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(Re-)Connecting Inflation and the Labor Market: A Tale of Two Curves[⋆]

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Abstract

We propose an empirical framework in which shocks to worker reallocation, aggregate activity, and labor supply drive the joint dynamics of the labor market and inflation, and where reallocation shocks take two forms depending on whether they result from quits or from job losses. We find that these structural shocks, which affect the Beveridge curve, have different effects on inflation. Our model fully decomposes shifts of or along the empirical Beveridge curve in terms of the contribution of each shock and also allows us to estimate the Phillips correlation associated with each shock; observed Beveridge and Phillips correlations change over time depending on what types of structural shocks predominate in a given period. We find that reallocation shocks that accompany job losses were a key source of labor market dynamics and the steepening of the reduced-form Phillips curve during the Covid-19 pandemic, and were an important driver of the post-pandemic "soft landing."

Keywords: Beveridge curve, Phillips curve, monetary policy
JEL classification: C11, C32, E24, E31, E52

Introduction

The Covid-19 pandemic saw a sudden surge in the unemployment rate that was accompanied by a drop in labor force participation. While the unemployment rate declined gradually and the participation rate remained low in the wake of the pandemic recession, job vacancy postings rose to a record-high level and both wage and price inflation rose sharply and persistently. The unprecedented shocks to the labor market created equally unprecedented movements in the Beveridge curve. The empirical Beveridge curve shifted out dramatically—first with the rapid rise in unemployment, then with the prolonged increase in job vacancies—leading some to conclude that the pandemic induced a large and persistent reallocation shock in the labor market.[1] Hidden in the outward shift, however, was a reduction in labor supply that shifted the Beveridge curve inward (Elsby et al., 2015); to make matters even more complicated, shocks to aggregate activity resulted in cyclical movements *along* the Beveridge curve.

Emerging evidence also suggests that the pandemic might have strengthened the link between real activity and inflation.[2] Plausibly, decreased labor supply combined with increased labor reallocation can be inflationary, with the former raising wage inflation and the latter raising the noncyclical portion of the unemployment rate (Lilien, 1982). As a result, the increased importance of these structural shocks might

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[1]See Barrero et al. (2021).
[2]See, for example, Hobijn et al. (2023).

have changed the inflation–unemployment tradeoff that would be captured by a reduced-form Phillips curve. This possibility shows that structural shocks in the labor market can link the Beveridge curve and the Phillips curve. Furthermore, joint consideration of the Beveridge and Phillips curves should help us to better identify the cyclical state of the economy than simply using the Phillips curve alone, especially given how flat this latter relation appears to have become in recent decades.

Previous research has examined worker and job reallocation to assess the relative impact of reallocation and cyclical shocks on labor market dynamics. (e.g., Lilien, 1982; Abraham and Katz, 1986). In a well-known paper, Blanchard and Diamond (1989) described labor market dynamics and the Beveridge curve in terms of shocks to aggregate activity, worker reallocation, and labor supply. They proposed an identification strategy where a positive aggregate activity shock raises job vacancies but lowers unemployment (a movement along the Beveridge curve); a positive labor reallocation shock raises both unemployment and vacancies (an outward shift in the Beveridge curve); and a positive labor supply shock raises labor force participation and unemployment (also an outward shift in the Beveridge curve). In this sense, the aggregate activity (demand) shock drives the cyclical dynamics of the unemployment rate, while the labor reallocation shock and labor-supply shock are associated with changes in the noncyclical rate of unemployment (NCRU).

Although Blanchard and Diamond's empirical model is a type of sign-restricted VAR, a suitable statistical approach for estimating these models was only developed recently.[3] To explore the empirical link between the Beveridge and Phillips curves, we identify the structural shocks in a way that is similar to Blanchard and Diamond but use the estimation methodology of Baumeister and Hamilton (2015). While Blanchard and Diamond's identifying restrictions are imposed on the impact matrix of the structural shocks, in Baumeister and Hamilton's algorithm priors incorporating sign and exclusion restrictions are imposed on the parameters of the *inverse* of the impact matrix. Because of this difference, Baumeister and Hamilton's method has some limitations when applied to Blanchard and Diamond's model. We therefore modify Baumeister and Hamilton's algorithm to allow the priors reflecting the identifying restrictions to be imposed directly on the structural parameters of the impact matrix.

