Finance and Economics Discussion Series

Federal Reserve Board, Washington, D.C.
ISSN 1936-2854 (Print)
ISSN 2767-3898 (Online)

What Does the Beveridge Curve Tell Us about the Likelihood of Soft Landings?

Andrew Figura, Chris Waller

2024-073

Please cite this paper as:
Figura, Andrew, and Chris Waller (2024). "What Does the Beveridge Curve Tell Us about the Likelihood of Soft Landings?," Finance and Economics Discussion Series 2024-073. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2024.073.

What Does the Beveridge Curve Tell Us about the Likelihood of Soft Landings?*

Andrew Figura and Chris Waller

February 1, 2024

Abstract

Any assessment of the likelihood and characteristics of a soft landing in the labor market should take into account the current state of the labor market and the likely dynamics in the labor market going forward. Modern labor market models centered around the Beveridge curve are a useful tool in this assessment. We use a simple model of the Beveridge curve to investigate what conditions are necessary for a soft landing in the labor market to occur and what the likelihood of these conditions was during the height of the pandemic-period inflation. We find that a soft landing was a plausible outcome at that time. Since then, the evolution of the labor market has borne out that prediction.

*This paper was prepared for the St. Louis Fed-JEDC-SCG-SNB Gerzensee Conference on October 13-14 2023, and provides an interpretation of the U.S. labor market at that time. The analysis and conclusions set forth are those of the authors and do not indicate concurrence by other members of the research staff or the Board of Governors. We would like to thank David Ratner, Charles Fleischman, the editors of the conference volume of the Journal of Economic Dynamics and Control in which this paper appears, and an anonymous referee for helpful comments. All errors are our own.

Any assessment of the likelihood and characteristics of a soft landing in the labor market should take into account the current state of the labor market and the likely dynamics in the labor market going forward. Modern labor market models centered around the Beveridge curve are a useful tool in this assessment. We use a simple model of the Beveridge curve to investigate what conditions are necessary for a soft landing in the labor market to occur and what the likelihood of these conditions was during the height of the pandemic-period inflation. We find that a soft landing was a plausible outcome at that time. Since then, the evolution of the labor market has borne out that prediction.

Introduction

The Covid pandemic generated historically unprecedented disruptions to the U.S. and global economies. In the U.S., output shrank at an annual rate of nearly 20 percent in the first half of 2020. U.S. unemployment shot up to almost 15 percent, the highest rate since 1940, in just two months, and then declined rapidly, as the economy started to quickly recover in response to the rapid development of vaccines, large fiscal stimulus, and very accommodative monetary policy. As the economy reopened, job vacancies surged to unprecedented levels. At the same time, labor supply remained well below pre-pandemic norms, as both immigration and labor force participation dropped sharply during the pandemic in response to border closures and Covid fears, resulting in severe labor shortages.[1] With demand well in excess of supply in many areas of the economy, PCE inflation, which had been mired below 2 percent for much of the preceding decade shot up to nearly 7 percent in the second quarter of 2022, while wage inflation (as measured by the Employment Cost Index) doubled relative to pre-pandemic levels.

[1] See Montes, Smith and Dajon (2022).

In this extremely challenging macroeconomic environment, some observers argued that it would not be possible to bring inflation back down to 2 percent without causing a recession.[2] A key tool for evaluating this argument and for assessing the possible outcomes for the labor market and the macroeconomy, more generally, was the Beveridge curve.

The Beveridge curve is named after William Beveridge, who first noted the correlation between unemployment and job vacancies that the curve describes. Blanchard and Diamond (1989, 1990) emphasized the utility of the Beveridge curve in understanding the various shocks affecting the labor market and the macroeconomy and brought the Beveridge curve to the forefront of labor and macroeconomic analysis. Pissarides (2000) describes the theoretical foundation of the Beveridge curve that is the basis for the simple model we describe below. The model has become a workhorse of modern labor and macroeconomics.

Theory suggests that movements along the downward sloping Beveridge curve are due to changes in labor demand and that shifts in the Beveridge curve are due to changes in the extent of frictions in the labor market arising, for example, from changes in the efficiency of matching the unemployed with job vacancies or changes in the pace of reallocation of workers across job opportunities.[3]

In our analysis, two aspects of the Beveridge curve merit particular attention. First, as emphasized by Petrosky-Nadeau, Zhang, and Kuehn (2016), the Beveridge curve is highly non-linear. In normal times, when the labor market is not at the extremes of the Beveridge curve, non-linearities can typically be safely ignored. But the first part of 2022 was a highly unusual

[2] See Blanchard, Domash and Summers (2022).
[3] Shifts can also arise from changes in labor supply or other factors. See Elsby, Michaels, and Ratner (2015) for a comprehensive discussion of movements in vacancies and unemployment.

economic environment, making it necessary to consider the non-linearity of the Beveridge curve. Second, a change in the pace of layoffs acts to shift the Beveridge curve, and, thus, it is important to consider whether such shifts will occur as labor demand changes. In past cyclical downturns, layoffs have increased, pushing out the Beveridge curve at the same time as a vacancy rate decline moves the economy down the Beveridge curve. As a result, the constellations of observations in unemployment-vacancy space appears to trace out a relatively flat relationship. However, in a situation where labor demand and vacancies are extremely high and labor shortages abound, it is possible for vacancies to decline without layoffs increasing, or at the least, it is advisable to consider this possibility. In this case, the constellation of vacancy-unemployment observations would, instead, trace out the relatively steep unshifted Beveridge curve.

The next section describes a simple model of the Beveridge curve and the steady state unemployment rate. Then we examine conditions in which it is possible for the economy to experience a soft landing starting from economic conditions similar to those prevailing in the first half of 2022 and taking into account how this possibility changes as the Beveridge curve becomes flatter and layoffs increase. Next, we describe the evolution of the labor market from early 2022 on and compare it to the conditions necessary for a soft landing. The behavior of a variety of labor market variables—vacancies, layoffs, quits, and wages—have all been in accord with that necessary for a soft landing. Finally, we show that the significant drop in vacancies with little change in unemployment that has characterized the U.S. labor market since the beginning of 2022 has also been a feature of regional U.S. labor markets and advanced foreign economy labor markets that also experienced a surge in vacancies during the pandemic. Thus, recent events in the national U.S. labor market are not a fluke. Instead, steepness in the

Beveridge curve at extremely high levels of vacancies seems to be a more general feature of advanced-economy labor markets.

Simple model of the Beveridge curve

We first present our Beveridge curve framework, which is quite standard. It is standard in the literature to account for the dynamics in the labor market by accounting for the flows of individuals in and out of unemployment. Consequently, the change in unemployment, ΔU, is given by

$$\Delta U = E * s - U * f$$

Flows into unemployment equal the separation rate, s, times the level of employment, E. Flows out of unemployment equal the rate of job finding, f, times the number of unemployed. We note that our simple model abstracts from the effects of flows into and out of the labor force, on-the-job search, and job-to-job flows. Since for simplicity we normalize the labor force to equal 1, employment equals 1 minus unemployment, U. In steady state, flows into unemployment must equal flows out of unemployment, the right side of the above equation. Thus, we can derive the Beveridge curve from a steady-state equation for unemployment, shown in equation (1).[4]

$$(1 - U) * s = U * f \tag{1}$$

[4] See, for example, Pissarides (2000).

Rearranging this equation yields an expression for the steady-state unemployment rate, equation (2).[5]

$$U = \frac{s}{s+f} \tag{2}$$

Because flows into and out of unemployment are quite high, the actual unemployment rate converges to the steady-state unemployment rate quickly, and the steady-state unemployment rate typically tracks the actual rate closely.[6]

The job finding rate can be related through a matching function to the *V-U* ratio. A matching function, shown in equation (3), posits that the number of hires is an increasing function of both the number of job vacancies and the number of unemployed individuals searching for jobs: The more firms there are looking for workers and the more workers there are looking for jobs, the more matches, or hires, there will be.

$$H = M(V, U) = \mu V^{\sigma} U^{1-\sigma} \tag{3}$$

As is standard in much of the literature, we assume the matching function takes a Cobb-Douglas form.[7] There are two key parameters in the matching function: μ and σ. The parameter μ measures matching efficiency. Matching efficiency represents factors that can increase (or

---

[5] If the labor force is allowed to vary, then the expression is similar but somewhat more complicated. Barnichon and Figura (2015b) and Elsby, Hobijn, Sahin (2015) describe the influence of changes in labor force participation on unemployment.

[6] For more on decomposing unemployment rate movements, see Shimer (2012), Elsby, Michaels and Solon (2009), Fujita and Ramey (2012), and Ahn and Crane (2020).

[7] Bok, Petrosky-Nadeau, Valletta, and Yilma (2022) show that assuming a matching function as in Den Haan, Ramey, and Watson (2000) also generates a very steep Beveridge curve as the labor market tightens.

decrease) hires without a change in labor market tightness. If the workers searching for jobs are well suited for the jobs that are available, matching efficiency will be high; on the other hand, if many searching workers are not well suited for the available jobs, matching efficiency will be low.[8] The parameter σ captures the relative importance of vacancies for creating hires. If σ is relatively low, vacancies are relatively less productive at creating matches than unemployed workers.

Dividing both sides of equation (3) by unemployment, we get equation (4), which expresses the job finding rate as a function of the ratio of vacancies to unemployment, or labor market tightness.

$$f = \frac{H}{U} = \mu \left(\frac{V}{U}\right)^{\sigma} \tag{4}$$

Because we have data for both the left and right sides of equation (4), we can estimate it and obtain parameter values for the elasticity of job finding with respect to labor market tightness, σ—the key parameter governing curvature of the Beveridge curve—and matching efficiency, μ. Specifically, using OLS, we regress $log(f)$ on $log\left(\frac{V}{U}\right)$ using JOLTS data on job openings for V, BLS data on unemployment for U, and BLS data on the rate of transitions from unemployment to employment for f. We use data from 2010 to 2019.

