The Dual Beveridge Curve

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Abstract

The recent behavior of the U.S. Beveridge curve — its outward shift and changing slope — has puzzled economists and is difficult to reconcile with standard explanations based on gradual structural change or declining matching efficiency. We propose a dual-vacancy model in which firms post two distinct types of vacancies: those targeting unemployed workers and those designed to hire alreadyemployed workers through poaching. These two types of vacancies operate in segmented sub-markets with separate matching processes. Using U.S. labor market data from 1978 to 2024, we estimate the evolution of both types of vacancies, and show that the share of poaching vacancies has risen significantly since the mid-2010s. This increase is closely linked to an upward trend in their estimated profit-cost ratio. When we adjust the Beveridge curve to include only non-poaching vacancies, its recent puzzling behavior disappears. We estimate the model using a flexible Bayesian framework across multiple data constructions and sectors, and find consistent evidence supporting the dual-vacancy mechanism.

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1 Introduction

The negatively sloped relationship between the number of unemployed individuals and the number of job openings over the business cycle, commonly known as the Beveridge curve, has served for decades as a central diagnostic tool in macroeconomics. First formalized in the postwar period, the curve provides a visual and quantitative representation of labor market tightness and matching efficiency, and has long been used by policymakers to assess the state of the labor market and gauge the distance to full employment.

In recent years, however, the behavior of the Beveridge curve has become increasingly difficult to interpret. As shown in Figure 1, the empirical curve has not only shifted outward but also changed slope in ways that depart significantly from historical patterns. Whereas previous recessions were characterized by movements along a relatively stable Beveridge curve with gradual shifts in intercept over time, the most recent episode—spanning the mid-2010s through the post-pandemic recovery—has seen abrupt and repeated changes in both slope and position. These changes have proven difficult to explain using standard narratives such as declining matching efficiency, structural mismatch, or changing labor force participation. This new behavior of the Beveridge curve presents an important puzzle.

In this paper, we offer a new explanation for this puzzle by proposing a simple but important refinement of standard search-and-matching models: the distinction between vacancies designed to hire unemployed workers and those intended to hire already-employed workers. While it is well understood that firms can choose to hire either from the pool of unemployed or by poaching workers already employed elsewhere, existing macroeconomic models typically treat all job vacancies as homogeneous. In contrast, we introduce a dual-vacancy model in which firms post two distinct types of vacancies: (i) those intended to be filled by unemployed individuals (non-poaching vacancies), and (ii) those targeting already-employed workers (poaching vacancies). These two vacancy types operate in segmented sub-markets with separate matching processes.

This distinction has direct implications for how we interpret movements in job vacancies. Vacancies targeting unemployed workers affect both the unemployment rate and the overall level of employment. In contrast, vacancies filled by poaching do not affect unemployment: they involve the reallocation of workers across jobs and may raise wages or improve match quality, but they do not alter employment aggregates. Therefore, in our framework, only non-poaching vacancies should be considered in the Beveridge curve relationship. Once we adjust the Beveridge curve to reflect this, the apparent breakdown in its behavior disappears.

To quantify these mechanisms, we estimate the dual-vacancy model using U.S. labor market data spanning 1978 to 2024. We draw on a wide array of data sources, including the Current Population Survey (CPS), the Job Openings and Labor Turnover Survey (JOLTS), and reconstructed historical vacancy measures, as well as flow data from recent literature. This allows us to construct consistent time series of stocks and transitions among employment, unemployment, and nonparticipation.

Our estimation recovers the time path of each vacancy type and characterizes their dynamics through



Figure 1: Beveridge Curves over Business Cycles.

Source: BLS. Notes: Henderson moving averages of the unemployment and vacancy rates are shown.

underlying drivers such as firms' perceived profitability of posting vacancies and the efficiency of the matching process. While we cannot separately identify these two components at business-cycle frequencies, we assume that matching efficiency evolves smoothly over time.¹ Under this assumption, the short-run variation we estimate reflects both shifts in the profitability of vacancy creation and modest fluctuations in matching efficiency.

Importantly, since the literature lacks consensus on how to best measure job flows, particularly EE rates

¹Matching efficiency and vacancy profitability are not separately identified in our framework. Both enter the model in a single composite term and affect hiring through the same structural channel. Without fundamentally new restrictions or data (e.g., firm-level cost or profit measures), these components remain indistinguishable. Our identifying assumption that matching efficiency evolves smoothly over time reflects a common finding in the literature. For instance, Sahin et al. (2014) find that compositional mismatch across sectors accounts for much of the perceived decline in matching efficiency during the Great Recession. This supports the view that true matching efficiency likely changes gradually, if at all, rather than fluctuating sharply at business-cycle frequencies.

and hires, we estimate the model under six plausible data configurations, spanning all combinations of CPS and JOLTS inputs and two alternative EE rate constructions. Our main findings hold robustly across all of them.

While direct data on vacancy intentions are not available, largely because equal opportunity employment laws prevent firms from stating explicit preferences for employed or unemployed applicants, we address this challenge by evaluating the extent to which our model fits the observed data better than a standard single-market model. We find that the dual-vacancy framework provides a significantly better fit to the data, particularly in its ability to jointly match the observed behavior of hires from unemployment and from employment. This improved fit reflects the fact that the responsiveness of these two flows to vacancy rates differs substantially — a feature the standard model cannot accommodate with a single elasticity.

In addition to showing that the dual-vacancy model fits the data better, we go further by explaining what drives the dynamics of the estimated vacancy split. A key contribution of the paper is a closed-form identification result that links the evolution of each vacancy type to the observed behavior of unemployment, hires from unemployment, total vacancies, and job-to-job transitions. This decomposition allows us to isolate the relative contribution of non-poaching versus poaching vacancies over time. We show that the increase in poaching vacancies since the mid-2010s is primarily driven by a rising trend in their estimated profit-cost ratio, a pattern that predates the pandemic and persists across sectors.

Although our paper does not focus on policy analysis, our results have implications for how vacancy data should be interpreted in macroeconomic settings. When the share of poaching vacancies is large and rising, a decline in aggregate vacancies may translate into only a modest increase in unemployment. In such environments, aggregate vacancy measures may overstate the extent of labor market tightness that is relevant for the unemployed. This insight helps reconcile the recent coexistence of historically high vacancy rates and low unemployment with relatively mild changes in unemployment in response to shifts in labor demand. We return to these implications in the conclusion.

The model we estimate is statistical in nature, but closely aligned with canonical search-and-matching theory. It incorporates constant-returns-to-scale matching functions, free-entry conditions for vacancy creation, and a segmented structure for unemployed and employed job seekers. We include mechanisms to account for cross-matching between vacancy types, on-the-job search, and flows into employment from out of the labor force. Although our framework is not derived from micro-foundations or optimal choice behavior, its equilibrium structure is consistent with widely used theoretical models in the literature. We estimate the model using Bayesian methods, which offer a transparent and flexible approach to inference across alternative data constructions. Bayesian estimation facilitates joint estimation of trends and business-cycle fluctuations, allows straightforward incorporation of prior information, and ensures convergence in settings where multiple data sources and specifications are used.

Across six data configurations and nine major sectors of the U.S. economy, we find robust and consistent evidence supporting the dual-vacancy framework. Our main empirical result is that the share of poaching vacancies has increased substantially and persistently since the mid-2010s, well before the onset of the COVID-19 pandemic. This rise is strongly associated with an upward trend in the estimated profit-cost ratio of these vacancies, suggesting a structural shift in the incentives for firms to recruit already-employed workers. We estimate that poaching vacancies now account for a majority of all job openings in many sectors. When we remove these vacancies from the Beveridge curve, leaving only non-poaching vacancies, the recent shifts and slope changes disappear, restoring a stable relationship between unemployment and job openings. These findings suggest that much of the recent turbulence in the Beveridge curve stems not from structural mismatches or declining matching efficiency, but from a shift in the composition of labor demand toward poaching.

Our analysis sheds new light on the medium-term dynamics of the U.S. labor market and provides a framework for interpreting aggregate vacancy data in the presence of firm-side market segmentation. While our paper is not focused on policy, our results suggest that conventional measures of labor market tightness may need to be reinterpreted when the composition of vacancies changes significantly over time. In particular, we show how the estimated structural trends in vacancy composition can be used to detrend aggregate vacancy and quit series, providing a clearer view of cyclical labor market dynamics. The finding that poaching vacancies have become more prevalent also raises questions for future work regarding their causes (technological, organizational, regulatory) and their implications for wages, productivity, and macroeconomic adjustment.

Our paper contributes to three strands of the literature. First, we build on work analyzing the Beveridge curve, the inverse relationship between unemployment and vacancies, originally noted by Beveridge (1944) and formalized by Dow and Dicks-Mireaux (1958). This relationship has been studied extensively in both U.S. (e.g., Diamond and Şahin, 2014; Ahn and Crane, 2020) and international contexts (Hobijn and Şahin, 2012; Bonthuis et al., 2016), with recent shifts, especially outward movement and flattening, spurring renewed interest (Elsby, Michaels, and Ratner, 2015). We offer a new explanation for these shifts based on vacancy composition: once we exclude poaching vacancies, the Beveridge curve regains stability, narrowing the range of needed explanations.

These recent shifts have fueled both academic and policy debates. Lubik (2021) links them to reduced matching efficiency from sectoral change; Rodgers and Kassens (2022) cite altered incentives and demographics; others point to changes in job search technology. Most of these assume homogeneous vacancies. We instead highlight a rising share of vacancies targeting employed workers, altering the relationship between aggregate vacancies and unemployment. Our mechanism complements structural mismatch and friction-based explanations while implying that, during periods of tightening (e.g., Figura and Waller, 2022; Blanchard et al., 2022), unemployment may respond less to vacancy fluctuations due to shifts in labor demand composition.

Second, we contribute to the literature on matching functions. Traditional models (Pissarides, 1985, 2000; Mortensen and Pissarides, 1994) use a single function matching all job seekers to total vacancies. We instead estimate separate matching functions for vacancies targeting unemployed and employed workers, finding that this structure fits the data far better. A central result is that the elasticity of matching with respect to unemployment (α) is low — between 0.1 and 0.3 — well below standard estimates of 0.5–0.7 (Broersma and van Ours, 1999, Petrongolo and Pissarides, 2001). Our findings align with Gottfries and Stadin (2024), who also find little evidence that higher unemployment increases vacancy filling speed, reinforcing our view that vacancy composition, not matching speed, drives Beveridge curve shifts.

Third, we contribute to the literature on labor market segmentation. Prior work has emphasized segmentation among workers: for example, Hall and Kudlyak (2020) and Ahn et al. (2022) identify heterogeneity in job seeker behavior. We extend segmentation to the firm side, estimating the composition of vacancies by intended hire type. While such targeting is not directly observable, we infer the split and its drivers, showing that the share of poaching vacancies has risen alongside their profit-cost ratio. This complements Menzio and Shi (2011), who model similar vacancy types in a directed search framework. Related work by Faberman et al (2022), and See, Birinci, and Wee (2024) documents systematic differences in job search behavior and transitions by employment status, supporting our model's behavioral foundation.

Our findings also relate to recent work on vacancy heterogeneity. Qiu (2022) argues that many vacancies are unfilled or not seriously pursued, overstating labor demand. In a complementary vein, we show that even filled vacancies differ in macro impact depending on their intended hire. Research on vacancy chains further supports our approach: Fujita and Nakajima (2016) show that poaching can trigger cascades of follow-up vacancies, while Elsby, Gottfries, Michaels, and Ratner (2025) provide direct evidence that many U.S. vacancies result from replacement hiring rather than net job creation. Mercan and Schoefer (2020) quantify how such chains shape aggregate vacancy dynamics. Together, these studies reinforce our finding that rising vacancies often reflect churn among employed workers, not increased hiring of the unemployed.

