# The Dual Beveridge Curve

Anton Cheremukhin*
Paulina Restrepo-Echavarria†

February 17, 2023

**Abstract**

This study introduces a dual vacancy model to explain the recent anomalous behavior of the Beveridge curve. The model proposes that job vacancies are partitioned into two categories, one for the unemployed and the other for job-to-job transitions, and that they function in separate markets. We estimate the monthly numbers of both job vacancy types for the U.S. economy and its subsectors starting from 2000 and find a significant surge in poaching vacancies in the mid-2010s. Our analysis indicates that the dual vacancy model provides a better fit to the data than traditional models. These findings suggest that a deceleration in worker demand can have a reduced impact on unemployment, with implications for monetary policy.

Keywords: Beveridge Curve, Vacancies, Unemployment.
JEL Codes: J23, J63, J64, E52

*Federal Reserve Bank of Dallas, chertosha@gmail.com
†Federal Reserve Bank of St. Louis, paulinares@me.com

We would like to thank Serdar Birinci, Andreas Mueller, Gianluca Violante, and several participants of the seminars at the Dallas Fed and St. Louis Fed for their insightful comments. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Reserve Banks of Dallas or St. Louis or the Federal Reserve System.

# 1 Introduction

The phenomenon of the inverse correlation between the count of jobless individuals and the count of employment opportunities throughout the business cycle in the U.S. is recognized as the Beveridge curve. This curve, introduced in the 1950s, has been employed by policymakers to evaluate the state of the labor market and to quantify the gap towards attaining maximum potential employment.

The recent behavior of the Beveridge curve exhibits a notable deviation from its past behavior during periods of economic recession, as illustrated in Figure 1. Prior observations have indicated movement along comparably sloped lines with modest intercept shifts between recessions. In the current economic downturn, the slope and intercept have undergone multiple shifts. This anomalous behavior of the Beveridge curve is difficult to explain.

Economists have naturally turned to conventional explanations that plausibly explain the gradual shifts of the curve in the past. This paper presents a novel and distinct explanation for the current perplexing behavior of the Beveridge curve: a dual vacancy model.

It is well established that firms engage in both hiring unemployed workers and recruiting workers from other firms, depending on the skill requirements of different job types and their position in the job hierarchy. Firms typically tailor their job advertisements to attract suitable candidates, leading to a division of vacancies into two categories in our model: those intended for unemployed workers and those designed to entice employees from their current positions at other firms.

The labor market is differentially affected by each type of job posting. When a job posting results in a hire from the unemployment pool, the unemployment rate decreases and the employment rate increases. Conversely, when a firm recruits an employee from another company, the worker transitions between two positions and may potentially receive a wage increase. However, this type of job posting does not have an impact on employment or unemployment rates.

Our dual vacancy model adopts a radical perspective that the two categories of job postings function in separate markets. This results in the partitioning of the overall search and matching process into two mutually exclusive processes. Specifically, unemployed workers search for and match only with job vacancies that are intended for the unemployed, whereas employed workers exclusively match with job vacancies that are open for individuals who are already employed. Given that job vacancies that target employed workers do not impact employment and unemployment, our model limits the application of the Beveridge curve relationship to the first sub-market, where unemployed workers match with job openings intended for them.

Employing the dual vacancy model and leveraging available data on labor market stocks and flows, we estimate model parameters as well as the monthly numbers of both job vacancy types, for the U.S. economy and its sub-sectors, beginning from 2000.