Our paper is the first to combine information from the Beveridge and Phillips curves to analyze the joint dynamics of labor markets and inflation within a Bayesian sign-restricted VAR framework. Though our model draws on Blanchard and Diamond's characterization of labor market dynamics, our approach differs from theirs in two important ways. First, we introduce wage and price inflation into the model, which provides additional useful information about the state of the labor market. Second, we distinguish between two different types of reallocation shocks—one that primarily raises involuntary separations and another that raises quits—by using reported reasons for unemployment. We refer the former as the *job-loss reallocation shock* and the latter as the *quits reallocation shock*.

The aggregate activity shock drives the cyclical tradeoff between real activity and inflation—the Phillips curve—and the size of that tradeoff is the slope of the Phillips curve. The effects of the other structural shocks on inflation are less clear. Increased reallocation, if driven by job quitters who seek out and then find better jobs with higher wages, puts *upward* pressure on inflation (all else equal).[4] It also shifts the Beveridge curve out: Typically, job quitters will experience a short spell of unemployment because of job-search frictions, and hence increased quits-related reallocation likely raises the frictional unemployment. In sharp distinction, if increased reallocation is primarily associated with job losses, the shock still shifts the Beveridge curve out but puts *downward* pressure on inflation: An increased unemployment rate owing to job-loss reallocation is likely to be related to worker–job mismatch, and thus to reflect a rise in structural unemployment. Similarly,

[3]More precisely, Blanchard and Diamond transformed their model into an over-identified system by imposing further restrictions on the structural parameters such that the implied impulse responses had the desired sign patterns.

[4]Other work has examined the relation between quits and inflation. Faccini and Melosi (2023) introduce a shock to the propensity to search on the job that is similar to our quits reallocation shock: When a larger fraction of workers start searching on the job, it shortens the time that it takes the economy to reach the optimal allocation of labor and makes overheating more likely, creating a positive association between quits and inflation. Moscarini and Postel-Vinay (2023) also study the inflationary effect of job-to-job transitions, but in their model a business-cycle shock is the key source of misallocation and quits. In addition, Birinci et al. (2024) embed the analysis of on-the-job search from Faccini and Melosi (2023) in a HANK model. But none of these studies explicitly connects the Beveridge and Phillips curves through the underlying structural shocks to the labor market. In addition, our analysis covers a longer sample period.

increased labor supply also raises the NCRU and puts *downward* pressure on inflation.[5] Hence, both of the reallocation shocks and the labor supply shock shift the Beveridge curve outward and all are associated with changes in the NCRU, but the quits reallocation shock has an effect on inflation that is opposite to the other two.

We find evidence for two types of reallocation shocks that do in fact have different effects on inflation: The job-loss reallocation shock lowers wage and price inflation, while the quits reallocation shock raises it. A positive labor supply shock lowers wage and price inflation, similar to the job-loss reallocation shock. This finding implies that relying solely on a Phillips curve model may provide misleading inference about the NCRU. Specifically, if the model relates price inflation negatively to the unemployment-rate gap (defined as the unemployment rate minus the NCRU), only changes in the unemployment rate driven by quits reallocation shocks will be detected as changes in the NCRU (or, alternatively, in the unemployment rate that is consistent with the absence of price pressures). Furthermore, if frictional and structural unemployment affect inflation differently—as implied by the effects that the two reallocation shocks have on inflation—we won't be able to correctly identify a change in the NCRU based on the Phillips curve alone. This highlights the importance of distinguishing among labor-market shocks, especially quits reallocation and job-loss reallocation shocks, and also of jointly analyzing the Beveridge and Phillips curves rather than relying on either one in isolation.

Overall, we find that shocks to aggregate activity are the main source of labor market fluctuations over the business cycle (in line with Abraham and Katz, 1986), and that these shocks induce persistent changes in wage and price inflation. The result is an economically and statistically significant cyclical tradeoff between unemployment and inflation; that tradeoff is the slope of the Phillips curve. Notably, however, job-loss reallocation shocks and labor supply shocks each imply an unemployment–inflation tradeoff that is *larger* in size to the one observed for aggregate activity shocks, while quits reallocation shocks create a positive correlation between the unemployment rate and inflation. Hence, the observed relation between the unemployment rate and inflation depends on what sort of structural shocks drive the dynamics of the unemployment rate. We find that, while the aggregate activity shock is the main driver of variations in the unemployment rate, the non-negligible roles of job-loss reallocation shocks and labor-supply shocks are likely to overstate the estimated slope of the Phillips curve if one does not properly control for these shocks that affect the NCRU. Our decomposition further suggests that any change in the incidence or size of specific structural shocks likely causes an estimated reduced-form Phillips correlation to vary.

