PIIE PETERSON INSTITUTE FOR INTERNATIONAL ECONOMICS

POLICY BRIEF

22-7 Bad News for the Fed from the Beveridge Space

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July 2022

Authors' Note: We thank Peter Diamond for stimulating discussions and our PIIE colleagues for their comments and suggestions.

INTRODUCTION

The US labor market is very tight. Not only is unemployment very low, but vacancies are exceptionally high. As shown in figure 1, in the unemployment/vacancy space, call it the Beveridge space, the most recent points available at the time of writing (the red dot represents April 2022, the latest point for which we had data on vacancies at the time of writing) are outliers, very high and very much to the left.

On the assumption that the labor market needs to cool off to decrease the pressure on inflation, several Federal Reserve officials have suggested that this could happen through a decrease in vacancies, leaving unemployment unaffected—in other words, that it could happen through a move down along the vacancy axis. Consider the following statements:

> "There's a path by which we would be able to have demand moderate in the labor market and therefore have vacancies come down without unemployment going up...."
> —Fed chair Jerome Powell, Federal Open Market Committee (FOMC) press conference, May 4, 2022

> "The vacancy rate can be reduced substantially, from the current level to the January 2019 level, while still leaving the level of vacancies consistent with a strong labor market and with a low level of unemployment, such as we had in 2019."
> —Fed governor Christopher Waller, speech at the Institute for Monetary and Financial Stability (IMFS), May 30, 2022

> "We've got twice as many job openings as unemployed. In those circumstances historically, businesses have brought down hiring and reduced openings rather than necessarily laid off workers."
> —Fed vice chair Lael Brainard, CNBC Interview, June 2, 2022

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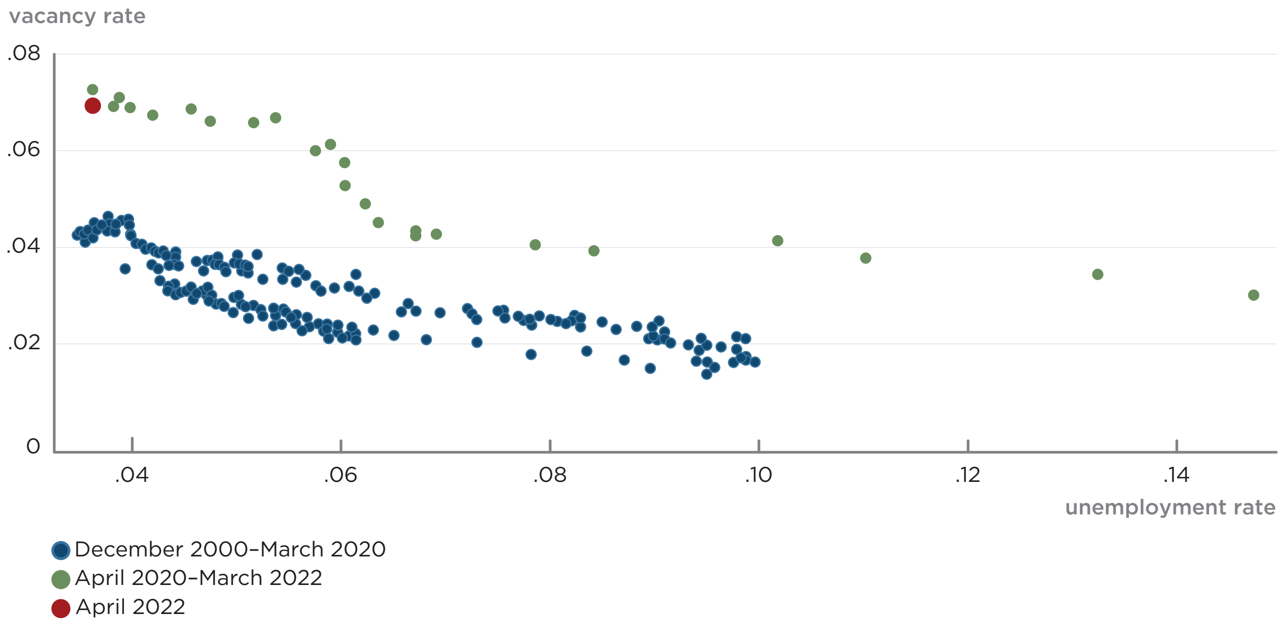
Figure 1
Vacancy and unemployment rates, December 2000 to April 2022



Note: The figure uses monthly data from the Job Openings and Labor Turnover Survey (JOLTS) from December 2000 to April 2022. We calculate the vacancy rate as the total number of nonfarm job openings divided by the size of the labor force. All values are seasonally adjusted.

Sources: Bureau of Labor Statistics, JOLTS; authors' calculations.

We are skeptical. In this Policy Brief, we offer an interpretation of the recent movements in vacancies and unemployment and identify two important policy implications.

Our interpretation is that one can think of any point in the Beveridge space as the intersection of two relations: one focusing on the effect of aggregate activity, the other on the effects of reallocation and matching. We conclude that the current point is the result of both strong aggregate activity and more difficult matching, reflecting both higher reallocation and a lower matching efficiency.

This has two important implications:

The first is that more difficult matching implies, ceteris paribus, that the natural rate of unemployment has increased. We estimate that, leaving aside other reasons why it may have increased, this implies an increase in the natural rate of about 1.3 percentage points from its pre-COVID level, and by implication an even tighter labor market than suggested by just looking at the current unemployment rate.

The second implication is that, contrary to the hopes of the Fed officials, it is highly unlikely that the decrease in the vacancy rate can be achieved without a substantial increase in the unemployment rate. Theory suggests that this would require a strong improvement in matching, through either a slowdown in reallocation or an improvement in matching efficiency, on which the Fed has no control and which we see no reason to expect—the empirical evidence indicates that it has never happened before.

Fighting inflation will require a decrease in vacancies and an increase in unemployment. There is no magic tool.

1. AN INTERPRETIVE FRAMEWORK

One can think of unemployment and vacancies as being determined by two relations[1]:

The first is a relation between activity, unemployment, and vacancies, call it the "activity relation."