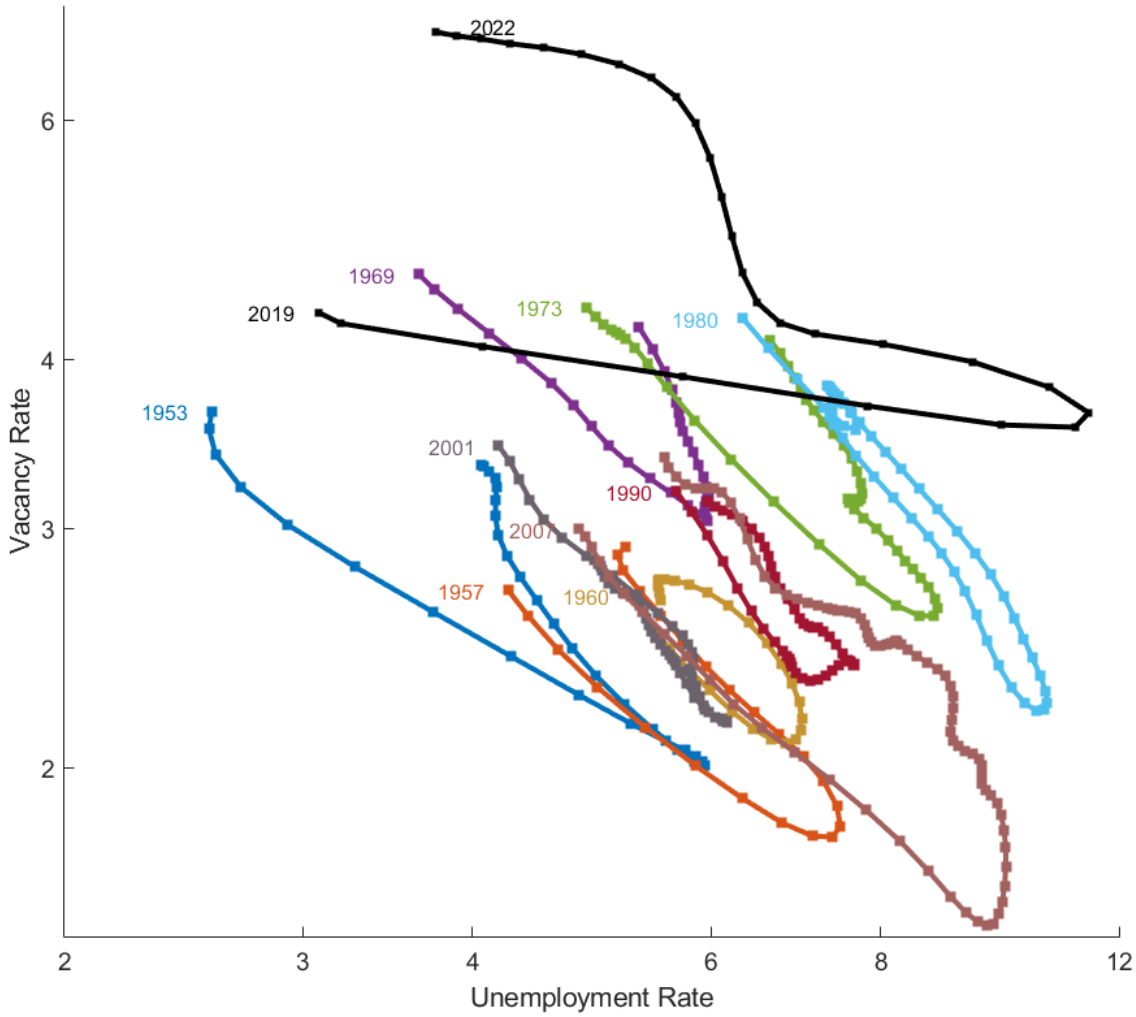


Figure 1: Beveridge Curves over Business Cycles.

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

Our findings indicate a significant and disproportionate surge in the number of poaching vacancies in the mid-2010s. When the Beveridge curve is adjusted to only include non-poaching vacancies, the anomalous behavior of the curve in recent times disappears. This result implies that a deceleration in worker demand will likely have a reduced impact on unemployment. These findings have critical implications for monetary policy and its effect on unemployment, which we discuss in greater detail in Section 6.

Our research makes contributions to three distinct areas of the literature. First, our work adds to the vast body of research on the Beveridge curve. This business cycle relationship between the numbers of unemployed and vacancies was initially observed by Beveridge (1944), with the Beveridge curve relationship first plotted by Dow and Dicks-Mireaux (1958). Numerous studies have explored the curve's significance, with surveys conducted by Elsby, Michaels, and Ratner (2015), among others. Much research has also been devoted to analyzing the shifts in the Beveridge curve, both for the U.S. (e.g., Ahn and Crane (2020), Diamond and Şahin (2014)) and for other developed countries (e.g., Bonthuis et al. (2016) and Hobijn and Şahin (2012)).

In recent years, the puzzling behavior of the Beveridge curve has sparked a lively discussion about its underlying causes and policy implications. Lubik (2021) suggests that the breakdown of the curve is due to a decline in matching efficiency caused by sectoral shifts and changes in skill requirements. Rodgers and Kassens (2022) attribute the flattening of the curve to changes in the cost of remaining unemployed and an unexpectedly large number of retirements. Another proposed explanation is that technological change has made it easier to search for a job but harder to convert a match into an offer. Regarding policy implications, Figura and Waller (2022) and Blanchard et al. (2022) offer their perspectives on the topic.

This paper contributes to the existing literature and ongoing discussion on the Beveridge curve by providing a better understanding of its behavior in the medium term, especially in the most recent episode. We also offer a novel explanation for the breakdown puzzle.

Second, our paper contributes to the literature on the matching function, eloquently summarized by Petrongolo and Pissarides (2001). Previous models have incorporated job-to-job flows into the matching process by assuming a joint matching function that combines all workers searching for a job, regardless of their employment status, with the total number of vacancies. We propose an alternative model that separates the search and matching processes for employed and unemployed workers. Our approach demonstrates a better fit to the available data (see Section 5). Furthermore, we advance the measurement of the search effort of employed workers, which enables us to estimate the coefficients of both matching functions for the U.S. economy and its sub-sectors.

