. Comparing the bubbles vertically, we see that

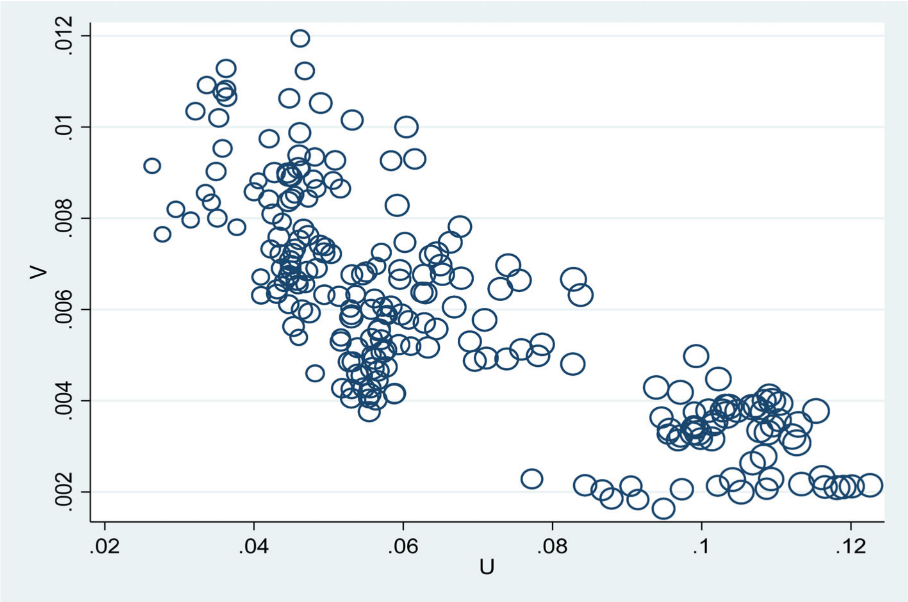

FIGURE 3 | Hiring from unemployment along the Beveridge curve. Horizontal axis: Unemployment. Vertical axis: Vacancies. Area of bubbles is proportional to hires from unemployment during the month. Aggregate data for Sweden from the Public Employment Service. All variables are measured relative to the labour force and seasonally adjusted. [Colour figure can be viewed at wileyonlinelibrary.com]

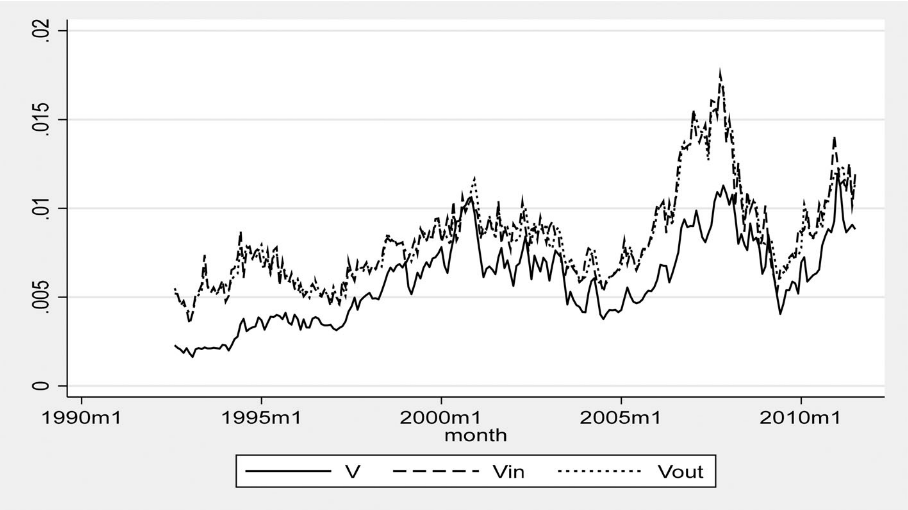

FIGURE 4 | Inflow, outflow and stock of vacancies. Stock of vacancies: Full line. Inflow of vacancies: – – –. Outflow of vacancies: · · ·. Aggregate data for Sweden from the Public Employment Service. All variables are measured relative to the labour force and seasonally adjusted.

more vacancies lead to more vacancies being de-registered for given unemployment. Comparing the bubbles horizontally, for given vacancies, we see no indication that vacancies are filled at a faster rate when unemployment is high. This is our main finding and it contradicts the standard explanation of the Beveridge curve that we discussed in the introduction.

Similar patterns can be observed when we look at data for individual local labour markets. However, this picture may be distorted because of common unobserved shocks and long-term structural changes. By including time trends and/or time dummies in our panel estimation, we can eliminate the effects of common unobserved factors, provided that they affect all labour markets in the same way. With panel data, we can investigate the robustness of our findings across labour markets and time.

3 | Estimation of Matching Functions

To further document the correlations that exist in the data, we estimate simple log-linear matching functions with hires of unemployed workers $\left(H^{u}_{i,t}\right)$ and de-registrations of vacancies $\left(V^{out}_{i,t}\right)$ as dependent variables. The month is denoted t and the local labour market is denoted i. Inspired by the stock-flow matching literature, we include the stocks at the beginning of the month and the inflows (new registrations) of vacancies

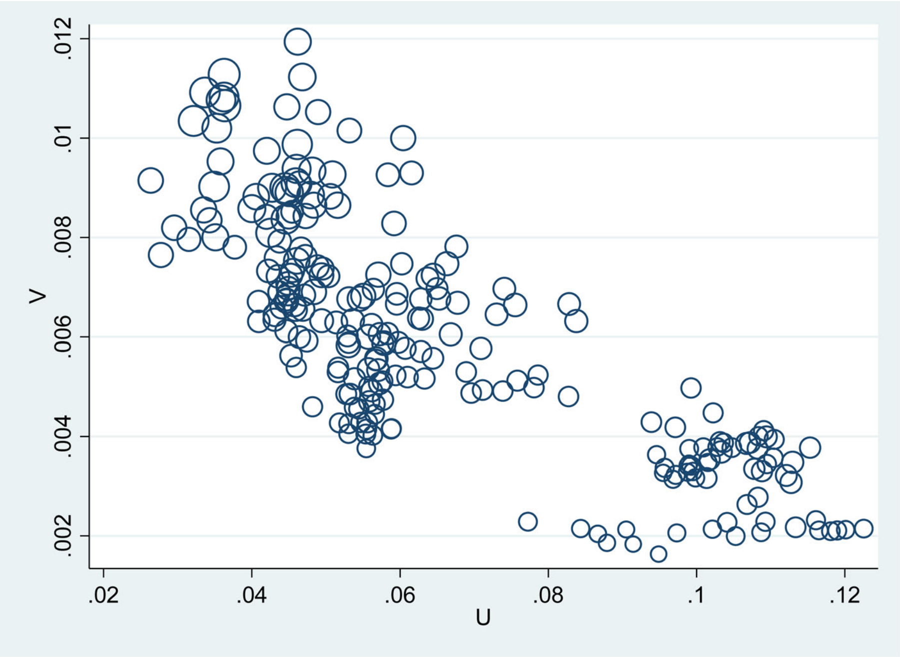

FIGURE 5 | Vacancy outflow along the Beveridge curve. Horizontal axis: Unemployment. Vertical axis: Vacancies. Area of bubbles is proportional to vacancy outflow (de-registrations) during the month. Aggregate data for Sweden from the Public Employment Service. All variables are measured relative to the labour force and seasonally adjusted. [Colour figure can be viewed at wileyonlinelibrary.com]

and unemployed workers during the month as explanatory variables:[12]

$$lnH^{\rm u}_{\rm i,t} = \ln\phi^u_i + a_{11}\ln U_{\rm i,t} + a_{12}\ln U^{\rm in}_{\rm i,t} + b_{11}\ln V_{\rm i,t} + b_{12}\ln V^{\rm in}_{\rm i,t} + \tau^u_{i,t} + s^u_{i,t} + \varepsilon^u_{\rm i,t} \quad (2)$$

$$lnV^{\rm out}_{\rm i,t} = \ln\phi^v_i + a_{21}\ln U_{\rm i,t} + a_{22}\ln U^{\rm in}_{\rm i,t} + b_{21}\ln V_{\rm i,t} + b_{22}\ln V^{\rm in}_{\rm i,t} + \tau^v_{i,t} + s^v_{i,t} + \varepsilon^v_{\rm i,t}. \quad (3)$$

$U_{i,t}$ is the number of workers who are registered as unemployed at the beginning of the month, $U^{\rm in}_{i,t}$ is the inflow during month t, $V_{i,t}$ is the stock of vacancies that are registered at the beginning of the month and $V^{\rm in}_{i,t}$ is the inflow of new vacancies during the month. The unobserved shock terms $\varepsilon^v_{i,t}$ and $\varepsilon^u_{i,t}$ may represent temporary variations of mismatch, the efficiency of the employment service and unobserved job seekers and job openings. We do not impose constant returns to scale, for two reasons. First, we see no compelling reason to do so. Second, if we estimate an equation of the form $H/V = \phi(U/V)^\alpha$, any measurement error with respect to vacancies will mechanically induce a positive bias in the estimate of α.

We include fixed effects $\left(\phi^u_i, \phi^v_i\right)$ for local labour markets in our baseline specification because the matching process may differ between labour markets due to geography and industry structure. To account for differing seasonal patterns across local labour markets, we include seasonal dummies interacted with dummies for the local labour markets $\left(s^u_{i,t}, s^v_{i,t}\right)$. To allow for structural changes in the labour market during this long estimation period, we include linear and quadratic time trends, which are specific for each labour market $\left(\tau^u_{i,t}, \tau^v_{i,t}\right)$. As a robustness check, we also include time dummies.

3.1 | Estimation Issues

In the presence of unobserved job seekers and unobserved job openings, this estimation will produce biased estimates of the parameters of the underlying matching technology, and these biases are well known; see Broersma and Van Ours [5], Petrongolo and Pissarides [6] and Sunde [7]. However, even if we are unable to recover structural coefficients of the underlying matching function, we may still be able to estimate *net effects* of vacancies and unemployment on the matching. In simple models with random search, more agents on the other side of the market should increase the probability of a match, and if that is the case, we should expect all coefficient estimates to be positive.