We now explain the reasons for these choices of data and sample period and consider alternative sample periods. We use data on unemployment-to-employment transitions (u-to-e) as our measure of job finding because we believe it is the most directly relevant measure when

[8] Changes in the intensity of firm recruiting or worker search can also affect job finding. See Davis, Faberman, and Haltiwanger (2012) on the behavior and effects of recruiting effort and Mukoyama, Patterson, and Sahin (2018) on the behavior and effects of worker search.

analyzing changes in unemployment. First, the underlying data used to estimate u-to-e transitions are the same as are used to compute the unemployment rate, the Current Population Survey (CPS). In addition, as shown in equation (1), in our simple model, flows from unemployment to employment is the theoretically correct measure. In contrast, hires from the JOLTS survey used by some researchers, include flows from out of the labor force to employment and job-to-job flows, which do not directly affect unemployment.

As pointed out by Shimer (2012), the raw transition rates published by the BLS suffer from time aggregation bias. In particular, some of the unemployed individuals who find a job between month t and month t+1 will be laid off before their labor force status is observed in period t+1. As a result, the true hazard rate for moving from unemployment to employment between t and t+1 will be understated by the published transition rates. In addition, the degree of bias will vary as the layoff rate varies over the cycle. To correct for time aggregation bias, we use the method proposed by Shimer (2012) to estimate the hazard rate.[9]

We use the 2010-2019 sample period because there is a one-time level shift in matching efficiency around the time of the Great Recession, as shown in figure 1. Figure 1 shows the ratio of the job finding rate to $\left(\frac{V}{U}\right)^{\sigma}$, where we use our preferred estimate of σ, 0.38, which as described below is quite stable over this period. As shown in equation (4), this ratio is equal to matching efficiency. Matching efficiency drops permanently during the Great Recession. We can include a dummy variable to control for this break, allowing us to extend the sample back to December 2000, when JOLTS data on job openings first became available. We can also use

[9] Elsby, Michaels, and Solon (2009) describe some potential problems with the continuous time assumption underlying the method in Shimer (2012)—as decisions about hiring and layoffs are not made on a continuous around-the-clock basis—and suggest that the continuous-time method may overstate somewhat time aggregation bias.

data from the Help Wanted Index to extend our vacancy measure back even further, as described in Barnichon (2010). As shown in table 1, for the periods 2001-2007 and 2001-2019 (excluding 2008 and 2009) the estimate of σ is identical to the estimate for the period 2010-2019.[10] For the 20 years before 2000, the estimate is slightly larger. We prefer the estimate from the most recent data as it uses a consistent estimate of job openings (JOLTS job openings). In addition, the more recent sample period likely reflects a labor market that is more similar to the current one. In sum, our estimates of σ are similar across various sample periods suggesting that for the U.S. labor market this parameter is quite stable at around our preferred estimate of 0.38. While we feel these estimates are reasonably robust, we also consider below how our analysis would change under alternative values.[11]

Other work using the Beveridge curve calibrates σ based on previous estimates in the literature. But this parameter is likely not the same in different labor markets or for different measures of job finding. Since our analysis applies specifically to the U.S. labor market and u-to-e transitions, we believe it is most appropriate to estimate this parameter using relatively recent U.S. data, especially since high-quality data is available.[12]

With estimates of matching-function parameters in hand, we can plug the expression for job finding into equation (2), the steady-state unemployment rate, yielding equation (5).

---

[10] The results in table 1 are based on OLS regressions of the log of the hazard rate of job finding in period t on the lagged log of the *V-U* ratio. For the 2000-2007 and 2010-2019 estimates, Newey-West standard errors are used to compute confidence intervals.

[11] One reason to think of this estimate as an upper bound is that the composition of the unemployed varies over the cycle in a way that increases the cyclicality of job finding. If one controls for these composition changes, estimates of σ decline. See Barnichon and Figura (2015a) and Ahn and Hamilton (2020) on compositional changes in unemployment over the cycle.

[12] Shimer (2012) proposes another method to measure the job finding rate based on the number of short-term unemployed. But this method includes flows from unemployed to out of the labor force, which can behave quite differently from job finding. As a result, we prefer measures of job finding based on unemployment-to-employment transitions.

$$U = \frac{s}{s+\mu\left(\frac{V}{U}\right)^{\sigma}} \tag{5}$$

Equation (5) shows how vacancies affect the unemployment rate. To illustrate this relationship, we solve equation (5) for different values of V and s, holding the matching efficiency parameter constant. The result is shown in figure 2, which plots four curves showing the effect of vacancies on unemployment for four different separation rates. The separations rate in the far-right curve is chosen to approximate values during the height of the pandemic when the unemployment rate surged well above 10 percent.[13] The separations rate for the far-left curve is chosen to correspond to values around the beginning of 2022, when the unemployment rate moved under 4 percent. The two remaining curves are equally spaced between these two labor-market poles.

At the onset of recessions vacancies typically plunge and separations increase. The consensus in the literature that has investigated the role of separations and job finding in driving cyclical fluctuations in unemployment is that separations contribute to the initial surge in the unemployment rate but that the persistent increase in unemployment during recessions is largely driven by a persistent reduction in job finding.[14] In mild recessions, such as in 2001, the recessionary spike in separations is subdued and fades fairly quickly. However, during deep recessions, such as the Great Recession in 2008-2009, the spike in separations in much more pronounced and can be somewhat persistent. Because the spike in recessions is generally relatively short-lived, even during the Great Recession, changes in the job finding rate account for most of the variation in the unemployment rate over the business cycle.

[13] The actual separations rate surged to an incredible 18 percent in April of 2020, and then fell to 5 percent in May, 4 percent in June, 3 percent in July, and around 2 percent for the remainder of the year.
[14] See, for example, Shimer (2012), Fujita and Ramey (2009), and Elsby, Michaels, and Solon (2009).

Each of the curves in figure 2 is convex; as the number of vacancies increases relative to the number of individuals looking for work, it becomes harder for firms to fill jobs with suitable workers, and more jobs remain vacant. Put differently, as firms compete for a diminishing number of workers, each vacancy has a smaller and smaller effect on unemployment and employment. This is exactly the situation many employers faced during the height of the labor supply shortages during the pandemic.

But even though additional vacancies don't increase employment by much, they continue to strongly affect wage growth. Intuitively, as firms compete for a diminishing supply of labor, wages get bid up. Standard Nash bargaining assumptions result in the following equation for steady-state wages, in which the effect of vacancies is linear and hence does not diminish as vacancies increase, unlike the relationship between vacancies and unemployment.[15]

$$w = (1 - \beta)z + \beta p \left(1 + c\frac{V}{U}\right) \tag{6}$$

Here, the wage, w, is equal to the weighted average of the worker's reservation wage, z, and a second term capturing the effect of the productivity of the job, p, and frictions in the labor market, $c\frac{V}{U}$, where c is the per period cost of maintaining an open vacancy. The relative weights on these two terms is determined by the worker's bargaining power, β.

Turning again to figure 2, the combination of movements in separations and vacancies is shown by the black curve in figure 2, which is fit to actual values of V and U. Decreases in the separations rate reduce the unemployment rate without changing vacancies, imparting a flatness to the fitted curve, relative to the steeper curves that only reflect the effect of vacancies. If we want to just focus on the effect of vacancies, then we should be looking at the steep curves.

---

[15] See, for example, Pissarides (2000). Of course, there are reasons to believe that wages are sticky and do not adjust immediately to the level implied by this steady-state equation.

Possibility of a soft landing in the first quarter of 2022

Next, we argue that whether the economy can experience a soft landing (which we define as a noticeably smaller increase in unemployment than has occurred in previous recessions) if the vacancy rate declines significantly depends on two important factors: (1) the slope of the Beveridge curve, which depends importantly on the current position of the labor market along the Beveridge curve, and (2) whether layoffs increase significantly.[16] We consider what these two important factors suggested for the possibility of a soft landing in the highly unusual circumstances of early 2022.

Regarding the slope of the Beveridge curve, a high *V-U* ratio, such as existed in the first part of 2022, implies that the labor market is on a very steep portion of the Beveridge curve. The stylized Beveridge curve in Figure 3 illustrates this point. When the *V-U* ratio is equal to the ray from the origin labeled "High *V-U* ratio", the slope of the convex Beveridge curve is much steeper than when the *V-U* ratio is equal to the ray labeled "Average *V-U* ratio". A steeper curve implies that the unemployment rate will change less for a given reduction in vacancies (holding separations and matching efficiency constant).

We consider how the steepness of the Beveridge curve affects the change in the unemployment rate for a 2.4 percentage point decline in the vacancy rate using equation (5) along with our preferred parameters and an assumption of no change in matching efficiency over the pandemic. A 2.4 percentage point decline in the vacancy rate would return the vacancy rate from its peak level during in the first half of 2022 of about 7 percent to the peak level prior to the pandemic of about 4.6 percent. We compute that the increase in the unemployment rate

[16] More specifically, we would define a soft landing as a trough-to-peak increase in the quarterly unemployment rate of less than 1.5 percentage points. Trough-to-peak increases in the unemployment rate around recessions (outside of the pandemic) have ranged from 1.9 percent (1960-1961 recession) to 5.4 percent (Great Recession).

produced by such a reduction in the vacancy rate when starting from a vacancy rate of 7 percent is 0.85 percentage point, as is shown in the top-middle cell of Table 2a. This result suggests that it is possible for the vacancy rate to normalize from its pre-pandemic extremes while causing only a relatively modest increase in unemployment that is well below what was experienced in prior recessions.

The top-middle cell of Table 2b shows the change in the unemployment rate for a similar 2.4 percentage point change in the vacancy rate when starting from a more normal vacancy rate of 4.6 percent. Now, the increase in the unemployment rate is a little over 2 percent, about the increase that has occurred in previous mild recessions, such as the recessions of 1960-1961 and 2001. The difference in unemployment rates changes, a little under 1 percent versus a little over 2 percent, illustrates the importance of taking into consideration the convexity of the Beveridge curve and whether the labor market is on a steep or a more normal position on the curve when considering the possibility of a soft landing.

Of course, we don't know precisely what the slope of the Beveridge curve is. In our model the slope depends on the parameter σ. While our estimates suggest a value of .38, it's possible σ could be larger, as common calibrations assume, or smaller, as taking into account cyclical changes in the composition of unemployment would imply (see footnote 11). Figure 4 shows three Beveridge curves with three difference values of σ: our preferred value, .38, 20 percent lower than this estimate, and 20 percent higher than this estimate. As shown in the figure, as σ increases, the Beveridge curve becomes flatter and vice versa. The different columns of Tables 2a and 2b consider how the computed changes in the unemployment rate would change for these different values of σ.