Higher activity leads firms to post more vacancies and, over time, decrease the number of unemployed. Ignoring dynamics (we shall go back to those), assume that, as a result, the ratio of vacancies to unemployment is a function of the level of activity: The stronger aggregate activity, the higher the number of vacancies, the smaller the number of unemployed.[2]

Thus, we write

$$V/U = x,$$

where V is vacancies, U is unemployment, and x is an index of activity. Equivalently, normalizing both vacancies and unemployment by dividing by the labor force N, we can write

$$v/u = x,$$

where $v = V/N$ is the vacancy rate and $u = U/N$ is the unemployment rate. For a given level of activity x, this relation is represented by a ray from the origin in the (v,u) space—the Beveridge space. A given level of activity is consistent with high v and high u, or low v and low u; what the level of activity determines is the ratio of the two.[3] The higher the level of activity, the steeper the slope of the ray, the higher v is relative to u. A ray corresponding to a given value of x is drawn in figure 2.

The second is a relation between gross hires, unemployment, and vacancies and captures the matching process going on in the labor market; call it the "matching relation."

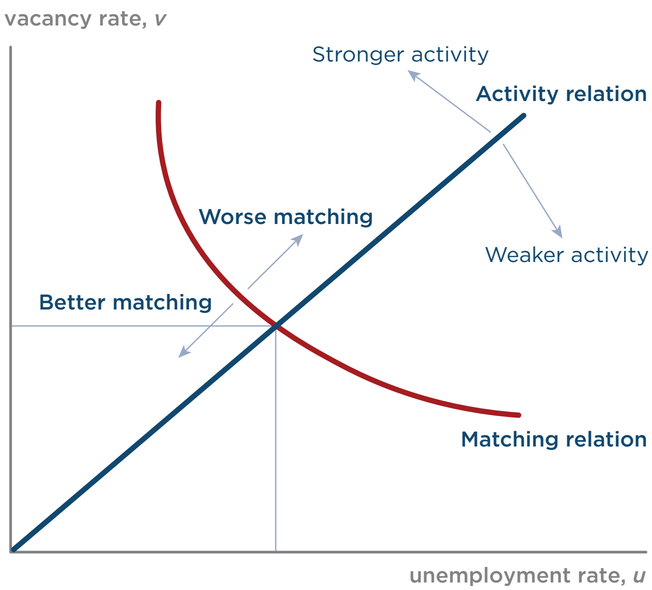
Gross hires depend on the number of vacancies posted by firms and the number of workers looking for jobs. For the moment assume (incorrectly, but we return to this assumption below) that only the unemployed are looking for jobs; we can then think of gross hires depending on the number of vacancies and the numbers of unemployed. The more jobs looking for workers, the more hires; the more workers looking for jobs, the more hires.

1 This presentation is a simplified version of the framework developed in Blanchard and Diamond (1989, 1990) focusing on the role of the matching function in the determination of unemployment and vacancies. This section presents the basic argument; the appendix considers complications and extensions.

2 The dynamics come from the fact that, faced with, say, an increase in demand, firms can increase vacancies instantaneously while it takes some time for unemployment to adjust. Empirically, these dynamics unfold very quickly. More on this below.

3 Looking across countries, there are sharp differences between the levels of u and v for given values of v/u. Some countries have, on average, low unemployment and low vacancies, others have high unemployment and high vacancies.

Figure 2
Beveridge space framework



Note: The vacancy rate is the total number of nonfarm job openings as a percentage of the labor force, and the unemployment rate is the number of unemployed as a percentage of the labor force.
Source: Authors' illustration.

We can write this relation as

$$H = a\, m(U,V)$$

where H is gross hires (a number considerably higher than net hires; average monthly net hires since December 2000 have been 80 thousands, compared to average monthly gross hires of 5 million), and $a\, m(U,V)$ is a matching function, where $m(U,V)$ is an increasing function of U and V and the parameter a reflects the efficiency of matching. If the geographic and skill characteristics of workers and jobs are very similar, hiring is easy and a is high; if not, a is lower.

Empirical evidence suggests that the function $m(U,V)$ has roughly constant returns to scale and that $m(U,V)$ can be written as a Cobb-Douglas function of unemployment and vacancies, $U^{\alpha} V^{1-\alpha}$, so the relation above can be rewritten as

$$H = a\, U^{\alpha} V^{1-\alpha}$$

Or equivalently, dividing both sides by the labor force N,

$$H/N = a\, (U/N)^{\alpha}\, (V/N)^{1-\alpha}$$

Or, defining the hiring rate $h = H/N$,

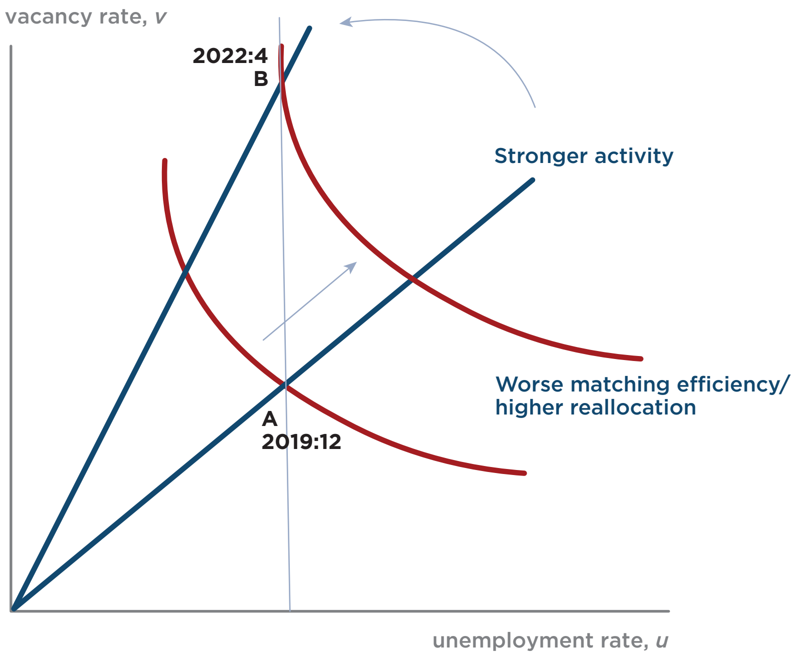
$$h = a\, u^{\alpha} v^{1-\alpha}$$

This gives us a convex relation between the unemployment rate, u, and the vacancy rate, v, the so-called Beveridge curve. This relation is drawn as the downward locus in figure 2. Its position depends on α, a, and h. A decrease in matching efficiency, a, shifts the matching relation up. An increase in the ratio of gross hires to the labor force, h, which we can think of as reflecting the level of labor reallocation, also shifts the matching relation up.