The identifying assumption is that variations of the explanatory variables depend on shocks to labour demand and labour supply and not on shocks to the matching technology. *Persistent* shocks to matching efficiency will lead to biased estimates of the causal effects because of reverse causation. For given inflows, a persistent decline in matching efficiency will increase the stocks, and this may lead us to underestimate the effects of the stocks on the matching. On the other hand, an endogenous response of the vacancy inflow to matching efficiency may induce a positive correlation between vacancies and matches that leads us to overestimate the effect of the vacancies on the number of matches [18]. These biases should go in the same direction independent of whether we have the matching of vacancies or the matching of unemployed workers as the dependent variable.

3.2 | Results

The first three columns in Table 2 show estimates of equation (2) with hiring from unemployment as the dependent variable. We

TABLE 2 | Hires of unemployed workers (H^u) and de-registrations of vacancies (V^{out}).

lnH^u *t*	**(1)** lnH^u	**(2)** lnH^u	**(3)** lnV^{out}	**(4)** lnV^{out}	**(5)** lnV^{out}	**(6)**
ln$U$	0.566***	0.514***	0.576***	0.020	0.052**	−0.012
	(0.013)	(0.027)	(0.023)	(0.014)	(0.022)	(0.022)
lnU^{in}	−0.006	0.051***	0.000	−0.016	−0.004	−0.016
	(0.011)	(0.019)	(0.013)	(0.014)	(0.024)	(0.019)
ln$V$	0.020***	0.006	0.009***	0.409***	0.412***	0.415***
	(0.003)	(0.004)	(0.003)	(0.009)	(0.009)	(0.009)
lnV^{in}	0.088***	0.030***	0.038***	0.469***	0.506***	0.462***
	(0.006)	(0.006)	(0.005)	(0.012)	(0.015)	(0.013)
Local trends	ν		ν	ν		ν
Time dummies		ν	ν		ν	ν
Observations	20,394	20,394	20,394	20,391	20,391	20,391
Number of llc	90	90	90	90	90	90

Note: Dependent variables are logs of monthly hires from unemployment (H^u) and de-registrations of vacancies (V^{out}). Explanatory variables are logs of initial stocks (U, V) and inflows during the month (U^{in}, V^{in}). Estimation with fixed effects for local labour markets and local seasonal dummies. Robust standard errors (clustered on local labour market) in parentheses; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Estimation period: 1992:8–2011:6.

report results for three specifications: with local time trends, with time dummies, and including both local time trends and time dummies. We find that unemployment has a strong effect on the hiring of unemployed workers. An estimate of α around 0.6 is in line with previous findings and many researchers have interpreted this large effect as evidence that unemployed workers play an important role in the formation of matches. Vacancies have a statistically significant but surprisingly small effect on hires from unemployment: the sum of the coefficients on the vacancy inflow and the initial stock is on the order of 0.1 or less.

Columns 4–6 in Table 2 show estimates of equation (3) with the outflow of vacancies as the dependent variable. The initial stock and the inflow of new vacancies both contribute to the outflow of vacancies, but neither the initial stock of unemployment nor the unemployment inflow has important effects on the deregistration of vacancies.

These results are quite robust across time and space. Estimating these equations on the first half of the sample period, the second half of the sample period, and for large and small labour markets, we find similar results; see Supplementary Appendix A. Estimation on aggregate data indicates that unemployment has a small *negative* effect on the matching of vacancies, but this may be a spurious result because of structural changes that are hard to control for using macroeconomic data; see Supplementary Appendix A.

3.3 | Comparison With Previous Empirical Results

Thus, we obtain very different estimates of matching functions depending on whether we have hires from unemployment or deregistrations of vacancies as the dependent variable. We find it most relevant to compare our results with studies using panel data and where constant returns to scale is not imposed in the estimation of the matching function.[13] Taking a close look at the literature, we find that similar results have been found in several studies.

3.3.1 | Matching of Unemployed Workers

Studies with hiring from unemployment as the dependent variable have typically found a coefficient for unemployment around 0.6–0.7 and a coefficient for vacancies in the range 0.1–0.3; see the overviews of studies by Broersma and Van Ours [5] and Petrongolo and Pissarides [6].[14] Compared to these studies, we get a similar effect of unemployment, but a relatively weak effect of vacancies on hires from unemployment. Araranki and Löf [19] estimated panel regressions similar to ours with data for provinces, also finding small effects of vacancies on the outflow from unemployment, and Sunde [7] found a similar result for Germany. Forslund and Johansson [20] used aggregate data for Sweden and found a somewhat higher coefficient of approximately 0.2 for vacancies.

3.3.2 | Matching of Vacancies

The most similar study is Kangasharju et al. [21]. They studied vacancy matching in Finland with similar panel data, including both stocks and inflows as explanatory variables, and they found remarkably similar results. They concluded that '… matches are mainly driven by the demand side of the labour market … the elasticity with respect to the stock of old vacancies is 0.3 and with respect to new vacancies 0.6. The corresponding effect from the supply side (job seekers) is only around 0.1.' Similarly, Broersma and van Ours [5] found no effect of unemployment on the flow of filled vacancies using panel data for the Netherlands when they estimated separate equations for filled vacancies and the outflow from unemployment. Anderson and Burgess [22] found a statistically insignificant effect of unemployment on hiring for given vacancies when they removed seasonality using time effects.

However, Sunde [7] found a substantial positive effect of unemployment on the matching of vacancies using panel data for Germany. Two key differences are that he used yearly data for occupations while we have monthly data for local labour markets, and that he included only the initial stocks but not the inflows during the year. This may matter because of the short duration of vacancies. The inflow of new vacancies during the year should be a more important determinant of the outflow than the stock at the beginning of the year.

Edin and Holmlund [23] estimated matching functions using aggregate data for Sweden. With the outflow of vacancies as the dependent variable, they found an elasticity of 0.23 with respect to unemployment. One reason for the positive effect may be that they had data for the period 1970–1988, when unemployment was very low, while our sample covers a period with substantial slack in the labour market.[15] Michaillat [24] argues that matching frictions may be less important in bad times.

We conclude that some studies using similar data and methods have found similar results: unemployment has a strong effect on the matching of unemployed workers but a weak effect on the matching of vacancies. Our contribution to this empirical literature is that we have documented this discrepancy carefully, using a large panel dataset and estimating symmetric equations for the two flows, controlling for structural changes by including trends and fixed effects for local labour markets.

As concerns theory, none of the papers cited above try to interpret these divergent findings, nor do they investigate the implications of their results for the Beveridge curve. In the following, we argue that these findings should lead to a fundamental reinterpretation of the matching process and the Beveridge curve.

4 | Lags, Heterogeneity and On-the-Job Search

In this section, we allow for lags in the hiring process, heterogeneity, and on-the-job search in the estimation of matching functions.

4.1 | Lags and Heterogeneity

Hiring takes time, and sorting and scarring effects suggest that workers who have been unemployed a longer time are less able to compete for jobs. To account for this, we define the effective unemployment rate that is relevant for hiring in period t as

$$U_t^e = \sum_{j=0}^{3} a_j U_{t-j}^{in} + a_4 U_{t-3} \tag{4}$$

where we have simplified notation by omitting the index for the local labour market. We need to choose some scale for the measurement of effective unemployment, and we do this by setting $a_1 = 1$ so that the worker who entered unemployment 1 month ago performs one unit of job seeking. Similarly, we assume that the effective vacancies, relevant for hiring in period t, are a weighted average of flows up to 3 months back and the initial stock 3 months back:

$$V_t^e = \sum_{j=0}^{3} b_j V_{t-j}^{in} + b_4 V_{t-3}. \tag{5}$$

where $\sum_{j=0}^{4} b_j = 1$. These specifications allow for heterogeneity and arbitrary time lags in the hiring process and they should make the results more robust to timing errors in the registration of the flows. The normalisations $a_1 = 1$ and $\sum_{j=0}^{4} b_j = 1$ affect the interpretations of the parameters κ and Λ below.

4.2 | On-the-Job Search

Search on the job is important. Survey evidence of the share of workers doing on-the-job search gives numbers ranging from 5% to over 20%; see for example, Blau and Robins [25], Pissarides [26] and Faberman, Mueller, Sahin and Topa [27]. As pointed out by Anderson and Burgess [22], the presence of on-the-job search means that ‘commonly estimated parameters of a matching function are in fact likely to be a reduced-form combination of a structural matching function and a job competition model’. The problem, of course, is that we have very little data on the incidence, intensity and efficiency of on-the-job search. However, we can still allow for on-the-job search in a simple way by assuming that employed workers make a constant amount of job search, as in Fujita and Nakajima [11] and Elsby and Gottfries [28]. Thus, we assume that employed workers make, on average, κ units of job search. Then, the matching of unemployed workers is determined by

$$H_t^u = \Phi\left(U_t^e + \kappa N_t\right)^{\alpha}\left(V_t^e\right)^{\beta}\frac{U_t^e}{U_t^e + \kappa N_t}e^{\varepsilon_t^u}, \tag{6}$$

where N_t is employment at the beginning of the month, and the matching of vacancies is determined by

$$V_t^{\text{out}} = \Phi\left(U_t^e + \kappa N_t\right)^{\alpha}\left(V_t^e\right)^{\beta}e^{\varepsilon_t^v}. \tag{7}$$

4.3 | Estimation

We estimated these equations in log form by nonlinear least squares on seasonally adjusted and detrended data.[16] As concerns identification, the basic idea is that shocks to productivity and aggregate demand lead to variations in unemployment and vacancies that allow us to estimate the parameters in these equations. For our estimation to make sense, we need to assume that there are only temporary and unexpected shocks to matching efficiency and on-the-job search. Persistent variations in matching efficiency and the intensity of job search would affect the dependent variables as well as the explanatory variable in these equations, and we have not found a way to deal with the biases that may arise because of this. Like most of the literature on empirical matching functions, we assume that matching efficiency and search intensity are stable parameters.[17]

TABLE 3 | Matching of unemployed workers: Heterogeneity, lags and on-the-job search. Equation (6) estimated by NLS. Dependent variable: Hires from unemployment.

(a) κ set to zero

(1) Φ	(2) α	(3) a_2	(4) a_3	(5) a_4	(6) β	(7) b_0	(8) b_1	(9) b_2	(10) b_3
0.158***	0.679***	0.739***	0.521***	0.302***	0.153***	0.464***	0.185***	0.221***	0.135***
(0.008)	(0.010)	(0.066)	(0.054)	(0.015)	(0.005)	(0.023)	(0.020)	(0.020)	(0.019)

(b) κ set to 0.05

(1) Φ	(2) α	(3) a_2	(4) a_3	(5) a_4	(6) β	(7) b_0	(8) b_1	(9) b_2	(10) b_3
0.045***	0.003	0.460***	0.340***	0.218***	0.147***	0.471***	0.180***	0.221***	0.134***
(0.004)	(0.039)	(0.051)	(0.044)	(0.011)	(0.005)	(0.024)	(0.020)	(0.021)	(0.020)

Note: Local seasons and trends have been removed from the data. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Number of observations: 20012.

