Federal Reserve
Bank of Dallas

The Dual Beveridge Curve

Anton Cheremukhin and Paulina Restrepo-Echavarria

Working Paper 2221 **November 2022**

Research Department

https://doi.org/10.24149/wp2221

The Dual Beveridge Curve*

Anton Cheremukhin† and Paulina Restrepo-Echavarria‡

November 1, 2022

Abstract

When firms decide to post a vacancy they can hire from the pool of unemployed workers or they can poach a worker from another firm. In this paper we show that if there are two different matching processes, one for unemployed workers and another one for job-to-job transitions, then implications for the Beveridge curve are potentially very different, influencing the effects of monetary policy on unemployment. We show that over the years the hiring process and how job postings are used as an input into this process have changed dramatically.

Keywords: Beveridge Curve, Vacancies, Unemployment

JEL Codes: J23, J63, J64, E52

*The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Reserve Banks of Dallas and St. Louis or the Federal Reserve System.

†Anton Cheremukhin, Federal Reserve Bank of Dallas, chertosha@gmail.com.

‡Paulina Restrepo-Echavarria, Federal Reserve Bank of St. Louis, paulinares@me.com.

1 Introduction

The negatively sloped relationship between the number of unemployed and the number of job openings over the business cycle in the U.S. is known as the Beveridge curve. Since its inception in the 1950s, this curve has been used by policymakers to assess the health of the labor market and measure the distance to full employment.

As shown in Figure 1, the recent behavior of the Beveridge curve is strikingly different from its behavior in previous recessionary episodes. Historically we have observed movements along lines of similar slope, with only gradual shifts of the intercept in between recessions. However, in the current episode, both the slope and the intercept seem to have shifted multiple times. This breakdown of the Beveridge curve is puzzling.

Economists have naturally turned to explanations that can account for the past gradual shifts of the curve. In this paper, we propose a new and completely different explanation for the recent puzzling behavior of the Beveridge curve: a dual vacancy model.

We know that firms sometimes hire unemployed workers and sometimes poach workers from other firms. This choice depends on the various skill requirements for various types of jobs, including their location on the job ladder. Naturally, firms tailor their job postings to attract the workers they are more interested in hiring. Therefore, in the model, we separate vacancies into two types: those designed for unemployed workers and those designed to poach workers from existing positions at other firms.

Each type of job posting has a different effect on the labor market. If a job posting leads to a hire from the unemployment pool, it reduces the unemployment rate and increases the employment rate. In contrast, when a firm poaches an employee, a worker moves between two positions and potentially increases his or her wage in the process, but employment and unemployment are unaffected.

Our dual vacancy model takes the extreme view that these two types of job postings operate in separate, segmented markets, breaking the overall search and matching process into two non-overlapping processes. In our model, unemployed workers search for and match only with vacancies intended for unemployed workers, while employed workers match only with the vacancies that are open for workers who are already employed. Since vacancies that are intended to be filled from the employed pool do not affect employment and unemployment, in our model the Beveridge curve relationship applies only to the first sub-market that matches unemployed workers with the vacancies that are intended for them.

We use the dual vacancy model and available data on labor market stocks and flows to estimate the numbers of both types of vacancies, for the U.S. economy, and its sub-sectors at a monthly frequency, starting from the year 2000.