Together, these two relations determine the unemployment rate and the vacancy rate, and by implication their ratio. Stronger activity rotates the activity relation to the left, leading to a higher vacancy rate and a lower unemployment rate. Lower matching efficiency shifts the matching relation up, leading to a higher vacancy rate and a higher unemployment rate. Higher reallocation leads to higher gross hires and shifts the matching relation up, also leading to a higher vacancy rate and a higher unemployment rate.

Using this framework, we can decompose movements in the vacancy and unemployment rates between movements due to aggregate activity, matching efficiency, and reallocation. For example, we can decompose the movements in unemployment and vacancies between 2019:12 and the most recent data (2022:4) as the result of two shifts, as shown in figure 3. An increase in aggregate activity rotates the activity line to the left, and a shift upward in the matching relation reflects a combination of a decrease in matching efficiency, *a*, and an increase in reallocation, *h*.

Figure 3
Stronger activity, lower matching efficiency, and higher reallocation



Source: Authors' illustration.

We can go further and construct time series for each of the three shifters. Shifts in activity, *x*, are simply proxied by movements in *v*/*u*. Shifts in matching efficiency, *a*, require an assumption about the value of α. Estimates of α in the literature range from 0.3 to 0.5.[4] We use 0.4 below, but the results are very

4 See, for example, Blanchard and Diamond (1990) and, more recently and with better data, Barnichon and Figura (2015). Using monthly observations on hires, unemployment, and vacancies from JOLTS from 2000 on, the estimated parameter α in a regression of the log of hires on the log of unemployment and the log of vacancies (both lagged once) is equal to 0.35.

similar for values of α within the range. We then construct the time series for *a* as $a = h/u^{\alpha} v^{1-\alpha}$. Shifts in reallocation are simply given by movements in *h*, the ratio of gross hires to the labor force.

The evolution of the three shifters since 2019:1 is shown in figures 4a, 4b, and 4c.

Figure 4a shows that the ratio of vacancies to unemployment, which was stable until the COVID-19 crisis, decreased sharply at the start of the pandemic, reflecting the sudden drop in activity, but then steadily recovered and now stands at 1.5 times its precrisis level.

Figure 4b shows that matching efficiency dropped sharply at the start of the COVID crisis. Despite a very large increase in the pool of unemployed and a small decrease in vacancies, hires decreased.[5] It has since partly recovered, but to a lower level. If normalized to be equal to 1 in December 2019, matching efficiency was equal to 0.8 in April 2022.

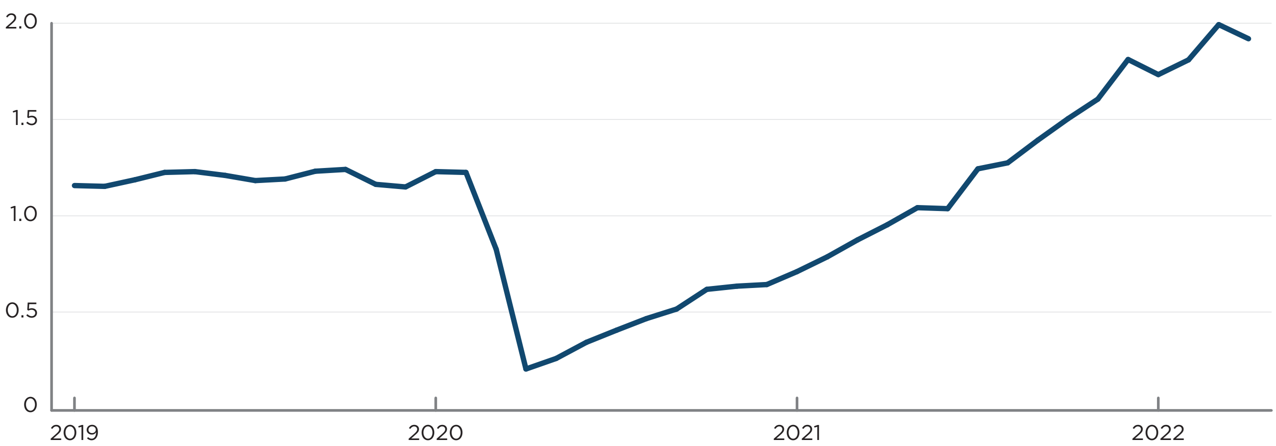
Figure 4c shows that, leaving aside the sharp drop and sharp recovery at the start of the COVID crisis, reallocation appears to have stabilized at a higher level, 0.40, compared to the 0.36 average for 2019.

Our framework yields three conclusions. The very high ratio of vacancies to unemployment suggests a very strong level of activity and potential overheating of the labor market (more on this below). The outward shift of the Beveridge curve suggests that other factors have been at work, namely lower matching efficiency and higher reallocation.

How robust are these conclusions? The framework, as conceptually useful as it is, makes several simplifications and counterfactual assumptions. We discuss robustness and show various extensions in the appendix. Our conclusions can be stated as follows.