Parameter estimates for equation (6) are reported in Table 3. As mentioned above, the coefficient a_1 is normalised to unity. The estimate of a_0 came out negative and, for consistency with theory, we set it to zero.[18] Aside from this, the lag structure is reasonable. Those who were unemployed 3 months ago play a smaller role in the matching compared to those who became unemployed 1 or 2 months ago. This may reflect selection and scarring effects, but it is partly a mechanical effect since some of those workers already found jobs.

Attempts to estimate α and κ simultaneously led to convergence problems. These parameters play similar roles in equation (6): in both cases, a positive value implies that hires from unemployment increase with unemployment for given vacancies. We therefore set κ exogenously to two different values: zero and 0.05. As seen in Table 3, this choice has a big effect on the estimation: setting $\kappa = 0$ we get an estimate of $\alpha = 0.679$ but with a reasonable amount of on-the-job search ($\kappa = 0.05$) the estimate of α drops to zero. High unemployment leads to more hiring of unemployed workers, for given vacancies, simply because unemployed workers fill a larger share of the job openings and this effect is sufficient to explain a commonly estimated elasticity of the matching of unemployed workers with respect to unemployment in the order of 0.6.

It has long been well known that the estimate of α is biased upwards if on-the-job search is ignored; see Broersma and Van Ours [5], Petrongolo and Pissarides [6] and Fahr and Sunde [29]. What we have shown here is that α falls to zero once we allow for a plausible amount of on-the-job search in the specification of the matching function.

Estimates of equation (7), with the vacancy outflow as dependent variable, produced values of β close to unity and slightly negative values of α. A negative value of α makes little sense so we do not report these estimates. Instead, we conclude that we have confirmed the result in Section III: we do not find evidence that vacancies are matched more quickly when there is high unemployment.

In this Section, we have found an explanation of the differing effects of unemployment on the matching of unemployed workers and vacancies that we reported in Table 2. Once we allow for a reasonable amount of on-the-job search, our estimates of α are close to zero in both equations. A natural interpretation is that, most of the time, firms get several acceptable applicants for a job opening. They post the vacancy for some time, collect and review the applications, and offer the job to the best applicant. If the preferred applicant declines, they offer the job to the next best applicant.[19] Of course, it takes time and effort to recruit a worker, but a longer list of applicants does not speed up the hiring process. This interpretation is consistent with the findings of van Ours and Ridder [30, 31] who studied search strategies of employers, concluding that '… almost all vacancies are filled from a pool of applicants that is formed shortly after the posting of the vacancy. Hence vacancy durations should be interpreted as selection periods and not as search periods for applicants'.

5 | Mismatch and Hiring via Informal Contacts

One mystery remains, however. While the estimate of β is close to unity in the matching function for vacancies, it is surprisingly small in the equation for hires from unemployment. A plausible interpretation is that registered vacancies are a very imperfect measure of the job openings that are relevant for the average unemployed worker. Thus, our final modification of the matching function is to allow for vacancies to be an imperfect measure of job openings. We do this by assuming that the jobs that the unemployed workers can compete for are given by a linear function of effective vacancies as defined above: $H^0 + \Lambda V_t^e$. We interpret the constant H^0 as hiring that occurs via informal contacts and Λ as the fraction of all registered vacancies that the average unemployed worker can compete for.[20] This specification is motivated by four observations:

i. Table 1 shows that total hiring was about three times larger than the inflow of registered vacancies in this period.

ii. In a typical month during the Swedish financial crisis in the 1990s, when the unemployment rate was 12% and there were very few registered vacancies, 6%–7% of the unemployed still reported that they found jobs. Clearly, many found jobs that were not registered as vacancies.

iii. There may be a mismatch between demand and supply. The typical unemployed worker may have a hard time competing for registered vacancies because of selection into unemployment and heterogeneity across sections of the labour market. Many vacancies may appear in submarkets where there are few unemployed workers.

iv. Personal networks are limited, so we should expect hiring via informal networks (e.g., recalls) to be less procyclical than hiring via registered vacancies.

Thus, we assume that hires from unemployment are determined by

$$H_t^u = \Phi\left(U_t^e + \kappa N_t\right)^\alpha \left(H^0 + \Lambda V_t^e\right)^\beta \frac{U_t^e}{U_t^e + \kappa N_t} + \tilde{\varepsilon}_t^u \tag{8}$$

where V_t^e and U_t^e were defined in the previous section and where $\tilde{\varepsilon}_t^u$ is an unobserved shock. We assume that the remaining vacancies $(1 - \Lambda)V_t^e$ match with a subset of the employed job seekers, zN_t. Thus, the matching of vacancies is determined by.

$$V_t^{\text{out}} = \Phi\left(U_t^e + \kappa N_t\right)^\alpha \left(H^0 + \Lambda V_t^e\right)^\beta \frac{\Lambda V_t^e}{H^0 + \Lambda V_t^e} + \Phi\left(zN_t\right)^\alpha \left((1 - \Lambda)V_t^e\right)^\beta + \tilde{\varepsilon}_t^v \tag{9}$$

where $\tilde{\varepsilon}_t^v$ is an unobserved shock.

5.1 | Estimation

These two equations contain many parameters and attempts to estimate them separately led to convergence problems. We therefore focus on simultaneous estimation by nonlinear SUR. Unrestricted estimation led to negative values of α and a_0. Even if we set the amount of on-the-job search to some plausible value such as $\kappa = 0.05$ we get a small negative estimate of α as seen in the upper part of Table 4.[21] Since our aim is to construct an interpretation of the Beveridge curve that makes economic sense, we set $\alpha = a_0 = 0$. The estimate of β is below unity, which may be interpreted as evidence of congestion, but congestion should imply a positive value of α. Alternatively, an estimate of β below unity may be due to measurement errors for vacancies. For consistency with economic theory, we set $\beta = \Phi = 1$ and this leads to the estimates reported in the lower part of Table 4.

Vacancy inflows up to 3 months back have statistically significant effects on the hiring of unemployed workers and since $b_4 = 1 - b_0 - b_1 - b_2 - b_3 = 0.049$ the vacancy stock 3 months back has a small effect. This reflects the short duration of vacancies. According to these estimates, the average unemployed worker can compete for 35% of the vacancies reported at the Public Employment Service and hiring without registered vacancies corresponds to 2.1% of the labour force. Since the average vacancy outflow corresponds to 0.82% of the labour force, this implies that more than two-thirds of all job seekers find jobs via channels other than vacancies posted at the Public Employment Service. This result is roughly consistent with data reported in Table 1 showing that the inflow of vacancies to the Public Employment Service corresponds to 31% of all hires.

The estimate of $\kappa = 0.076$ suggests that 100 employed workers perform 7.6 units of job seeking. To interpret this value, recall our normalisation that a worker who entered unemployment 1 month ago performs one unit of job search ($a_1 = 1$). As mentioned in Section 4, survey evidence of on-the-job search gives numbers ranging from 5% to over 20% of employed workers doing some job search, so our estimate is in the ballpark, but it is hard to know how the intensity and efficiency of search on the job compares to search by unemployed workers. Still, we can get a reality check of this estimate by calculating what it implies for worker flows. Our estimates imply that, when all variables are at their means, 31% of all hires come from unemployment:

$$\frac{H^u}{H} = \frac{\Lambda V^{\text{in}} + H^0}{U^e + \kappa N} \frac{U^e}{V^{\text{in}} + H^0} = \frac{0.345 \cdot 0.0082 + 0.021}{0.043 + 0.076 \cdot 0.928} \frac{0.043}{0.0082 + 0.021} = 0.31, \tag{10}$$

where $U^e = \sum_{j=0}^{3} a_j U^{\text{in}} + a_4 U = 2.80 \cdot 0.0097 + 0.291 \cdot 0.072 = 0.043$. This number matches well with data in Table 1 showing that 30% of all external hires came from unemployment in 2006. Thus, our estimate of the intensity of on-the-job search is reasonably consistent with what we know about the magnitudes of the flows.[22]

5.2 | Resolution of the Puzzle

Our alternative model can explain the diverging results that we found when we estimated conventional log-linear matching functions in Section 3. Vacancies are filled at a constant rate, but higher unemployment increases hires from unemployment, for given vacancies, with an elasticity equal to 0.62 when evaluated at the mean values of the variables:

$$\frac{\partial H^u}{\partial U^e} \frac{U^e}{H^u} = 1 - \frac{U^e}{U^e + \kappa N} = \frac{\kappa N}{U^e + \kappa N} = \frac{0.076 \cdot 0.928}{0.043 + 0.076 \cdot 0.928} = 0.62. \tag{11}$$

Under our identifying assumptions, this is a *causal effect* of unemployment on hires from unemployment, but it arises solely because unemployed workers crowd out employed job seekers, filling a larger share of the job openings. Without on-the-job search, this elasticity would be zero: higher unemployment would not increase hiring of unemployed workers. If unemployment was close to zero, the elasticity would be unity because unemployed workers would not be competing with each other. In fact, the unemployed constitute a clear minority of job seekers, so there is considerable potential for unemployed workers to crowd out employed job seekers for a given number of job openings.

Also, our alternative model provides an interpretation of the weak effect of vacancies on hires from unemployment: unemployed workers have difficulties competing for registered

TABLE 4 | Mismatch in the matching of unemployed workers and vacancies. Equations (8) and (9) estimated by NLSUR. Dependent variables: Hires from unemployment and vacancy outflow.