In sum, our dual-vacancy framework offers a new lens on Beveridge curve dynamics and labor market tightness. It also cautions against interpreting aggregate vacancy data as a proxy for slack when poaching dominates vacancy growth. Beyond improving fit, our structure lays a foundation for future models incorporating vacancy types, search channels, and segmented labor market adjustment.

The paper is organized as follows. Section 2 presents the dual-vacancy model. Section 3 describes the data sources and measurement strategy. Section 4 presents our main empirical estimates and model parameters. Section 5 analyzes the implications of our results for interpreting the Beveridge curve. Section 6 compares the fit of the dual-vacancy model to that of the standard single-vacancy framework. Section 7 concludes with a discussion of broader implications and directions for future research.

2 Dual Beveridge Curve Model

Our statistical model builds on standard search-and-matching frameworks but does not explicitly model optimizing behavior. Instead, we specify matching functions, flow identities and equilibrium conditions rooted in canonical theory. These conditions will be familiar to readers from the search and matching literature. Rather than deriving each equation from first principles, we adopt a reduced-form approach that emphasizes identification and tractability while retaining a close structural link to the underlying theory.

The labor market in period t is characterized by a number of unemployed workers U_t searching for jobs,

and a number of employed workers E_t , making together the labor force:

$$L_t = U_t + E_t. \tag{1}$$

Firms interested in employing workers post a number of vacancies V_t . A subset of employed workers, H_t , are interested in better job opportunities and actively search on the job. Some firms are interested in experienced workers and know that there is supply of such workers among the employed, so they design a subset of vacancy postings $V_{\epsilon,t}$ specifically to poach already employed workers. The rest of the vacancies $V_{u,t}$ (presumably low-level or entry positions) will consider and hire mostly unemployed workers. The total number of vacancies is a combination of these two types:

$$V_t = V_{u,t} + V_{\epsilon,t}.\tag{2}$$

The unemployed U_t search for non-poaching vacancies $V_{u,t}$ and get hired according to a standard constantreturns-to-scale matching function:

$$M_{u,t} = B_{u,t} U_t^{\alpha} V_{u,t}^{1-\alpha},$$

where $M_{u,t}$ is the number of hires from the unemployment pool, $\alpha \in [0, 1]$ is the matching elasticity, and $B_{u,t}$ characterizes the efficiency of the matching process.

A subset of employed workers H_t engage in on-the-job search and match with poaching vacancies $V_{\epsilon,t}$. The number of such matches is described by a second matching function:

$$M_{\epsilon,t} = B_{\epsilon,t} H_t^{\beta} V_{\epsilon,t}^{1-\beta},$$

where $M_{\epsilon,t}$ is the number of workers who quit their positions to join a new employer, $\beta \in [0,1]$ is the matching elasticity, and $B_{\epsilon,t}$ is the efficiency of the matching process for already-employed workers.

We use a simplified version of a targeted search model (see Cheremukhin, Restrepo-Echavarria, and Tutino (2020)) as an inspiration to generalize our matching function specifications to the case where both types of workers sometimes confuse the two vacancy types and therefore apply to the wrong type of vacancy, so both types of vacancies run the risk of being filled by workers for which they were not originally designed. This confusion creates additional cross-matches, and their numbers should have the following forms: $M_{u,t}^+ = A_u U^{\alpha} V_{\epsilon,t}^{1-\alpha}$, and $M_{\epsilon,t}^+ = A_{\epsilon} H_t^{\beta} V_{u,t}^{1-\beta}$. These matches would be counted as unemployment-to-employment and employment-to-employment transitions respectively.

In addition, to accommodate the effect of substantial flows of workers between employment and outof-the-labor-force states, we add a term capturing the potential matches of workers out of the labor force with total vacancies to produce additional flows into employment: $M_{u,t}^{++} = B_L N_t^{\psi} V_t^{1-\psi}$ To make the overall estimated expressions somewhat more flexible, we postulate the following general functional forms:

$$M_{u,t} = B_{u,t} U_t^{\alpha} V_{u,t}^{1-\alpha} \left[1 + A_u \left(\frac{V_{\epsilon,t}}{V_{u,t}} \right)^{\gamma} \right] + B_L N_t^{\psi} V_t^{1-\psi}, \tag{3}$$

$$M_{\epsilon,t} = B_{\epsilon,t} H_t^{\beta} V_{\epsilon,t}^{1-\beta} \left[1 + A_\epsilon \left(\frac{V_{u,t}}{V_{\epsilon,t}} \right)^{\gamma} \right], \tag{4}$$

where the mixing coefficients A_u and A_{ϵ} are the fractions of unemployed workers that are able to get a job with a firm that intended to poach and of employed workers that take up jobs intended for the unemployed. The elasticity γ adds flexibility by allowing the cross terms to reflect variations in either of the vacancy types. The parameter ψ captures the matching elasticity with respect to the number of civillians out of the labor force N_t and total vacancies V_t , and parameter B_L captures the matching efficiency.

The stock of employment increases when unemployed (or out of the labor force) workers find jobs, but declines when employed workers are laid off:

$$E_{t+1} = E_t \left(1 - s_t \right) + M_{u,t},\tag{5}$$

where s_t is the layoff/separation rate. Note that matches created by employed workers and vacancies do not enter this equation. This is because when a person leaves a job and moves into a different job, the number of employed workers does not change.

We also need to make assumptions about the search effort of employed workers, H_t . In a study of search effort of workers searching on the job Faberman et al (2022) find that on average 78 percent of employed workers do not search at all, while the remaining 22 percent search even more effectively than the unemployed. While this study does not shed light on how this share varies over the business cycle, it stands to reason that it should vary with employment. As the baseline, we assume that there is the slow-moving bulk of employed workers, on average accounting for 78 percent of employment, that do not search. A simple proxy for this fraction would be a smoothed out trend of employment multiplied by 0.78. To compute a smoothed trend we HP-filter the employment series with parameter 10^6 , and denote it E_t^* . We assume that the rest of employed search at full strength, as much as the unemployed:

$$H_t = E_t - \xi_t E_t^*,\tag{6}$$

where ξ_t is the share of employed that do not search. We calibrate it to be 0.78 on average but let it vary over time and estimate it as an unknown shock.

To close the model, we need to add equations determining how many vacancies of each type are posted. The search and matching literature usually does this by assuming a free entry of vacancies, whereby vacancies are added until their expected benefit equals their cost. As a result, the vacancy filling rate times the profitcost ratio for each vacancy type equals one:

$$\frac{M_{u,t}}{V_{u,t}}y_t = 1,\tag{7}$$

$$\frac{M_{\epsilon,t}}{V_{\epsilon,t}}z_t = 1,\tag{8}$$

where y_t and z_t denote the profit-cost ratios for vacancies designed for the unemployed and poaching vacancies respectively.

We further simplify the model and notation by detrending by the labor force, for each variable X defining a lower case detrended analog $x_t = X_t/L_t$. This simplifies the model to the following 8-equation system:

$$(1) \qquad m_{t}^{u} = B_{t}^{u} u_{t}^{\alpha} v_{u,t}^{1-\alpha} \left(1 + A_{u} \left(\frac{v_{\varepsilon,t}}{v_{u,t}} \right)^{\gamma} \right) + B_{L} n_{t}^{\psi} v_{t}^{1-\eta}$$

$$(2) \qquad m_{t}^{\varepsilon} = B_{t}^{\varepsilon} h_{t}^{\beta} v_{\varepsilon,t}^{1-\beta} \left(1 + A_{\varepsilon} \left(\frac{v_{u,t}}{v_{\varepsilon,t}} \right)^{\gamma} \right)$$

$$(3) \qquad v_{u,t} + v_{\varepsilon,t} = v_{t}$$

$$(4) \qquad h_{t} = e_{t} - \xi_{t} e_{t}^{*}$$

$$(5) \qquad e_{t} + u_{t} = 1$$

$$(6) \qquad e_{t+1} \delta_{l,t} = e_{t} \left(1 - s_{t} \right) + m_{t}^{u}$$

$$(7) \qquad v_{u,t} = 0$$

$$(7) v_{u,t} = m_t^a y_t$$

(8)
$$v_{\varepsilon,t} = m_t^{\varepsilon} z_t$$

where $\delta_{l,t}$ is the growth rate of the labor force. This system now contains 8 endogenous variables $e_t, u_t, v_{u,t}, v_{\epsilon,t}, m_t^u, m_t^\epsilon, h_t, v_t$ and 9 exogenous variables $y_t, z_t, s_t, \xi_t, \delta_{l,t}, e_t^*, n_t, B_t^u, B_t^\epsilon$. We allow the matching efficiencies $B_t^u B_t^\epsilon$ to follow linear trends, but not independently fluctuate at business cycle frequencies, as then they would be impossible to distinguish from fluctuations in y_t and z_t . Therefore, all the short-term fluctuations in matching efficiencies will show up in estimated series for y_t and z_t .

We observe 9 variables with white-noise error: the unemployment rate u_t , the vacancy rate v_t , the matching rate of the unemployed m_t^u , the matching rate of the employed m_t^ϵ , the separation rate s_t , the employment-to-employment transition rate ee_t , the growth rate of the labor force $\delta_{l,t}$, the out of the labor force rate n_t , and the hp-filtered employment rate e_t^* . The observed employment-to-employment rate could correspond to two different specifications, either the ratio of hires from employment to employment $ee_t = \frac{m_t^\epsilon}{e_t}$, or the ratio of hires from employment to the search effort of the employed $ee_t = \frac{m_t^\epsilon}{h_t}$. We consider both specifications in the estimation, labeling them with the letters A and B respectively.

We assume that the 7 exogenous variables follow piece-wise linear time trends and fluctuate around them in an autoregressive way. We parameterize the trends in the exogenous variables and derive the corresponding trends in the endogenous variables. From this derivation, as shown in Appendix A, we can link the parameters of the trends of the exogenous variables and the observed variables. We use the observed variables to estimate the parameters of the underlying trends in all the variables of the model, and detrend the observed variables correspondingly. We then log-linearize the model around the estimated trends, as shown in Appendix A.

3 Data

Here we describe the data we use for our estimation. The first primary source of data is the Bureau of Labor Statistics, from which we use the Household Survey (HS), the Current Population Survey (CPS), and the Job Openings and Labor Turnover Survey (JOLTS). We use the HS as a source of data on the Civillian Labor Force (1), composed of Employed (2) workers and Unemployed (3) workers, and the Civillians Not in the Labor Force (4), all four series for at least 16 year-olds, for the period from January 1978 to December 2024.

The CPS provides a Research dataset measuring flows of workers between the three states - Employment, Unemployment and Not-in-the-Labor-Force. We use headcounts measuring flows from Employment to Unemployment (EU flow, 5) and from Unemployment to Employment (UE flow, 6), for the period from February 1990 to December 2024.

The CPS dataset has been used by Fujita, Moscarini and Postel-Vinay (FMP, 2024), our second data source, to compute the rate at which workers transit between jobs (EE rate, 7), for the period from October 1994 to December 2024. We use their rate and multiply it by the number of Employed workers (2) to obtain a measure of employed workers that found a new job each month (EE flow).

The JOLTS provides monthly headcounts for total Hires (8), total Separations, containing Quits (9) and Layoffs (10), as well as total Job Openings (11), for the period from December 2000 to December 2024.

The CPS dataset has also been used by Ellieroth and Michaud (2024), our third data source, to measure transition rates from Employment to Unemployment (EU rate, 12) and Employment to Not-in-the-Labor-Force (EN, 13), and break each of these flows into voluntary separations (Quits,14, EUQ,15, ENQ,16) and involuntary separations (Layoffs, 17, EUL, 18, ENL, 19), for the period from January 1978 to December 2024. This dataset is notable because it infers from the CPS a series for Quits (14) which for the overlapping period is very similar to JOLTS data (9), and a series for Layoffs (17) which also for the overlapping period is very similar to JOLTS data (10). At the same time, the total EN flow (13) thus measured from the CPS is nearly indistinguishable from the EE rate (7), and both the EN and EU flows (12,13) are consistent with those reported by the CPS directly (5). The rates measured by Ellieroth and Michaud (EM, 2024) therefore bring together in a consistent way the CPS and JOLTS datasets, and extend both back in time to January 1978.