Figure 4a
Evolution of the ratio of vacancies to unemployment

vacancy-to-unemployment ratio, January 2019–April 2022

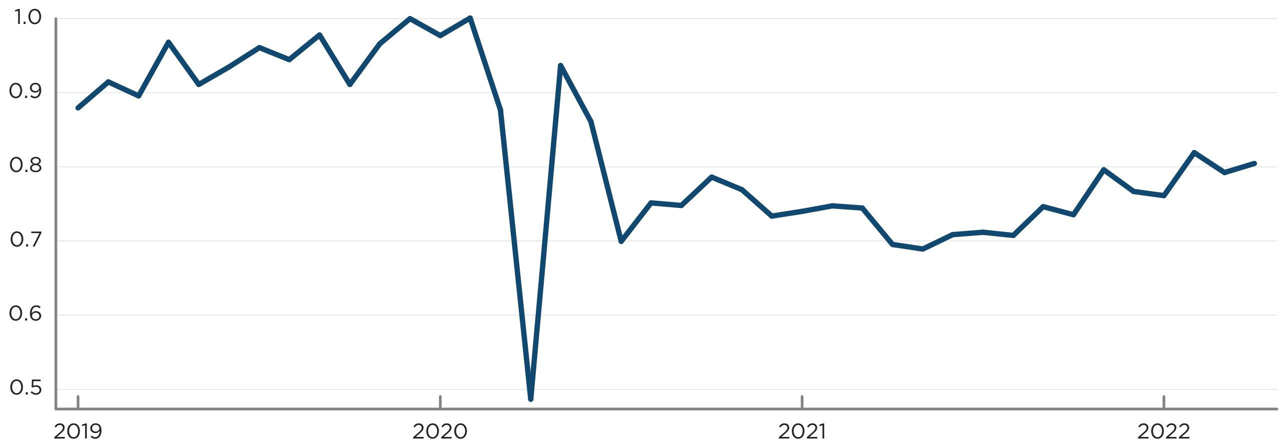


Sources: Bureau of Labor Statistics, JOLTS; authors' calculations.

5 In terms of the equation above, at the very start of the COVID-19 crisis, *u* went up a lot and *v* went down a little, so $u^{\alpha} v^{1-\alpha}$ went up, but *h* went down.

Figure 4b
Evolution of the matching efficiency parameter (*a*)

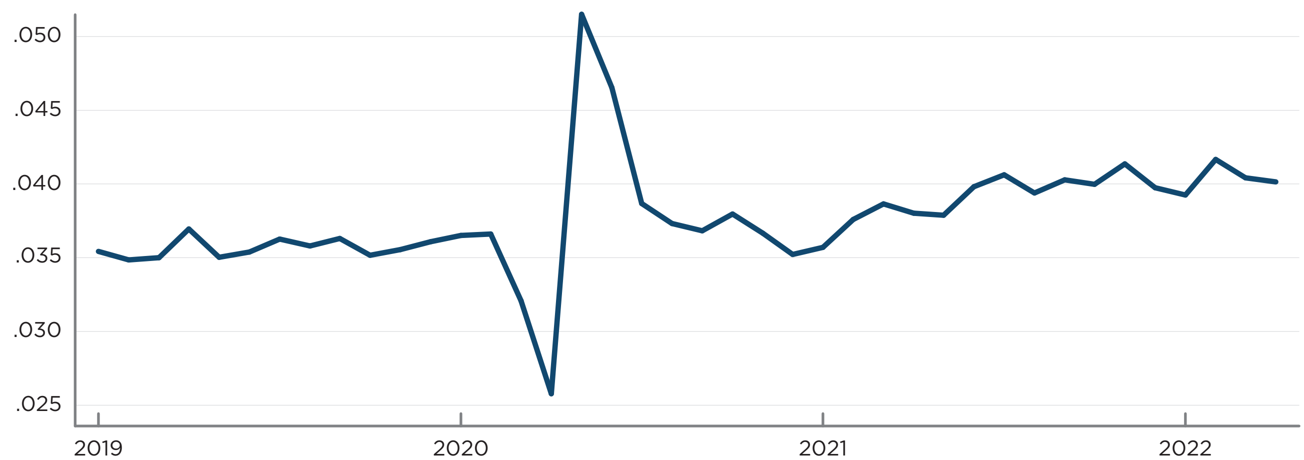
matching efficiency (*a*), January 2019–April 2022 (normalized, December 2019 = 1)



Sources: Bureau of Labor Statistics, JOLTS; authors' calculations.

Figure 4c
Evolution of the reallocation parameter (*h*)

reallocation intensity (*h*), January 2019–April 2022



Sources: Bureau of Labor Statistics, JOLTS; authors' calculations.

Recalls

Hires include recalls, which do not require matching: firms know which workers they want back. This is clearly potentially relevant as the start of the COVID-19 crisis was characterized by extremely large layoffs, with the anticipation that workers would be recalled soon after. This suggests rewriting the matching relation excluding recalls from hires and excluding workers on temporary layoffs from the unemployment pool. The results of estimation and the implications for the time series of the matching efficiency are given in the appendix. While this adjustment makes a large difference at the very start of the COVID-19 crisis, leading to a much lower initial decrease in matching efficiency, it makes practically no difference, from mid-2020 on, to the estimated value of the matching parameter *a*.

Net changes in employment

By computing the reallocation coefficient as the ratio of gross hires to the labor force, we implicitly assumed away the fact that, if activity is rapidly expanding, net hires may be large and gross hires will overstate the degree of underlying reallocation. One rough way of adjusting the computation is to run gross hires on net hires and use the residual series for computing *h*. Except for a few months during the crisis, when net hires were extremely large, whether positive or negative, the value of the reallocation parameter *h* is very much the same, reflecting the fact that gross flows are much larger than variations in net flows.

Hires from employment and from out of the labor force

As is well known, flows from employment and flows from out of the labor force actually exceed in size flows from unemployment (The exit rate from unemployment to employment is obviously much higher than the exit rate from employment to employment or from out of the labor force to employment, but the size of the unemployment pool is much smaller.) In other words, the pool of potential workers is larger than unemployment, implying that the matching function we used is misspecified.

The right way to proceed would be to extend the specification of the matching function, allowing for different search and matching rates for the different categories of workers. This is difficult and we know of no such specification.[6] A shortcut is to assume that the flows from unemployment to employment proxy for the other flows to employment, so that, as long as proportions of each pool are roughly stable, shifts in the estimated matching function capture true shifts, not just pool composition effects.

The appendix shows the evolution of the different flows into employment, decomposing flows from unemployment between workers laid off and others, flows from employment to employment, and flows from out of the labor force to employment. Figure A.1 shows a sharp increase in recalls relative to other flows at the start of the COVID-19 crisis, but today the proportions of the different flows are very similar to what they were before the pandemic. Also, the proportion of long-term unemployed (more than 27 weeks) in total unemployment, which one might expect to be harder to match and thus decrease measured matching efficiency, increased initially, to more than 40 percent, but has now returned to roughly its pre-pandemic value. Composition effects do not seem important.