(a) Setting $a_0 = 0$ and $\kappa = 0.05$

α	a_2	a_3	a_4	κ
−0.082**	0.497***	0.343***	0.224***	0.05
(0.041)	(0.057)	(0.048)	(0.012)	

β	Λ	b_0	b_1	b_2	b_3	H^0
0.907***	0.695***	0.439***	0.386***	0.128***	0.039***	0.043***
(0.010)	(0.055)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)

(b) Setting $\alpha = a_0 = 0$ and $\beta = \Phi = 1$

α	a_2	a_3	a_4	κ
0	0.748***	0.532***	0.291***	0.076***
	(0.072)	(0.058)	(0.016)	(0.005)

β	Λ	b_0	b_1	b_2	b_3	H^0
1	0.345***	0.434***	0.407***	0.085***	0.025***	0.021***
	(0.016)	(0.005)	(0.005)	(0.004)	(0.004)	(0.000)

Note: Number of observations: 20012. Local seasons and trends have been removed from the data. Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

vacancies, and most of them find jobs in other ways. For given unemployment, a 10% increase in registered vacancies increases hires from unemployment by only 1.2%:

$$\frac{\partial H^u}{\partial V^e}\frac{V^e}{H^u} = \frac{\Lambda V^e}{H^0 + \Lambda V^e} = \frac{0.345 \cdot 0.0082}{0.021 + 0.345 \cdot 0.0082} = 0.12. \quad (12)$$

Thus, we have provided a possible interpretation of the regression results that we presented in Section 3. There are many ways in which this specification of the matching technology could be modified and generalised. For example, we could allow for cyclical variations of search effort.[23] However, with the data that we have, it would probably be hard to identify additional parameters.

6 | Turnover and the Inflow Into Unemployment

Following Mortensen and Pissarides [4] and many others, we think of a point on the Beveridge curve as a combination of vacancies and unemployment that makes the flow into unemployment equal to the flow out of unemployment. This means that we focus on situations when unemployment remains high or low rather than transitions between those states. This approximation is useful because turnover is high compared to the changes of the stocks.[24] So far, we have analysed how hires from unemployment are related to vacancies and unemployment, but the shape of the Beveridge curve depends also on how the inflow into unemployment varies with the state of the labour market.

With a constant separation rate, s, the inflow into unemployment $s \cdot N$ would be slightly procyclical but, as we noted in Section 2, the inflow into unemployment is clearly *countercyclical*, in Sweden and several other countries. Since our ambition is to construct a model of the Beveridge curve that is reasonably consistent with the cyclicality of the flows into and out of unemployment, we need to model countercyclical inflows into unemployment.

In this section, we add three factors that make the inflow into unemployment countercyclical. Following Shimer [32] we assume that those who find out that they have to leave their jobs search on the job. When there is high unemployment, they have a harder time finding new jobs before the current job expires, so *more job leavers pass through unemployment*. Following Holmlund and Storrie [33] we assume that workers hired from unemployment are more likely to accept *temporary jobs*. Finally, we assume that in periods of high unemployment, more workers return to unemployment after a period as *discouraged workers* out of the labour force. We do not have direct evidence on these flows, but we can estimate the corresponding parameters with the data that we have.

6.1 | Quits and Layoffs

To model turnover, we assume that employed job seekers consist of two groups.

6.1.1 | Potential Job Switchers

Each month, a share z of those employed at the beginning of the month search on the job and switch jobs if they find a new job—otherwise they stay in their old job. In practice, the parameter z reflects the occurrence, intensity and efficiency of on-the-job search.[25] We assume that these potential job switchers are more able to compete for vacancies compared to other job seekers. Thus, a fraction $1 - \Lambda$ of vacancies go exclusively to potential job switchers. Hence, the probability that a potential job switcher finds a new job is:

$$F_t^z = \frac{\Lambda V_t^e + H^0}{U_t^e + \kappa N_t} + \frac{(1-\Lambda)V_t^e}{zN_t}. \quad (13)$$

6.1.2 | Job Leavers

A share s of the workers who were employed at the beginning of the month find out that they must leave their jobs for exogenous reasons, which may have to do with the job, the worker, or the match. These workers seek new jobs and find jobs with probability θF_t where $F_t = H_t^u / U_t^e$ and where the parameter θ reflects the intensity and efficiency of job search by job leavers. Job leavers who do *not* find jobs enter into unemployment in the following month.[26] These assumptions imply that effective search on the job is given by $\kappa N_t = (\theta s + z)N_t$.

6.2 | Temporary Jobs

Holmlund and Storrie [33] documented a higher incidence of temporary jobs in bad times. Their interpretation is that adverse macroeconomic conditions make firms more prone to offer fixed-term contracts and workers more willing to accept them. In line with this evidence, we assume that when unemployment has been high, there are more workers in temporary jobs and hence more separations from employment. To represent this in a simple way, we assume that there are exogenous separations from employment equal to δU_{t-1}.[27]

6.3 | Discouraged Workers

The data show that some unemployed workers leave unemployment without finding jobs and that some workers enter unemployment after being out of the labour force. To account for this in a simple way, we assume that, at the beginning of each month, a share x of the unemployed workers leaves the labour force and that these workers return to unemployment in the following month. We measure these exits as $U_t^{\text{ex}} = U_t + U_t^{\text{in}} - H_t^u - U_{t+1}$ and we estimate x by the regression $U_t^{\text{ex}} = xU_t$. Our estimate is $x = 0.00882$: almost 1% of the unemployed leave the labour force each month.

6.4 | Inflow Into Unemployment

With these assumptions, the inflow into unemployment is

$$U_t^{\text{in}} = \left(1 - \theta H_{t-1}^u / U_{t-1}^e\right) sN_{t-1} + \delta U_{t-1} + xU_{t-1} + \varepsilon_t^{\text{in}}, \quad (14)$$

where $\varepsilon_t^{\text{in}}$ is an unobserved shock. Table 5 shows parameter estimates for this equation. According to these estimates, 1% of the employed workers have to leave their jobs each month and the number of workers who return to unemployment after a spell at a temporary job corresponds to 2.3% of unemployment.

If we would set θ equal to zero, this equation would simply say that the inflow into unemployment is a linear function of the level of unemployment with intercept s and slope $\delta + x - s$.[28] However, θ is estimated to be close to unity indicating that job leavers have the same chance to find a job as a worker who entered unemployment 1 month ago. This supports the argument made by Shimer [32] that job leavers are more likely to switch employers immediately when jobs are plentiful.

This completes our model of labour market flows. Note that a countercyclical inflow into unemployment *decreases* the slope of the Beveridge curve compared to a model with a constant separation risk because more vacancies are needed to balance the inflow into unemployment in bad times. Figure 6 illustrates the relationships between the stocks and the flows in our alternative model.

7 | The Beveridge Curve and Vacancy Chains

In this section, we first derive the equation for the Beveridge curve in our alternative model. Then we analyse what implications our findings have for job creation, and we argue for an interpretation of the Beveridge curve in terms of vacancy chains.

7.1 | The Beveridge Curve

To derive the Beveridge curve that is implied by our model, we ignore transitional dynamics and we consider an equilibrium where hires from unemployment equal separations into unemployment (or, equivalently, hires equal separations) and we set $V^e = V^{\text{in}} = V^{\text{out}} = \phi V$:

$$\phi V + H^0 - (\theta s H^u / U^e + zF^z)N = (1 - \theta s H^u / U^e)sN + \delta U. \quad (15)$$

Substituting for F^z and using $\kappa = \theta s + z$ we get the equation for the Beveridge curve:

$$\frac{U^e + \theta sN}{U^e + \kappa N}\left(\Lambda \phi V + H^0\right) = sN + \delta U. \quad (16)$$

From this equation, we see that the Beveridge curve could slope either way. When unemployment is high, unemployed job seekers fill a larger share of the relevant job openings, so fewer vacancies are needed to balance separations. On the other hand, high unemployment means that more workers leave temporary jobs, creating a need for more vacancies. With our estimated parameter values, the first effect dominates, so the Beveridge curve slopes down.

TABLE 5 | Inflow into unemployment. Equation (14) estimated by NLS. Dependent variable: Inflow into unemployment.

(1)	(2)	(3)
θ	s	δ
0.9958***	0.0104***	0.0227***
(0.031)	(0.000)	(0.001)

Note: Standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Parameter x is set equal to 0.00882. Number of observations: 20160.

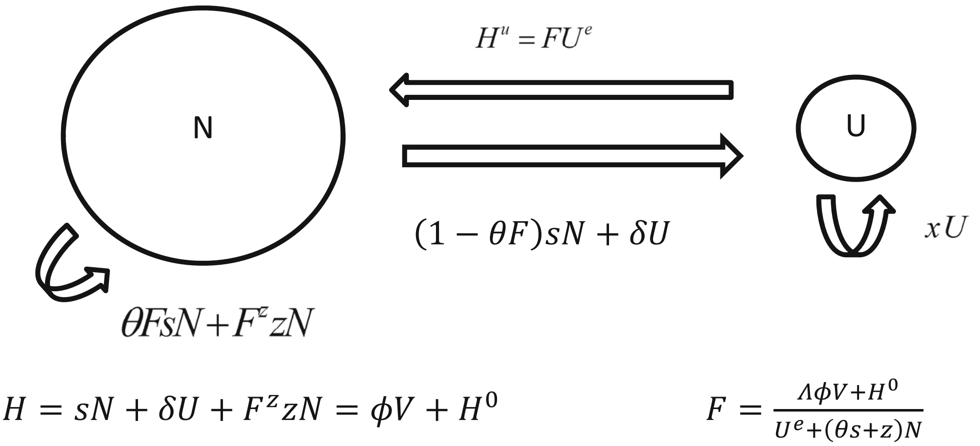

FIGURE 6 | Stocks and flows in steady state.

7.2 | Implications for Job Creation

Some theory of job creation is required in order to determine where on the Beveridge curve the full equilibrium will be. Job creation is not the topic of this paper, but our findings have implications for job creation. In the basic search-matching model, job creation is determined by a zero-profit condition for vacancies that determines the number of vacancies for a given level of unemployment. Such an analysis builds on the assumption that $\alpha > 0$ in the matching function but it cannot be applied if $\alpha = 0$. So, how should we think about labour demand and job creation if α is close to zero, as our estimates suggest?