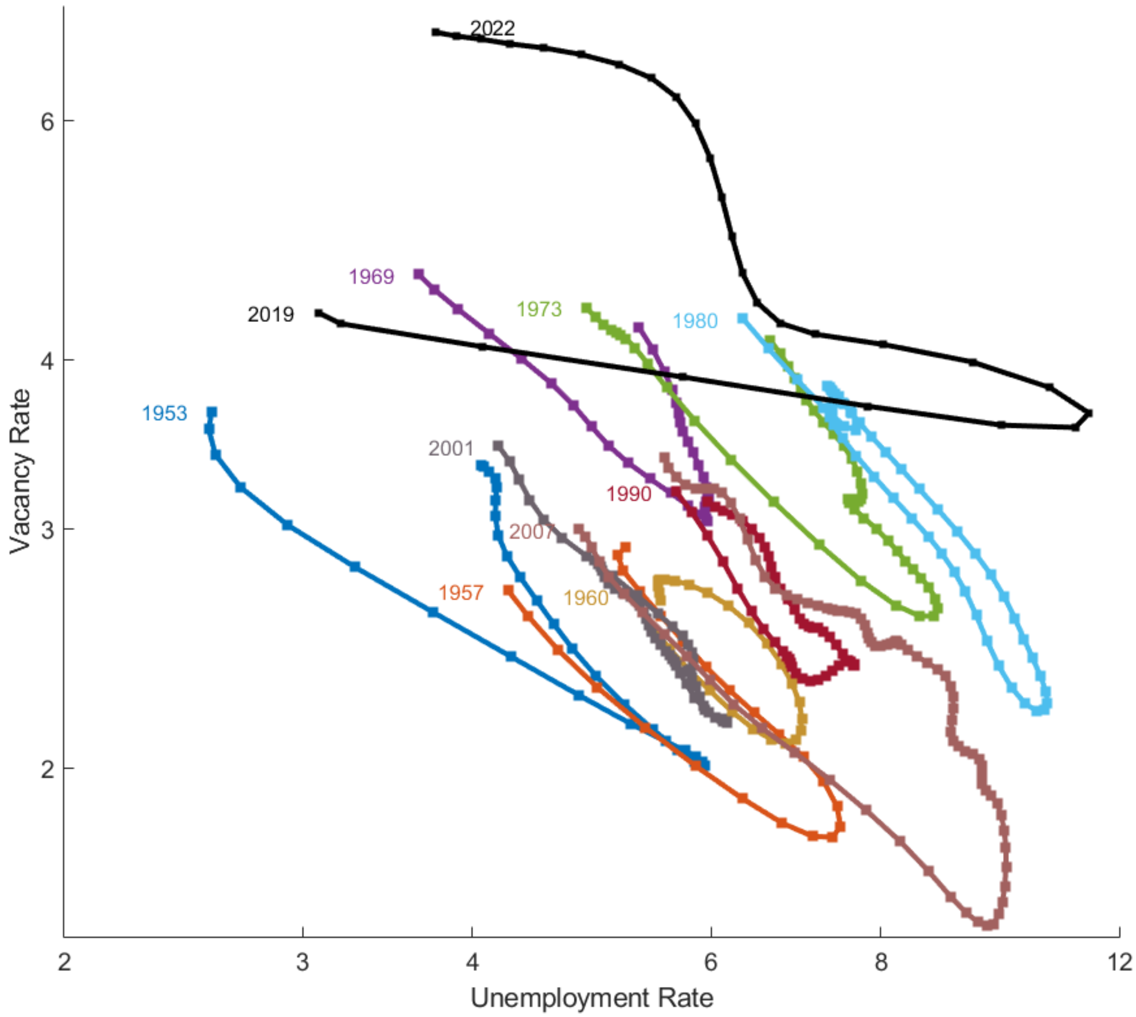

Figure 1: Beveridge Curves over Business Cycles.

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

We find that there has been a large disproportionate increase in the number of poaching vacancies starting in the mid-2010s. If we adjust the Beveridge curve by considering only the non-poaching vacancies, the recent puzzling behavior of the Beveridge curve disappears. This result suggests that the slowdown in the demand for workers is likely having a diminished effect on unemployment. This has implications for monetary policy and its effects on unemployment. We discuss policy implications of our findings more broadly in Section 5.

We contribute to three strands of the literature. First, the extensive literature on the Beveridge curve, the business cycle relationship between the numbers of unemployed and vacancies was first noted by Beveridge (1944) and the Beveridge curve relationship first plotted by Dow and Dicks-Mireaux (1958). The interest in the curve has been summarized in surveys by Elsby, Michaels, and

Ratner (2015) among others. The shifts in the Beveridge curve were analyzed both for the U.S. (see e.g. Ahn and Crane (2020), Diamond and Sahin (2014)) and for other developed countries (see Bonthuis et al. (2016) and Hobijn and Sahin (2012)).

The puzzling behavior that we have observed recently has led to both a lively discussion of its causes and a policy debate. Lubik (2021) has attributed the breakdown puzzle to a decline in matching efficiency due to sectoral shifts and a change in skill requirements. Rodgers and Kassens (2022) have attributed the flattening of the curve to changes in the cost of remaining unemployed and the larger-than-expected 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. For the policy discussion, see Figura and Waller (2022a) and Blanchard et al. (2022).

Our paper contributes to this literature and discussion by enhancing our understanding of the medium-term behavior of the Beveridge curve, including the most recent episode. We propose a novel explanation of the breakdown puzzle.

Second, we contribute to the understanding of the matching function. According to the survey by Petrongolo and Pissarides (2001), models used in the literature have traditionally incorporated job-to-job flows into the matching process by assuming a joint matching function that combines all workers searching for a job, both employed and unemployed, with the total number of vacancies. In this paper, we propose an alternative model with two separate processes for the employed and unemployed workers. We advance the measurement of the search effort of employed workers, which allows us to estimate the coefficients of both matching functions for the whole U.S. economy and its sub-sectors.