V/U as a measure of activity?

There are two potential issues here.

The first is that there is a dynamic relation between the vacancy/unemployment ratio and the level of activity: Firms can adjust vacancies instantaneously, but unemployment adjusts only as layoffs and hires take place. Thus, for example, when activity decreases, vacancies decrease first and unemployment increases over time. This is why movements in activity give rise to "Beveridge loops," counterclockwise movements in the vacancy unemployment

6 For an exploration, see Blanchard and Diamond (1990).

space.[7] But the dynamics of adjustment are very fast, a few months at the most and the loops are typically very thin, so for the issue at hand, the comparison of pre- and post-COVID periods, these loops are largely irrelevant.

The second is whether firms' posting of vacancies reflects not only the need to hire but also the fact that the labor market is currently very tight. One might argue that, in a very tight labor market, firms post more vacancies than positions to fill, just in case. If so, the increase in the vacancy/unemployment ratio would be partly spurious, and so would the decrease in measured matching efficiency. To the extent that the data on vacancies came from the Bureau of Labor Statistics Job Openings and Labor Turnover Survey (JOLTS) and not a matching site or newspaper ads, we believe this is unlikely.[8] But we cannot fully dismiss it.

In short, our conclusions about the role of aggregate activity, matching efficiency, and reallocation appear fairly robust.

2. IMPLICATIONS

Increase in the natural rate of unemployment

While discussion of the natural rate typically focuses on the unemployment rate, *u*, theory strongly suggests that vacancies should play a role and that the relevant variable should be the ratio of vacancies to unemployment, or equivalently the ratio of the vacancy rate to the unemployment rate, (v/u).[9] The reason is straightforward: What matters for wage determination (and by implication for the determination of labor market equilibrium) is how easy it is for firms to hire workers versus how easy it is for workers to find jobs; both depend on the ratio of vacancies to unemployment.

For a given ratio (v/u), the unemployment rate is then given by

$$h = a\, u^{\alpha}\, v^{1-\alpha}$$

or, rewriting,

$$u = h/(a\,(v/u)^{1-\alpha})$$

So for a given (v/u), increases in reallocation, *h*, or decreases in matching efficiency, *a*, imply a higher unemployment rate. For example, using the estimated values of *a* and *h* for 2019:12 and 2022:4 for a given value of (v/u)—say, for example, the value of (v/u) in 2019:12—this formula implies an increase in the unemployment rate of 1.3 percentage points, from 3.6 to 4.9 percent.

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7 This is indeed what happened in May 2022 (the numbers for vacancies for May were published just after this Policy Brief was written). Vacancies decreased from 11.680 million to 11.250 million, while unemployment barely moved, increasing from 5.941 million to 5.950 million.

8 The definition of a job opening in JOLTS requires three conditions: (1) A specific position exists and there is work available for that position; the position can be full-time or part-time, and it can be permanent, short-term, or seasonal. (2) The job could start within 30 days, whether or not the establishment finds a suitable candidate during that time. (3) There is active recruiting for workers from outside the establishment location that has the opening.

9 This is a short summary of the discussion in formal models of the labor market, such as Pissarides (2000). Under Nash bargaining, for example, the wage set in bargaining depends on (v/u), not on *u*. In Blanchard and Diamond (1990), for example, the bargained wage takes the form $w = y\,(z\,(v/u)/(z\,(v/u) + 1-z)$, where *z* is the share of the surplus of the match going to workers and *y* is the output associated with each job. The argument is, however, more general. Empirically, it is difficult to identify which labor market variable wages depend on, but there is strong evidence that vacancies (and quits, which move a lot like vacancies) play an important role. See Domash and Summers (2022).

If we think that the labor market was roughly in equilibrium at the end of 2019, so that the ratio of vacancies to unemployment was roughly equal to the natural ratio and, by implication, the unemployment rate was roughly equal to the natural unemployment rate, this implies that the natural rate of unemployment has increased from 3.6 percent, its value in December 2019, to 4.9 percent. Given a current unemployment rate of 3.6 percent, this implies a positive unemployment rate gap of 1.3 percentage points, thus substantial overheating of the economy.

We have focused on matching issues. The natural unemployment rate depends on many other factors, which we have left aside: the markup decisions of firms, the reservation wage of workers, the degree of real wage rigidity in the face of adverse supply shocks. If anything, these factors have probably contributed to further increase the natural rate of unemployment. There is much discussion about whether some firms have increased their markups, whether some workers have decided to leave the labor force (or equivalently, have increased their reservation wage), and how much workers are willing to accept the decrease in real income due to the increase in energy and food prices. Thus, our estimate of the unemployment rate gap is likely conservative.

Vacancies will not decrease without an increase in unemployment

Going back to figure 3, a decrease in the equilibrium from B to A—which is what some Fed officials would like to achieve—would require a large downward shift of the matching relation.

This could happen if either matching efficiency increased or reallocation decreased sufficiently. Figures 4b and 4c show that this is not happening so far, and there is little reason to expect it to happen: It is clear that the COVID-19 crisis will have substantial reallocation implications, especially as the implications of telework become more apparent.[10] And it is not surprising that higher reallocation, with workers moving across sectors and across space, may lead to a sustained decline in matching efficiency. Tighter monetary policy, which will rotate the aggregate activity relation to the right, is unlikely to shift the matching relation at all. Thus, one must expect movements along the matching relation, with the decrease in vacancies associated with an increase in unemployment.

Turning to the empirical evidence, looking at the historical relation between job vacancies and unemployment going back to the 1950s and analyzing the trajectory of unemployment after vacancies come down from a peak, there has never been a historical example where the job vacancy rate came down in a substantial way without a significant increase in unemployment. To look at the evidence over a long time period, one can extend the JOLTS vacancy series back to the 1950s using data constructed by Regis Barnichon (2010), who makes use of the Help-Wanted Index published by the Conference Board to create a vacancy rate series from 1951 to 2000. This is done in figure 5.