In addition, we use the methodology developed by Barnichon (2010) that extends the JOLTS measure of total job openings (11) back in time to 1951 using the Conference Board help-wanted index of online and newspaper advertising (20), our fourth data source.

To remove structural trends relating to the size of labor supply, we convert all the raw headcounts we described earlier to rates relative to the labor force. This brings the measured series close to stationarity and in accordance with the assumptions of our model. As the measure of the unemployment rate u_t we take the number of unemployed (3) divided by the labor force (1). As the measure of the vacancy rate v_t we take the number of vacancies (11,20) divided by the labor force (1). As the measure of the exogenous variable $\delta_{l,t}$ we take the growth rate of the labor force (1). As the measure of not in the labor force n_t we take the number of not in the labor force (4) divided by the labor force (1). As the measure of HP-filtered employment e_t^* we take the number of employed (2) divided by the labor force (1) HP-detrended with parameter 10^6 .

For the remaining measures of (EU,UE,EE flows) we are left with more than one option. For the hires from unemployment flow m_t^u we have two options: 1) UE flow from the CPS (6) for 1990-2024, 2) Hires (8)



Source: BLS, Fujita, Moscarini, Postel-Vinay (2024), Ellieroth, Michaud (2024), Barnichon (2010), Conference Board.

minus Quits (9) from JOLTS for 2000-2024, — each in turn divided by the labor force (1) and in natural logs. For the hires from employment flow m_t^{ϵ} we also have two options: 1) EE flow computed from the CPS as EE rate by FMP (7) multiplied by Employment (2) for 1995-2024, 2) Quits (9) from JOLTS extended using the series by EM (14) for 1978-2024, — each in turn divided by the labor force (1) and in natural logs. For the layoff/separation rate s_t we have two options as well: 1) EU flow computed from the CPS extended using the series by EM (12) for 1978-2024, 2) Layoffs (10) from JOLTS extended using the series by EM (12) for 1978-2024, 2) Layoffs (10) from JOLTS extended using the series by EM (12) for 1978-2024, 2) Layoffs (10) from JOLTS extended using the series by EM (12) for 1978-2024, 2) Layoffs (10) from JOLTS extended using the series by EM (12) for 1978-2024, 2) Layoffs (10) from JOLTS extended using the series by EM (17) for 1978-2024, — each in turn divided by Employment (2) and in natural logs. Finally, the EE rate ee_t that we use in the estimation is computed by dividing the EE flow described earlier by Employment (2), and taking natural logs. We consistently use the the same option for hires from employment flow and the EE rate. Each of the series and their options are shown in Figure 2 below.

We estimate the model under six configurations, combining three sets of hiring/separation data with two methods of interpreting employment-to-employment (EE) rates: A-variant uses hires divided by employment; B-variant uses hires divided by estimated on-the-job search effort. The three sets of hiring separation data include: 1) all series are sourced from CPS; 2) hires rates from the CPS, but Separation/Layoff rates from JOLTS; 3) all four series from JOLTS. We label the six estimation configurations CPS-A/B, Hybrid-A/B, and JOLTS-A/B, respectively. This multi-pronged estimation strategy ensures our findings are not artifacts of a particular data source or flow measurement method. It highlights the model's ability to fit labor market dynamics robustly across all commonly used constructions.

4 Results

Aggregate estimation Using our detrending methodology, we find that the separation rate and the unemployment rate have long-term downward trends. This is consistent with the literature documenting a secular decline in labor market dynamism in the US, e.g., Molloy et al. (2016). The downward trend in separations accounts for the decline in the trend of the unemployment rate over the past 25 years, consistent with a downward trend in most existing measures of the natural rate of unemployment (see e.g. Crump et al (2019).) We find that the estimated profit-cost ratio for poaching vacancies, z_t , exhibits a break in trend around 2011, whereby a positive slope emerges after this date. This trend in profitability z_t generates the upward trends in vacancies, poaching vacancies and hires from employment.

We choose a Bayesian approach because some parameters may not be fully identified, and the likelihood surface can exhibit flat regions or multiple local maxima. In such cases, traditional maximum likelihood estimation may struggle to find a unique optimum. By combining the likelihood with a relatively uninformative prior, the Bayesian method introduces additional curvature into the parameter space, improving convergence and aiding exploration of the posterior distribution. It also provides a natural diagnostic: when a parameter is weakly identified, its posterior remains close to the prior, revealing the limits of what the data can pin down.

We evaluate the posterior distribution using a Random Walk Metropolis (RWM) algorithm, as described in An and Schorfheide (2007). For each model variant, we run multiple chains initialized at the posterior mode, generating a total of 100,000 draws. We monitor convergence by checking that acceptance rates stay between 0.2 and 0.5 and that posterior means are stable across chains.

In this section, we report the parameter values that we recover and the estimated split of total vacancies into non-poaching and poaching vacancies. Our estimated parameters using CPS-A and JOLTS-A data specifications are shown in Tables 1 and 2. Note that the estimates from both specifications are very similar for all of the key parameters of interest. This is true more broadly for the 6 specifications we consider, as

Parameter	P	rior		Posterior					
	mean	st.dev.	mode	mean	st. dev.	conf. int. [5-95]			
α	0.5	0.2	0.157	0.166	0.014	[0.137, 0.194]			
β	0.8	0.1	0.963	0.961	0.011	[0.939, 0.985]			
γ	0.5	0.2	0.055	0.0692	0.030	[0.007, 0.128]			
c_u	0.2	0.1	0.041	0.038	0.008	[0.022, 0.055]			
c_ϵ	0.2	0.1	0.080	0.096	0.033	[0.026, 0.160]			
b_L	0.2	0.1	0.098	0.089	0.029	[0.030, 0.147]			

Table 1: Parameter estimates of the model in the CPS-A specification

Notes: The priors for α , β , γ , c_u , c_{ϵ} were drawn from a beta distribution with support on the interval [0, 1], prior for b_L was drawn from a gamma distribution with positive support.

Parameter	P	rior	Posterior						
	mean	st.dev.	mode	mean	st. dev.	conf. int. [5-95]			
α	0.5	0.2	0.108	0.117	0.017	[0.090, 0.145]			
β	0.8	0.1	0.929	0.921	0.015	[0.892, 0.947]			
γ	0.5	0.2	0.017	0.025	0.013	[0.003, 0.046]			
c_u	0.2	0.1	0.144	0.140	0.013	[0.117, 0.164]			
c_ϵ	0.2	0.1	0.036	0.055	0.048	[0.009, 0.100]			
b_L	0.2	0.1	0.033	0.053	0.015	[0.012, 0.096]			

Table 2: Parameter estimates of the model in the JOLTS-A specification

Notes: The priors for α , β , γ , c_u , c_{ϵ} , were drawn from a beta distribution with support on the interval [0, 1], prior for b_L was drawn from a gamma distribution with positive support.



Figure 3: Prior and Posterior Estimates of Parameters for 6 estimation setups.

shown graphically in Figure 3. We estimate the elasticities of the matching functions, α in the [0.1-0.3] range and β in the [0.8-1] range. We also find that the elasticity of the cross-matches γ is close to zero. The parameters c_u and c_{ϵ} are the log-linear analogs of parameters A_u and A_{ϵ} in the full model, measuring the fractions of hires from employment and unemployment pools respectively that are formed using the wrong types of vacancies. Across all 6 specifications, we find that the fraction of hires from employment using non-poaching vacancies typically does not exceed 20 percent, and the fraction of hires from employment using non-poaching vacancies typically does not exceed 10 percent, with average modal values of $c_u = 10\%$ and $c_{\epsilon} = 3\%$ respectively. We find that the estimated share of net flows from out of the labor force into employment also typically does not exceed 10% with the average modal value of $b_L = 3\%$. The rest of the parameters reflect the properties of the estimated underlying exogenous shocks and we report them in full in Appendix C.

The estimated model under the modal estimated parameters also recovers the exogenous shocks y_t and



Figure 4: Estimated Shocks and Vacancy Split from 6 estimation setups.

 z_t representing the profit-cost ratios for the two types of vacancies, and the split of job openings themselves into the two types of vacancies. We report the split of vacancies and the underlying shocks, calculated for the period 1978 to 2024 at a monthly frequency, in Figure 4. Not to overload the Figure, yet to reflect the uncertainties coming both from differences in measured data and in estimated parameters, we report the average of shocks and vacancy split series from all six specifications, as well as the 90-percent confidence intervals around them.

There are two important observations one can make from Figure 4. First, the fraction of poaching vacancies has increased significantly since at least 2015, compared with the preceding period. This trend increase is closely associated both in timing and in magnitude with the trend increase in the profit-cost ratio for poaching vacancies, suggesting it as the causal factor. Second, while the business cycle behavior of the two types of vacancies was similar in the period prior to 2015 (both dropped during recessions and recovered during booms) it was dramatically different in the most recent recession episode. Although poaching vacancies fell in 2020, but quickly recovered soon after, the non-poaching vacancies increased in the recession period.

Sectoral estimation The data from JOLTS for 2000-2024 allows the application of exactly the same estimation procedure for 9 sub-sectors of the economy: Manufacturing, Construction, Transportation and Utilities, Wholesale Trade, Retail Trade, Business Services, Education and Health, Leisure, and Government. We show the full results of the estimation in Appendix C. Here we only report the important estimates of parameters and vacancy decomposition, in Table 3 and Figure 5. We see that for all the sub-sectors of the economy the results are broadly consistent with the aggregate results: α takes low values in the [0-0.1]

	α	β	γ	c_u	c_{ϵ}	b_L
Construction	0.066	0.990	0.014	0.109	0.057	0.047
Manufacturing	0.029	0.985	0.006	0.164	0.136	0.120
Transportation, Utilities	0.045	0.978	0.011	0.098	0.089	0.053
Wholesale Trade	0.081	0.967	0.016	0.090	0.060	0.040
Retail Trade	0.082	0.964	0.013	0.071	0.073	0.060
Business Services	0.037	0.979	0.013	0.141	0.081	0.052
Education, Health	0.019	0.944	0.007	0.124	0.144	0.079
Leisure	0.038	0.948	0.021	0.073	0.109	0.073
Government	0.003	0.975	0.010	0.106	0.134	0.035

Table 3: Posterior (mode) estimates of parameters for sectors of the economy in the JOLTS-A specification

Notes: The priors for α , β , γ , c_u , c_{ϵ} were drawn from a beta distribution with support on the interval [0, 1], prior for b_L was drawn from a gamma distribution with positive support.

interval, β takes high values in the [0.9-1] interval, γ is close to zero, c_u , c_{ϵ} and b_L are all low, in the [0-0.15] interval, and the apparent upward trend in sectoral vacancies in each case appears driven by an increase in the poaching component driven by the profit-cost ratio z_t .

Business cycle variations in profit-cost ratios y_t and z_t capture not only changes in the relative profitability of vacancy creation, but also potential fluctuations in matching efficiency in each sub-market. Since these two factors cannot be separately identified from the data, we impose a smooth-trend restriction on matching efficiency. We assume that efficiency follows a log-linear trend over time. Under this assumption, shortrun variation in y_t and z_t reflects changes in vacancy profitability and subsumes fluctuations in matching efficiency.

Identification Appendix B describes in detail how shocks are identified in our model. We log-linearize the model and invert the mapping between observed and unobserved variables in closed form. The identification logic can be understood in terms of how the model attributes the observed trends and fluctuations in vacancies and hiring flows.