It's also possible that matching efficiency has declined during the pandemic. For example, Blanchard, Domash, and Summers (2022) estimate that matching efficiency decreased 20 percent during the pandemic. Decreases in matching efficiency will shift out the Beveridge curve but also change its slope. The different rows in Tables 2a and 2b show changes in the unemployment rate in response to a 2.4 percentage point reduction in the vacancy rate for different levels of matching efficiency. In particular, we consider both a 20 percent lower level of matching efficiency (relative to the pre-pandemic level) and a 10 percent lower level, which we find to be more consistent with our estimated matching function. In our calculations of the change in the unemployment rate, matching efficiency is assumed to have declined prior to the beginning of 2022 and to remain constant at that lower level as the vacancy rate declines 2.4 percentage points.

Tables 2a and 2b show that as σ increases, and we move to the right across the columns in the tables, the implied increase in the unemployment rate is larger, as one would expect. Similarly, as the level of matching efficiency is lowered, and we move down the rows in the tables, the increase in the unemployment rate also increases somewhat. But the two results highlighted above for the top-middle cells of the tables still hold for the different values of the matching function parameters in the other cells of the table. First, as shown in Table 2a, the increase in unemployment when starting on a steep portion of the Beveridge curve is smaller than in any previous recession and in most cases much smaller. Second, when comparing cells across Tables 2a and 2b, the computed increase in the unemployment rate is 2 to 3 times larger when the vacancy rate starts at 4.6 percent than when it starts at 7 percent, illustrating the importance of taking into account the labor market's current position on the Beveridge curve.

In a very tight labor market, such as in early 2022, vacancies are so high relative to available workers, that a marginal increase in vacancies results in a much lower increase in the job finding rate over a given period of time than in a more balanced labor market. As a result, a given decline in vacancies has a smaller effect on hires and, thus, a smaller effect on unemployment than in a more typical labor market. In short, the unemployment rate should increase as vacancies fall back to pre-pandemic levels (absent a reduction in matching efficiency or separations), but the increase should be significantly smaller than would be the case if the labor market were currently on a flatter portion of the Beveridge curve.

The second key question when assessing the chances of a soft landing is whether the separations rate increases significantly. As we noted earlier, increases in the separations rate shift out the Beveridge curve and lead to increases in unemployment. Tables 3a, 3b, and 3c illustrate this fact by showing how the changes in unemployment in Table 2a are affected if the separations rate increases at the same time as the assumed decline in vacancies.[17] We consider increases in separations of 5, 15, and 30 percent. For context, the 12-month moving average of the separations hazard rate increased about 30 percent from late 2007 to late 2009, during the Great Recession, and by about 15 percent from 2000 to 2002, during the relatively mild early 2000s recession.

Table 3a shows that if separations increase by 5 percent, the increase in the unemployment rate will be about 35 percent larger than if the separations rate remains constant, though still consistent with a soft landing given our preferred estimate of σ. By contrast, if separations increase 30 percent, the increase in the unemployment rate will be around three times

[17] We choose a baseline separations rate of 1.65 percent. Using equation (5) and an assumption that matching efficiency is unchanged from the pre-pandemic level, it delivers an unemployment rate of 3.7 percent, the same as the actual unemployment rate in April 2022.

larger than if separations are unchanged. The numbers in the tables clearly indicate that the chances of a soft landing in early 2022 depended critically on avoiding a significant increase in layoffs.

To sum up, the calculations in Table 2a suggest that under most assumptions about current levels of matching efficiency and the curvature of the Beveridge curve, a decline in the vacancy rate from 7 percent to 4.6 percent would lead to an increase in the unemployment rate of about 1 percentage point or less, assuming a stable layoff rate. This increase would put the unemployment rate at a level below 5 percent, which in historical terms is quite low and, in our view, consistent with a soft landing. (However, we are cognizant that any increase in unemployment is not simply a number and reflects substantial change for any household.)

However, the exception to this conclusion is when a substantial increase in layoffs occurs. Table 3a suggests that the unemployment rate would increase by much less than in previous mild recessions if separations increase by only 5 percent, given our preferred parameters ($\sigma = .38$ and matching efficiency 10 percent lower than pre-pandemic). However, increases in the separations rate of 15 percent, given our preferred parameters, would be consistent with the unemployment rate rising about 2 percent, close to the increase experienced in previous mild recessions. An increase in separations of 30 percent would imply a large increase in unemployment of over 3 percentage points.

Most observers of the labor market agree that a return to 2 percent inflation is predicated on a better balance between supply and demand in the labor market than existed in early 2022 and a decline in vacancies back to a more normal levl.[18] A critical question then is whether the

---

[18] See, for example, Bernanke and Blanchard (2023).

economy can experience a considerable decline in vacancies without a significant increase in unemployment. Based on the above analysis, we think the answer is yes if the labor market is positioned on the extreme northwest end of the Beveridge curve. In this case, the non-linearity in the Beveridge curve implies that vacancies can be reduced significantly without reducing hires significantly. Moreover, because such a decline in vacancies would still leave labor demand strong (a 4.6 vacancy rate is historically still quite high), it seems plausible that layoffs, which historically are only elevated (above their longer-run trend) when labor demand is weak, would not rise significantly.

While we recognize that it is unprecedented for vacancies to decline by a large amount without the economy falling into recession, it is also important to recognize that the situation in early 2022 was also unprecedented.

Possibility of a Soft Landing in late 2023

We revisit the possibility of a soft landing from the perspective of late 2023. The labor market has changed significantly in some ways since early 2022. Employment growth has decelerated significantly. Vacancies have also declined significantly. Has a soft landing played out as one might have expected from the perspective of early 2022? If not, how has it differed, and what might explain the differences?

We first describe how the labor market has evolved since early 2022. The vacancy rate fell by a little over 20 percent from its peak in early 2022 through August of 2023. Such a decline has never been experienced before outside of recessions. As expected, based on our preferred matching function parameters, the decline in vacancies has led to only a relatively modest decline in the job finding rate from the first half of 2022 to September 2023. As shown in figure 5, the decline is about what one would have expected given our estimation of equation (4) and, thus, implies little change in matching efficiency since early 2022.

Given our preferred estimates of matching function parameters, such declines in vacancies and the job finding rate, would, absent any change in matching efficiency and the layoff rate, be expected to lead to only a modest rise in unemployment of 0.6 percentage point. This is illustrated in Figure 6, which shows the path of the unemployment and vacancy rates since early 2022, the yellow dots, and compares them to a Beveridge curve based on equation (5). The steep Beveridge curve in the figure shows the level of the unemployment rate we would expect as the vacancy rate declines from a little above 7 percent, the level in April 2022, when matching efficiency and the layoff rate remain constant.[19] Thus far, the yellow dots appear reasonably consistent with the labor market traveling down the steep Beveridge curve shown in the figure, as our soft-landing analysis would have predicted. In fact, the unemployment rate has risen by somewhat less than we would have predicted (0.2 percentage point versus 0.6 percentage point), and we discuss the likely reason for that below.[20] But first, we examine the behavior of layoffs since early 2022 and compare this behavior to our soft-landing scenario.

As noted above, we would only expect observations to line up with our estimated Beveridge curve if there have been no changes in matching efficiency and the layoff rate. As discussed above, figure 5 shows no noticeable change in matching efficiency. Figure 7 shows

[19] JOLTS reports the level of vacancies as of the last business day of the month. The BLS measures unemployment status as of the week containing the 12th of the month. Figure 6 shows vacancies for month t-1 and unemployment for month t.

[20] Interestingly, in the period immediately prior to early 2022, it was the vacancy rate that changed little while the unemployment rate continued to decline. The vacancy rate plateaued at around 7 percent in 2021:Q4 and 2022:Q1, while the unemployment rate continued to decline from 4.2 percent in 2021:Q4 to 3.8 percent in 2022:Q1. In periods where the vacancy rate changes quickly, such as 2021, frictions in the labor market imply that it can take time for the unemployment rate to fully adjust to the large change in vacancies. Put differently, the actual unemployment rate converges with a modest delay to its steady state value after a large change to vacancies. See chapter 1 of Pissarides (2000) for a discussion.

three measures of the layoff rate: the hazard rate of transitioning from employment to unemployment from the CPS, the JOLTS layoff rate, and the number of job losers unemployed for less than 5 weeks, as a share of prior period employment, from the CPS.[21] All three measures have changed little since early 2022 and remain around levels seen immediately prior to the pandemic. However, the measure most directly related to our model, the hazard rate from employment to unemployment, has moved somewhat lower since early 2022, and our model would attribute the small difference between the September 2023 observation and the curve in figure 6 to this small decline in separations.[22]

There are at least a couple other possible explanations for the smaller than predicted increase in the unemployment rate, but they don't appear to be responsible. First, as noted earlier, our model is of the steady-state unemployment rate, and there can be temporary deviations of the unemployment rate from the steady-state level. For example, as the vacancy rate declines, it typically takes time for the unemployment rate to fully respond to the lower level of vacancies. However, the change in the unemployment rate since early 2022 is quite similar to the change in the steady state unemployment rate. Second, as noted earlier, our simple model doesn't take into account flows into and out of the labor force. We focus on the most cyclical components of unemployment, layoffs and job finding. Because flows into and out of the labor force aren't as cyclical as flows between unemployment and employment, our model may exaggerate to some extent the cyclical movements in unemployment relative to a model that incorporates flows into and out of the labor force and relative to the actual behavior of

[21] We adjust the hazard rate of transitioning from employment to unemployment for time aggregation bias, following Shimer (2012).
[22] A comparison of the middle cell of table 3A to that of table 2A shows that a decline in the separations rate of 5 percent, similar to the decline in the hazard rate from employment to unemployment shown in figure 7 from early 2022 through September 2023, would decrease the unemployment rate by 0.3 percentage point.

unemployment. However, the steady-state unemployment rate calculated using flows into and out of the labor force has changed similarly to both the actual and the 2-state steady state unemployment rates since early 2022, suggesting that our model has not been misled by its failure to account for flows into and out of the labor force. Thus, we conclude that the small drop in the separations rate is likely responsible for the smaller increase in unemployment than our model would have expected.[23]

As noted earlier, our framework would also suggest a significant cooling in wage inflation as the *V-U* ratio declines. And as shown in figure 8, wages do appear to have cooled significantly since early 2022, especially those most closely associated with vacancies. For example, the blue line in figure 8 is the 12-month percent change in wages associated with job postings from the Indeed job posting site. The change in wages associated with job postings are an early indicator of wage inflation for new jobs and for overall wage inflation. Posted wages rose sharply over the pandemic and peaked in early 2022 at the same time as the peak in the *V-U* ratio. And the fall in vacancies since early 2022 has been associated with a sharp fall in posted wage inflation.