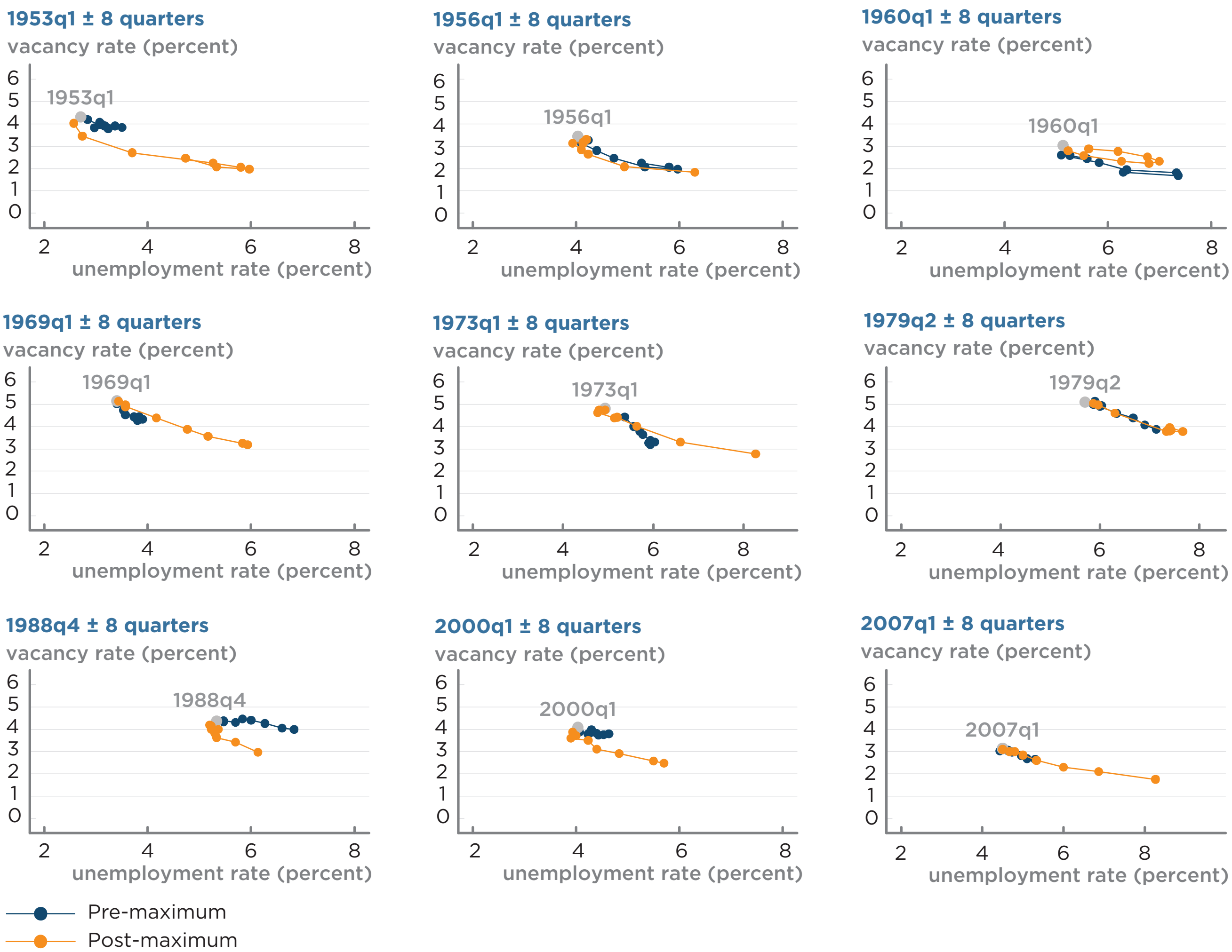
Figure 5 plots separately each vacancy rate peak plus and minus eight quarters to visualize the movement in the unemployment rate after each vacancy peak between 1951 and 2019. The eight quarters before a peak are shown in blue and

10 See BLS (2021).

Figure 5

After vacancies reached a peak, the unemployment rate always rose as the vacancy rate fell

Historical Beveridge Curve: Maximum vacancies ± 8 quarters



Note: Vacancy rate peaks were determined using the quarter when vacancies reached a local maximum and were nonincreasing for two consecutive quarters. Quarterly data are calculated using the average monthly vacancy and unemployment rate within each quarter. The vacancy rate is defined as the total number of nonfarm job openings divided by the size of the labor force. Vacancy data from 2001 onwards use estimates from the Job Openings and Labor Turnover Survey, while vacancy data before 2001 use vacancy estimates constructed from Barnichon (2010) using the Help-Wanted Index published by the Conference Board. All values are seasonally adjusted. Figure is adapted from Diamond and Şahin (2015).

Sources: Bureau of Labor Statistics, JOLTS, Barnichon (2010); authors' calculations.

the eight quarters after a peak are shown in orange (this is related to Diamond and Şahin (2015), who instead look at movements in unemployment and vacancies after each business cycle trough). The figure shows that in every historical example, the unemployment rate rose substantially in the eight quarters after the vacancy rate reached its maximum.

Table 1 presents the same evidence in quantitative terms. It computes for each episode the change in the vacancy rate and the unemployment rate from the month of the peak vacancy rate, and the ratio of the change in the unemployment rate over the change in the vacancy rate, over the next 6 months, 12 months, and 24 months after the peak.

Table 1
Change in the unemployment rate (*UR*) and the vacancy rate (*Vac*) after a peak vacancy rate

Month of peak vacancy rate (*t*)	Vacancy rate (percent)	Unemployment rate (percent)	Δ Vac	Δ UR	Δ UR/Δ Vac	Δ Vac	Δ UR	Δ UR/Δ Vac	Δ Vac	Δ UR	Δ UR/Δ Vac
			t + 6			*t + 12*			*t + 24*		
March 1953	4.4	2.6	-1.1	0.3	-0.3	-2.3	3.1	-1.4	-1.8	2.0	-1.1
February 1956	3.5	3.9	-0.4	0.2	-0.5	-0.5	0	0	-1.7	2.5	-1.5
February 1960	3.1	4.8	-0.5	0.8	-1.7	-0.9	2.1	-2.4	-0.2	0.7	-3.5
May 1969	5.2	3.4	-0.3	0.1	-0.3	-1.4	1.4	-1.0	-2.0	2.5	-1.3
July 1973	4.8	4.8	-0.4	0.3	-0.8	-0.7	0.7	-1.0	-1.9	3.8	-2.0
October 1979	5.2	6.0	-1.2	0.9	-0.7	-1.3	1.5	-1.2	-1.9	1.9	-1.0
November 1987	4.6	5.8	-0.1	-0.2	2.2	-0.3	-0.5	1.9	-0.7	-0.4	0.6
February 2000	4.1	4.1	-0.5	0	0	-0.6	0.1	-0.2	-1.8	1.6	-0.9
March 2007	3.2	4.4	-0.2	0.3	-1.4	-0.5	0.7	-1.4	-1.6	4.3	-2.7
Average			**-0.5**	**0.3**	**-0.4**	**-0.9**	**1.0**	**-0.7**	**-1.5**	**2.1**	**-1.5**