Third, we contribute to the emerging literature on segmented labor markets as our analysis focuses on market segmentation on the firm side. While recent studies by Hall and Kudlyak (2020) and Ahn et al. (2022) have identified segments of the labor market that differ in behavior on the worker side, we propose a split of job openings into those designed for different types of workers. Our estimation of this split is a novel contribution to the literature.

## 2 A Simple Model

We adopt the assumption of the existence of two distinct matching functions in the labor market: one designed for unemployed workers, and the other for employed workers. Consequently, we identify two types of job openings: those designed for the unemployed, $V_t^u$, and those designed to poach from other firms, $V_t^e$. The sum of the two types of job openings in each period $t$ equals the total number of job openings, $V_t^u + V_t^e = V_t$.

In the first matching function, the unemployed, $U_t$, search for job openings (vacancies) designed for the unemployed, $V_t^u$, and get hired according to a standard constant-returns-to-scale matching function:

$$M_t^u = B^u \left(U_t\right)^{\alpha} \left(V_t^u\right)^{1-\alpha},$$

where $M_t^u$ is the number of hires from the unemployment pool, $\alpha \in (0, 1)$ is an elasticity, and $B^u$ is a parameter characterizing the efficiency of the matching process.

A subset of all employed workers, $E_t^s$, engage in on-the-job search and, hence, search for job openings designed to poach them from their current positions, $V_t^e$, and switch jobs according to a second matching function:

$$M_t^e = B^e \left(E_t^s\right)^{\beta} \left(V_t^e\right)^{1-\beta},$$

where $M_t^e$ is the number of workers who voluntarily quit their positions to join a new employer, $\beta \in (0, 1)$ is an elasticity, and $B^e$ is a parameter characterizing the efficiency of the second matching process.

# 3 Methodology

We want to be able to break down the total vacancies $V_t$, into vacancies intended for the unemployed, $V_t^u$, and vacancies intended for the employed, $V_t^e$, and estimate the matching efficiencies $B^e$, $B^u$, and the elasticities $\alpha$, and $\beta$. To do so, we use the two matching functions stipulated in Section 2, together with observed data for $M_t^e$, $M_t^u$, $U_t$, $E_t^s$, and $V_t$.

We approximate the number of hires from the employment pool, $M_t^e$, by the number of quits in the Job Openings and Labor Turnover Survey (JOLTS) data, since the majority of voluntary separations are due to job switches. The number of hires from the unemployment pool, $M_t^u$, is then equal to the difference between total hires and quits in the JOLTS data. The total number of vacancies, $V_t$ we also measure as the number of job openings from JOLTS.

The key question is how to approximate the search effort of the unemployed and of the employed workers. Theoretically, a transition rate is calculated by dividing the total number of matches by the total number of searchers. However, this calculation may not be accurate if the total number of searchers is measured imprecisely or there are systematic factors that affect their search effort. In such cases, one can estimate this unobserved search effort by measuring the difference between the ratio of the number of matches to the number of searchers and the corresponding transition rate.

The search input of the unemployed, $U_t$, is traditionally approximated by the total number of unemployed persons as reported by the Bureau of Labor Statistics (BLS). This is consistent with both

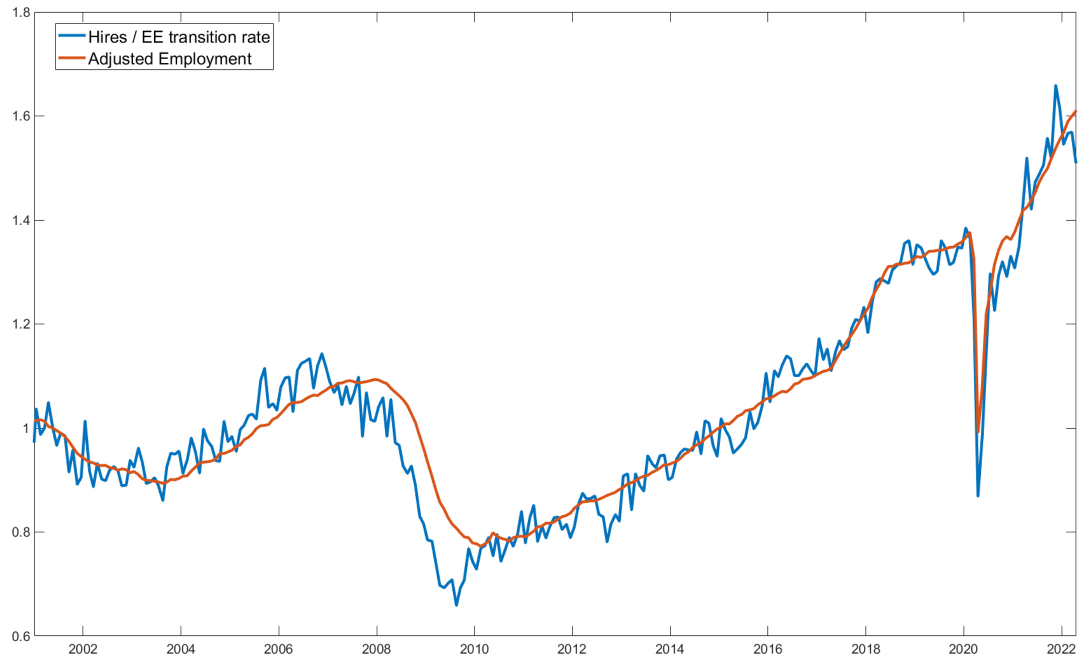


Figure 2: Ratio of Hires to EE Transitions vs Adjusted Employment

the BLS definition of an unemployed person as a person that actively searches for a job and survey evidence that more than 99 percent of the unemployed spend time actively searching for a job.