Previous research has tied cyclical movements in wage growth to job switchers and to job-to-job flows.[24] Intuitively, in a tight labor market where qualified unemployed workers are hard to find, employers will increasingly fill vacancies by poaching workers from other employers, bidding up wages in the process.[25] Figure 9 shows a measure of job-to-job flows

---

[23] Barlevy, Faberman, Hobijn, and Sahin (2023) argue that an increase in on-the-job search during the pandemic and the subsequent normalizing of search more recently are responsible for some of the very high level of vacancies and lower matching efficiency (for the unemployed) during the pandemic and the more recent drop in vacancies (with little effect on unemployment).
[24] See,Moscarini and Postel-Vinay (2017) and Karahan, Michaels, Pugsley, and Sahin (2017).
[25] Cheremukhin and Restrepo-Echavarria (2023) argue than an increase in the number of “poaching” vacancies can help explain the large increase in vacancies during the pandemic.

from Fujita, Moscarini, and Postel-Vinay (2023) using data from the CPS together with a measure of quits from JOLTS. Quits are highly procyclical and likely driven by fluctuations in flows of workers across employers. Both measures rose noticeably as the labor market tightened, and both have come down significantly since then, as vacancies have fallen. In fact, quits are now back to their pre-pandemic level, suggesting that declining vacancies have coincided with a normalization in worker poaching and a reduction in wage pressures.

Consistent with this hypothesis, the fall in quits and job-to-job flows has coincided with a sharp slowing in wage growth for job switchers. The red line in figure 8 is a measure of the wage growth of job switchers from the payroll processing firm ADP. The ADP-based measure uses confidential, anonymized individual wage data and computes the median change in an individual's wage in a given month compared with that individual's wage 12 months ago for workers who are at a different employer than 12 months ago. According to this measure, the wage growth of job switchers has declined significantly since early 2022, after surging over the prior year, and is also now back to pre-pandemic levels. Looking beyond job switchers, figure 8 shows that a broader measure of wages of all workers, private-sector average hourly earnings from the BLS, has also experienced a marked deceleration since early 2022. In sum, growth in posted wages, job switching, wage growth of job switchers, and broader measures of wage inflation have all cooled significantly as vacancies have declined, as the soft-landing scenario would have predicted.

Of course, the simple theory behind equation (6) relates to real wages, not nominal wages. When inflation is relatively stable, changes in nominal wage growth will likely closely align with changes in real wage growth. However, inflation was obviously not stable during the pandemic. One can easily construct measures of real wages, but interpreting movements in real wage is challenging, especially during the pandemic. While large demand shocks likely pushed real wage growth higher during the pandemic, adverse global supply shocks likely pushed real wages lower. Further complications arise from the fact that wages are typically set infrequently and so will respond with a lag to labor market conditions. In addition, during the pandemic there were large swings in the industry-composition of employment, as low-wage sectors initially experienced the largest employment declines, pushing up some measures of aggregate wages. Industry composition then gradually normalized, pushing down aggregate wage growth. As a result of all of these factors, it is necessary to proceed cautiously when constructing and interpreting measures of real wage growth.

We use Indeed wage postings and ADP wage changes for job switchers as our measures of nominal wage growth. Both these measures should respond relatively quickly to changes in labor market conditions, and both control for changes in the composition of the workforce.

We use the PCE deflator to deflate nominal wages. The PCE deflator is broader than the Consumer Price Index, likely has more appropriate weights for the individual items in the consumption basket than the CPI (because it uses National Accounts to construct weights rather than the Consumer Expenditure Survey, which likely does not capture all expenditures by households) and has weights that adjust in response to changes in the consumption basket, which can be important when relative prices change rapidly, as they did during the pandemic.[26]

As noted above, the pandemic was a complicated confluence of demand and supply shocks, which affect real wages differently. For example, important supply shocks—such as the shortage of semi-conductors that reduced motor vehicle production and led to dramatic increases

[26] See Sabelhaus et. al. (2013) on the underreporting of expenditures in the CES. See Cavallo (2020) on the importance of time-varying weights in price indexes.

in used and new vehicle prices, firms' ability to maintain or increase markups given strong product demand during the pandemic, and the global commodity price increases following the Russian invasion of Ukraine—occurred while the labor market was tightening or was very tight and would be expected to have the opposite effect on real wages as tight labor markets. Real wages would reflect the net effect of these shocks, not just the increase in labor market tightness.

As shown in figure 10, while our two measures of real wages behave somewhat differently, they have a couple features in common. First, both fell at the outset of the pandemic, when labor demand fell sharply. They both increased aa the labor market tightened over 2021 and 2022 with the ADP series lagging the Indeed job postings series. Finally, both fell after then Russian invasion of Ukraine, when increases in global commodity prices boosted inflation.

Summing up, the behavior of the labor market since 2022 has performed almost exactly as we would have predicted in a soft-landing scenario. The one small exception, as note earlier, is that we would not have expected the separations rate to edge down further as the vacancy rate declined, and this appears to have occurred.

Why have separations not increased since 2022, a period during which the labor market cooled significantly? We do not engage in a complete examination of this question here but offer a few tentative hypotheses.

First, because layoffs are insensitive to changes in cyclical conditions relative to job finding, one should not have expected much of a change in layoffs given the modest decrease in job finding that has taken place. Previous research has highlighted the cyclical insensitivity of layoffs relative to job finding: On average, separations account for about one-third of cyclical fluctuations in unemployment, with job finding accounting for the remainder.[27] At the onset of deep recessions, there can be a large surge in layoffs, as the number of firms facing adverse shocks increases significantly and profitability plummets, but otherwise layoffs move relatively little compared to job finding. Since early 2022, the decline in job finding has been small enough to increase the unemployment rate by only 1/2 percentage point, see figures 5 and 6, while profitability has remained high. Given such a modest reduction in job finding, along with the cyclical insensitivity of layoffs relative to job finding, layoffs would have been expected to increase enough to generate only two tenths of a percentage point increase in the unemployment rate over this period (one-third of the increase due to the decline in job finding).

It may also be that employers were scarred by the period of extremely tight labor markets, during which many employers lost key employees (to quits) and struggled to fill open positions with qualified workers. If, due to an extended period of extreme labor market tightness, firms came to believe that they could no longer count on filling open positions relatively easily, they may have wanted to "hoard" labor and would have been reluctant to engage in (what might turn out to be temporary) layoffs, reducing the layoff response below even the modest uptick that the historical relationship between layoffs and job finding would suggest.

Finally, it could be that the Covid period produced a temporary increase in reallocation. Some research suggests a pickup in reallocation during the pandemic.[28] Some of this reallocation may have required contracting firms to lay off workers into unemployment for a period before they found new employment at expanding firms. Suppose there was a one-time

---

[27] See Shimer (2005), Fujita and Ramey (2009), and Elsby, Michaels and Solon (2009). Changes in flows into and out of the labor force can also be important contributors to fluctuations in unemployment, see Elsby, Hobijn, and Sahin (2015).
[28] See, for example, Barrero, Bloom, and Davis (2020) and Barrero, Bloom, Davis, and Meyer (2021).

burst in reallocation needed to respond to the pandemic shock, that it occurred as the labor market tightened, preventing layoffs from falling as low as they would have otherwise, and then faded as the labor market loosened. In this case, a modest cyclical response of layoffs to a reduction in labor demand since the beginning of 2022 would have been offset by a reduction in reallocation-related layoffs as the reallocation shock faded, leaving layoffs flatter than they would otherwise have been, or even on a slightly downward trajectory.

To the extent that some combination of the first two explanations is correct, one would expect the same lack of responsiveness of layoffs in a future episode of the labor market cooling from extreme tightness to still very tight conditions. To the extent that pandemic-related reallocation was important, the unresponsiveness of layoffs was likely unique to the pandemic period. We suspect the answer includes elements of both of these explanations, but we leave it to future research to assess which one is most responsible for the absence of a layoff response to a reduction in labor demand over 2022 to 2023.

Looking across regions and countries

The convexity of the Beveridge curve and its steepening as the level of vacancies rises to extremely high levels should be a common feature of all labor markets, though identifying this feature is challenging because outside of the pandemic vacancies haven't risen to extremely high levels in recent history. Moreover, cyclical changes in layoffs and shifts in the Beveridge curve, more generally, can make it difficult to measure the steepness in the Beveridge curve. However, the unprecedented surge in vacancies during the pandemic has offered an opportunity to investigate the influence of a steep Beveridge curve. In this section, we take a cursory look at Beveridge curves across regions and countries, saving for future work a more complete analysis.

Within the U.S., we focus on four regions: Northeast, Midwest, South, and West. As shown in figure 11, in each of these regions, the level of vacancies rose to levels well above those seen prior to the pandemic. And in each region, there has been a pronounced drop in vacancies since early 2022 and little to no increase in unemployment, suggesting that the steepness in the Beveridge curve has been a common feature of labor markets in the U.S. that experienced very high levels of vacancies during the pandemic. In addition, although we do not estimate matching functions and Beveridge curves for each region, the extreme verticality of *V-U* observations since early 2022 in all regions, also suggests that, as in the national data, some other factor, such as a decline in the separations rate, may have shifted regional Beveridge curves in modestly since early 2022.