Note: The month of the peak vacancy rate is identified using the local maximum vacancy rate. In a few cases, this month differs from the maximum identified in figure 5, which uses quarterly averages. The vacancy rate is calculated as the total number of nonfarm job openings divided by the size of the labor force. Job vacancy data from 2001 onwards use estimates from the Job Openings and Labor Turnover Survey, while vacancy data before 2001 use job vacancy estimates constructed from Barnichon (2010) using the Help-Wanted Index published by the Conference Board. All values are seasonally adjusted.

Sources: Bureau of Labor Statistics (BLS), JOLTS; Barnichon (2010); authors' calculations.

The data in table 1 yield two conclusions.

The first is the presence of Beveridge loops. In each episode (with the exception of November 1987), the increase in the unemployment rate relative to the decrease in the vacancy rate increased over time. Put another way, the vacancy rate declined initially faster than the unemployment rate increased. The average of the ratio of the change in unemployment to the change in the vacancy rate was −0.4 after 6 months, and increased to −0.7 after 12 months and −1.5 after 24 months.

The second, and most important, is that in all episodes when the vacancy rate came down in a meaningful way, the unemployment rate increased substantially.[11,12] There was no free lunch, and there is no reason to expect one today.

CONCLUSIONS

The analysis in this Policy Brief is discouraging with respect to the prospects of quieting the labor market without substantial unemployment pain. We believe that the news from the Beveridge space is bad. The low unemployment rate and the very high vacancy-to-unemployment ratio suggest that not only is the labor market overheating but also the natural unemployment rate has substantially increased, reflecting worse matching and higher reallocation. And the hope that a decrease in the vacancy-to-unemployment ratio can be achieved without much of an increase in unemployment flies in the face of theoretical and empirical evidence.

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11 In one historical example—November 1987—the vacancy rate declined from its peak of 4.55 percent at a very slow rate, with little initial movement in the unemployment rate. But once the vacancy rate began to come down in a substantial way (dropping below 3.6 percent in June 1990—a 20 percent decline from its peak), the unemployment rate increased by 1.7 percentage points over the subsequent 12 months.

12 Using the number for $\Delta u/\Delta v$ two years out in the table, we can derive the increase in the unemployment rate needed to reestablish the same vacancy-to-unemployment ratio as in 2019:

A first relation is obtained by differentiating v/u: $\Delta (v/u) = (\Delta v)/u - ((\Delta u)/u)\, v/u$. A second relation comes from table 1: $\Delta u = -1.5\, \Delta v$, or equivalently $(\Delta v)/u = -1/1.5\, (\Delta u)/u$. Together these two relations imply: $u\, \Delta (v/u) = (-1/1.5 - v/u)\, \Delta u$, so Δu satisfies: $u\, \Delta (v/u) = (-1/1.5 - v/u) * \Delta u$.

Given a vacancy-to-unemployment ratio of 1.2 in December 2019 versus 1.9 today, we need v/u to decline by −0.7; i.e., $\Delta (v/u) = -0.7$. If we use the average value of v/u in December 2019 and April 2022, 1.5, the relation above implies an increase in the unemployment rate of 1.2 percentage points (pp), from 3.6 to 4.8 percent, close to the 1.3 percentage points we derived earlier using the matching function. (Using either starting or ending values for v/u gives a range of 1 pp to 1.4 pp for the increase in the unemployment rate.)

Obviously, if the Fed wants to reduce inflation, it will have to push the unemployment rate even beyond this higher natural rate, an issue we have left aside in this Policy Brief.

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APPENDIX

Recalls. Hires include recalls. Recalls do not require matching; the workers on temporary layoffs do not search for other jobs. This suggests using the following specification:

H = Recalls + $a\ m(U - Utemp, V)$, where *Utemp* is workers on temporary layoffs,

and thus constructing the parameter a as

$a = (H - \text{Recalls})/(U - Utemp)^{\alpha}\ V^{(1-\alpha)}$

(Recalls are not available in JOLTS and are constructed from the Current Population Survey [CPS], applying the proportion of recalls in total hires from CPS and multiplying it by hires from JOLTS [because hires in JOLTS are less than constructed total flows into employment from CPS, likely reflecting classification errors in CPS].)

This is what the blue line in figure A.1 shows. Note that the blue and orange lines differ at the start of COVID-19. Firms, having laid off a high number of workers, relied heavily on recalls but the normal pattern has returned since late 2020. Thus the previous conclusion about the decrease in matching efficiency remains.

Net changes in employment. The computation assumed that hires were equal to job destruction. This is not typically the case as firms may hire fewer or more workers than they lost, reflecting both underlying growth and cyclical movements.

One rough way of adjusting the computation is to run gross hires on net hires and use the residual series for computing h. The regression yields a coefficient of 0.12 on net hires, so we construct an alternative series for h as (gross hires minus 0.12 times net hires) divided by the labor force. Except for a few months during the crisis, when net hires were extremely large positive or negative, the value of the reallocation parameter h is very much the same as without the adjustment.