In the specific case of the pandemic period, we find that job-loss reallocation shocks *also* became a key driver of labor market dynamics (in line with Barrero et al., 2021). In particular, these shocks were the main driver of the rapid outward shift in the Beveridge curve during the pandemic recession and its apparent inward shift during the subsequent recovery, implying a path for the NCRU that rises at the onset of the pandemic and declines after the pandemic recession. The shocks also contributed to a steepening of the observed reduced-form Phillips curve. Relative to the job-loss reallocation shocks, the quits reallocation shocks and labor supply shocks played a small role.

Our analysis also speaks to the "soft landing" debate of 2022. According to Blanchard et al. (2022), the relatively flat empirical Beveridge curve during the pandemic implied that even a modest reduction in job vacancies would raise the unemployment rate significantly. By contrast, Figura and Waller (2022) claimed that increased unemployment inflows temporarily flattened the Beveridge curve, but that the slope of the structural Beveridge curve remained steep.[6] Our model directly addresses this debate by estimating the changes in the vacancy and unemployment rates that were driven by the aggregate activity shock (as well as the other structural shocks, which shifted the curve), thereby recovering the slope of the structural Beveridge curve. Our findings support the conclusion of Figura and Waller, but are distinct in that our formal statistical model identifies and quantifies an important driver of labor market dynamics during this period—namely, job-loss reallocation shocks.

[5] A positive labor supply shock can raise frictional unemployment if it increases the number of job seekers who find a job quickly, but it can raise structural unemployment if it results in more job seekers facing long jobless spells.

[6] We use the term "structural Beveridge curve" to distinguish it from the empirical Beveridge curve—the observed locus of vacancy and unemployment rates. Figura and Waller's 2022 analysis has been extended and published as Figura and Waller (2024).

In particular, because the job-loss reallocation shock was responsible for much of the rise in vacancy rates, the cyclical strength of the vacancy rate was smaller than what a simple read of the data suggested. Therefore, the decline in the vacancy rate in 2022 and 2023 was able to occur without the dramatic rise in the unemployment rate that Blanchard et al. predicted. Also during this period, job-loss reallocation gradually unwound and put modest downward pressure on the unemployment rate; a soft landing with lower inflation was further facilitated because the job-loss reallocation shocks pushed down inflation through 2022. This episode once again underscores that it is vital to consider the underlying shocks driving the joint dynamics of the labor market and inflation to understand developments in the economy.

1. Data

We use monthly data on the labor force participation rate and the unemployment rate by reason for unemployment from the Current Population Survey. We consider two reasons for unemployment: quits (job leavers), and any other reason including involuntary separation or entrance into the labor force.[7] For data on vacancy postings, we use the composite measure of job vacancies compiled by Barnichon (2010), which covers the period prior to when the Job Openings and Labor Turnover Survey (JOLTS) data become available (December 2000). This series ends in September 2021; we extend it through December 2023 with the growth rate of total vacancy postings from JOLTS.

We use the 12-month percent change in average hourly earnings of production and nonsupervisory workers (AHE) as our measure of wage inflation. The AHE data are monthly and available from January 1965 (among available monthly wage indicators, it is the only series that extends back into the 1960s). AHE is likely affected by shifts in the composition of the workforce; however, to the extent that these shifts are unrelated to underlying labor market strength, they can be captured with the model's wage-specific disturbances.[8]

For price inflation, we use the percent change in the core market-based personal consumption expenditures (PCE) price index from the Bureau of Economic Analysis (BEA). We use market-based core as our principal price measure because several nonmarket components of PCE are priced using input-cost indexes that are in turn derived from wage or compensation measures. Official data for this price index start in 1987; to compute a market-based series prior to 1987, we strip out the prices of core nonmarket PCE components from the published overall core PCE price index using BEA's definitions and procedures. The market-based PCE inflation series that we use for the extended-sample VARs subtracts out Blinder and Rudd's (2013) estimates of the effects of the Nixon-era price controls.

2. Linking the Beveridge Curve and the Phillips Curve

We first discuss the identification of structural shocks in Blanchard and Diamond's model (BD, henceforth), and then extend that model to have two different reallocation shocks and to include wage and price inflation.