One way to check this assumption is to use data on the unemployment-to-employment (UE) transition rate measured from the Current Population Survey (CPS). The ratio of the number of hires from the unemployment pool to the search input of the unemployed must equal the transition rate. Therefore, the ratio of hires to the transition rate should give a measure of the search input by the unemployed. In fact, this ratio closely matches the total number of unemployed.

We employ the same method to obtain a measure of search input of the employed, $E_t^s$. Fallick and Fleischman (2004) and then Moscarini and Postel-Vinay (2022) have used CPS data to measure an employment-to-employment (EE) transition rate. We obtain our measure of the search input of the employed by dividing the number of hires from the employed pool by the EE transition rate.

An alternative way to obtain this measure is to use observations from the Survey of Consumer Expectations (SCE). Using these data, Faberman et al. (2022) document that only a small fraction of the employed (22%) engage in active search, but those who do engage are much more efficient than the unemployed at finding new jobs. We subtract from the total number of employed workers a highly smoothed measure of trend employment scaled by a factor of 0.78, representing the 78% of employed who do not engage in active search. With this method, we obtain a measure of search input of the employed, which behaves very similarly to the ratio of hires to EE transitions, as shown in Figure

2. Although this method is somewhat less precise, we use it to study sectoral data for which EE transition rates are not available.

We observe all of these data at a monthly frequency starting from December 2000. Thus, for a sector of the economy, or for the economy as a whole, we can measure the variables $M_t^u, M_t^e, U_t, V_t, E_t^s$. The remaining unknowns to be estimated are the split of vacancies into two types, $V_t^u, V_t^e$, and the parameters $B^u$, $B^e$, $\alpha$, and $\beta$. We assume random white-noise measurement errors on each of the matching functions.

For the economy as a whole, and for its sectors, we estimate the parameters of the model jointly using Bayesian methods. We compute the likelihood of the data given the parameters and multiply it by a relatively uninformative prior for the parameters. We evaluate the posterior distribution using a Random Walk Metropolis (RWM) algorithm as described in An and Schorfheide (2007). We use multiple chains all starting from the posterior mode that amount to a total of 100,000 posterior draws and make sure that the acceptance rates remain in the range from 0.2 to 0.5.

There are a few technical details to clarify. First, we do not estimate the standard deviations of measurement errors together with other parameters. This is because doing so would make the likelihood function flat, regardless of the other parameter values. Instead, we compute the likelihood of the data conditional on the parameters and their posterior distributions while keeping the standard deviations of the shocks fixed at their sample means. The likelihood function weighs both equations' errors equally. Hence, it aims to make the standard errors of the two equations equal and, with T+4 degrees of freedom for 2*T observations, is able to achieve that goal. Therefore, through maximizing the likelihood, we arrive at an estimate of the vacancy split that implies equal standard deviations of errors in the two equations, which is demonstrated in Table 3.

The second technical detail to note is that in some cases, other parameters may not be fully identified. This means that using pure likelihood maximization may result in multiple local maximums and relatively flat areas connecting them. As a result, finding a unique maximum can be challenging. To address this issue, we use a Bayesian framework that introduces additional curvature by multiplying the likelihood by a relatively flat prior. This approach helps explore the parameter space, improves convergence, and provides a diagnostic method to detect cases where the parameters are not well-identified. In our results, we can easily detect such cases by comparing the shapes of the prior and posterior distributions, which should be similar.

# 4 Results

Our estimated parameters for the economy as a whole and for its sectors are shown in Table 1. For the whole economy, we estimate $\alpha = 0.2$ and $\beta = 0.9$, and the level shifters $B^u$ and $B^e$ simply