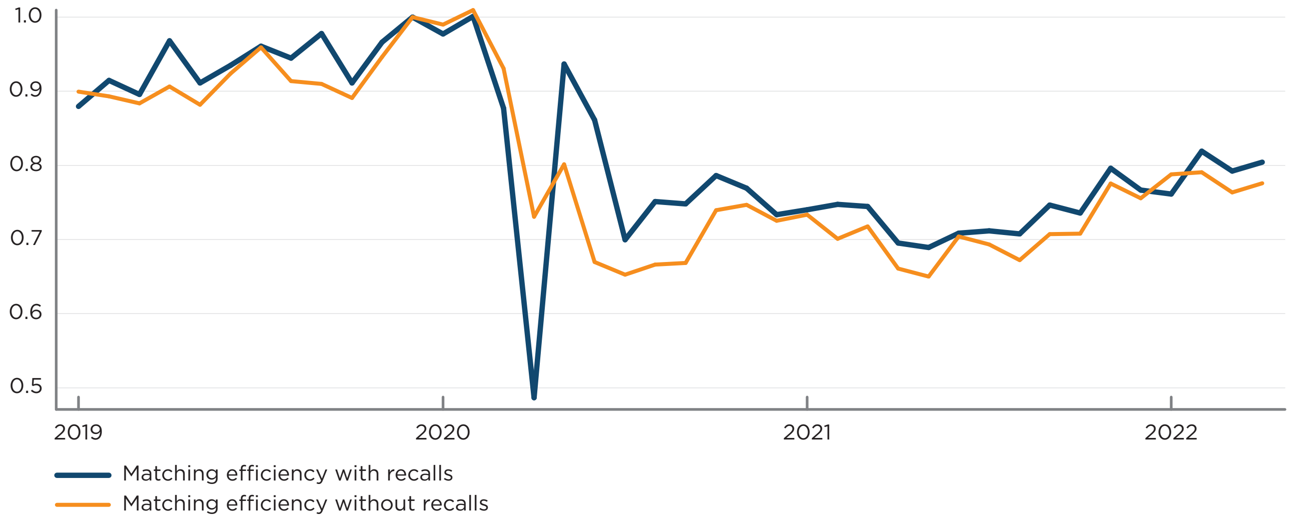
Hires from employment and from out of the labor force. As is well known, flows from employment and flows from out of the labor force exceed in size flows from unemployment. In other words, the pool of potential workers is larger than unemployment, implying that the matching function we used is misspecified.

As long as the proportions coming from different pools are roughly stable, shifts in the estimated matching function are likely to capture true shifts, not just pool composition effects.

With this in mind, figure A.2, based on CPS data, shows the evolution of the different flows into employment, decomposing flows from unemployment between workers laid off and others, from employment to employment, and from out of the labor force to employment. The figure shows the sharp increase in recalls at the start of the COVID-19 crisis and that, today, the proportions of the different flows are very similar to what they were before the pandemic. (It is known that these constructed flows suffer from classification errors in the CPS and thus spurious transitions [some more than others], but we are not concerned with specific proportions, just their stability.)

Figure A.1
Evolution of the matching efficiency parameter (*a*), with and without recalls

matching efficiency (*a*), January 2019–April 2022 (normalized, December 2019 = 1)

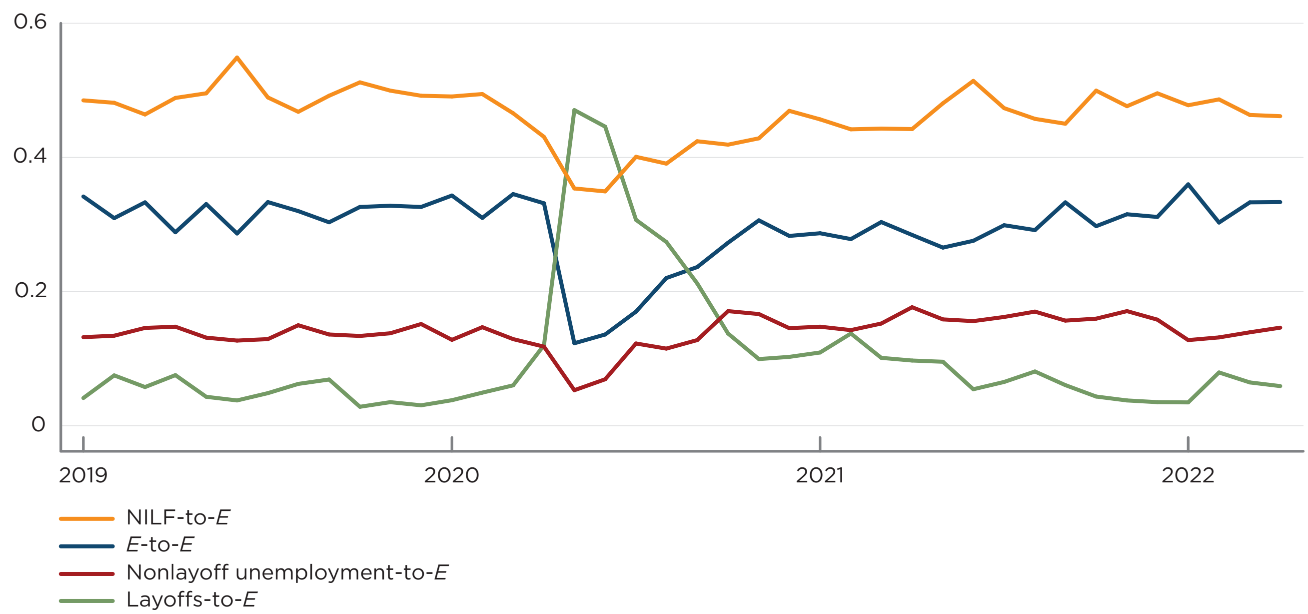


Note: The blue line shows a time series of matching efficiency assuming $a = H/U^{\alpha} V^{(1-\alpha)}$. The orange line adjusts hires to account for recalls (which do not require matching), and calculates matching efficiency as $a = (H - \text{Recalls})/(U - Utemp)^{\alpha} V^{(1-\alpha)}$, where *Utemp* is workers on temporary layoffs.

Sources: Bureau of Labor Statistics, JOLTS; authors' calculations.

Figure A.2
Flows into employment (*E*), January 2019-April 2022

share of flows into employment



NILF = not in the labor force

Note: Flows into employment are calculated using microdata from the Current Population Survey (CPS). The flows from unemployment are decomposed between workers on temporary layoff and all others. It is known that these constructed flows suffer from classification errors in the CPS and thus spurious transitions, but we are not concerned with specific proportions, only their stability over time.

Source: Authors' calculations using data from the Current Population Survey.

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