2.1. Identification of structural shocks

BD identify three types of structural shocks—reallocation shocks, aggregate activity shocks, and labor supply shocks—based on how each shock affects unemployment, job vacancies, and labor force participation on impact (Table 1). Conceptually, a negative aggregate activity shock, which reflects weakened demand, reduces job vacancies while increasing unemployment, resulting in movement along the Beveridge curve. In contrast, a positive reallocation shock leads to job creation in some sectors and job destruction in others. This type of shock raises both job vacancies and unemployment, yielding an outward shift of the Beveridge curve. Both negative aggregate activity shocks and positive reallocation shocks reduce employment through job destruction, thereby also lowering labor force participation. Finally, a positive labor supply shock raises both unemployment and labor force participation by bringing more job seekers into the labor market or increasing the labor-force attachment of job seekers, with no impact effect on job vacancies.

[7] Labor force entry covers new entrants (e.g., college graduates) and re-entrants (e.g., job losers who leave and then return to the labor force). Unemployment by reason is available starting in January 1967.

[8] For this reason, we view potential composition effects in AHE as less of a concern for our exercise.

Table 1: Identification of structural shocks in the Blanchard–Diamond model

Response of the following variables ...	**To a positive shock to ...**		
	Reallocation	Aggregate activity	Labor supply
Labor force participation	−	+	+
Vacancy	+	+	0
Unemployment	+	−	+

Notes: This table summarizes the sign of each shock's impact effect on the three variables: '+' and '–' denote positive and negative impact effects, respectively, and '0' denotes no impact effect.

We extend BD's model in two ways.[9] First, while retaining BD's identification of reallocation shocks, we further differentiate these shocks into *job-loss reallocation* shocks and *quits reallocation* shocks based on whether the shock affects the unemployment rate of job losers (U_t^l) or job leavers (U_t^q). We measure U_t^l with the unemployment rate excluding job leavers, and hence U_t^l is composed of those who experienced involuntary separation and entrants to the labor force. We interpret U_t^l as largely representing job losers, because job losers are the majority of this category and the main driver of its cyclical fluctuations.[10] These two types of reallocation shocks are likely to result in different labor market outcomes and to carry different implications for the NCRU. In particular, the quits reallocation shock can result in job seekers who experience frictional unemployment when switching jobs, while the job-loss reallocation shock can result in job seekers who experience a spell of structural unemployment owing to inefficient job searches or worker–job mismatch.

The second extension is to include measures of wage growth (W_t) and price inflation (Π_t), which lets us examine the effect of each structural shock on inflation within a coherent Bayesian structural VAR framework. This adds two more structural shocks (own shocks to wage and price inflation). Our extended model has a total of six structural shocks, and is a six-variable structural VAR.

Table 2 summarizes the identifying restrictions.[11] The elements in the first two columns identify the job-loss reallocation shock (u_t^l) and the quits reallocation shock (u_t^q). These two shocks still satisfy BD's identification of the reallocation shock, lowering the labor force participation rate ([1,1] and [1,2] entries) but raising both the vacancy rate ([2,1] and [2,2]) and unemployment rate ([3,1] and [4,2]). The key difference is that on impact, the job-loss reallocation shock u_t^l only raises the unemployment rate of job losers while the quits reallocation shock u_t^q only raises the unemployment rate of job leavers. These restrictions are captured with the zero restrictions in the [4,1] and [3,2] entries.

Following BD, the positive aggregate activity shock u_t^c raises the labor force participation rate ([1,3]) and vacancy rate ([2,3]) on impact. A departure from BD's model is that a positive aggregate activity shock lowers the unemployment rate of job losers at impact ([3,3]) but the sign of the effect on the unemployment rate of job leavers is unrestricted ([4,3]). The reason is that unemployment inflows and job-finding probabilities for unemployed job leavers are both procyclical (Ahn, 2023); we therefore let the data give us the net cyclical effect.

Finally, in line with BD a positive labor supply shock u_t^s raises the labor force participation rate ([1,4]) but is assumed to have no impact effect on the vacancy rate ([2,4]).[12] In the extended model, this positive labor

[9]Note that we use the unemployment, vacancy, and labor force participation *rates*, rather than the transformed levels that Blanchard and Diamond used.

[10]This group also includes individuals whose temporary jobs have ended and those entering or re-entering the labor force; note that re-entrants also include individuals who previously left the labor force after losing a job (Ahn, 2023). We do not exclude labor-force entrants from U_t^l so that the model parses variations in the *total* unemployment rate into the contributions of structural shocks. The online appendix considers excluding the entrant group from U_t^l and shows that the effects of the labor supply shocks largely disappear while the identification of the other structural shocks remains robust. This observation suggests that labor supply shocks are not well-identified if we rely primarily on the participation rate, but that our baseline model does so while maintaining robust identification of other structural shocks.