First, the model translates the downward trends in the separation rate and unemployment rate to a corresponding downward trend in non-poaching vacancies. The fluctuations in non-poaching vacancies are determined by a linear combination of hires from unemployment, the unemployment rate, and total vacancies, and depend only on parameters α , c_u , and γ .

Since total vacancies display a strong upward trend and higher cyclical volatility than hires or unemployment, the model improves fit (i.e., increases marginal data density) by minimizing the influence of total vacancies in this equation. This leads to estimates of c_u and γ close to zero. Meanwhile, the relative volatility of hires from unemployment and the unemployment rate drives the estimated value of α .



Figure 5: Estimated Shocks and Vacancy Split, across 9 sectors.

The residual difference between observed total vacancies and estimated non-poaching vacancies is then attributed to poaching vacancies, which must absorb the remaining trend and cyclical variation. The parameter β is identified from the relationship between hires from employment and these inferred poaching vacancies. Given that the poaching vacancy series is highly volatile, the model again favors a low sensitivity, pushing β close to 1, so that poaching vacancies explain most of the observed variation while contributing minimally to hires.

This identification logic yields a consistent interpretation: the observed post-2010 rise in vacancies is almost entirely attributable to poaching, while non-poaching vacancies remain closely tied to unemployment dynamics. This helps explain the puzzling shifts in the Beveridge curve without requiring unusual movements in unemployment or hires. Importantly, the rise in total vacancies after 2010 is well-documented (e.g., Mongey and Horwich, 2024) and is corroborated by alternative vacancy indicators, such as the Conference Board-Lightcast Help Wanted Online Index and the Indeed Hiring Lab postings tracker.

Our model offers a new explanation and quantitative interpretation of this structural change: the trend increase in poaching vacancies reflects a deeper shift in the composition of labor demand.

5 Dual Beveridge Curve

The estimate of vacancies for the unemployed then takes center stage for understanding the behavior of the unemployment rate. To better understand our results, we need to look at them through the lens of an adjusted Beveridge curve. Recall that only the non-poaching vacancies match with unemployed workers and lead to increases in employment. Thus, the proper Beveridge curve relationship should consider only non-



Figure 6: Classical and Adjusted Beveridge Curves

poaching vacancies and disregard poaching vacancies. The adjusted Beveridge curve for the whole economy is shown in the right panel of Figure 6 compared with the unadjusted (or classical) Beveridge curve in the left panel.

Figures 4 and 6 are illustrative of what happened in labor markets since the onset of the Covid pandemic. The first few months of the pandemic saw a decline in demand due to widespread social distancing, which increased unemployment and reduced poaching. In the next few months, mask and distancing mandates led to a separation shock where many more people were laid off than would be consistent with lower demand; so non-poaching vacancies increased, and a lot of people were hired back from unemployment very quickly. After the spike in hires from unemployment ended, stimulative fiscal and monetary policy increased purchasing power and created strong excess demand for goods. The excess demand prompted firms to expand, but this excess demand for workers could not be met by hiring from the unemployment pool. Together with supply chain bottlenecks, the excess demand for goods led to a surge in inflation; and excess demand for workers led to an increase in poaching, which then drove up nominal wage growth.

This interpretation provides us with two lessons. First, the (adjusted) Beveridge curve relationship between unemployed workers and non-poaching vacancies has not changed, at either the aggregate or sectoral level. In other words, the current puzzling behavior of the Beveridge curve disappears once we replace total vacancies with non-poaching vacancies. Second, abnormalities in the classical Beveridge curve are due to a disproportional expansion of poaching vacancies after 2010. Our estimation suggests that the underlying cause for this shift is the dramatic increase in the profit-cost ratio for poaching vacancies. To better understand the shift, we can think of the steady-state version of our model and consider how it would be affected by a trend increase in the profit-cost ratio and the increase in the steady-state share of poaching vacancies. Equations of the model can be further simplified by substituting the matching functions and the search effort of the employed to get:²

$$(1-u) s = B_u u \left(\frac{v_u}{u}\right)^{1-\alpha}$$
$$\left(\frac{v_u}{u}\right)^{\alpha} = B_u y,$$
$$\left(\frac{v_{\epsilon}}{0.27-u}\right)^{\beta} = B_{\epsilon} z.$$

where we omitted the mixing matching terms for simplicity. Although these three equations have three endogenous variables u, v_u, v_{ϵ} , the first two equations could be solved separately with respect to u and v_u — whose relationship determines the adjusted Beveridge curve. Poaching vacancies are then determined by the third equation, driven by fluctuations in their profitability z and the unemployment rate. The solution to the model then looks as follows:

$$u = \frac{1}{1 + \frac{B_u}{s} (B_u y)^{\frac{1}{\alpha} - 1}},$$
$$v_u = u (B_u y)^{\frac{1}{\alpha}},$$
$$v_{\epsilon} = (0.27 - u) (B_{\epsilon} z)^{\frac{1}{\beta}}.$$

Log-linearizing the model with respect to u and v_u , we find that the slope of the adjusted Beveridge curve is $-\frac{\alpha+u^*(1-\alpha)}{(1-u^*)(1-\alpha)}$. We further denote the "steady-state" share of poaching vacancies by $\phi^* = \frac{v_u^*}{v_u^* + v_t^*}$. To find the slope of the classical Beveridge curve, we need to understand the relationship between movements in y and z over the business cycle. In standard search models, movements in profitability of a match y reflect changes in productivity or demand driving the business cycle. It is natural to expect the profitability of poaching vacancies to be driven by similar factors. Therefore, we would expect y and z to have a common factor reflecting business-cycle fluctuations. We denote the elasticity of the co-movement between profitabilities by d_y , reflecting the ratio of their log standard deviations: $\ln\left(\frac{y}{y^*}\right) \propto d_y \ln\left(\frac{z}{z^*}\right)$. In fact, in our estimated model we estimated the factor x_t which is a common driver of both y_t and z_t and from the filtered estimates of the three shocks we can deduce a value for d_y of around 0.2. Then we can show that the slope of the classical Beveridge curve is:

$$-\phi^* \frac{\alpha + u^* (1 - \alpha)}{(1 - u^*) (1 - \alpha)} - (1 - \phi^*) \left(\frac{u^*}{0.27 - u^*} + \frac{1}{d_y \beta} \left(1 + \frac{\alpha + u^* (1 - \alpha)}{(1 - u^*) (1 - \alpha)} \right) \right).$$

The first term reflects movement in non-poaching vacancies in the adjusted Beveridge curve. The second term reflects the movements in search effort of the employed and the movements in the profitability of poaching vacancies over the business cycle.

To put some numbers to these slopes, we use the estimated parameters $\alpha = 0.16$, $\beta = 0.90$, the steadystate share of non-poaching vacancies $\phi^* = 0.45$,³ and the steady-state level of unemployment $u^* = 0.04$. For

²Note that based on our model approximation search effort of the employed can be expressed as a function of the number of unemployed $H_t = E_t - 0.78E_t^* = L_t - U_t - 0.78(L_t - U_t^*) = 0.22L_t + 0.78U_t^* - U_t \approx 0.27L_t - U_t$.

 $^{^{3}}$ To take a conservative approach, we use the estimated vacancy split that we observe prior to 2010.

this calibration, the slope of the adjusted Beveridge curve is -0.33, consistent with the slope of the adjusted Beveridge curve shown in Figure 6. Assuming the estimated parameter $d_y = 0.15$, we also get the slope of the classical Beveridge curve right at -1, consistent with Figure 6 and the commonly accepted value of the slope in the literature. If the steady-state level of poaching vacancies were to increase to 0.85, as we have seen recently, then the Beveridge curve could have steepened to a slope of -1.4.

Figure 6 compares the joint behavior of unemployment and vacancies with the predictions of our calibrated theoretical model for the dual Beveridge curve. Instead of parameter values for B_u , B_ϵ , s, z, and y, we input their estimated linear trend values for 2007 and 2019, two pre-recession peaks commonly used as reference points, and 2023, which is close to the end of observations at hand. The adjusted Beveridge curve in the right panel shifted down only mildly due to the reduced labor market dynamism, as captured by the decline in the trend separation rate. The classical Beveridge curve in the left panel both shifted outward and steepened its slope, due to the increase in steady-state profit-cost ratio z and the consequent expansion in the steady-state level of poaching vacancies. It expanded and steepened further for the estimated trend values of 2023, but we think it premature to project an indefinitely growing trend, and thus the estimate for 2019 represents a conservative estimate.

6 Model Fit and Comparison with Standard Model

Since we do not have direct evidence on the split of vacancies into poaching and non-poaching types, and it is not a given that such a clear split exists, it would be helpful to understand whether our new dual-vacancy model provides a better description of the data than existing models. In order to answer this question, we adopt the traditional model with a single matching function to fit our observables and estimate its parameters.

According to the standard model, a single constant-returns-to-scale matching function combines the total number of job seekers $U_t + H_t$ with the total number of vacancies V_t to produce the total number of matches $M_t^u + M_t^c$. In order to give the model the chance of matching the data, we add extra flexibility to this overly restrictive model. We allow the proportion of total matches going to the unemployed to differ from their share of the search effort and estimate an additional parameter responsible for this split. Thus, our version of the traditional model consists of two equations:

$$M_t^u = B_u U_t \left(\frac{V_t}{U_t + H_t}\right)^{1-\alpha},\tag{9}$$

$$M_t^{\epsilon} = B_{\epsilon} H_t \left(\frac{V_t}{U_t + H_t} \right)^{1-\alpha}.$$
 (10)

We replace the matching equations of our model with these alternative equations and estimate the traditional model using the same methods as the dual-vacancy model. This allows us to compare fit because both models approximate the same set of data, even though the two models differ in the number of estimated parameters and shocks. In particular, the traditional model has only one elasticity of the matching function,



Figure 7: Estimated parameters of restricted model.

Parameter	P	rior	Posterior					
	mean	st.dev.	mode	mean	st. dev.	conf. int. [5-95]		
			CPS	-A				
α	0.5	0.2	0.32	32 0.32 0.015		[0.31, 0.35]		
b_L	0.2	0.1	0.982	0.976	0.01	[0.956, 0.998]		
ψ	0.5	0.2	0.59	0.59	0.03	[0.56, 0.63]		
			JOLT	S-A				
α	0.5	0.2	0.141	0.145	0.005	[0.134, 0.155]		
b_L	0.2	0.1	0.992	0.986	0.006	[0.974, 0.998]		
ψ	0.5	0.2	0.46	0.46	0.01	[0.44, 0.49]		

Table 4: Parameter estimates of the model with a single matching function

Notes: The priors for α , ψ were drawn from a beta distribution with support on the interval [0, 1], prior for b_L was drawn from a gamma distribution with positive support.

Table 5: Comparison of model fit

Sector	Margina	l Data Density	Bayes factor				
	DVM	SMF					
CPS-A	9923	8972	$\exp(951)$				
CPS-B	9344	7940	$\exp(1404)$				
Hybrid-A	8985	7618	$\exp(1367)$				
Hybrid-B	9573	6086	$\exp(3486)$				
JOLTS-A	9427	7944	$\exp(1483)$				
JOLTS-B	9964	6406	$\exp(3559)$				

Notes: DVM stands for dual vacancy model, and SMF stands for single matching function model. The marginal data density was computed using Geweke's (1999) modified harmonic mean method.

 α , and combines vacancies into a single series; whereas, the dual-vacancy model has two elasticities of the matching function, α and β , and recovers a hidden variable, the split of the vacancies.

The parameter estimates for the traditional model are presented in Table 4 and Figure 7. The estimates of the matching elasticity tend to be driven by the matching process for the unemployed and therefore give values in a range similar to the dual-vacancy model (see Tables 1 and 2). However, the inability of the model with a single matching function to explain the matching process for the employed leads to much poorer fit.