Looking across countries, we focus on relatively large advanced economies that experienced both increases in vacancies to levels well-above those observed prior to the pandemic and a significant decline in vacancies over the past year or so. We identify three countries satisfying these criteria: the United Kingdom, Canada, and Australia. Figure 12 shows Beveridge curves for these countries. In all three, we see a pattern similar to the U.S., though the most recent observations in the United Kingdom suggest that the Beveridge curve may be starting to flatten out again. During the pandemic, vacancies soared to unprecedented levels but have come down noticeably in the past year or so. The increase in unemployment accompanying these vacancy declines has been relatively modest compared to the what the co-movement in vacancies and unemployment prior to the pandemic would suggest. We conclude that across U.S. regions and countries there is some evidence of Beveridge curves becoming quite steep at the extremely high levels of vacancies reached during the pandemic.

Conclusion

Looking ahead, we note that the labor market is not fully back to where it was prior to the pandemic, and inflation remains significantly above the FOMC's 2-percent target. As a result, it is possible that a soft landing will not occur. As the economy slows, households and firms could become extremely risk averse, pull back on spending and investment, and start to lay off workers. This is typically what happens in recessions. And if that happens going forward, we will not achieve a soft landing. In addition, if adverse supply shocks batter the economy again, inflation continues to be elevated, and inflation expectations drift higher, it will be extremely challenging to bring inflation lower and still have a soft landing. Though these are important risks, most professional forecasters continue to project a soft landing with the unemployment rate rising only modestly and the inflation rate moving down toward the FOMC's 2 percent target. Clearly, they also believe that a soft landing in the labor market is possible.

Table 1. Estimates of *σ*

Sample period	Estimate
2010-2019	0.38 [.36 - .40]
2000-2007	0.38 [.33 - .44]
2000-2019	0.38 [.36 - .40]
1980-2000	0.42 [.40 - .44]

Note. 95 percent confidence intervals are in brackets. Results are for OLS regressions of the log of the hazard rate of job finding in period t on the lagged log of the *V-U* ratio. For the 2000-2007 and 2010-2019 estimates, Newey-West standard errors (allowing for 3 lags) are used to compute confidence intervals.

Table 2a. Change in unemployment rate resulting from a decline in the vacancy rate from 7 percent to 4.6 percent

		σ	
μ	20 percent smaller	.38	20 percent larger
Pre-Covid	.64	.85	1.09
90 percent of pre-Covid	.73	.99	1.29
80 percent of pre-Covid	.85	1.16	1.54

Note. We assume a separations rate of 1.65 percent.

Table 2b. Change in unemployment rate resulting from a decline in the vacancy rate from 4.6 percent to 2.2 percent

		σ	
μ	20 percent smaller	.38	20 percent larger
Pre-Covid	1.40	2.04	2.90
90 percent of pre-Covid	1.60	2.35	3.39
80 percent of pre-Covid	1.84	2.74	4.0

Note. We assume a separations rate of 1.65 percent.

Table 3a. Change in unemployment rate resulting from a decline in the vacancy rate from 7 percent to 4.6 percent and a 5 percent increase in the separations rate

	σ		
μ	20 percent smaller	.38	20 percent larger
Pre-Covid	0.91	1.15	1.42
90 percent of pre-Covid	1.04	1.33	1.68
80 percent of pre-Covid	1.20	1.57	2.01

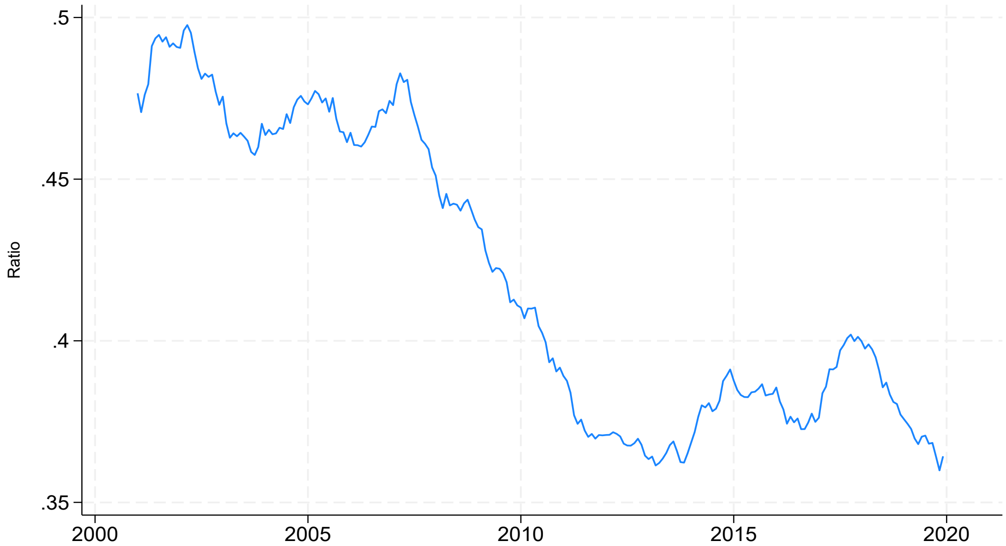
Table 3b. Change in unemployment rate resulting from a decline in the vacancy rate from 7 percent to 4.6 percent and a 15 percent increase in the separations rate

	σ		
μ	20 percent smaller	.38	20 percent larger
Pre-Covid	1.47	1.77	2.12
90 percent of pre-Covid	1.67	2.05	2.50
80 percent of pre-Covid	1.93	2.40	2.98

Table 3c. Change in unemployment rate resulting from a decline in the vacancy rate from 7 percent to 4.6 percent and a 30 percent increase in the separations rate

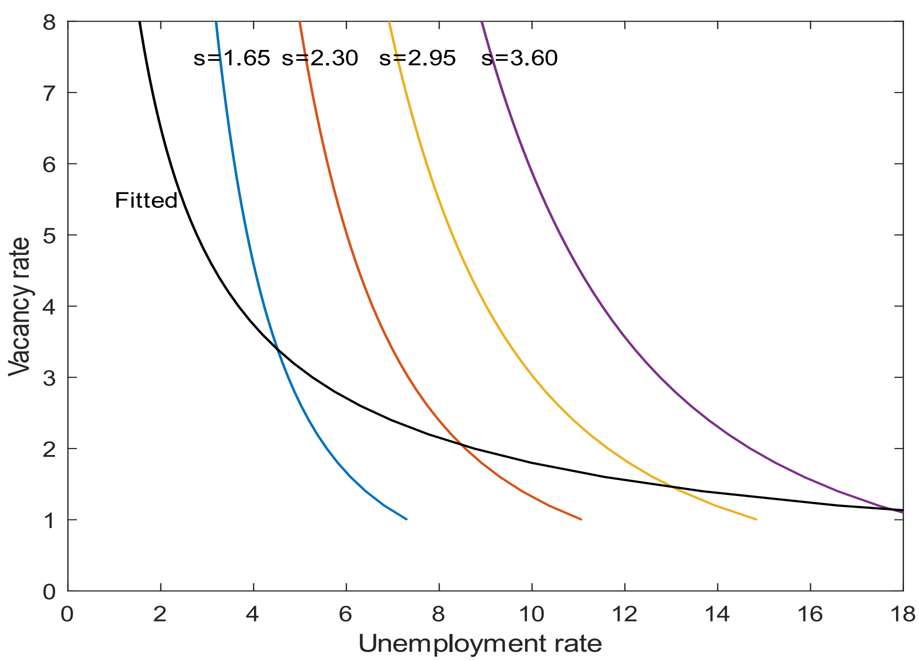
	σ		
μ	20 percent smaller	.38	20 percent larger
Pre-Covid	2.32	2.73	3.22
90 percent of pre-Covid	2.64	3.15	3.78
80 percent of pre-Covid	3.05	3.69	4.50

Figure 1. Matching Efficiency (Ratio of Job Finding to $\left(\frac{V}{U}\right)^{\sigma}$)



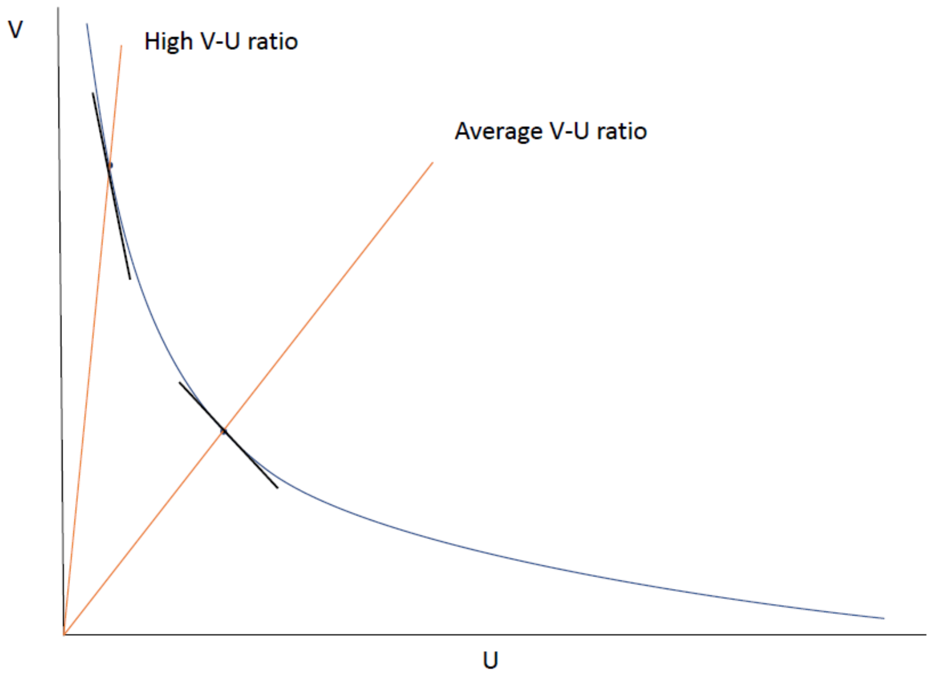
Note. 12-month moving average. Source. Authors' calculations, BLS.