To clarify this, we consider a model of a firm which sells its output in a product market with monopolistic competition and hires its workers in a labour market with search frictions, which are represented by a matching function.[29] Let the production of firm k be $A_t N_{k,t+1}$ where $N_{k,t+1}$ is employment after hiring in period t and let $P\left(A_t N_{k,t+1}/D_t\right)$ be the inverse demand function for the firm-specific product where D_t is a factor that shifts product demand. Vacancies are filled at the rate $q_t = \phi\left(\left(U_t + \kappa N_t\right)/V_t\right)^\alpha$ and the cost of keeping a vacancy is c per period. The assumptions made in previous sections imply that employment in firm k is determined by

$$N_{k,t+1} = \left(1 - s - zF_t^z\right)N_{k,t} - \delta U_{t\text{-}1} + q_t V_{k,t} + H^0. \tag{17}$$

To simplify, we take the wage W_t as given and we consider a symmetric Nash equilibrium where firms are identical and have perfect foresight about the state of the labour market in the current period. By choosing vacancies, firms effectively decide how many workers they will have, and they do this so as to maximise the expected present value of profits:

$$E_t \sum_{j=0}^{\infty} \beta^j \left[A_{t+j} N_{k,t+1+j} P\left(\frac{A_{t+j} N_{k,t+1+j}}{D_{t+j}}\right) - W_{t+j} N_{k,t+1+j} - \frac{c}{q_{t+j}}\left(N_{k,t+1+j} - \left(1 - s - zF_{t+j}^z\right)N_{k,t+j} + \delta U_{t+j-1} - H^0\right)\right] \tag{18}$$

7.2.1 | Perfect Competition

We first consider the case of *perfect competition* in the product market. In this case, the price is given for the firm and the first-order condition is $A_t P_t = W_t + c/q_t - \beta E_t\left[\left(1 - s - zF_{t+1}^z\right)c/q_{t+1}\right]$. Substituting forward, we get a standard zero profit condition for vacancies:

$$c = \phi\left(\frac{U_t + \kappa N_t}{V_t}\right)^\alpha \left[A_t P_t - W_t + E_t \sum_{j=1}^{\infty} \beta^j \prod_{v=1}^{j} \left(1 - s - zF_{t+v}^z\right)\left(A_{t+j} P_{t+j} - W_{t+j}\right)\right]. \tag{19}$$

If $\alpha > 0$ this condition determines the *equilibrium* number of vacancies in the labour market for a given level of unemployment. However, if $\alpha = 0$ this condition can no longer determine the number of vacancies. There must be some other factor that constrains hiring and a plausible factor is that firms face limited demand for their products.

7.2.2 | Imperfect Competition

With $\alpha = 0$ and a downward-sloping product demand curve, the firm will choose employment so that the marginal revenue product of labour equals the wage plus the marginal hiring cost minus the expected savings of hiring costs next period if an additional worker is hired today:

$$A_t\left[P\left(\frac{A_t N_{k,t+1}}{D_t}\right) + \frac{A_t N_{k,t+1}}{D_t} P'\left(\frac{A_t N_{k,t+1}}{D_t}\right)\right] = W_t + \frac{c}{\phi} - \beta\frac{c}{\phi}\left(1 - s - zE_t F_{t+1}^z\right). \tag{20}$$

Now, this equation determines the desired level of *employment* as a function of demand, productivity and the wage. The probability that a worker quits next period matters for hiring, but the *current* state of the labour market does not enter the equation. Given this desired level of employment, vacancies are determined by:

$$\phi V_{t,k} = N_{k,t+1} - \left(1 - s - zF_t^z\right)N_{k,t} + \delta U_{t-1} - H^0. \tag{21}$$

In a tight labour market, F_t^z is high, many employed workers quit their jobs and many vacancies are needed in order to sustain the firm's desired level of employment.

In this setting, it is natural to think of the Beveridge curve as a relation that determines vacancies for a given level of (un)employment:

$$\phi V = \frac{1}{\Lambda}\left[\frac{U^e + \kappa N}{U^e + \theta s N}(sN + \delta U) - H^0\right]$$
$$= \frac{1}{\Lambda\left(1 - \frac{zN}{U^e + \kappa N}\right)}\left[sN + \delta U - \left(1 - \frac{zN}{U^e + \kappa N}\right)H^0\right]. \quad (22)$$

Exogenous separations from jobs are equal to $sN + \delta U$ and a share $1 - zN/(U^e + \kappa N)$ of hiring via other channels (H^0) contributes to filling these job openings with unemployed job seekers and job leavers.[30] Remaining job openings lead to *vacancy chains*. When a worker is hired directly from another job, a new job opening is created and this continues until an unemployed worker is hired [9]. The resulting multiplier effect is $1 + p + p^2 + p^3 + \ldots = 1/(1-p)$ where $p = 1 - \Lambda + \Lambda zN/(U^e + \kappa N)$ is the probability that a vacancy is filled by a potential job switcher.

This interpretation is consistent with the strong relation between quits and hires, which can be observed in establishment-level data [34]. Mercan and Schoefer [35] reported that, according to German employers, 56% of hiring is quit-driven replacement hiring, and they estimate an almost one-to-one effect of quits on replacement hiring. Elsby et al. [36] show that replacement hiring constitutes a large share of hiring and that U.S. establishments frequently report no net change in employment for long periods despite substantial gross turnover in the form of quits. Apparently, these establishments adjusted hiring so as to replace the workers who quit.

Studies of employment dynamics also support this interpretation. Carlsson et al. [37] and Stadin [38] used firm-level panel data to study job creation. They showed that product market demand and wages affect labour demand, but they found no evidence that higher unemployment in the local labour market induced firms to hire more workers. Christiano et al. [39] and Christiano et al. [40] estimated macro models where the recruitment cost per hired worker could potentially vary with labour market tightness, finding no evidence of such an effect.

8 | Matching Macro Data

In this section, we use our model and our estimated parameters to examine how well the model can explain stylized facts in the labour market. We focus on variations over the cycle and we use the level of unemployment as the indicator of the state of the labour market. The solution of the model is explained in Supplementary Appendix C. We set $\phi = 1.53$ to match the average ratio of the flow to the stock of vacancies.

8.1 | The Beveridge Curve and Labour Market Flows

Figure 7 shows that our model explains the Beveridge curve fairly well. Figure 8 shows that hires from unemployment relative to vacancies decrease with labour market tightness. As seen from $H_t^u/V_t^e = \left(\Lambda + H^0/V_t^e\right)U_t^e/\left(U_t^e + \kappa N_t\right)$ this is explained by two factors. Hires via other channels play a relatively smaller role when there are many vacancies and unemployed workers fill a smaller share of the vacancies when there is low unemployment.

Figure 9 shows that the average job finding rate among the unemployed (H^u/U) falls as unemployment increases and that the model over-predicts the aggregate job finding rate, especially when unemployment is low. Figures 10 and 11 show that the inflow into unemployment and hiring from unemployment are both countercyclical and more so in the data than in the model.

8.2 | Total Hires

As noted by Davis et al. [41] hires per vacancy tend to be high when there are many unemployed workers per vacancy. In line with this observation, estimation of matching functions with constant returns to scale and total hires as the dependent variable, $H/V = \phi(U/V)^\alpha$, tends to produce estimates of α around 0.3–0.4; see overviews by Broersma and Van Ours [5] and Petrongolo and Pissarides [6]. Provided that vacancies are seen as a good index of all job openings in the economy, this result may be taken as evidence that vacancies are filled quickly when unemployed is high.

However, much recruitment occurs without registered vacancies and if hiring via informal networks varies less than vacancies over the business cycle, hires per vacancy will be countercyclical even if vacancies are filled at a constant rate. In our model, total hires are a linear function of vacancies $H = H^0 + \phi V$, so a positive estimate of H^0 implies that hires per registered vacancy are countercyclical: $H/V = H^0/V + \phi$.

Our estimation gives only indirect evidence on this, however, because total hires cannot be observed in the panel. However, we can use survey data for aggregate hires to examine how well our model predicts aggregate hiring. These data are quarterly, so we calculate total hires predicted by our model as $H_\tau = 0.063 + V_{\tau-1}^{\text{in}}$ where τ denotes the quarter and where the intercept reflects our estimate $H^0 = 0.021$ for monthly data. We assume that all vacancies are filled with a one-quarter time lag from the registration of the vacancy to the actual hire. Figure 12 shows that this equation explains aggregate hires fairly well and that vacancies do indeed vary more (in percent) than total hires over the cycle.

These results are not directly comparable to those of Davis et al. [41] because we do not use survey data for our estimation. However, Table 1 shows that Swedish survey data also fail to cover all hiring, and the same is probably true of JOLTS. To count as a vacancy in JOLTS, a job opening must meet three conditions: (i) a *specific* position exists, (ii) work could start *within 30 days* and (iii) the firm is *actively seeking workers* from outside their location to fill the position. Most likely, much hiring via informal contacts, including recalls, occurs without firms reporting vacancies that fulfil these conditions. In fact, Davis et al. [41] report that 42% of the hires were made by establishments reporting zero vacancies. Many of the hires that we observe are not hires to the vacancies that we observe.

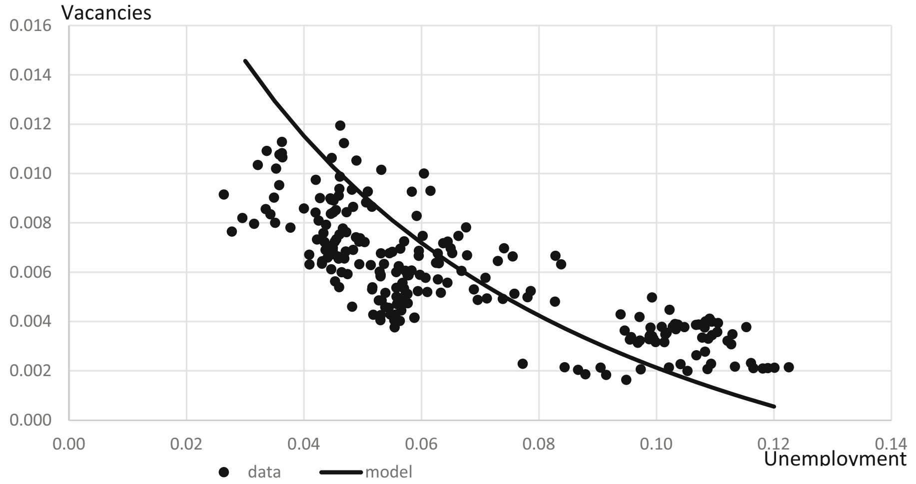

FIGURE 7 | Beveridge curve: Model and data. All variables are measured relative to the labour force and seasonally adjusted.