In Table 5 we present measures of model fit. The dual-vacancy model fits the data uniformly better based on marginal data density: in all six cases Bayes factors strongly favor the dual-vacancy model. This is because the business cycle responsiveness of job-to-job flows and hires from unemployment to the vacancy rate differs substantially, making it hard to match both with a single matching function elasticity. The dual-vacancy model does a much better job at fitting both rates because it has two elasticity parameters rather than one, and also because it has the ability to split vacancies into two subsets - one for each matching rate. The dual-vacancy model consistently outperforms the standard model in all configurations due to its ability to separately match poaching and non-poaching flows.

7 Broader Implications and Future Directions

Our results are important for policy considerations, in particular, for monetary policy's effect on unemployment. As argued by Figura and Waller (2022), a steeper Beveridge curve could imply that tighter monetary policy would result in a larger decline in vacancies corresponding to only a mild increase in the unemployment rate.

In this paper, we attribute the Beveridge curve puzzle to the disproportional expansion of poaching vacancies. Our estimates combined with a theoretical model indicate that the slope of the Beveridge curve has indeed steepened from -1 to at least -1.25 and possibly -1.4. This coefficient implies that a decline in the vacancy rate from 7% to 5% should correspond to an increase in the unemployment rate from 3.5 to at most 4.6 percent, and possibly 4.4 percent, as opposed to 4.9 percent previously. Another consequence of the expansion of poaching vacancies is the outward movement of the Beveridge curve, which suggests that a coexistence of a 6% vacancy rate (rather than 4% vacancy rate) with a 4% unemployment rate may be the new normal. Consequently, a monetary tightening in the 2020s is likely to lead to a larger decline in job openings corresponding to a milder increase in the unemployment rate, consistent with a notion of a "soft landing."

The future is uncertain, however. The interpretation of the most recent behavior of the Beveridge curve depends on the reason for the expansion in poaching vacancies and whether it is likely to continue. Among the possible explanations are both factors that reduced the costs associated with filling vacancies and factors that increased their benefits to firms. The first set of factors includes the effects of the expansion of online job search tools and increased use of AI (Acemoglu et al, 2022), the expansion of available temporary and remote work (Bloom et al, 2023), and the expansion of the online gig economy (Stanton and Thomas, 2021).



Figure 8: Detrended vacancies and quits.

The second set of factors could include rising market concentration and markups (Autor et al, 2020, De Loecker et al, 2020) and the associated expansion of monopsony power of firms (Azar et al, 2019, Berger et al, 2022). If some of these factors are at play, the expansion of poaching vacancies could continue for as long as these trends continue. Therefore, more changes in monetary policy could be absorbed by poaching vacancies, with little impact on non-poaching vacancies and only a small increase in unemployment.

Alternatively, the expansion of poaching vacancies could be due to a reduction in mis-measurement: according to Davis et al. (2013), as of 2011, 42% of hires occurred at establishments that did not have any job openings. If those firms have gradually improved their reporting of vacancies that had not been reported previously, then the aggregate Beveridge curve has shifted outward, but there are limits to such an expansion. In this case, the Beveridge curve will stabilize at a new level and slope.

The main lesson from our exercise, however, is that instead of looking at the classical Beveridge curve

and interpreting its increasingly chaotic movements, we should shift our attention to the adjusted Beveridge curve, which is unlikely to change much, and will therefore remain a good indicator of the state of the labor market going forward.

In addition to clarifying how to interpret the Beveridge curve, our model also offers a practical tool for disentangling structural and cyclical components in key labor market indicators. Because the estimated trends in poaching and non-poaching profitability reflect slow-moving changes in firm hiring strategies, we can use them to construct detrended versions of observed series such as vacancies and quits. Figure 8 shows the raw and adjusted vacancy and quits series after removing the structural trend components implied by our estimated model. This adjustment reveals that much of the increase in aggregate vacancies in recent years reflects long-term shifts in vacancy composition, rather than heightened cyclical labor demand. These adjusted series may serve as more reliable indicators for short-run policy analysis going forward.⁴

Another important takeaway point is that economists and statistical agencies need to put resources into more and better measurement of the vacancy split, between vacancies targeting unemployed workers and vacancies designed for hiring workers that already have a job. Surveys of firms conducted by statistical agencies could ask the firms a question that would shed light on this issue and enable direct measurement of the vacancy split. Such measurement would both enable the development of better theoretical models and a better real-time assessment of the state of the labor market.

Declaration of Generative AI and AI-assisted technologies in the writing process During the preparation of this work the authors used OpenAI in order to improve readability and language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

8 References

- Acemoglu, Daron, Autor, David, Hazell, Jonathon, and Pascual Restrepo (2022) "Artificial Intelligence and Jobs: Evidence from Online Vacancies," Journal of Labor Economics, 40 (S1), pp. S293–S340. DOI: https://doi.org/10.1086/718327
- Ahn, Hie Joo and Leland D. Crane (2020) "Dynamic Beveridge Curve Accounting," BOG DP No. 2020-027, DOI: https://doi.org/10.17016/FEDS.2020.027
- Ahn, Hie Joo, Hobijn, Bart and Ayşegül Şahin (2022) "The Dual U.S. Labor Market Uncovered," mimeo, DOI: https://doi.org/10.20955/wp.2022.021
- An, Sunbae and Frank Schorfheide (2007) "Bayesian analysis of DSGE models," Econometric Reviews, 26 (2-4), 113-172. DOI: https://doi.org/10.1080/07474930701220071

⁴While our adjusted vacancy and quit series are not intended as real-time policy tools, they provide a proof of concept for improving cyclical indicators by accounting for the composition of labor demand. Future work could explore operationalizing this adjustment using higher-frequency job posting data.

- Autor, David, Dorn, David, Katz, Lawrence F., Patterson, Christina, and John Van Reenen (2020)
 "The Fall of the Labor Share and the Rise of Superstar Firms." The Quarterly Journal of Economics, 135 (2), pp. 645–709. DOI: https://doi.org/10.1093/qje/qjaa004
- Azar, José, Marinescu, Ioana, and Marshall Steinbaum (2019) "Measuring Labor Market Power Two Ways" AEA Papers and Proceedings, 109, pp. 317–321. DOI: https://doi.org/10.1257/pandp.20191068
- Barnichon, Regis (2010) "Building a composite Help-Wanted Index" Economics Letters, 109(3), pp. 175-178. DOI: https://doi.org/10.1016/j.econlet.2010.08.029
- Berger, David W., Herkenhoff, Kyle F. and Simon Mongey (2022) "Labor Market Power" American Economic Review, 112(4), pp. 1147–1193. DOI: https://doi.org/10.1257/aer.20191521
- Beveridge, William H. (1944) Full Employment in a Free Society. New York: W. W. Norton & Company, DOI: https://doi.org/10.4324/9781315737348
- Birinci, Serdar, See, Kurt and Shu Lin Wee (2024) "Job Applications and Labour Market Flows" Review of Economic Studies, forthcoming. DOI: https://doi.org/10.1093/restud/rdae064
- Blanchard, Olivier, Domash, Alex and Lawrence H. Summers (2022) "The Fed is wrong: Lower inflation is unlikely without raising unemployment," PIIE Realtime Economic Issues Watch, August 2022, DOI: http://dx.doi.org/10.2139/ssrn.4174601
- Bloom, Nicholas, Davis, Steven J., Hansen, Stephen, Lambert, Peter John, Sadun, Raffaella, and Bledi Taska (2023) "Remote Work across Jobs, Companies, and Space" NBER Working Paper No. 31007. DOI: http://doi.org/10.3386/w31007
- Bonthuis, Boele, Jarvis, Valerie and Juuso Vanhala (2016) "Shifts in Euro Area Beveridge Curves and Their Determinants," IZA Journal of Labor Policy, 5 (20), 1-17, DOI: https://doi.org/10.1186/s40173-016-0076-7
- Broersma, Lourens, and Jan C. Van Ours (1999) "Job searchers, job matches and the elasticity of matching" Labour Economics, 6(1), pp. 77-93. DOI: https://doi.org/10.1016/S0927-5371(98)00017-7
- Cheremukhin, A., Restrepo-Echavarria P. and A. Tutino (2020) ""Targeted Search in Matching Markets." Journal of Economic Theory, vol 185, pp. 1-43. DOI: https://doi.org/10.1016/j.jet.2019.104956
- Crump, Richard K., Stefano Eusepi, Marc Giannoni, and Ayşegül Şahin (2019): "A Unified Approach to Measuring u*," Brookings Papers on Economic Activity. DOI: https://doi.org/10.3386/w25930
- Davis, Steven J., Faberman, R. Jason and John C. Haltiwanger (2013) "The Establishment-Level Behavior of Vacancies and Hiring," The Quarterly Journal of Economics, 128(2), 581-622, DOI: https://doi.org/10.1093/qje/qjt002
- De Loecker, Jan, Eeckhout, Jan, and Gabriel Unger (2020) "The Rise of Market Power and the Macroeconomic Implications." The Quarterly Journal of Economics, 135 (2), pp. 561–644. DOI: https://doi.org/10.1093/qje/qjz041

- Diamond, Peter A. and Ayşegül Şahin (2014) "Shifts in the Beveridge curve," Staff Reports 687, FRB NY, DOI: http://dx.doi.org/10.2139/ssrn.2488141
- Dow, J.C.R. and L.A. Dicks-Mireaux (1958) "The Excess Demand for Labour. A Study of Conditions in Great Britain, 1946-56." Oxford Economic Papers, 10 (1), 1-33, DOI: https://doi.org/10.1093/oxfordjournals.oep.a040791
- 21. Ellieroth, Kathrin and Amanda M. Michaud (2024) "Quits, Layoffs, and Labor Supply." OIGI Working Papers 094, Federal Reserve Bank of Minneapolis.
- 22. Elsby, Michael W. L., Gottfries, Axel, Michaels, Ryan and David Ratner (2025) "Vacancy Chains," Journal of Political Economy, forthcoming. DOI: https://doi.org/10.7910/ DVN/HMRU7M
- 23. Elsby, Michael W. L., Michaels, Ryan and David Ratner (2015) "The Beveridge Curve: A Survey," Journal of Economic Literature, 53(3), 571-630, DOI: https://doi.org/10.1257/jel.53.3.571
- 24. Faberman, R. Jason, Mueller, Andreas I., Şahin, Ayşegül and Giorgio Topa (2022) "Job Search Behavior Among the Employed and Non-Employed," Econometrica, 90: 1743-1779, DOI: https://doi.org/10.3982/ECTA18582
- 25. Figura, Andrew, and Chris Waller (2022) "What does the Beveridge curve tell us about the likelihood of a soft landing?" BOG Fed Notes, July 2022, DOI: https://doi.org/10.17016/2380-7172.3190
- 26. Fujita, Shigeru and Makoto Nakajima (2016) "Worker flows and job flows: A quantitative investigation," Review of Economic Dynamics, vol. 22, pp. 1-20, DOI: https://doi.org/10.1016/j.red.2016.06.001
- 27. Fujita, Shigeru and Moscarini, Giuseppe and Fabien Postel-Vinay (2024) "Measuring Employer-to-Employer Reallocation," American Economic Journal: Macroeconomics, 16(3), pp. 1-51, DOI: https:// doi.org/10.1257/mac.20210076
- Geweke, J. (1999). "Using simulation methods for bayesian econometric models: inference, development and communication," Econometric Reviews, 18 (1), 1–126. DOI: https://doi.org/10.1080/ 07474939908800428
- Gottfries, Nils and Karolina Stadin (2024). "The Beveridge Curve, Matching, and Labour Market Flows: A Reinterpretation," CESifo Working Paper Series 7689, CESifo.
- Hall, Robert E. and Marianna Kudlyak (2020) "Job-Finding and Job-Losing: A Comprehensive Model of Heterogeneous Individual Labor-Market Dynamics," FRB SF WP No. 2019-05, DOI: https://doi.org/10.24148/wp2019-05
- Hobijn, Bart and Ayşegül Şahin (2012) "Beveridge Curve Shifts across Countries since the Great Recession," FRB SF WP No. 2012-24, DOI: https://doi.org/10.24148/wp2012-24
- 32. Lubik, Thomas A. (2021) "Revisiting the Beveridge Curve: Why has it shifted so Dramatically," FRB Richmond, Economic Brief No. 21-36, October.