Figure 2. Beveridge curves



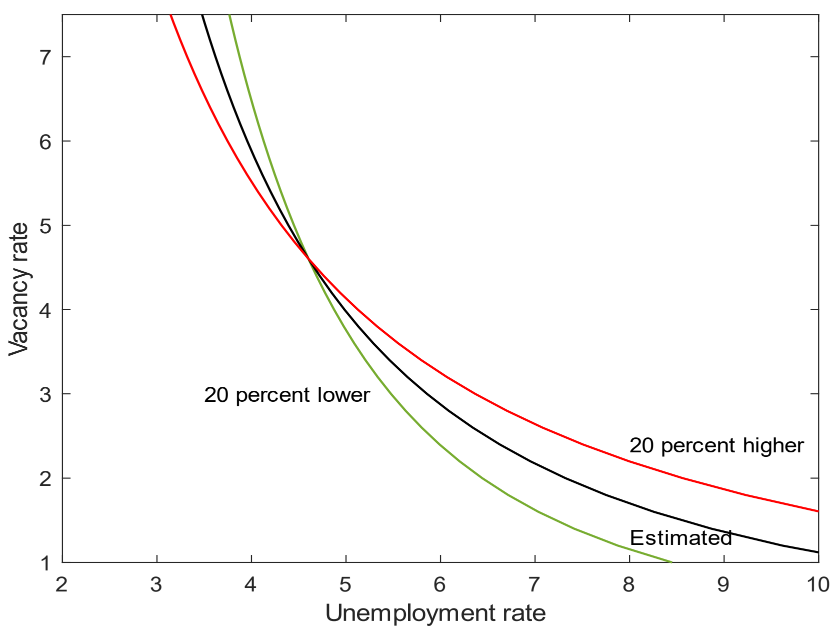
Note. The steep curves in the figure are produced using equation (5), assuming the values of the separations rate shown for each curve and a matching efficiency parameter equal to its estimated pre-pandemic level. The curve labeled "fitted" represents fitted values from a regression of the log vacancy rate on the log unemployment rate using JOLTS data on vacancies and the unemployment rate from 2000 to 2019. Source. Authors' calculations.

Figure 3. Effect of non-linear Beveridge Curve



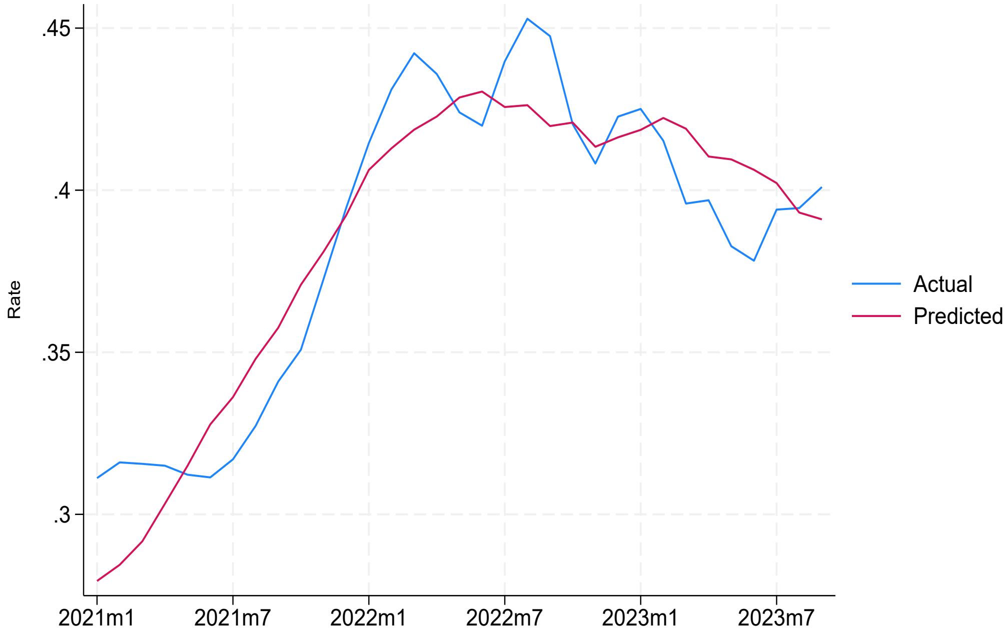
Source. Authors' calculations.

Figure 4. The Beveridge curve for different values of *σ*



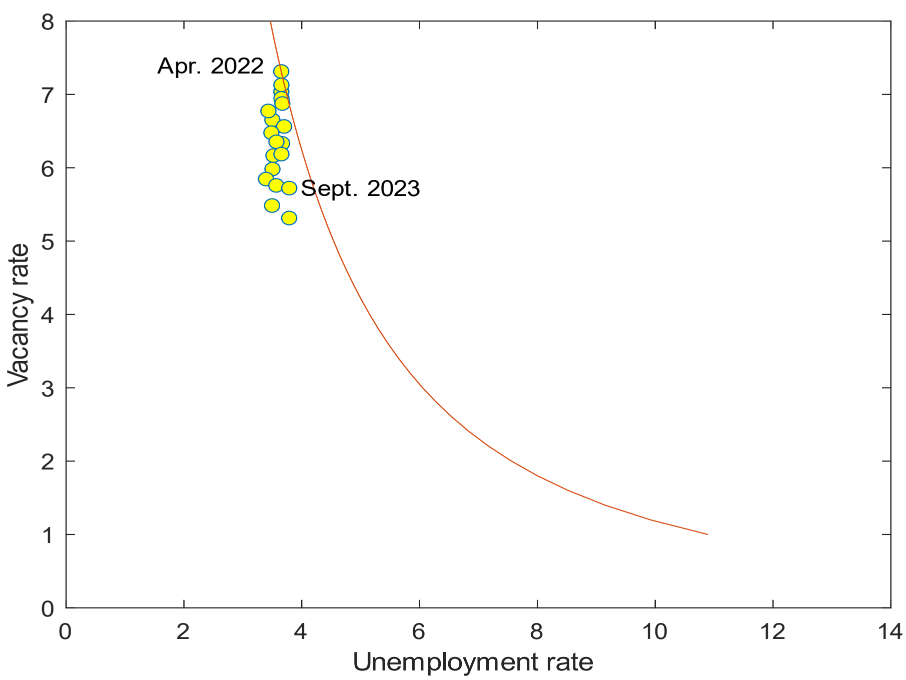
Note. Matching efficiency is assumed to be 90 percent of pre-Covid level, and the separations rate is assumed to be 1.65 percent. Source. Authors' calculations.

Figure 5. Actual and Predicted Job Finding Rates (2021-2023)



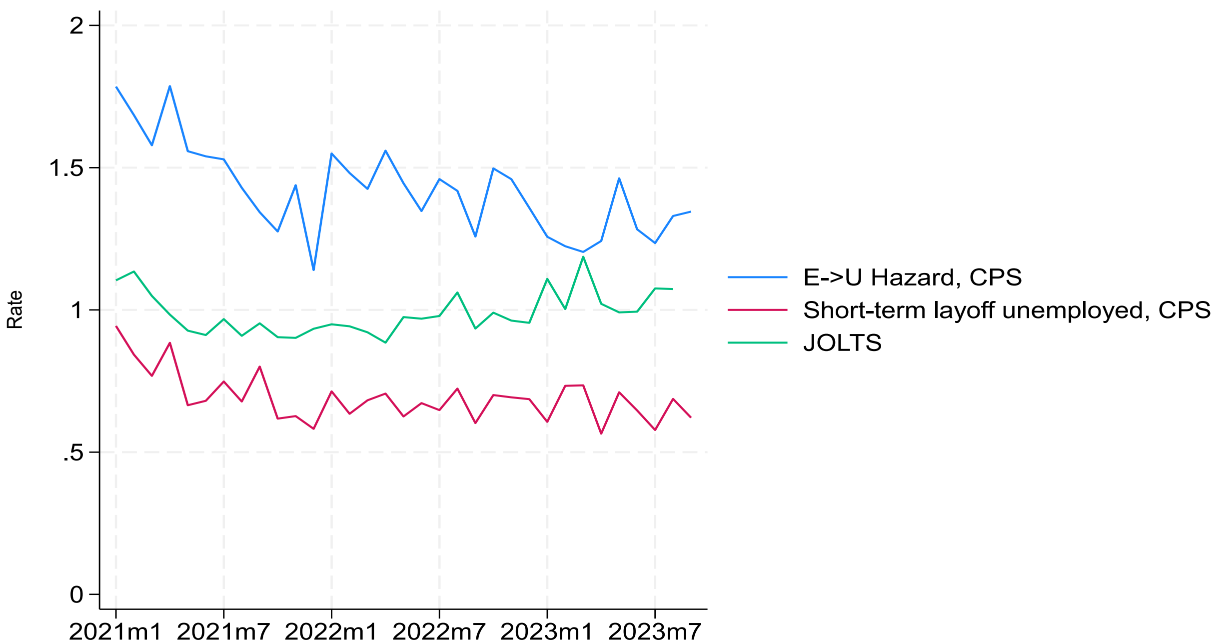
Note. 3-month moving average. Source. Authors' calculations, BLS.

Figure 6. Comparing Estimated Beveridge Curve to V-U Observations (2021-2023)



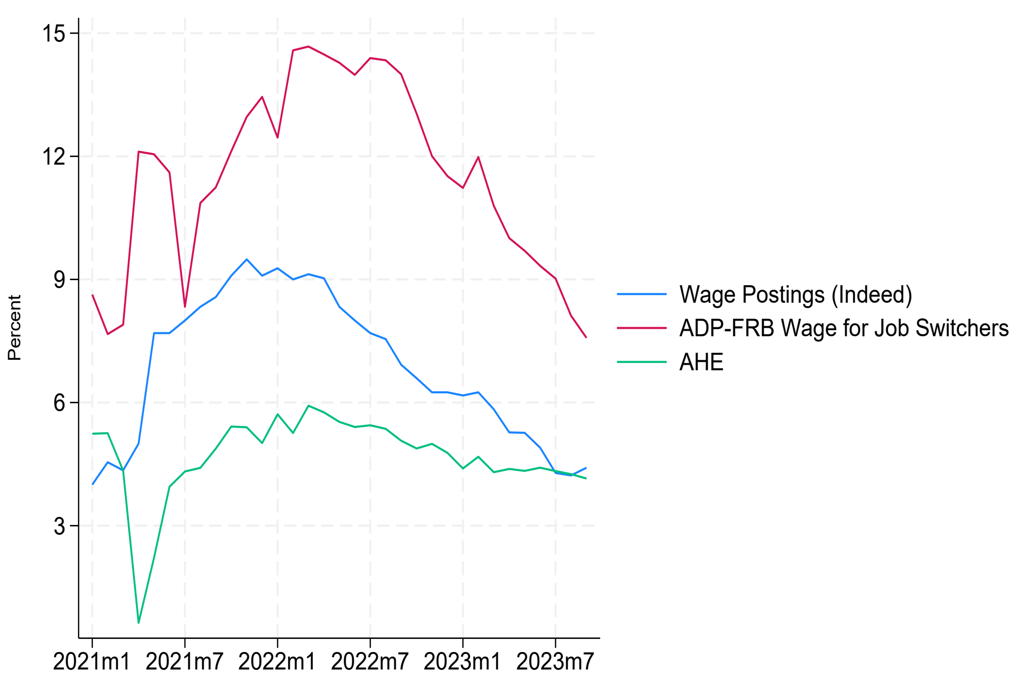
Source. Authors' calculations, BLS.