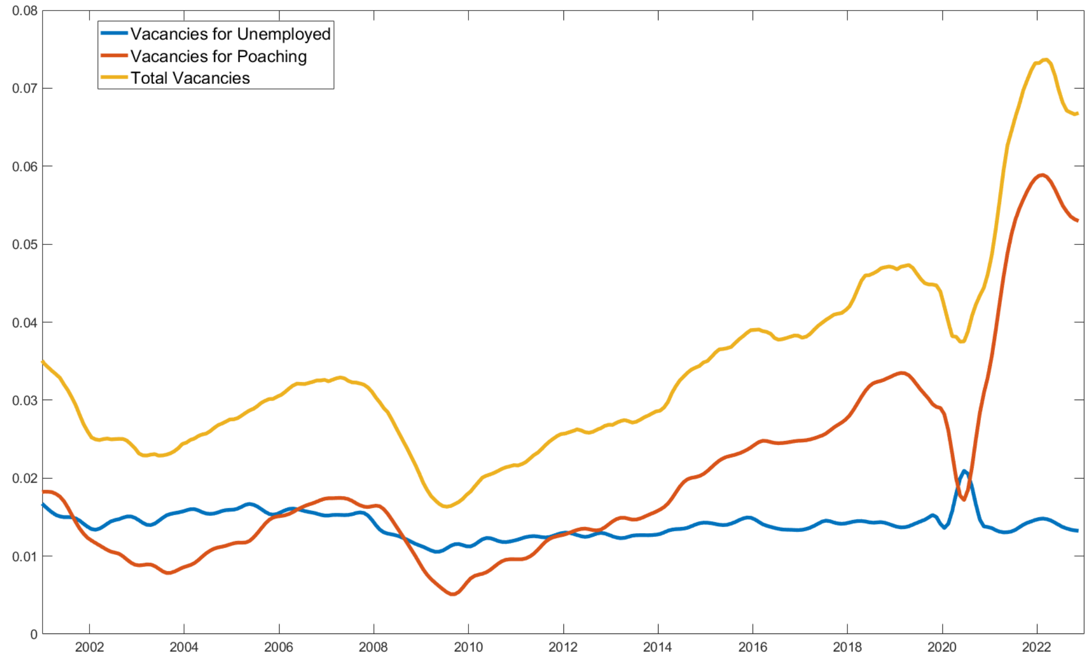


Figure 3: Total Vacancies: Poaching vs Unemployed

reflect proper scale. We also estimate these parameters for sectors that combine 1) manufacturing and construction ($\alpha = 0.6$, $\beta = 0.7$), 2) business services and retail trade ($\alpha = 0.3$, $\beta = 0.8$) and 3) education, health and leisure services ($\alpha = 0.6$, $\beta = 0.5$). Using the estimated parameters we also are able to split job openings for the U.S. economy, and for each subsector, into those designed for the unemployed and those designed for poaching. This breakdown, calculated for the period 2000 to 2023, at a monthly frequency, is shown in Figure 3.

There are two important observations one can make from Figure 3. First, the fraction of poaching vacancies has increased significantly since approximately 2015, compared with the preceding period. This suggests that the reason the Beveridge curve has shifted upward is due to the dramatic increase in non-productive poaching vacancies. 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 vacancies designed for the unemployed increased in the recession period.

To understand these observations, we need to look at them through the lens of an adjusted Beveridge curve. Recall that only the vacancies designed for the unemployed match with unemployed workers and lead to increases in employment. Thus, the proper Beveridge curve relationship should only consider vacancies for the unemployed and disregard poaching vacancies. The adjusted Beveridge curves for the whole economy and for three broad sectors are shown in the bottom row of Figure 4

Table 1: Parameter estimates of the dual vacancy model

| Parameter | Prior | | Posterior | | | |
|---|---|---|---|---|---|---|
| | mean | st.dev. | mode | mean | st. dev. | conf. int. [5-95] |
| Total private industries | | | | | | |
| $\alpha$ | 0.5 | 0.2 | 0.22 | 0.20 | 0.04 | [0.14, 0.28] |
| $\beta$ | 0.5 | 0.2 | 0.90 | 0.89 | 0.004 | [0.89, 0.90] |
| $B^u$ | 0.2 | 0.1 | 0.84 | 0.75 | 0.16 | [0.49, 1.01] |
| $B^e$ | 0.2 | 0.1 | 0.11 | 0.15 | 0.11 | [0.03, 0.37] |
| Construction and Manufacturing | | | | | | |
| $\alpha$ | 0.5 | 0.2 | 0.65 | 0.66 | 0.08 | [0.48, 0.75] |
| $\beta$ | 0.5 | 0.2 | 0.74 | 0.71 | 0.09 | [0.52, 0.80] |
| $B^u$ | 0.2 | 0.1 | 0.54 | 0.55 | 0.08 | [0.39, 0.66] |
| $B^e$ | 0.2 | 0.1 | 0.14 | 0.15 | 0.05 | [0.06, 0.20] |
| Business services and retail trade | | | | | | |
| $\alpha$ | 0.5 | 0.2 | 0.29 | 0.30 | 0.07 | [0.21, 0.43] |
| $\beta$ | 0.5 | 0.2 | 0.82 | 0.80 | 0.05 | [0.72, 0.86] |
| $B^u$ | 0.2 | 0.1 | 0.80 | 0.77 | 0.15 | [0.56, 1.05] |
| $B^e$ | 0.2 | 0.1 | 0.20 | 0.26 | 0.17 | [0.10, 0.61] |
| Other services | | | | | | |
| $\alpha$ | 0.5 | 0.2 | 0.60 | 0.55 | 0.10 | [0.41, 0.71] |
| $\beta$ | 0.5 | 0.2 | 0.53 | 0.44 | 0.12 | [0.26, 0.63] |
| $B^u$ | 0.2 | 0.1 | 0.46 | 0.41 | 0.12 | [0.20, 0.61] |
| $B^e$ | 0.2 | 0.1 | 0.27 | 0.23 | 0.06 | [0.13, 0.34] |