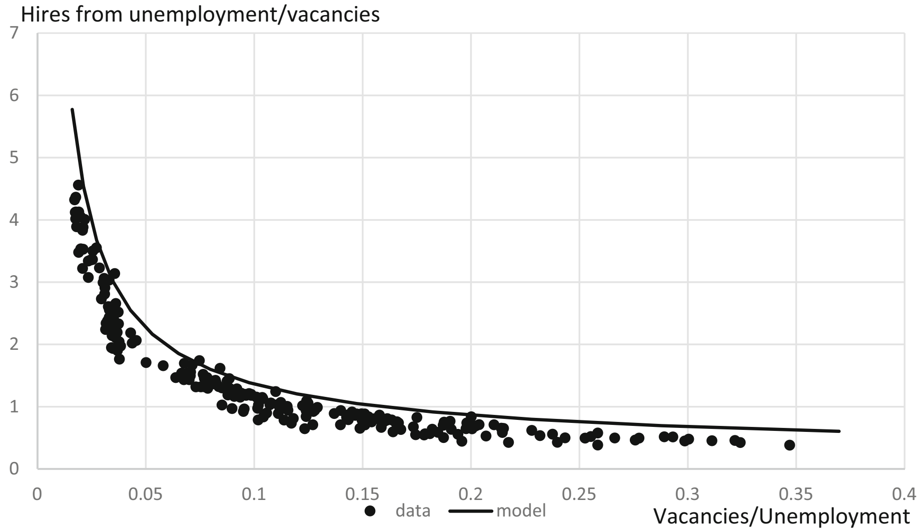

FIGURE 8 | Hiring from unemployment relative to vacancies. All variables are seasonally adjusted.

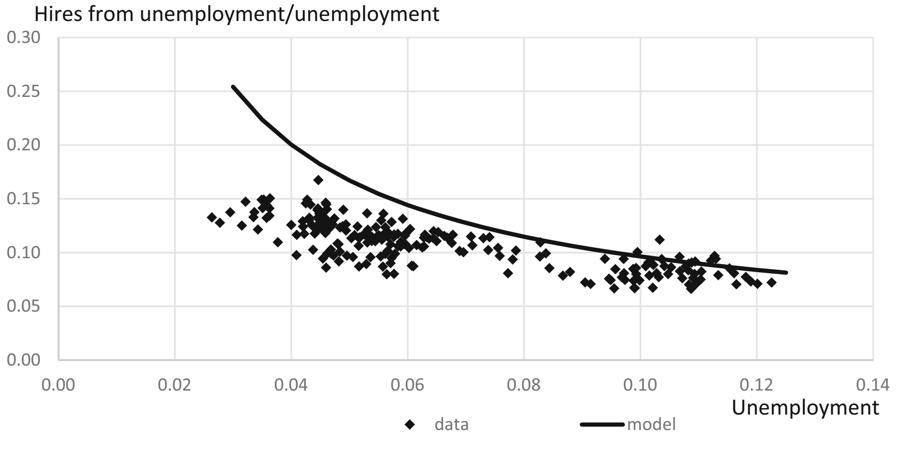

FIGURE 9 | Average job finding rate. All variables are measured relative to the labour force and seasonally adjusted.

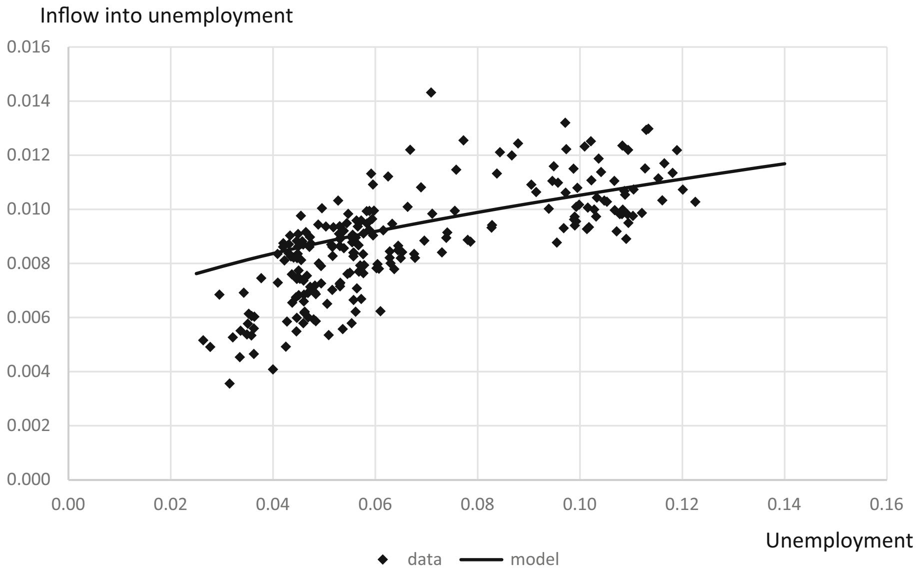

FIGURE 10 | Inflow into unemployment. All variables are measured relative to the labour force and seasonally adjusted.

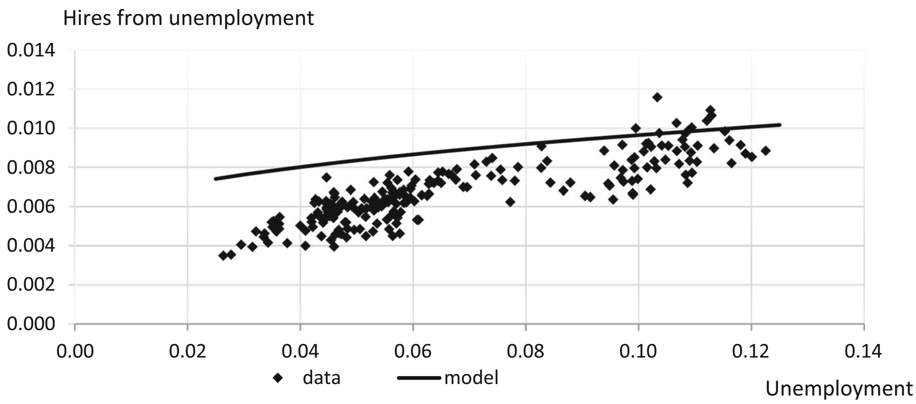

FIGURE 11 | Hires from unemployment. All variables are measured relative to the labour force and seasonally adjusted.

8.3 | Related Studies

Sedláček [42] uses aggregate data for hires from unemployment, employment and inactivity to estimate a matching function. Thus, he allows for job seekers who are not counted as unemployed, but he does not allow for job openings that are not counted as vacancies. Furthermore, he allows the efficiency of job search of the different groups to vary over time. In terms of our notation, he allows ϕ and κ to follow first-order autoregressive stochastic processes. He finds that the job finding rate of employed job seekers is more procyclical than the job finding rate of unemployed workers and he attributes this to exogenous changes of search efficiency. Specifically, he estimates a large decline of effective on-the-job search during the global financial crisis 2007–9.

We do not have panel data for hires from employment, but our theoretical model is qualitatively consistent with the findings of Sedláček [42]: job finding rates of employed job seekers are more procyclical than job finding rates of unemployed workers. Our interpretation is that employed workers have an advantage in the competition for registered vacancies, which are more procyclical than other hiring. Thus, one could argue that we endogenise the procyclical advantage of employed job seekers that Sedláček [42] documented. With panel data on turnover, it would be possible to investigate these explanations in more detail.

Often, an increase of vacancies is interpreted as a predictor of future employment growth or a sign that firms have difficulties filling their vacancies. Our analysis suggests that vacancies are primarily an indicator of turnover. Vacancies are high when employment is high because many employed workers find new jobs, leaving empty positions to be filled. This interpretation is consistent with the findings of Fujita [43]. He identified aggregate shocks to labour demand using sign restrictions and showed that such shocks have delayed effects on employment, but also on vacancies. Maximum effects occur about five quarters after the shock with only a slight lead for vacancies relative to employment. This result is inconsistent with the standard Mortensen-Pissarides [26] model, which implies an immediate and mostly temporary spike in vacancies when the shock occurs. More recent models include stochastic setup costs

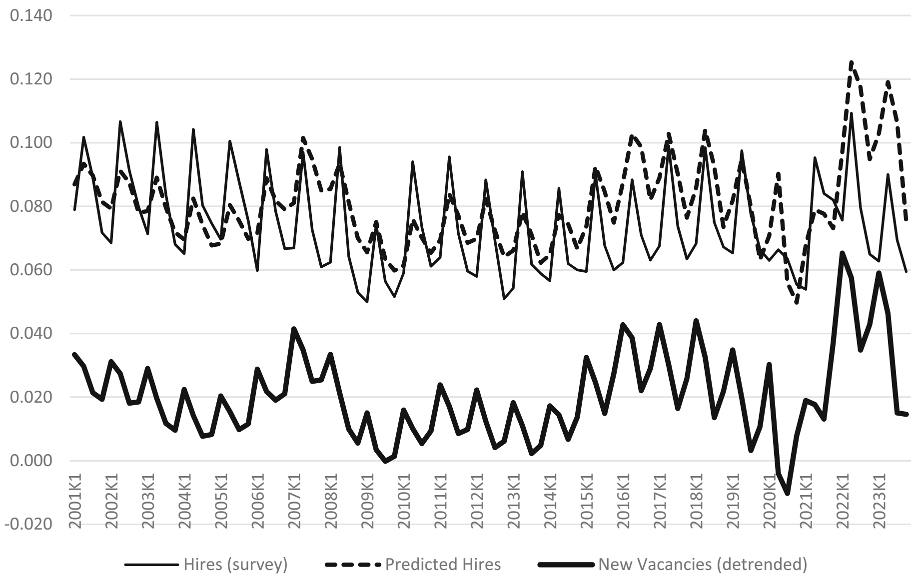

FIGURE 12 | Quarterly hiring: Actual and predicted. New vacancies are from the Public Employment Service. There is a strong upward trend in the number of vacancies and we interpret this trend as a structural change due to electronic registration of vacancies and other institutional changes. Therefore, we used detrended vacancies for this calculation. Aggregate hires are calculated from survey data from the Short-Term Employment Survey for the private sector and industry, scaled up as if hires relative to employment were the same in all sectors of the economy. All variables are measured relative to the labour force and not seasonally adjusted.

for vacancies, leading to a sluggish adjustment of the vacancy stock. These models match the data better but, contrary to the present analysis, they rely on unemployment having a substantial effect on the depletion of vacancies; see Fujita and Ramey [44], Coles and Moghaddasi-Kelishomi [45] and Haefke and Reiter [46].

9 | Conclusion

Estimating two standard matching functions with hires from unemployment and de-registrations of vacancies as dependent variables, we found some intriguing results. Unemployment has a big effect on the matching of unemployed workers, but we found no (or very weak) evidence that vacancies are filled more quickly when unemployment is high. Most of the variation of the vacancy stock is explained by the inflow of new vacancies, and vacancies have a weak effect on hires from unemployment.