Figure 7. Separations and Layoff rates



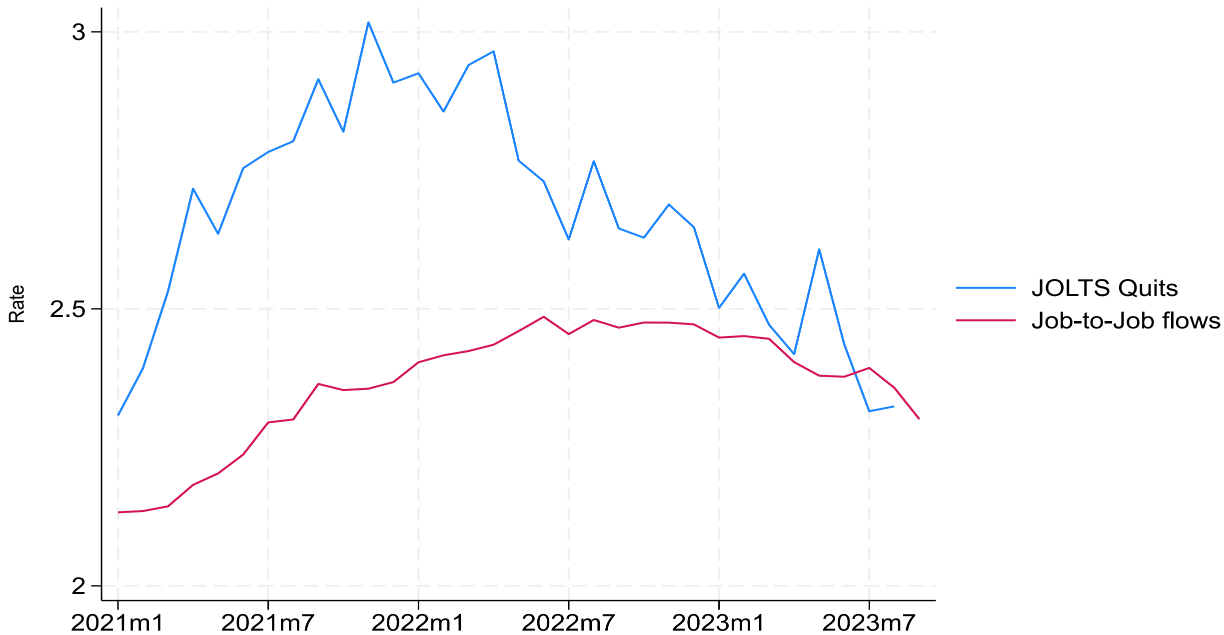
Source. Authors calculations, BLS.

Figure 8. Wage Postings and Job-Switcher Wages



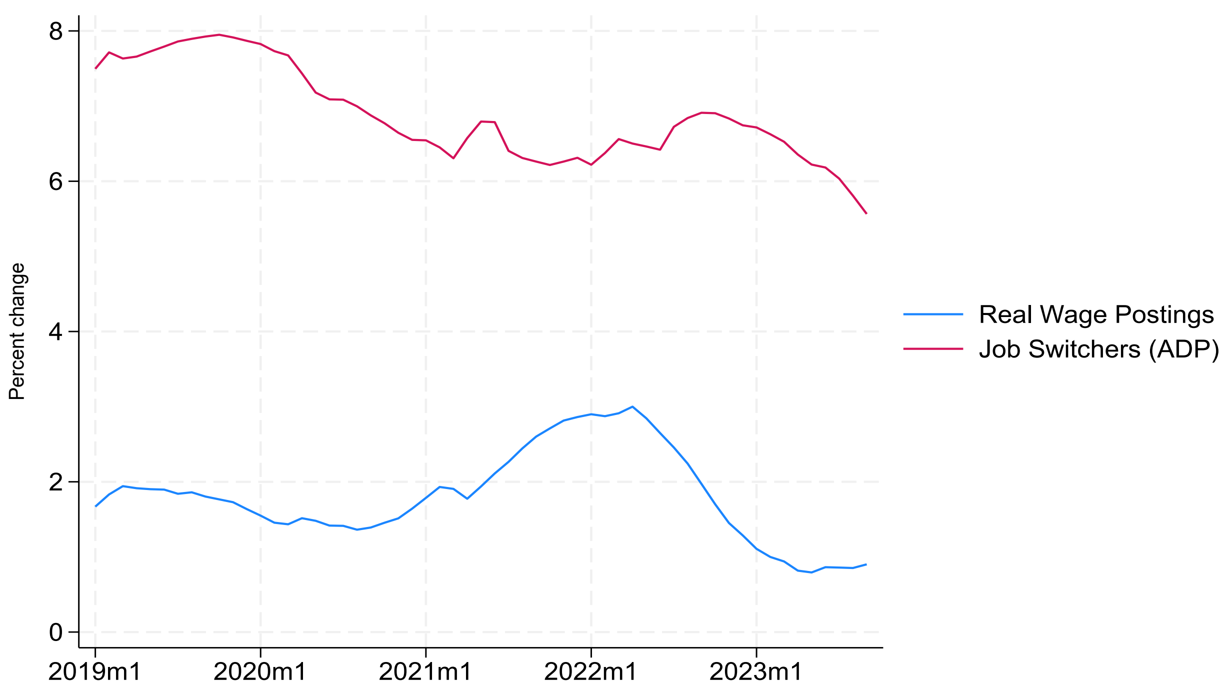
Note. 12-month changes. For wage postings, 3-month moving average of the 12-month change. Source. Haver and Indeed, Inc., FRB staff calculations using confidential, anonymized payroll data from ADP, BLS.

Figure 9. Quits and Job-to-Job Flows



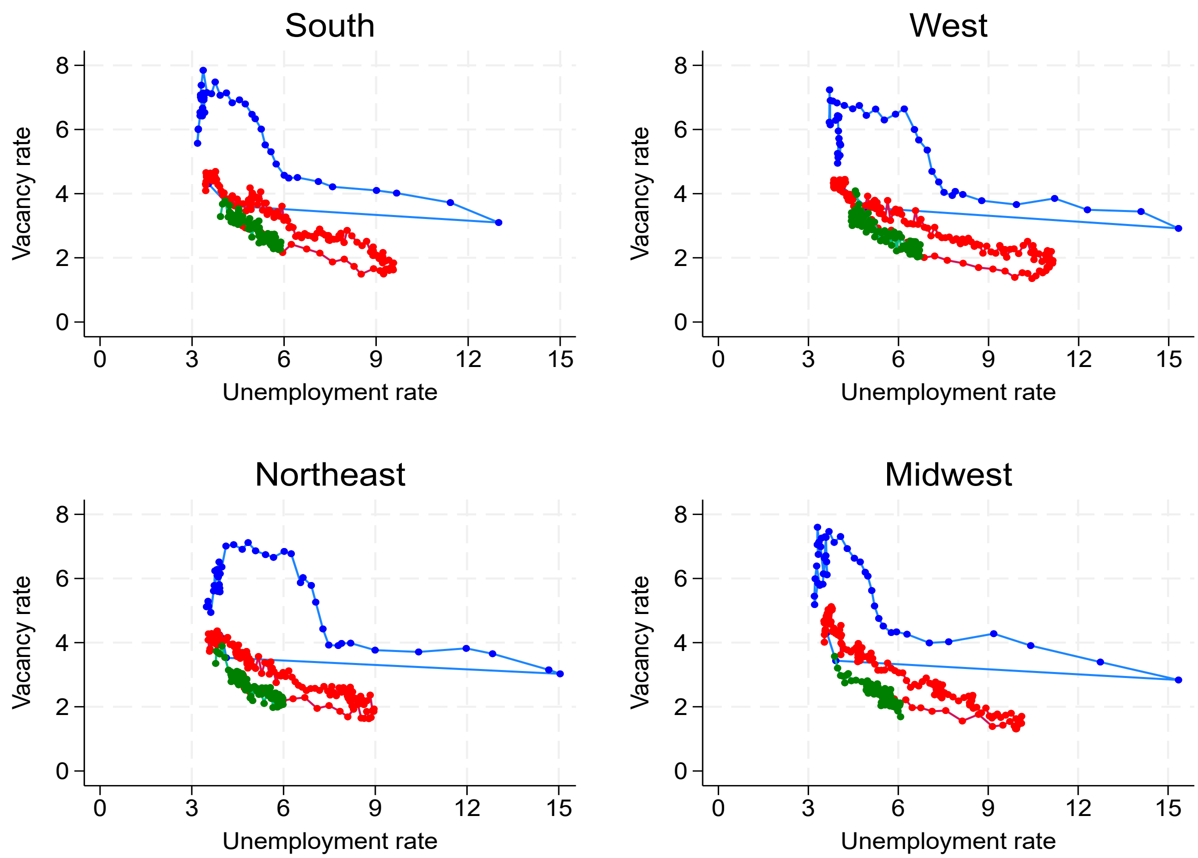
Note. Job-to-job flows is the 12-month moving average. Source. BLS, website of Giuseppe Moscarini.