*Notes*: The priors for $\alpha$ and $\beta$ were drawn from a beta distribution with support on the interval $[0.1, 0.9]$, and priors for $B^u$ and $B^e$ were drawn from a gamma distribution with positive support.

compared with the unadjusted Beveridge curves in the top row. Together with Figure 3 the adjusted Beveridge curves provide a clear interpretation of the events.

In the initial months of the pandemic, demand for labor decreased due to widespread social distancing measures, resulting in increased unemployment and reduced poaching. However, as mandates for masks and distancing were implemented, a separation shock occurred, resulting in more layoffs than expected given the decrease in demand. This led to an increase in vacancies designed for unemployed workers and a quick rehiring of many individuals. Following the spike in hires, stimulative fiscal and monetary policies created excess demand for goods, leading firms to expand. However, this demand for workers could not be met by hiring from the unemployment pool. The resulting excess

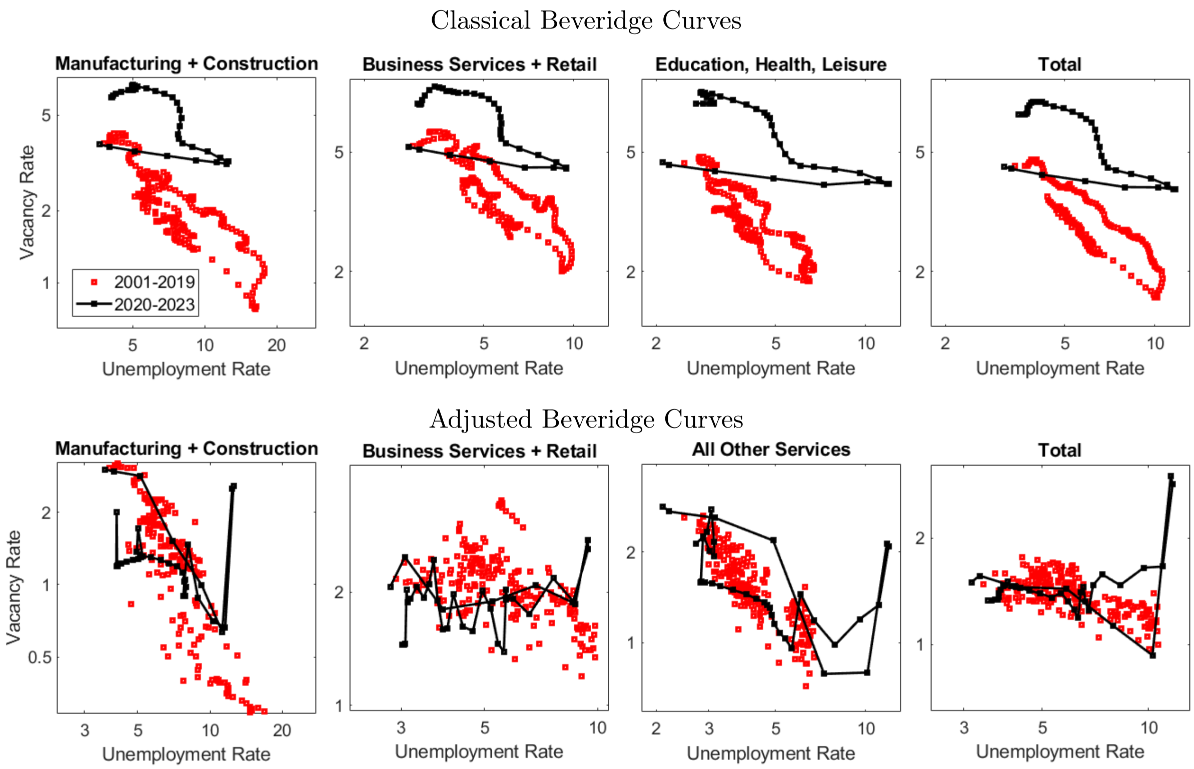


Figure 4: Classical and Adjusted Beveridge Curves

*Source*: BLS, authors' calculations. *Notes*: Henderson moving averages of the unemployment and vacancy rates are shown in the top four panels. Moving averages were not used in the estimation for the bottom four panels.

demand for workers, coupled with supply chain bottlenecks, led to a surge in inflation and an increase in poaching, ultimately driving up wages.