In this paper, we suggest an interpretation of these findings based on on-the-job search, mismatch and recruitment without any vacancies being registered. High unemployment leads to more hiring of unemployed workers for given vacancies, but not because more matches are formed. Instead, it is because unemployed job seekers fill a larger share of the relevant jobs, crowding out employed job seekers. When it is hard to find a job, few employed job seekers find new jobs, so few jobs become vacant and there is a low inflow of new vacancies. Also, we argue that vacancies have a weak effect on hires from unemployment because unemployed workers have a hard time competing for registered vacancies and most of them find jobs in other ways. We show that a model with these features can explain the estimation results described above and also generate a Beveridge curve that is broadly consistent with the data and countercyclical flows into and out of unemployment.

Our analysis points to the importance of developing models with multi-worker firms and on-the-job search. Firm size may be limited by decreasing returns to scale as in Michaillat [24], Elsby and Michaels [47], Elsby and Gottfries [28], and Elsby et al. [36] or inelastic product demand as in Krause and Lubik [70], Thomas and Zanetti [48], Carlsson et al. [37] and Stadin [38]. Also, fixed costs for creating new positions give firms incentives to replace workers who quit; see Fujita and Ramey [44] and Elsby et al. [36].

On-the-job search and turnover have implications for wage formation. Moscarini and Postel-Vinay [49] show that wage growth is strongly related to turnover, which points to the importance of on-the-job search. Eriksson and Gottfries [50] analyse wage and employment dynamics in a macro model where unemployed workers are at a disadvantage in the competition for jobs.

How we understand the Beveridge curve is important for policy. If information problems are important, giving unemployed workers assistance and incentives to search more intensively should be an efficient way to combat unemployment. If unemployed workers are unable or unwilling to compete for some of the jobs, this means that skill formation, wage flexibility and incentives to accept jobs are more important factors that policy needs to focus on.

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Endnotes

[1] See also Blanchard and Diamond [51]. For surveys of this literature, see Petrongolo and Pissarides [6], Yashiv [52], Daly et al. [53], and Elsby et al. [8].

[2] The slight negative slope reflects a mechanical effect as higher unemployment means lower employment and somewhat fewer workers leaving jobs that have to be filled or replaced in order for employment to stay constant.

[3] Mortensen and Pissarides [4] consider a model with endogenous job destruction. They write that 'On the one hand, higher vacancies imply more job matchings, so unemployment needs to be lower for stationary matching rate. On the other hand, higher vacancies also imply more job destruction …' They assume that the former (matching) effect dominates, so that the Beveridge curve slopes down.

[4] These numbers are similar for the other years when this survey was carried out and they are similar to the numbers for the US and the UK summarised by Pissarides [26] and the numbers for Germany reported by Fahr and Sunde [29]. According to Fallick and Fleischman [54], employer-to-employer transitions make up around one-third of all hires in the US. Bjelland et al. [55] emphasise the importance of employer-to-employer flows.

[5] This development is discussed in Håkanson [56]. See also Supplementary Appendix B. Estimation of log-linear matching functions on data for the period 1992–2018 produces similar results to those for the baseline period (see Table B1).

[6] The 90 local labour markets are listed in Supplementary Appendix A. Johansson and Persson [57] report that 80%–90% of all hired workers came from the local labour market area where the firm was located.

[7] Workers in labour market programmes are not included in the baseline estimation because earlier research indicates that they contribute to matching to a significantly smaller extent than do openly unemployed workers; see Forslund and Johansson [20]. However, the results are very similar if we include participants in labour market programmes.

[8] A recruitment survey occasionally published by Svenskt Näringsliv shows that the fraction of failed recruitment attempts was on the same level in 2010, just after the financial crisis (19%) as in the boom year 2007 (18%).

[9] We use register data on employment (RAMS) to measure employment in the local labour market area. Since monthly data are very noisy, we use a 12 month moving average of the monthly series.

[10] These are unweighted means across local labour markets. If we instead consider aggregate numbers, we find that unemployment was, on average, 6.18% of the labour force, the monthly inflow into unemployment was 0.85% and hiring from unemployment was 0.65% of the labour force. The vacancy stock corresponded to 0.54% of the labour force and the monthly inflow and outflow of vacancies both corresponded to 0.79% of the labour force.

[11] Figures 6 and 7 in Elsby et al. [16] show clearly countercyclical flows into and out of unemployment in France, Ireland, Japan, Portugal, Spain, Sweden and the United States. There is no clear cyclical pattern in Australia, Canada, Germany, Italy, New Zealand and the United Kingdom, while the flows appear to be procyclical in Norway.

[12] Studies of stock-flow matching include Coles and Smith [58], Gregg and Petrongolo [59], Coles and Petrongolo [60] and Ebrahimy and Shimer [61]. Our estimated equations can be seen as log-linear approximations of the matching functions that arise in the stock-flow matching model—see Equations (7–13) in Coles and Petrongolo [60].

[13] Cross-section estimates such as Coles and Smith [58] answer very different questions about how the size of the labour market affects the matching. Estimation on aggregate data entails a big risk of spurious correlations because of structural changes.

[14] Burda and Wyplosz [14] found similar results using aggregate data for several countries and imposing constant returns to scale.

[15] For the period 1970–1988 we can replicate their results using aggregate data. Running the same regression, with only initial stocks as explanatory variables for the period 1992–2011, we obtain a coefficient close to zero for the initial stock of unemployment and 0.64 for the initial stock of vacancies.

[16] The nonlinear estimation procedure in Stata is unable to handle a large number of seasonal dummies and trends so we first regressed log variables on fixed effects, seasonal dummies and trends, then we took the residuals from those regressions, added back the means, and estimated the matching functions by nonlinear least squares.

[17] Borowczyk-Martins et al. [18] deal with persistent variations of matching efficiency by quasi-differencing the matching equation and using lagged stocks as instruments. We allow for general lags in the matching process, so lagged inflows (and implicitly stocks) belong in the equations.

[18] Alternatively, we could have imposed some smoothness on the lag structure.

[19] Albrecht et al. [62, 63] consider a model where job seekers can make several applications simultaneously but firms can make only one job offer to one worker and if the offer is rejected, the process starts again. Our evidence is consistent with the view that there are normally many applicants for a job and if the best applicant rejects the offer, the firm can hire another applicant with little delay.

[20] This specification encompasses the possibility that $H^0 = 0$ so that registered vacancies are a perfect index of total job openings. Forsythe and Weinstein [64] document cyclical variations of recruiting effort and such variation may also be reflected in the parameter Λ.

[21] We set $z = \kappa - 0.01$ based on the specification in the next Section. However, trying different plausible values of z and κ we still obtained negative estimates of α.

[22] We omit hires from inactivity in our simplified model, but we could generalise the model by letting some of the employed job seekers pass through inactivity; see footnote in the next section.

[23] Evidence of countercyclical variations of the search effort has been found for workers searching on the job (Elsby et al. [8]), unemployed workers (Mukoyama et al. [65]) and employers (Forsythe and Weinstein [64]).

[24] Consistent with this view, the graphs in Elsby et al. [16] show that the outflow from unemployment tracks the inflow very closely—except in periods when unemployment is rising or falling very rapidly. Blanchard and Diamond [12], Burda and Wyplosz [14] and Fontaine [15] also document close correlations between inflows and outflows.

[25] We take z as exogenous and we do not model the reasons why some workers want to switch jobs. Job-ladder models provide micro-foundations for workers wanting to switch jobs; see for example, Burdett and Mortensen [66] and Moscarini and Postel-Vinay [67]. Akerlof et al. [9] emphasise that non-pecuniary rewards appear to be important for turnover because many job-switchers do not increase their wages by switching jobs.

[26] More generally, we may think of the flow sN as representing not only a share of employees who must leave their jobs and search for another job, but also employed workers who leave the labour force for exogenous reasons and who are replaced by new entrants, who apply for jobs and register as unemployed if they do not find a job immediately. In such a model, entrants who find jobs immediately will flow directly into employment and this flow will be procyclical in line with

the findings of Blanchard and Diamond [12], Burda and Wyplosz [14], and Fontaine [15].

[27] The term δU_{t-1} may also reflect other factors. Workers who have been unemployed for some time may get subsidised training jobs with limited duration. If unemployment takes the form of temporary layoffs, as in the model of Merz [68], this will also lead to high turnover in bad times. Fredriksson et al. [69] show that hires from unemployment are more likely to be mismatched compared to those hired directly from another employer and this should increase the probability of a separation.

[28] Recall that all variables are measured relative to the labour force.

[29] Examples of such models are Krause and Lubik [70], Krause et al. [71, 72], Thomas and Zanetti [48], Carlsson et al. [37] and Stadin [38].

[30] If a potential job switcher finds a job via informal channels, he takes one job and his old job becomes vacant, so this does not change the need to post vacancies.

References

1. W. Beveridge, *Full Employment in a Free Society* (Allen, 1944).

2. C. Pissarides, "Short-Run Equilibrium Dynamics of Unemployment, Vacancies, and Real Wages," *American Economic Review* 75 (1985): 676–690.

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

4. D. Mortensen and C. Pissarides, "Job Creation and Job Destruction in the Theory of Unemployment," *Review of Economic Studies* 61 (1994): 397–415.

5. L. Broersma and J. Van Ours, "Job Searchers, Job Matches and the Elasticity of Matching," *Labour Economics* 6 (1999): 77–93.

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

7. U. Sunde, "Empirical Matching Functions: Searchers, Vacancies, and (Un-)Biased Elasticities," *Economica* 74 (2007): 537–560.

8. M. Elsby, R. Michaels, and D. Ratner, "The Beveridge Curve: A Survey," *Journal of Economic Literature* 53 (2015): 571–630.

9. G. Akerlof, A. Rose, and J. Yellen, "Job Switching and Job Satisfaction in the U.S. Labor Market," *Brookings Papers on Economic Activity* 1988, no. 2 (1988): 495–594.

10. S. Fujita and G. Ramey, "Exogenous and Endogenous Separation," *American Economic Journal: Macroeconomics* 4 (2012): 68–93.

11. S. Fujita and M. Nakajima, "Worker Flows and Job Flows: A Quantitative Investigation," *Review of Economic Dynamics* 22 (2016): 1–20.

12. O. Blanchard and P. Diamond, "The Cyclical Behavior of the Gross Flows of U.S. Workers," *Brookings Papers on Economic Activity* 1990, no. 2 (1990): 85–155.