Third, we contribute to the emerging literature on segmented labor markets. 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 analyze market segmentation on the firm side, proposing a split of job openings into those designed for different types of workers. An estimation of this split is new to the literature.

2 A Simple Model

We assume that there are two separate matching functions operating in the labor market. One that is intended for unemployed workers and another one that is intended for employed workers. This means that there are two types of job openings – those designed for the unemployed, V_u, and those designed to poach from other firms, V_e. The two types of job openings have to sum up to the total number of job openings, such that, $V_u + V_e = V$.

In the first matching function, the unemployed, U, search for job openings (vacancies) designed for the unemployed, V_u, and get hired according to a standard constant-returns-to-scale matching function:

$$M_u = B_u U^{\alpha} V_u^{1-\alpha},$$

where M_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.

We know that a subset of all employed workers, E_s, engage in on-the-job search and hence search for job openings designed to poach them from their current positions, V_e, and switch jobs according to a second matching function:

$$M_e = B_e E_s^{\beta} V_e^{1-\beta},$$

where M_e is the number of workers that 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 total vacancies V, into vacancies intended for the unemployed, V_u, and vacancies intended for the employed, V_e, and estimate the matching efficiencies B_e, B_u, plus the elasticities α, and β. To do so, we use the two matching functions stipulated in Section 2, together with observed data for M_e, M_u, U, E_s, and V.

We approximate the number of hires from the employment pool, M_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_u, is then equal to the difference between total hires and quits in the JOLTS data. The total number of vacancies we also measure as the number of job openings from JOLTS.

The search input of the unemployed, U, is traditionally approximated by the total number of unemployed persons as reported by the Bureau of Labor Statistics (BLS). This is consistent with both 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. Indeed this ratio matches the total number of unemployed closely.

We employ the same method to obtain a measure of search input of the employed. Fallick and

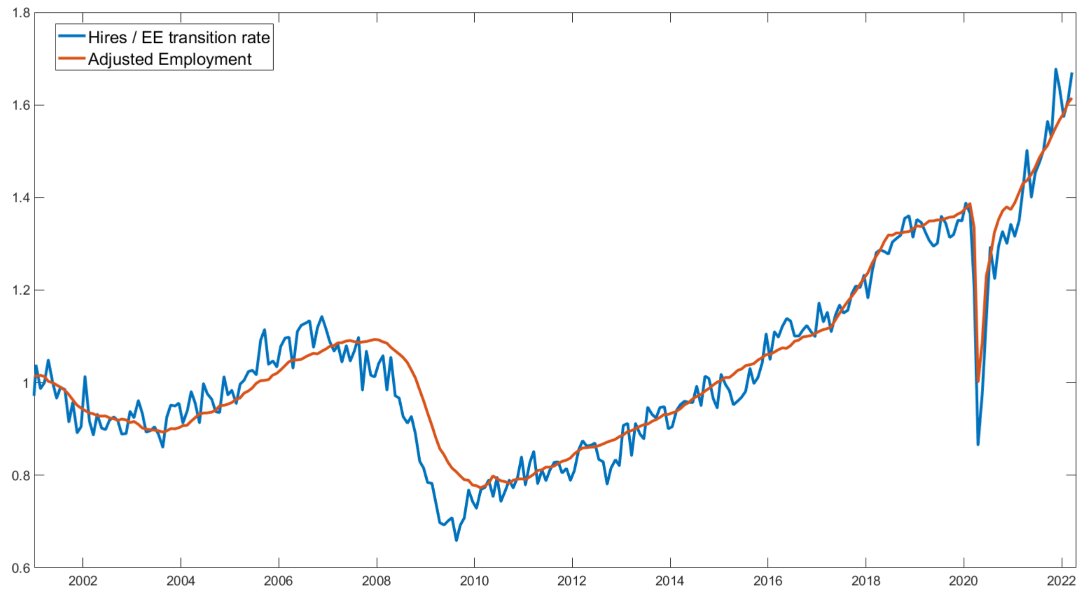

Figure 2: Ratio of Hires to EE Transitions vs Adjusted Employment

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 the 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 that do 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 0.78, representing the 78% of employed that 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 shall 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_u, M_e, U, V, E_s. The remaining unknowns to be estimated are the split of vacancies into the two types, V_u, V_e, and the parameters B_u,B_e,α, and β. We estimate them jointly using maximum likelihood by assuming random white noise measurement errors on each of the matching functions.