- Menzio, Guido and Shouyong Shi (2011) "Efficient Search on the Job and the Business Cycle," Journal of Political Economy, 119 (3), pp. 468-510. DOI: https://doi.org/10.1086/660864
- 34. Mercan, Yusuf and Benjamin Schoefer (2020) "Jobs and Matches: Quits, Replacement Hiring, and Vacancy Chains," American Economic Review: Insights, 2 (1), pp. 104-124. DOI: https://doi.org/10.1257/ aeri.20190023
- 35. Molloy, Raven, Christopher L. Smith, Riccardo Trezzi, and Aabigail Wozniak (2016): "Understanding Declining Fluidity in the U.S. Labor Market," Brookings Papers on Economic Activity. DOI: https://doi.org/10.1353/eca.2016.0015
- 36. Mongey, Simon and Jeff Horwich (2024): "Fewer openings, harder to get hired: U.S. labor market likely softer than it appears" Federal Reserve Bank of Minneapolis article, September 5, 2024.
- 37. Mortensen, Dale T. and Christopher A. Pissarides (1994) "Job Creation and Job Destruction in the Theory of Unemployment," Review of Economic Studies, 61(3), 397-415, DOI: https://doi.org/10.2307/ 2297896
- 38. Pissarides, Christopher A. and Barbara Petrongolo (2001) "Looking into the Black Box: A Survey of the Matching Function," Journal of Economic Literature, 39(2), 390-431, DOI: https://doi.org/10.1257/jel.39.2.390
- Pissarides, Christopher A. (1985). "Short-Run Equilibrium Dynamics of Unemployment, Vacancies, and Real Wages." American Economic Review, 75(4), pp. 676-690. DOI: https://www.jstor.org/stable/1821347
- Pissarides, Christopher A. (2000). Equilibrium Unemployment Theory. 2nd ed., Cambridge, MA, MIT Press.
- 41. Qiu, Xincheng (2022) "Vacant Jobs" University of Pennsylvania, unpublished manuscript.
- 42. Rodgers, William M. and Alice L. Kassens (2022) "What Does the Beveridge Curve Tell Us about the Labor Market Recovery?" FRB SL, On The Economy Blog, July 2022.
- Şahin, Ayşegül, Song, Joseph, Topa, Giorgio and Giovanni L. Violante (2014) "Mismatch Unemployment" American Economic Review, 104(11), pp. 3529-3564. DOI: https://doi.org/10.1257/aer.104.11.3529
- 44. Stanton, Christopher T. and Catherine Thomas (2021) "Who Benefits from Online Gig Economy Platforms?" NBER Working paper 29477. DOI: https://doi.org/10.3386/w29477

Appendix A: Full Model

Main equations for endogenous variables:

(1)	$m_t^u = B_t^{u,tr} u_t^\alpha v_{u,t}^{1-\alpha} \left(1 + A_t \right)$	$u\left(\frac{v_{\varepsilon,t}}{v_{u,t}}\right)^{\gamma} + B_L n_t^{\psi} u$	$y_t^{1-\psi}$	matching of unemployed
(2)	$m_t^{\varepsilon} = B_t^{\varepsilon, tr} h_t^{\beta} v_{\varepsilon, t}^{1-\beta} \left(1 + A_{\varepsilon} \right)$	$\left(\frac{v_{u,t}}{v_{\varepsilon,t}}\right)^{\gamma}$ n	natching	g of employed
(3)	$v_{u,t} + v_{\varepsilon,t} = v_t$	vacancy split		
(4)	$h_t = e_t - \xi_t e_t^*$	search effort of emp	ployed	
(5)	$e_t + u_t = 1$	labor force identi	ity	
(6)	$e_{t+1}\delta_{l,t} = e_t\left(1 - s_t\right) + m_t^u$	evolution of em	ploymer	nt
(7)	$v_{u,t} = m_t^u y_t$	free entry of nor	n-poachi	ng vacancies
(8)	$v_{\varepsilon,t} = m_t^{\varepsilon} z_t$	free entry of poa	ching va	acancies

Exogenous variables of the model:

(9)	$s_t = s_t^{tr} \exp \varphi_{1t}$	separation shock
(10)	$y_t = y_t^{tr} \exp\left(d_y x_t\right) \exp\varphi_{2t}$	low skill productivity shock
(11)	$z_t = z_t^{tr} \exp x_t \exp \varphi_{3t}$	high skill productivity shock
(12)	$\xi_t = \xi_0 \exp \varphi_{4t}$	share of ss employed that do not search
(13)	$\delta_{l,t} = \delta_{l0} \exp \varphi_{5t}$	growth rate of labor force
(14)	$n_t = n_0 \exp \varphi_{6t}$	evolution of not in the labor force
(15)	$e_t^* = e_0^* \exp \varphi_{7t}$	evolution of hp-filtered employment

Log-linearized version of the model (relative to trend, to be described below):

(1)
$$\widehat{m}_t^u = \alpha \widehat{u}_t + (1 - \alpha) \,\widehat{v}_{u,t} + c_u \gamma \left(\widehat{v}_{\varepsilon,t} - \widehat{v}_{u,t}\right) + b_L \left(\psi \widehat{n}_t + (1 - \psi) \,\widehat{v}_t\right)$$

(2)
$$\widehat{m}_{t}^{\varepsilon} = \beta \widehat{h}_{t} + (1 - \beta) \,\widehat{v}_{\varepsilon,t} + c_{\varepsilon} \gamma \left(\widehat{v}_{u,t} - \widehat{v}_{\varepsilon,t}\right)$$

(13)	$\widehat{\delta}_{l,t} = \varphi_{5t}$	growth rate of labor force

- (14) $\widehat{n}_t = \varphi_{6t}$ evolution of not in the labor force
- (15) $\hat{e}_t^* = \varphi_{7t}$ evolution of hp-filtered employment

Evolution of shocks:

$$\begin{aligned} x_t &= \rho_1^x x_{t-1} + \rho_2^x x_{t-2} + \sigma^x \varepsilon_t^x \qquad \text{common component of productivity in both sectors} \\ \varphi_{it} &= \rho_i^{\varphi} \varphi_{it-1} + \sigma_i^{\varphi} \varepsilon_{it}^{\varphi} \qquad \text{unknown shocks} \qquad i = [1, 7] \end{aligned}$$

Measurement equations:

(M1) $\widetilde{u}_t = \widehat{u}_t + \omega_{1t}$ unemployment rate $\widetilde{v}_t = \widehat{v}_t + \omega_{2t}$ vacancy rate (M2) $\widetilde{m}_t^u = \widehat{m}_t^u + \omega_{3t}$ hires-quits/LF, UE flow/LF (M3)(M4) $\widetilde{m}_t^{\varepsilon} = \widehat{m}_t^{\varepsilon} + \omega_{4t}$ quits/LF, EE flow/LF $\widetilde{s}_t = \widehat{s}_t + \omega_{5t}$ Layoffs/Employment, EU flow/Employment (M5) $\widetilde{e}e_t = \widehat{m}_t^{\varepsilon} - \widehat{e}_t + \omega_{6t}$ E-E rate, version 0 (M6)(M6') $\widetilde{ee}_t = \widehat{m}_t^{\varepsilon} - \widehat{h}_t + \omega_{6t}$ E-E rate, version 1 $\widetilde{\delta}_{l,t} = \widehat{\delta}_{l,t} + \omega_{7t} \qquad \frac{LF_t}{LF_{t+1}}$ (M7)growth rate of labor force $\widetilde{n}_t = \widehat{n}_t + \omega_{8t}$ $\frac{N_t}{LF_t}$ out of the labor force rate (M8) $\tilde{e}_t^* = \hat{e}_t^* + \omega_{9t}$ hp-filtered (1000000) employment rate (M9)

Measurement errors:

$$\omega_{jt} = \sigma_j^{\omega} \varepsilon_{jt}^{\omega}$$
 white noise measurement errors $j = [1, 9]$

Endogenous variables:

$$\widehat{e}_{t}, \widehat{u}_{t}, \widehat{v}_{u,t}, \widehat{v}_{\varepsilon,t}, \widehat{v}_{t}, \widehat{m}_{t}^{u}, \widehat{m}_{t}^{\varepsilon}, \widehat{h}_{t}, \widehat{s}_{t}, \widehat{y}_{t}, \widehat{z}_{t}, \widehat{\xi}_{t}, \widehat{\delta}_{l,t}, \widehat{n}_{t}, \widehat{e}_{t}^{*}$$

$$\widetilde{u}_{t}, \widetilde{v}_{t}, \widetilde{m}_{t}^{u}, \widetilde{m}_{t}^{\varepsilon}, \widetilde{s}_{t}, \widetilde{e}_{t}, \widetilde{\delta}_{l,t}, \widetilde{n}_{t}, \widetilde{e}_{t}^{*}$$

$$(15)$$

Exogenous variables: x_t, φ_{it}

41 equations, 41 variables, 17 shocks

Estimated parameters: $\alpha, \beta, \gamma, c_u, c_{\varepsilon}, \psi, b_L, \rho_1^x, \rho_2^x, \sigma^x, \rho_i^{\varphi}, \sigma_i^{\varphi}, \sigma_j^{\omega}$

Calibrated parameters: $\phi = 0.45, \xi_0 = 0.78, u_0 = 0.04, s_0 = 0.013, \sigma_i^{\omega} = 0.03$ for $i \in [1, 6], \sigma_i^{\omega} = 0.005$ for $i \in [7, 9]$

We allow for non-linear trends in the data series. More specifically, we assume that underlying shocks are the source of trends, and derive the correspondence to the trends in the data. We then estimate trends in the data from which we infer parameters of trends in the underlying shocks. We assume the following trends in shock variables:

$$B_t^{u,tr} = B_0^u \exp(-a_u t) \qquad B_t^{\varepsilon,tr} = B_0^\varepsilon \exp(-a_\varepsilon t)$$

$$s_t^{tr} = s_0 \exp(-a_s t) \qquad y_t^{tr} = y_0 \exp(a_y t) \qquad z_t^{tr} = z_0 \exp\left(a_z \left[t - \tau\right]_+\right)$$

If we substitute these trends into equations (1 - 15), we can derive the following trend properties of observed variables:

$$\widetilde{m}_{u,t}^{tr} = -a_s t \qquad \qquad \widetilde{s}_t^{tr} = -a_s t$$

Estimate $-a_s$ as average of the regression coefficients of $\ln m_{u,t}$ and $\ln s_t$ on a constant and time trend.

$$\widetilde{u}_t^{tr} = (1 - u_0) \left(-a_s + \frac{a_u}{\alpha} + \frac{\alpha - 1}{\alpha} a_y \right) t$$

Estimate $\left(-a_s + \frac{a_u}{\alpha} + \frac{\alpha - 1}{\alpha}a_y\right)$ as $\frac{1}{(1 - u_0)}$ of the regression coefficient $\ln u_t$ on a const and time trend. $\widetilde{v}_t^{tr} = \phi \left(-a_s + a_y\right)t + (1 - \phi)\left(-\frac{1}{\beta}a_{\varepsilon}t + \frac{1}{\beta}a_z\left[t - \tau\right]_+ - u_0\left(-a_s + \frac{a_u}{\alpha} + \frac{\alpha - 1}{\alpha}a_y\right)t\right)$ $\widetilde{m}_{\varepsilon,t}^{tr} = -\frac{1}{\beta}a_{\varepsilon}t + \frac{1 - \beta}{\beta}a_z\left[t - \tau\right]_+ - u_0\left(-a_s + \frac{a_u}{\alpha} + \frac{\alpha - 1}{\alpha}a_y\right)t$