In light of the recent economic developments, our analysis provides two important insights. First, the Beveridge curve relationship between the unemployed and vacancies specifically designed for the unemployed has not been affected, as we show at both the aggregate and sectoral levels. Secondly, the puzzling behavior of the Beveridge curve can be attributed to a disproportionate increase in the number of poaching vacancies since 2015. However, the underlying cause for this shift is still unclear. Hence, examining job openings microdata and investigating the behavior of different types of vacancies holds great promise for future research.

## 5 Model Fit and Comparison to Standard Model

In the absence of direct empirical evidence on the split of job vacancies into poaching and unemployed designations, and given the lack of certainty surrounding the existence of a clear vacancy split, it is important to investigate whether our novel dual vacancy model is superior to current models in accurately representing labor market dynamics. To address this concern, we utilize a conventional model with a single matching function in order to compare its fit to observable data and estimate its coefficients.

According to the conventional model, a single constant-returns-to-scale matching function combines the total number of job seekers $U_t + E_t^s$ with the total number of vacancies $V_t$ to produce the total number of matches $M_t^u + M_t^e$. To enhance the model's ability to capture the data, we introduce additional flexibility to the previously rigid model. Specifically, we introduce an additional parameter to account for the proportion of total matches going to unemployed workers, which may differ from their share of search effort. By estimating this split, we improve the model's ability to accurately reflect the observed patterns in the labor market data. Thus, our version of the traditional model consists of two equations:

$$M_t^u = B^u U_t \left( \frac{V_t}{U_t + E_t^s} \right)^{1-\theta},$$
$$M_t^e = B^e E_t^s \left( \frac{V_t}{U_t + E_t^s} \right)^{1-\theta}.$$

We estimate this model using the exact same procedure as the dual vacancy model. This allows us to compare model fit since both models approximate the same set of data, with a different number of parameters. In particular, the traditional model has only one elasticity of the matching function, $\theta$, and combines vacancies into a single series, while the dual vacancy model has two elasticities of the matching function, $\alpha$ and $\beta$, and recovers a hidden variable, the split of the vacancies.

The parameter estimates for the traditional model are presented in Table 2. The estimates of the matching elasticity tend to hit the upper bound of the support range both for the whole economy and for its subsectors, while for the dual vacancy model it is common to have interior estimates of both elasticities (see Table 1).

In Table 3 we present measures of model fit. The dual vacancy model fits the data uniformly better based on smaller estimated standard errors for each of the two equations of each model. This is because the business cycle responsiveness of quits and residual hires 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 superior fit of the dual vacancy model is also supported by the marginal data densities, which we report further in Table 3. In all four cases, Bayes factors strongly favor the dual vacancy model.

Table 2: Parameter estimates of the model with a single matching function

| Parameter | Prior | | Posterior | | | |
|---|---|---|---|---|---|---|
| | mean | st.dev. | mode | mean | st. dev. | conf. int. [5-95] |
| | | | Total private industries | | | |
| $\theta$ | 0.5 | 0.2 | 0.90 | 0.89 | 0.003 | [0.89, 0.90] |
| $B^u$ | 0.2 | 0.1 | 0.22 | 0.22 | 0.08 | [0.12, 0.37] |
| $B^e$ | 0.2 | 0.1 | 0.07 | 0.09 | 0.12 | [0.003, 0.38] |
| | | | Construction and Manufacturing | | | |
| $\theta$ | 0.5 | 0.2 | 0.90 | 0.89 | 0.004 | [0.89, 0.90] |
| $B^u$ | 0.2 | 0.1 | 0.20 | 0.22 | 0.09 | [0.08, 0.40] |
| $B^e$ | 0.2 | 0.1 | 0.06 | 0.07 | 0.11 | [0.002, 0.35] |
| | | | Business services and retail trade | | | |
| $\theta$ | 0.5 | 0.2 | 0.90 | 0.90 | 0.004 | [0.89, 0.90] |
| $B^u$ | 0.2 | 0.1 | 0.33 | 0.31 | 0.09 | [0.15, 0.46] |
| $B^e$ | 0.2 | 0.1 | 0.10 | 0.08 | 0.11 | [0.003, 0.36] |
| | | | Other services | | | |
| $\theta$ | 0.5 | 0.2 | 0.90 | 0.90 | 0.004 | [0.89, 0.90] |
| $B^u$ | 0.2 | 0.1 | 0.25 | 0.21 | 0.11 | [0.04, 0.41] |
| $B^e$ | 0.2 | 0.1 | 0.07 | 0.09 | 0.11 | [0.003, 0.37] |

*Notes*: The priors for $\alpha$ were drawn from a beta distribution with support on the interval $[0.1, 0.9]$, and priors for $B^u$ and $B^e$ were drawn from a gamma distribution with positive support.