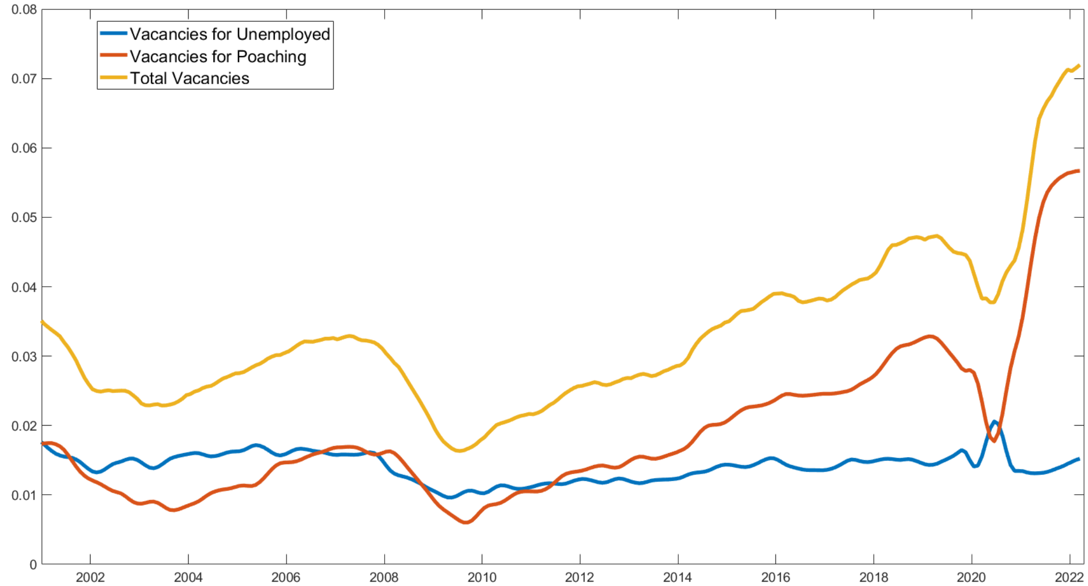

Figure 3: Total Vacancies: Poaching vs Unemployed

4 Results

Our estimated parameters for the economy as a whole are $\alpha = 0.3$ and $\beta = 0.9$, and the level shifters B_u and B_e simply reflect proper scale. We also estimate these parameters for sectors combining 1) manufacturing and construction ($\alpha = 0.6$, $\beta = 0.9$), 2) business services and retail trade ($\alpha = 0.45$, $\beta = 0.8$), and 3) education, health, and leisure services ($\alpha = 0.3$, $\beta = 0.65$). Using the estimated parameters we also are able to split job openings for the U.S. economy into those designed for the unemployed and those designed for poaching. This breakdown, computed for the period from 2001 to 2022, 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 that the Beveridge curve has shifted upwards 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. While poaching vacancies dropped 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