13. S. Fujita and G. Ramey, "The Cyclicality of Separation and Job Finding Rates," *International Economic Review* 50 (2009): 415–430.

14. M. Burda and C. Wyplosz, "Gross Worker and Job Flows in Europe," *European Economic Review* 38 (1994): 1287–1315.

15. I. Fontaine, "French Unemployment Dynamics: A "Three-State" Approach," *Revue d'Economie Politique* 126 (2016): 835–869.

16. M. Elsby, B. Hobijn, and A. Şahin, "Unemployment Dynamics in the OECD," *Review of Economics and Statistics* 95 (2013): 530–548.

17. J. Barron, M. Berger, and D. Black, "Employer Search, Training, and Vacancy Duration," *Economic Inquiry* 35 (1997): 167–192.

18. D. Borowczyk-Martins, G. Jolivet, and F. Postel-Vinay, "Accounting for Endogeneity in Matching Function Estimation," *Review of Economic Dynamics* 16 (2013): 440–451.

19. T. Aranki and M. Löf, "The Matching Process on the Swedish Labor Market – A Regional Analysis," *Sveriges Riksbank Economic Review* 2008, no. 1 (2008): 49–59.

20. A. Forslund and K. Johansson, "Random and Stock-Flow Models of Labor Market Matching – Swedish Evidence," IFAU Working Paper 2007:11 (2007).

21. A. Kangasharju, J. Pehkonen, and S. Pekkala, "Returns to Scale in a Matching Model: Evidence From Disaggregated Panel Data," *Applied Economics* 37 (2005): 115–118.

22. P. Anderson and S. Burgess, "Empirical Matching Functions: Estimation and Interpretation Using State-Level Data," *Review of Economics and Statistics* 82 (2000): 93–102.

23. P.-A. Edin and B. Holmlund, "Unemployment, Vacancies and Labor Market Programs: Swedish Evidence," in *Mismatch and Labor Mobility*, ed. F. P. Schioppa (Cambridge University Press, 1991).

24. P. Michaillat, "Do Matching Frictions Explain Unemployment? Not in Bad Times," *American Economic Review* 102 (2012): 1721–1750.

25. D. Blau and P. Robins, "Job Search Outcomes for the Employed and Unemployed," *Journal of Political Economy* 98 (1990): 637–655.

26. C. Pissarides, "Search Unemployment With On-The-Job Search," *Review of Economic Studies* 61 (1994): 457–475.

27. R. J. Faberman, A. I. Mueller, A. Sahin, and G. Topa, "Job Search Among the Employed and Non-Employed," *Econometrica* 90 (2022): 1743–1779.

28. M. Elsby and A. Gottfries, "Firm Dynamics, On-the-Job Search and Labor Market Fluctuations," *Review of Economic Studies* 89 (2022): 1370–1419.

29. R. Fahr and U. Sunde, "Occupational Job Creation: Patterns and Implications," *Oxford Economic Papers* 56 (2004): 407–435.

30. J. van Ours and G. Ridder, "Vacancies and the Recruitment of New Employees," *Journal of Labor Economics* 10 (1992): 138–155.

31. J. van Ours and G. Ridder, "Vacancy Durations: Search or Selection?," *Oxford Bulletin of Economics and Statistics* 55 (1993): 187–198.

32. R. Shimer, "Mismatch," *American Economic Review* 97 (2007): 1074–1101.

33. B. Holmlund and D. Storrie, "Temporary Work in Turbulent Times: The Swedish Experience," *Economic Journal* 112 (2002): F245–F269.

34. R. J. Faberman and E. Nagypal, "Quits, Worker Recruitment, and Firm Growth: Theory," (FRB Philadelphia WP 08–13, 2008).

35. Y. Mercan and B. Schoefer, "Jobs and Matches: Quits, Replacement Hiring, and Vacancy Chains," *American Economic Review: Insights* 2 (2020): 101–124.

36. M. Elsby, A. Gottfries, R. Michaels, and D. Ratner, "Vacancy Chains," *Journal of Political Economy* (2025).

37. M. Carlsson, S. Eriksson, and N. Gottfries, "Product Market Imperfections and Employment Dynamics," *Oxford Economic Papers* 65 (2013): 447–470.

38. K. Stadin, "Firms' Employment Dynamics and the State of the Labor Market," *Macroeconomic Dynamics* 27 (2023): 27–55.

39. L. Christiano, M. Trabandt, and K. Walentin, "Introducing Financial Frictions and Unemployment Into a Small Open Economy Model," *Journal of Economic Dynamics & Control* 35 (2011): 1999–2041.

40. L. Christiano, M. Eichenbaum, and M. Trabandt, "Unemployment and Business Cycles," *Econometrica* 84 (2016): 1523–1569.

41. S. Davis, J. Faberman, and J. Haltiwanger, "The Establishment-Level Behavior of Vacancies and Hiring," *Quarterly Journal of Economics* 128 (2013): 581–622.

42. P. Sedláček, "The Aggregate Matching Function and Job Search From Employment and Out of the Labor Force," *Review of Economic Dynamics* 21 (2016): 16–28.

43. S. Fujita, "Vacancy Persistence," Working Paper 04-23 (Federal Reserve Bank of Philadelphia, 2004).

44. S. Fujita and G. Ramey, "Job Matching and Propagation," *Journal of Economic Dynamics & Control* 31 (2007): 3671–3698.

45. M. Coles and A. Moghaddasi-Kelishomi, "Do Job Destruction Shocks Matter in the Theory of Unemployment?," *American Economic Journal: Macroeconomics* 10 (2018): 118–136.

46. C. Haefke and M. Reiter, "Long Live the Vacancy," IZA Working Paper 13666 (2020).

47. M. Elsby and R. Michaels, "Marginal Jobs, Heterogeneous Firms, and Unemployment Flows," *American Economic Journal: Macroeconomics* 5 (2013): 1–48.

48. C. Thomas and F. Zanetti, "Labor Market Reform and Price Stability: An Application to the Euro Area," *Journal of Monetary Economics* 56 (2009): 885–899.

49. G. Moscarini and F. Postel-Vinay, "The Relative Power of Employment-To Employment Reallocation and Unemployment Exits in Predicting Wage Growth," *American Economic Review: Papers and Proceedings* 107 (2017): 364–368.

50. S. Eriksson and N. Gottfries, "Ranking of Job Applicants, On-the Job Search, and Persistent Unemployment," *Labour Economics* 12 (2005): 407–428.

51. O. Blanchard and P. Diamond, "The Beveridge Curve," *Brookings Papers on Economic Activity* 1989, no. 1 (1989): 1–76.

52. E. Yashiv, "Labor Search and Matching in Macroeconomics," *European Economic Review* 51 (2007): 1859–1895.

53. M. Daly, B. Hobijn, A. Sahin, and R. Valletta, "A Search and Matching Approach to Labor Markets: Did the Natural Rate of Unemployment Rise?," *Journal of Economic Perspectives* 26 (2012): 3–26.

54. B. Fallick and C. Fleischman, "Employer-to-Employer Flows in the U.S. Labor Market: The Complete Picture of Gross Worker Flows," (Board of Governors of the Federal Reserve Finance and Economics Discussion Paper 2004-34, 2004).

55. M. Bjelland, B. Fallick, J. Haltiwanger, and E. McEntarfer, "Employer-to-Employer Flows in the United States: Estimates Using Linked Employer-Employee Data," *Journal of Business & Economic Statistics* 29 (2011): 493–505.

56. C. Håkanson, "A Divided Labor Market – On Matching in the Swedish Labor Market After the Economic Crisis," *Sveriges Riksbank Economic Review* 2014, no. 2 (2014): 52–70.

57. M. Johansson and L. O. Persson, "Regionalpolitiska utredningen," (SOU 2000:36, Fritzes, Stockholm, 2000).

58. M. Coles and E. Smith, "Marketplaces and Matching," *International Economic Review* 39 (1998): 239–597.

59. P. Gregg and B. Petrongolo, "Stock-Flow Matching and the Performance of the Labor Market," *European Economic Review* 49 (2005): 1987–2011.

60. M. Coles and B. Petrongolo, "A Test Between Stock-Flow Matching and the Random Matching Approach," *International Economic Review* 49 (2008): 1113–1141.

61. E. Ebrahimy and R. Shimer, "Stock-Flow Matching," *Journal of Economic Theory* 145 (2010): 1325–1353.

62. J. Albrecht, P. Gautier, and S. Vroman, "Matching With Multiple Applications," *Economics Letters* 78 (2003): 67–70.

63. J. Albrecht, P. Gautier, and S. Vroman, "Matching With Multiple Applications Revisited," *Economics Letters* 84 (2004): 311–314.

64. E. Forsythe and R. Weinstein, "Recruiting Intensity, Hires and Vacancies: Evidence From Firm-Level Data," *Economic Journal* (2025).

65. T. Mukoyama, C. Patterson, and A. Şahin, "Job Search Behavior Over the Business Cycle," *American Economic Journal: Macroeconomics* 10 (2018): 190–215.

66. K. Burdett and D. Mortensen, "Wage Differentials, Employer Size, and Unemployment," *International Economic Review* 39 (1998): 257–273.

67. G. Moscarini and F. Postel-Vinay, "Stochastic Search Equilibrium," *Review of Economic Studies* 80 (2013): 1545–1581.

68. M. Merz, "Heterogeneous Job-Matches and the Cyclical Behavior of Labor Turnover," *Journal of Monetary Economics* 43 (1999): 91–124.

69. P. Fredriksson, L. Hensvik, and O. Nordström Skans, "Mismatch of Talent: Evidence on Match Quality, Entry Wages and Job Mobility," *American Economic Review* 108 (2018): 3303–3338.

70. M. U. Krause and T. A. Lubik, "The (IR)Relevance of Real Wage Rigidity in the New Keynesian Model With Search Frictions," *Journal of Monetary Economics* 54, no. 3 (2007): 706–727.

71. M. U. Krause, D. Lopez-Salido, and T. A. Lubik, "Inflation Dynamics With Search Frictions: A Structural Econometric Analysis," *Journal of Monetary Economics* 55, no. 5 (2008): 892–916.

72. M. U. Krause, D. J. Lopez-Salido, and T. A. Lubik, "Do Search Frictions Matter for Inflation Dynamics?," *European Economic Review* 52, no. 8 (2008): 1464–1479.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.