Table 3: Comparison of model fit

| Sector | Standard Errors | | Marginal Data Density | | Bayes factor |
|---|---|---|---|---|---|
| | DV | SMF | DV | SMF | |
| Total private industries | 0.06, 0.06 | 0.32, 0.07 | -484.2 | -545.2 | exp(61.0) |
| Construction and manufacturing | 0.09, 0.09 | 0.40, 0.18 | -508.6 | -563.8 | exp(55.2) |
| Business services and retail trade | 0.08, 0.08 | 0.32, 0.16 | -500.3 | -543.4 | exp(43.1) |
| Other services | 0.12, 0.12 | 0.33, 0.25 | -517.9 | -547.3 | exp(29.4) |

*Notes*: DVM stands for dual vacancy model, and SMF stands for single matching function model. Standard errors report two numbers - representing standard errors on each of the two equations of each model. The marginal data density was computed using the method of Chib and Jeliazkov (2001). Using Geweke's (1999) modified harmonic mean leads to similar results.

# 6 Final Remarks and Policy Implications

The results of our study have notable policy implications, especially regarding the impact of monetary policy on unemployment. As pointed out by Figura and Waller (2022), a steeper Beveridge curve implies that enacting stricter monetary policies may result in a substantial decrease in job vacancies, but with only a slight increase in the unemployment rate.

The present study offers a novel explanation for the Beveridge curve conundrum by attributing it to the disproportionate growth of poaching vacancies. To examine the implications of tightened monetary policy on job openings, we compare the response of vacancies and unemployment in two periods: the mid-2000s and the 2020s. Our findings reveal that while in the mid-2000s, job vacancies were almost evenly distributed between poaching and unemployed worker categories, the majority of vacancies in the 2020s were for poaching.

Therefore, in a hypothetical scenario where monetary policy is tightened, and there is a slowdown in labor demand, a higher fraction of the decrease in job openings is expected to impact poaching vacancies, which do not have a significant effect on unemployment. Consequently, our results suggest the possibility of a soft landing, wherein a decline in labor demand can lead to a relatively large reduction in job openings associated with a moderate increase in the unemployment rate.

However, it is important to exercise caution as the implications of our findings for policy decisions depend on the underlying cause of the expansion of poaching vacancies. Different explanations for this shift would yield distinct policy implications. One potential explanation for the surge in poaching vacancies is a significant improvement in vacancy posting technology. If this is the case, then poaching vacancies would become more sensitive to changes in aggregate demand, such that a tightening of monetary policy could result in a disproportionate decline in poaching vacancies, with little effect on vacancies intended for the unemployed, and thus only a small increase in unemployment.

Alternatively, the expansion of poaching vacancies could be attributed to a reduction in mismeasurement, as noted by Davis et al. (2013), wherein 42% of hires in 2011 occurred at establishments without any job openings reported. If these firms gradually enhance their reporting of previously unreported vacancies, then the aggregate Beveridge curve would shift outward, but its slope would remain unchanged, resulting in monetary policy tightening causing a reduction in both vacancies and an equivalent increase in the unemployment rate.

However, a definitive conclusion on the underlying reasons for the shifts we observed is not yet possible. In-depth exploration of job opening microdata and the behavior of various vacancy types through future research is required for a more comprehensive understanding.

# 7 References


1. Ahn, Hie Joo and Leland D. Crane (2020) "Dynamic Beveridge Curve Accounting," BOG DP No. 2020-027.

2. Ahn, Hie Joo, Hobijn, Bart and Ayşegül Şahin (2022) "The Dual U.S. Labor Market Uncovered," mimeo.

3. An, Sunbae and Frank Schorfheide (2007) "Bayesian analysis of DSGE models," Econometric Reviews, 26 (2-4), 113-172.

4. Beveridge, William H. (1944) Full Employment in a Free Society. New York: W. W. Norton & Company.

5. 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.

6. 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.

7. Chib, S., Jeliazkov, I. (2001). "Marginal likelihood from the metropolis-hastings output," Journal of the American Statistical Association, 96 (453), 270–281.

8. 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.

9. Diamond, Peter A. and Ayşegül Şahin (2014) "Shifts in the Beveridge curve," Staff Reports 687, FRB NY.

10. 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.

11. Elsby, Michael W. L., Michaels, Ryan and David Ratner (2015) "The Beveridge Curve: A Survey," Journal of Economic Literature, 53(3), 571-630.

12. 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.

13. Fallick, B., and C. A. Fleischman (2004) "Employer-to-Employer Flows in the U.S. Labor Market: The Complete Picture of Gross Worker Flows," BOG DP No. 2004-34.

14. 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.

15. Fujita, Shigeru and Moscarini, Giuseppe and Fabien Postel-Vinay (2020) "Measuring Employer to Employer Reallocation," NBER WP No. 27525.

16. Geweke, J. (1999). "Using simulation methods for bayesian econometric models: inference, development and communication," Econometric Reviews, 18 (1), 1–126.

17. 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.

18. Hobijn, Bart and Ayşegül Şahin (2012) "Beveridge Curve Shifts across Countries since the Great Recession," FRB SF WP No. 2012-24.

19. Lubik, Thomas A. (2021) "Revisiting the Beveridge Curve: Why has it shifted so Dramatically," FRB Richmond, Economic Brief No. 21-36, October.

20. 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.

21. 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.