We can use the parameters we already measured from other series to derive that

$$\frac{\widetilde{v}_t^{tr} - \phi(-a_s + a_y)}{(1 - \phi)} - \widetilde{m}_{\varepsilon, t}^{tr} = a_z \left[t - \tau \right]_+$$

If we assume a value for a_y (we set it to 0), use the calibrated steady-state share of non-poaching vacancies ϕ , then we can directly measure the trend in $\ln z_t$ as the trend in the difference between the rescaled log vacancies and log EE matches. We estimate a break in this trend in τ = December 2010 and therefore obtain estimates of a_{ϵ} and a_z . Given all the trend parameters $a_s, a_u, a_y, a_{\epsilon}, a_z, \tau$, we can subtract the trends from the measured series to obtain

$$\begin{split} \widetilde{u}_t &= \ln u_t - (1 - u_0) \left(-a_s + \frac{a_u}{\alpha} + \frac{\alpha - 1}{\alpha} a_y \right) t \\ \widetilde{v}_t &= \ln v_t - \phi \left(-a_s + a_y \right) t - (1 - \phi) \left(-\frac{1}{\beta} a_\varepsilon t + \frac{1}{\beta} a_z \left[t - \tau \right]_+ - u_0 \left(-a_s + \frac{a_u}{\alpha} + \frac{\alpha - 1}{\alpha} a_y \right) t \right) \\ \widetilde{m}_t^u &= \ln m_t^u - a_s t \\ \widetilde{m}_t^\varepsilon &= \ln m_t^\varepsilon + \frac{1}{\beta} a_\varepsilon t - \frac{1 - \beta}{\beta} a_z \left[t - \tau \right]_+ + u_0 \left(-a_s + \frac{a_u}{\alpha} + \frac{\alpha - 1}{\alpha} a_y \right) t \\ \widetilde{s}_t &= \ln s_t - a_s t \\ \widetilde{e}_t &= \ln ee_t + \frac{1}{\beta} a_\varepsilon t - \frac{1 - \beta}{\beta} a_z \left[t - \tau \right]_+ + u_0 \left(-a_s + \frac{a_u}{\alpha} + \frac{\alpha - 1}{\alpha} a_y \right) t + \frac{u_0}{1 - u_0} a_s t \\ \widetilde{\delta}_{l,t} &= \ln \delta_{l,t} \\ \widetilde{h}_t &= \ln n_t \\ \widetilde{e}_t^* &= \ln e_t^* \end{split}$$

All of the series are then de-meaned to be consistent with a steady-state value of zero.

Appendix B: Identification

The log-linearized model (1-15) can be separated into the endogenous block, containing equations (1, 2, 3, 7, 8) and the exogenous block containing the rest of the equations. Because through equation (6) employment \hat{e}_t is the state variable of the model determined one period in advance, and through equation (5) the same is true for unemployment \hat{u}_t , and so the search effort \hat{h}_t is also exogenous through equation (4), they can be all substituted in to obtain the following system of equations.

(1)
$$(1 - \alpha - c_u \gamma) \,\widehat{v}_{u,t} + c_u \gamma \widehat{v}_{\varepsilon,t} = \widehat{m}_{u,t} - \alpha \widehat{u}_t - b_L \psi \widehat{n}_t - b_L \left(1 - \psi\right) \widehat{v}_t$$

(2)
$$(1 - \beta - c_{\varepsilon}\gamma)\,\widehat{v}_{\varepsilon,t} + c_{\varepsilon}\gamma\widehat{v}_{u,t} = \widehat{m}_{\varepsilon,t} + \beta \frac{u_0}{1 - u_0} \frac{1}{1 - \xi_0}\widehat{u}_t + \beta \frac{\xi_0}{1 - \xi_0}\widehat{\xi}_t$$

(3)
$$\phi \widehat{v}_{u,t} + (1-\phi) \widehat{v}_{\varepsilon,t} = \widehat{v}_t$$

(7)
$$\widehat{v}_{u,t} = \widehat{m}_{u,t} + \widehat{y}_t$$

(8)
$$\widehat{v}_{\varepsilon,t} = \widehat{m}_{\varepsilon,t} + \widehat{z}_t$$

This system can be written in matrix form as follows:

$\left[1 - \alpha - \gamma c_u \right]$	γc_u	0	0	0	v_u		$b_L \psi$	$-\alpha$	$-b_L(1-\psi)$	1	0	n
γc_{ε}	$1-\beta-\gamma c_{\varepsilon}$	0	0	$-a_{2}$	v_{ε}		0	a_1	0	0	1	u
ϕ	$1-\phi$	0	0	0	y	=	0	0	1	0	0	v
1	0	-1	0	0	z		0	0	0	1	0	m_u
0	1	0	-1	0	ξ		0	0	0	0	1	m_{ε}

where we denoted $a_1 = \beta \frac{u_0}{1-u_0} \frac{1}{1-\xi_0}$ $a_2 = \beta \frac{\xi_0}{1-\xi_0}$. This form can be used to understand the mapping from observables to unobservables. Inverting the system (and assuming $b_L = 0$, we obtain:

$$\begin{vmatrix} v_u \\ v_\varepsilon \\ y \\ z \\ \xi \end{vmatrix} = \begin{vmatrix} 0 & -\alpha \left(1-\phi\right) D & -\gamma c_u D & D \left(1-\phi\right) & 0 \\ 0 & \alpha \phi D & \left(1-\alpha-\gamma c_u\right) D & -\phi D & 0 \\ 0 & -\alpha \left(1-\phi\right) D & -\gamma c_u D & D \left(1-\phi\right)-1 & 0 \\ 0 & \alpha \phi D & \left(1-\alpha-\gamma c_u\right) D & -\phi D & -1 \\ 0 & \frac{\alpha G-a_1}{a_2} D & \frac{F}{a_2} D & -\frac{G}{a_2} D & -\frac{1}{a_2} D \end{vmatrix} \begin{vmatrix} n \\ u \\ v \\ m_u \\ m_\varepsilon \end{vmatrix}$$
where $D = \frac{1}{\left(1-\phi\right)\left(1-\alpha\right)-\gamma c_u}, F = \left(\left(1-\beta\right)\left(1-\alpha\right)-\gamma c_u \left(1-\beta\right)-\gamma c_\varepsilon \left(1-\alpha\right)\right), G = \left(\left(1-\beta\right)\phi-\gamma c_\varepsilon\right)$

From this expression we can deduce how the vacancy split (on the left) and parameters are identified from properties of the data (on the right). The series for both types of vacancies, v_u and v_{ϵ} , and the shock y only depend on the number of matches made by unemployed, the number of unemployed and the total number of vacancies. Since vacancies and unemployment are quite volatile compared with the matching rate for the unemployed, the estimated model tends to give low estimates of parameters c_u and α . It is notable that none of the variables v_u, v_{ϵ}, y, z depend on the behavior of out of the labor force, or the parameters $\beta, c_{\epsilon}, \psi, b_L$. The high estimate of β is likely determined by the fact that it only enters in the last line determining the search effort of the employed always in the form $1 - \beta$. Making β close to 1, and therefore this value close to zero, minimizes the variance of the unobserved search effort.

The system of 5 equations can also be written to determine endogenous variables as a function of exogenous variables:

$(1 - \alpha - c_u \gamma)$	$c_u\gamma$	$b_L \left(1 - \psi\right)$	-1	0	v_u		$-\alpha$	0	0	0	$-b_L\psi$	[u
$c_{arepsilon}\gamma$	$(1 - \beta - c_{\varepsilon}\gamma)$	0	0	-1	v_{ε}		a_1	0	0	a_2	0		y
ϕ	$1-\phi$	-1	0	0	v	=	0	0	0	0	0		z
1	0	0	-1	0	m_u		0	1	0	0	0		ξ
0	1	0	0	$^{-1}$.	m_{ε}		0	0	1	0	0		n

This system can also be inverted in closed form (we again assume $b_L = 0$ for simplicity):

$$\begin{bmatrix} v_{u} \\ v_{\varepsilon} \\ v \\ m_{u} \\ m_{\varepsilon} \end{bmatrix} = E \cdot \begin{bmatrix} \alpha(\beta + \gamma c_{\varepsilon}) - a_{1}\gamma c_{u} & \beta + \gamma c_{\varepsilon} & \gamma c_{u} & \gamma c_{u} & 0 \\ \alpha\gamma c_{\varepsilon} - a_{1}(\alpha + \gamma c_{u}) & \gamma c_{\varepsilon} & \alpha + \gamma c_{u} & \alpha + \gamma c_{u} & 0 \\ \alpha(\beta + \gamma c_{\varepsilon}) - & & & \\ a_{1}(\alpha(1 - \phi) + \gamma c_{u}) & \beta\phi + \gamma c_{\varepsilon} & \gamma c_{u} + \alpha(1 - \phi) & \gamma c_{u} + \alpha(1 - \phi) & 0 \\ & & \beta(1 - \alpha - \gamma c_{u}) \\ \alpha\gamma c_{\varepsilon} - a_{1}\gamma c_{u} & + \gamma c_{\varepsilon}(1 - \alpha) & \gamma c_{u} & \gamma c_{u} & 0 \\ & & & \alpha(1 - \beta - \gamma c_{\varepsilon}) \\ \alpha\gamma c_{\varepsilon} - a_{1}(\alpha + \gamma c_{u}) & \gamma c_{\varepsilon} & + \gamma c_{u}(1 - \beta) & \alpha + \gamma c_{u} & 0 \end{bmatrix} \begin{bmatrix} u \\ y \\ z \\ -a_{2}\xi \\ n \end{bmatrix}$$

where we denoted $E = \frac{1}{\alpha\beta + \beta\gamma c_u + \alpha\gamma c_{\varepsilon}}$. When c_{ε} and c_u approach 0, this further simplifies to:

$$\begin{array}{c} v_{u} \\ v_{\varepsilon} \\ v \\ m_{u} \\ m_{\varepsilon} \end{array} \right] = \left[\begin{array}{ccccc} 1 & \frac{1}{\alpha} & 0 & 0 & 0 \\ -\frac{a_{1}}{\beta} & 0 & \frac{1}{\beta} & \frac{1}{\beta} & 0 \\ 1 - \frac{a_{1}(1-\phi)}{\beta} & \frac{\phi}{\alpha} & \frac{1-\phi}{\beta} & \frac{1-\phi}{\beta} & 0 \\ 0 & \frac{1-\alpha}{\alpha} & 0 & 0 & 0 \\ -\frac{a_{1}}{\beta} & 0 & \frac{1-\beta}{\beta} & \frac{1}{\beta} & 0 \end{array} \right] \left[\begin{array}{c} u \\ y \\ z \\ -a_{2}\xi \\ n \end{array} \right]$$

It is clear that v_u and m_u are driven only by u and y. The parameter c_u controls the spillovers from z. The remaining vacancies, as well as matches of the employed, are in addition affected by z and ξ , and the strength of these effects are controlled by parameters β and c_{ϵ} . Parameter ϕ enters to determine total vacancies as the sum of the two types.

Appendix C: Estimation Results

In Figure 9 and Tables 6 and 7 we report the estimates of parameters. We estimate α to be low (in the 0.1-0.2 range) and β to be high (in the 0.8-1 range). Figures 10-11 report the fit to the data and the estimated shocks for two most important specifications, when data are taken from the CPS or from JOLTS, and Figure 4 shows the estimated of the vacancy split and profit-cost ratios, with averages and confidence bounds over all six estimated specifications. All specifications find that the share of poaching vacancies increased after 2010 and that this was driven by an increase in the profit-cost

ratio for poaching vacancies. Estimates of parameters with restrictions on the matching functions are presented in Tables 8 and 9.