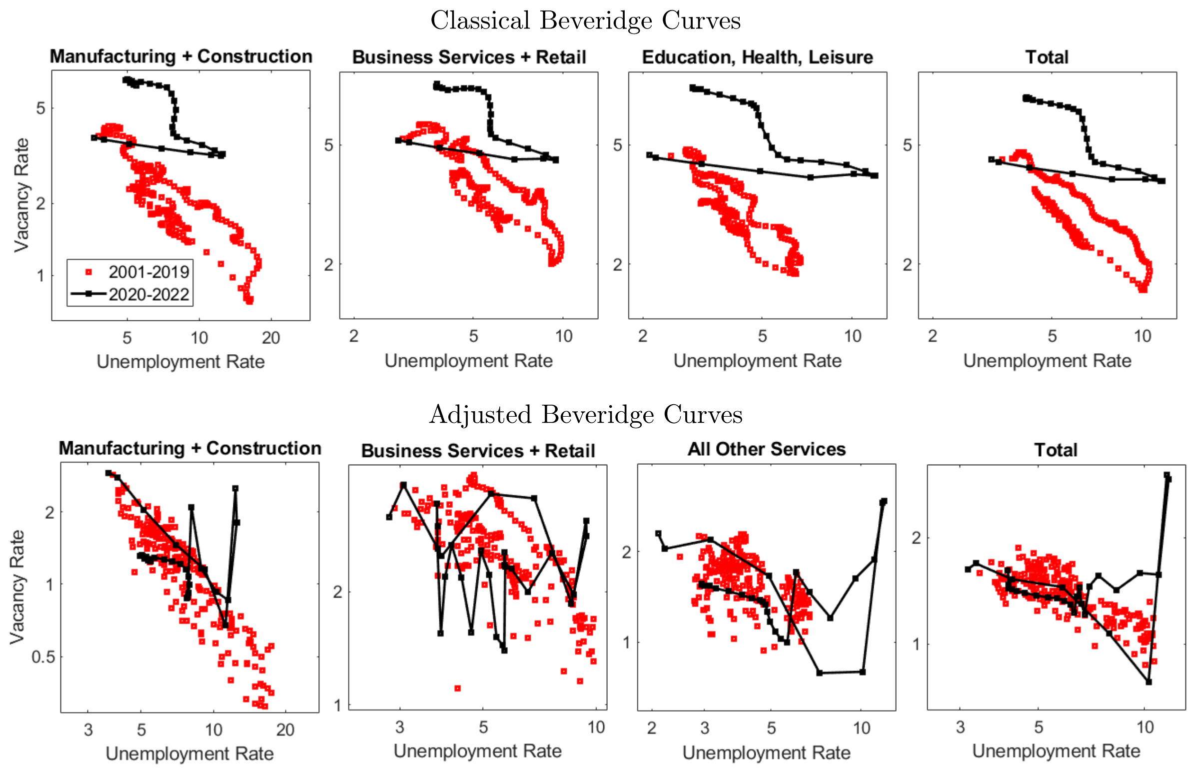

Figure 4: Classical and Adjusted Beveridge Curves

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.

only consider vacancies for the unemployed and disregard poaching vacancies. The adjusted Beveridge curves for the whole economy and for 3 broad sectors are shown in the bottom row of Figure 4 compared with the unadjusted Beveridge curves in the top row. Together with Figure 3 the adjusted Beveridge curves provide a clear interpretation of events.

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 vacancies designed for the unemployed 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. Excess demand prompted firms to expand, but this excess demand for workers could not be met by hires 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 wages.

This interpretation provides us with two lessons. First, the (adjusted) Beveridge curve for the unemployed and vacancies designed for the unemployed remained intact. We demonstrate this both at the aggregate and sectoral levels. Second, abnormalities in the classical Beveridge curve are due to a disproportional expansion of poaching vacancies after 2015. However, we do not know the reason for this shift. Therefore, studying the micro data on job openings and shedding light on the behavior of different types of vacancies provides a very promising area of future research.

5 Final Remarks and Policy Implications

Our results are important for policy consideration, in particular 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 large 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. Consider a monetary tightening that reduces demand and suppresses job openings proportionally. Compare the response of vacancies and unemployment in the mid 2000s and mid 2020s. In the 2000s, job openings were nearly evenly split between the two types of vacancies, while in the 2020s the majority of job openings are poaching vacancies. Therefore, in the second period a disproportionately large fraction of the decline in overall job openings would likely apply to poaching vacancies, which do not affect unemployment. Thus, our results suggest that the response of unemployment to a slowdown in the demand for workers has likely decreased. Namely, a monetary tightening in the 2020s could lead to a relatively large decline in job openings corresponding to only a mild increase in the unemployment rate, consistent with a notion of a "soft landing."

However, a note of caution is in order. These policy implications depend on the reason for the expansion in poaching vacancies. Different explanations for the shift would lead to different policy implications. One explanation for the expansion of poaching vacancies could be a dramatic improvement in vacancy posting technology. In this case, the sensitivity of poaching vacancies to aggregate demand has increased, and therefore tightening of monetary policy could lead to a disproportionate decline in poaching vacancies, with little impact on vacancies designed for the unemployed and, therefore, 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 gradually improved their reporting of vacancies that had not been reported previously, then the aggregate Beveridge curve has shifted outwards, but its slope going forward has not changed, and therefore monetary policy tightening could lead not only to a decrease in vacancies but also to a proportional increase in the unemployment rate.

6 References

1. 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

2. 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

3. Beveridge, William H. (1944) Full Employment in a Free Society. New York: W. W. Norton & Company, DOI: https://doi.org/10.4324/9781315737348

4. 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

5. 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

6. 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

7. 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

8. 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

9. 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

10. 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

11. 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.

12. 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

13. Fujita, Shigeru and Moscarini, Giuseppe and Fabien Postel-Vinay (2020) "Measuring Employer to Employer Reallocation," NBER WP No. 27525, DOI: https://doi.org/10.21799/frbp.wp.2021.22

14. 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

15. 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

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

17. 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

18. 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.