Figure 10. Real Wage Growth



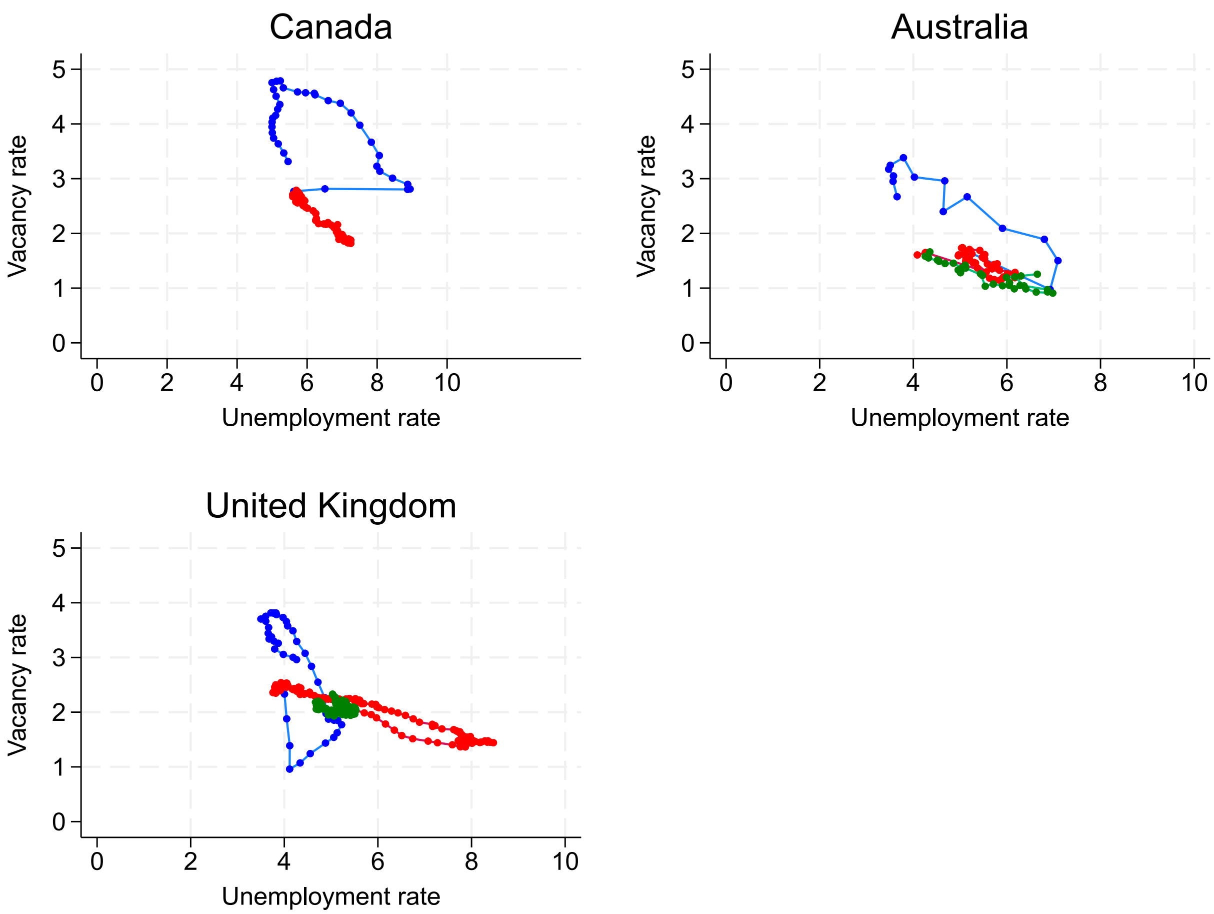
Note. 12-month moving average of 12-month change. Source. Indeed, Inc. FRB staff calculations using confidential, anonymized payroll data from ADP, BEA, Authors calculations.

Figure 11. Regional Beveridge Curves



Note. Green dots are for 2000-2007, red dots for 2008-2019, blue dots for 2020 and on. Source. Haver.

Figure 12. International Beveridge Curves



Note. Green dots are for 2000-2007, red dots for 2008-2019, blue dots for 2020 and on. Observations for Australia are quarterly. Observations for the United Kingdom and Canada are centered 3-month moving averages. Source. BLS.

References

Ahn, Hie Joo, and Leland Crane (2020). "Dynamic Beveridge Curve Accounting," Finance and Economics Discussion Series 2020-027. Washington: Board of Governors of the Federal Reserve System, March, https://doi.org/10.17016/FEDS.2020.027.

Ahn, Hie Joo, and James Hamilton (2020). "Heterogeneity and Unemployment Dynamics," *Journal of Business & Economic Statistics,* vol. 38 (July), pp. 554–69.

Barlevy, Gadi, R. Jason Faberman, Bart Hobijn and Asegul Sahin (2023) "The Shifting Reasons for Beveridge-Curve Shifts," NBER working paper no. 31783.

Barnichon, Regis (2010), "Building a composite Help-Wanted Index," *Economic Letters*, Vol. 109, pp. 175-178.

Barnichon, Regis, and Andrew Figura (2015a). "Labor Market Heterogeneity and the Aggregate Matching Function," *American Economic Journal: Macroeconomics,* vol. 7 (October), pp. 222–49.

Barnichon, Regis and Andrew Figura (2015b). "Declining Desire to Work and Downward Trends in Unemployment and Participation," *NBER Macroeconomics Annual*, volume 30.

Barrero, Jose Maria, Nicholas Bloom, and Steven J. Davis (2020). "Covid-19 is also a Reallocation Shock," NBER working paper 27137.

Barrero, Jose Maria, Nicholas Bloom, Steven J. Davis, and Brent H. Meyer (2021). "Covid-19 is a Persistent Reallocation Shock," AEA papers and Proceedings, Vol. 111, pp. 287-91.

Bernanke, Ben and Olivier Blanchard (2023). "What Caused the U.S. Pandemic-Era Inflation?" Peterson Institute for International Economics Working Paper 23-4, June.

Blanchard, Olivier and Peter Diamond (1989) "The Beveridge Curve," *Brookings Papers on Economic Activity*," Vol. 1989, no. 1, pp. 1-76.

Blanchard, Olivier and Peter Diamond (1990) "The Cyclical Behavior of the Gross Flows of U.S. Workers," *Brookings Papers on Economic Activity*, Vol 1990, no. 2, pp. 85-155.

Blanchard, Olivier, Alex Domash, and Lawrence H. Summers (2022). "Bad News for the Fed from the Beveridge Space," Peterson Institute for International Economics, Policy Brief 22-7.

Bok, Brandyn, Nicolas Petrosky-Nadeau, Robert G. Valletta, and Mary Yilma (2022). "Finding a Soft Landing along the Beveridge Curve," Federal Reserve Bank of San Francisco Economic Letter, August 29.

Cavallo, Alberto (2020). "Inflation with Covid Consumption Baskets," NBER working paper no. 27352.

Cheremukhin, Anton and Paulina Restrepo-Echavarria (2023) "The Dual Beveridge Curve," Federal Reserve Bank of St. Louis working paper 2022-021C.

Davis, Steven J., R. Jason Faberman, and John C. Haltiwanger (2012), "Recruiting Intensity During and After the Great Recession: National and Industry Evidence," *American Economic Review*, Vol. 102, No. 3, pp 584-88.

Den Haan, Gary Ramey, and Joel Watson (2000). "Job Destruction and Propagation of Shocks," *American Economic Review*, vol. 90, no. 3, pp. 482-498.

Elsby, Michael, Bart Hobijn, and Aysegul Sahin (2015). "On the Importance of the Participation Margin for Labor Market Fluctuations," *Journal of Monetary Economics,* vol. 72 (May), pp. 64–82.

Elsby, Michael, Ryan Michaels, and David Ratner (2015). "The Beveridge Curve: A Survey," *Journal of Economic Literature,* vol. 53 (September), pp. 571–630.

Elsby, Michael, Ryan Michaels, and Gary Solon (2009). "The Ins and Outs of Cyclical Unemployment," *American Economic Journal: Macroeconomics,* vol. 1 (January), pp. 84–110.

Fujita, Shigeru, and Garey Ramey (2009). "The Cyclicality of Separation and Job Finding Rates," *International Economic Review,* vol. 50 (May), pp. 415–30.

Fujita, Shigeru, Giuseppe Moscarini and Fabien Postel-Vinay (2023) "Measuring Employer-to-Employer Reallocation," *American Economic Journal: Macroeconomics*, forthcoming.

Karahan, Fatih, Ryan Michaels, Benjamin Pugsley, Asegul Sahin, and Rachel Schuh (2017). "Do Job-to-Job Transitions Drive Wage Fluctuations over the Business Cycle?" *American Economic Review*, Vol. 107, no. 5, pp. 353-57.

Moscarini, Giuseppe, and Fabien Postel-Vinay (2017). "The Relative Power of Employment-to-Employment Reallocation and Unemployment Exits in Predicting Wage Growth," *American Economic Review*, Vol. 107, no. 5, pp. 364-68.

Montes, Joshua, Christopher Smith and Juliana Dajon (2022). "'The Great Retirement Boom': The Pandmic-Era Surge in Retirements and Implications for Future Labor Force Participation," Finance and Economics Discussion Series Working Paper 2022-081, Board of Governors of the Federal Reserve Board.

Mukoyama, Toshihiko, Christina Patterson, and Aysegul Sahin (2018). "Job Search Behavior over the Business Cycle," *American Economic Journal: Macroeconomics*, Vol. 10, no.1, pp. 190-215.

Petrosky-Nadeau, Nicolas, Lu Zhang, and Lars-Alexander Kuehn (2018) "Endogenous Disasters," *American Economic Review*, Vol. 108, no. 8, August, pp. 2212-45.

Pissarides, Christopher (2000). Unemployment, MIT Press.

Sabelhaus, John, David Johnson, Stephen Ash, David Swanson, Thesia Garner, John Greenlees, and Steve Henderson (2013), "Is the Consumer Expenditure Survey Representative by Income?", NBER working paper no. 19589.

Shimer, Robert (2012). "Reassessing the Ins and Outs of Unemployment," *Review of Economic Dynamics,* vol. 15 (April), pp. 127–48.