We estimate the same specification of the model for 12 two-digit sectors of the economy using the JOLTS version of the data (as the only one available for the sectors). Estimates of parameters, reported in Figure 12, show that estimates for the sectors are largely consistent with the aggregate estimates. The behavior of the underlying shocks, illustrated for the manufacturing, business services, trade, transportation and utilities, and health and education services in Figures 13-16 show the same general pattern for the shocks as for the overall economy.



Figure 9: Prior and Posterior Estimates of Parameters for 6 estimation setups.



Figure 10: Model Fit and Shocks for CPS-A estimation.



Figure 11: Model Fit and Shocks for JOLTS-A estimation.

Parameter	P	rior			Posterio	r		
	mean	st.dev.	mode	mean	st. dev.	conf. int. [5-95]		
α	0.5	0.2	0.179	0.182	0.020	[0.150, 0.214]		
eta	0.8	0.1	0.967	0.961	0.012	[0.938, 0.984]		
γ	0.5	0.2	0.106	0.079	0.036	[0.008, 0.148]		
c_u	0.2	0.1	0.026	0.029	0.008	[0.011, 0.045]		
c_ϵ	0.2	0.1	0.065	0.102	0.029	[0.018, 0.178]		
ψ	0.5	0.2	0.74	0.70	0.09	[0.44, 0.97]		
b_L	0.2	0.1	0.091	0.078	0.031	[0.016, 0.135]		
d_y	0.5	0.2	0.20	0.23	0.06	[0.14, 0.32]		
$ ho^x$	0.5	0.2	0.90	0.86	0.08	[0.74, 0.98]		
$ ho_2^x$	0.0	0.5	0.08	0.13	0.08	[0.01, 0.25]		
σ^x	0.05	0.02	0.024	0.024	0.004	[0.018, 0.029]		
$ ho_1^{arphi}$	0.9	0.03	0.81	0.81	0.012	[0.77, 0.85]		
$ ho_2^{arphi}$	0.5	0.2	0.47	0.48	0.05	[0.38, 0.58]		
$ ho_3^{arphi}$	0.5	0.2	0.955	0.953	0.015	[0.932, 0.973]		
$ ho_4^{arphi}$	0.5	0.2	0.15	0.13	0.05	[0.05, 0.21]		
$ ho_5^{arphi}$	0.1	0.03	0.08	0.08	0.02	[0.04, 0.12]		
$ ho_6^{arphi}$	0.9	0.03	0.950	0.948	0.010	[0.931, 0.965]		
$ ho_7^{arphi}$	0.9	0.03	0.928	0.936	0.011	[0.915, 0.960]		
σ_1^{arphi}	0.1	0.05	0.118	0.118	0.005	[0.111, 0.126]		
σ_2^{arphi}	0.05	0.02	0.016	0.017	0.002	[0.015, 0.020]		
σ_3^{arphi}	0.1	0.05	0.081	0.082	0.004	[0.075, 0.090]		
σ_4^{arphi}	0.01	0.005	0.016	0.017	0.001	[0.015, 0.019]		
σ_6^{φ}	0.005	0.002	0.005	0.005	0.0002	[0.005, 0.006]		

Table 6: Parameter estimates of the DV model in the CPS-A specification

Notes: The priors for α , β , γ , c_u , c_{ϵ} , ψ , ρ^x , ρ^{φ}_i were drawn from a beta distribution with support on the interval [0, 1], priors for b_L and d_y were drawn from a gamma distribution with positive support, priors for σ^x and σ^{φ}_i were drawn from an inverse gamma distribution with positive support, prior for ρ^x_2 was drawn from a normal distribution.

Parameter	P	rior			Posterio	r
	mean	st.dev.	mode	mean	st. dev.	conf. int. [5-95]
α	0.5	0.2	0.119	0.123	0.042	[0.094, 0.150]
eta	0.8	0.1	0.935	0.932	0.017	[0.906, 0.959]
γ	0.5	0.2	0.021	0.028	0.020	[0.003, 0.053]
c_u	0.2	0.1	0.139	0.137	0.013	[0.115, 0.157]
c_ϵ	0.2	0.1	0.028	0.051	0.021	[0.011, 0.091]
ψ	0.5	0.2	0.421	0.501	0.098	[0.198, 0.820]
b_L	0.2	0.1	0.021	0.038	0.017	[0.008, 0.067]
d_y	0.5	0.2	0.249	0.309	0.067	[0.197, 0.426]
$ ho^x$	0.5	0.2	0.775	0.820	0.086	[0.683, 0.965]
$ ho_2^x$	0.0	0.5	0.215	0.166	0.085	[0.026, 0.307]
σ^x	0.05	0.02	0.024	0.022	0.003	[0.017, 0.026]
$ ho_1^{arphi}$	0.9	0.03	0.782	0.793	0.022	[0.757, 0.823]
$ ho_2^{arphi}$	0.5	0.2	0.235	0.255	0.319	[0.127, 0.383]
$ ho_3^{arphi}$	0.5	0.2	0.983	0.981	0.029	[0.971, 0.992]
$ ho_4^{arphi}$	0.5	0.2	0.540	0.552	0.060	[0.480, 0.628]
$ ho_5^{arphi}$	0.1	0.03	0.273	0.283	0.010	[0.230, 0.328]
$ ho_6^{arphi}$	0.9	0.03	0.940	0.943	0.008	[0.928, 0.959]
$ ho_7^{arphi}$	0.9	0.03	0.937	0.936	0.017	[0.917, 0.956]
σ_1^{arphi}	0.1	0.05	0.102	0.102	0.003	[0.097, 0.107]
σ_2^{arphi}	0.05	0.02	0.017	0.017	0.003	[0.014, 0.019]
σ^{arphi}_3	0.1	0.05	0.054	0.054	0.007	[0.048, 0.059]
σ_4^{arphi}	0.01	0.005	0.014	0.014	0.001	[0.013, 0.016]
σ_6^{arphi}	0.005	0.002	0.005	0.005	0.0002	[0.005, 0.006]

Table 7: Parameter estimates of the DV model in the JOLTS-A specification

Notes: The priors for α , β , γ , c_u , c_{ϵ} , ψ , ρ^x , ρ^{φ}_i were drawn from a beta distribution with support on the interval [0, 1], priors for b_L and d_y were drawn from a gamma distribution with positive support, priors for σ^x and σ^{φ}_i were drawn from an inverse gamma distribution with positive support, prior for ρ^x_2 was drawn from a normal distribution.

	P						
Parameter	Prior		Posterior				
	mean	st.dev.	mode	mean	st. dev.	conf. int. [5-95]	
α	0.5	0.2	0.332	0.338	0.012	[0.315, 0.360]	
ψ	0.5	0.2	0.982	0.974	0.016	[0.952, 0.996]	
b_L	0.2	0.1	0.575	0.572	0.020	[0.534, 0.612]	
d_y	0.5	0.2	0.341	0.362	0.218	[0.127, 0.573]	
$ ho^x$	0.5	0.2	0.917	0.849	0.109	[0.701, 0.990]	
$ ho_2^x$	0.0	0.5	0.052	0.100	0.103	[-0.031, 0.248]	
$ ho_1^{arphi}$	0.9	0.03	0.815	0.808	0.026	[0.769, 0.849]	
$ ho_2^{arphi}$	0.5	0.2	0.960	0.804	0.039	[0.530, 0.989]	
$ ho_3^{arphi}$	0.5	0.2	0.970	0.971	0.013	[0.956, 0.987]	
$ ho_4^{arphi}$	0.5	0.2	0.824	0.817	0.030	[0.765, 0.868]	
$ ho_5^{arphi}$	0.1	0.03	0.084	0.083	0.017	[0.047, 0.119]	
$ ho_6^{arphi}$	0.9	0.03	0.949	0.948	0.009	[0.930, 0.965]	
$ ho_7^{arphi}$	0.9	0.03	0.942	0.937	0.015	[0.917, 0.958]	
σ^x	0.05	0.02	0.029	0.028	0.003	[0.020, 0.036]	
σ_1^{arphi}	0.1	0.05	0.117	0.118	0.004	[0.111, 0.124]	
σ_2^{φ}	0.05	0.02	0.031	0.031	0.005	[0.020, 0.041]	
σ^{arphi}_3	0.1	0.05	0.052	0.054	0.005	[0.045, 0.063]	
σ_4^{arphi}	0.01	0.005	0.029	0.030	0.002	[0.027, 0.033]	
σ_6^{arphi}	0.005	0.002	0.005	0.005	0.0003	[0.005, 0.006]	

Table 8: Parameter estimates of the SMF model in the CPS-A specification

Notes: The priors for α , ψ , ρ^x , ρ^{φ}_i were drawn from a beta distribution with support on the interval [0, 1], priors for b_L and d_y were drawn from a gamma distribution with positive support, priors for σ^x and σ^{φ}_i were drawn from an inverse gamma distribution with positive support, prior for ρ^x_2 was drawn from a normal distribution.

Parameter	Prior		Posterior			
	mean	st.dev.	mode	mean	st. dev.	conf. int. [5-95]
α	0.5	0.2	0.137	0.142	0.010	[0.130, 0.153]
ψ	0.5	0.2	0.989	0.985	0.016	[0.971, 0.999]
b_L	0.2	0.1	0.473	0.465	0.012	[0.441, 0.488]
d_y	0.5	0.2	0.451	0.375	0.059	[0.152, 0.578]
$ ho^x$	0.5	0.2	0.945	0.923	0.039	[0.864, 0.987]
$ ho_2^x$	0.0	0.5	0.021	0.031	0.040	[-0.045, 0.104]
$ ho_1^{arphi}$	0.9	0.03	0.798	0.800	0.007	[0.772, 0.827]
$ ho_2^{arphi}$	0.5	0.2	0.909	0.882	0.026	[0.788, 0.976]
$ ho_3^{arphi}$	0.5	0.2	0.969	0.964	0.025	[0.943, 0.985]
$ ho_4^{arphi}$	0.5	0.2	0.973	0.973	0.011	[0.958, 0.987]
$ ho_5^{arphi}$	0.1	0.03	0.379	0.377	0.005	[0.374, 0.379]
$ ho_6^{arphi}$	0.9	0.03	0.941	0.947	0.004	[0.926, 0.969]
$ ho_7^{arphi}$	0.9	0.03	0.937	0.932	0.008	[0.910, 0.953]
σ^x	0.05	0.02	0.023	0.024	0.003	[0.020, 0.029]
σ_1^{φ}	0.1	0.05	0.101	0.101	0.003	[0.096, 0.107]
σ^{arphi}_2	0.05	0.02	0.026	0.027	0.002	[0.021, 0.033]
σ^{arphi}_3	0.1	0.05	0.038	0.038	0.003	[0.033, 0.044]
σ_4^{arphi}	0.01	0.005	0.017	0.018	0.001	[0.016, 0.020]
σ_6^{φ}	0.005	0.002	0.005	0.005	0.0001	[0.005, 0.006]

Table 9: Parameter estimates of the SMF model in the JOLTS-A specification

Notes: The priors for α , ψ , ρ^x , ρ^{φ}_i were drawn from a beta distribution with support on the interval [0, 1], priors for b_L and d_y were drawn from a gamma distribution with positive support, priors for σ^x and σ^{φ}_i were drawn from an inverse gamma distribution with positive support, prior for ρ^x_2 was drawn from a normal distribution.



Figure 12: Prior and Posterior Estimates of Parameters for 12 sectors of the economy using JOLTS data.



Figure 13: Model Fit and Shocks for Manufacturing Sector estimation.



Figure 14: Model Fit and Shocks for Trade, Transportation and Utilities estimation.



Figure 15: Model Fit and Shocks for Business Services estimation.



Figure 16: Model Fit and Shocks for Health and Education estimation.