[11]In what follows, table entries are identified by [*row*, *column*].

[12]Assuming a zero impact effect of the labor supply shock on the vacancy rate is also in line with the empirical treatment of

Table 2: Identification of structural shocks in the extended model

Response of the following variables ...	**To a positive shock to ...** Job-loss reallocation	Quits reallocation	Aggregate activity	Labor supply	Wage-specific	Price-specific
Labor force participation rate	−	−	+	+	0	0
Vacancy rate	+	+	+	0	0	0
Unemployment rate (job losers)	+	0	−	+	+	?
Unemployment rate (job quitters)	0	+	?	0	0	0
Wage inflation	?	?	?	?	+	0
Price inflation	?	?	?	?	0	+

Notes: This table summarizes the sign of each shock's impact effect on the six variables: '+' and '–' denote positive and negative impact effects, respectively; '0' denotes no impact effect; and '?' denotes an unrestricted effect.

supply shock raises the unemployment rate of job losers at impact ([3,4]) because the shock can encourage job losers or those who re-entered the labor force after a job loss to continue their job searches rather than exiting the labor force.[13] We assume that the labor supply shock has no impact effect on the unemployment rate of job quitters ([4,4]).

Note that we do not impose any sign restrictions on the impact effects of the structural labor-market shocks on wage and price inflation (see the fifth and sixth rows and first through fourth columns), which allows the model to estimate the sign and magnitude of each shock's effect.

The last two columns summarize the impact effects of own shocks to wage and price inflation. By definition, both shocks increase wage and price inflation at impact ([5,5] and [6,6]) but do not influence each other directly at impact ([6,5] and [5,6]). The wage-specific shock u_t^w represents innovations like changes in bargaining power, minimum wage increases, or wage markup shocks, while the price shock u_t^π captures factors such as cost-push shocks (e.g., supply bottlenecks) and changes in inflation expectations (e.g., from monetary policy actions). Both shocks are allowed to affect the unemployment rate of job losers: The wage shock is assumed to raise it ([3,5]), reflecting higher labor costs, while the price shock's effect ([3,6]) is unrestricted, as a positive innovation to price inflation can raise it (supply disruptions) or lower it (a reduction in the real wage). For the other variables we impose zero restrictions on the nominal shocks' impact effects, as most of the high-frequency variability of inflation reflects idiosyncratic movements that should have minimal within-month effects on job search and labor force entry.[14]

Foroni et al. (2018). It is important to note that the zero impact effect does not preclude a case where a positive labor supply shock raises vacancy postings in the subsequent months after the impact. However, it differs from the prediction of the search and matching model in Pissarides (2000), which suggests that an increase in labor supply makes it easier to fill vacant jobs, causing a positive labor supply shock to have an immediate positive effect on the vacancy rate. We explore this case in our robustness analyses. In this alternative case, both positive labor supply shocks and reallocation shocks move the vacancy rate and the unemployment rate in the same direction, but the former raises labor force participation, while the latter lowers it.

[13] A positive labor supply shock can also raise the unemployment rate of new entrants to the labor force, a relatively small component of U_t^l.

[14] Own shocks to wage and price inflation capture the *nominal* effects of cost-push shocks; they are identified from their limited impact effects on the labor market. The labor market shocks themselves will capture the *real* effects of cost-push shocks; for example, if an oil shock has real effects on the labor market it can show up as an aggregate activity shock or a reallocation shock. Hence, the own shocks to prices and wages in our model control for the portion of a cost-push shock that is orthogonal to the four labor market shocks, particularly the aggregate activity shock. This treatment is in line with standard models of the Phillips curve, where the unemployment-rate gap captures the state of the business cycle and cost-push shocks (which shift the Phillips curve) are directly controlled for with variables such as import or energy prices.

2.2. Empirical model and estimation

With the extended identification scheme, the dependent variables $\mathbf{y}_t$, structural shocks $\mathbf{u}_t$, and impact matrix $\mathbf{H}$ can be written as:

$$\begin{aligned}\mathbf{y}_t &= [L_t, V_t, U_t^l, U_t^q, W_t, \Pi_t]' \\ \mathbf{u}_t &= [u_t^l, u_t^q, u_t^c, u_t^s, u_t^w, u_t^\pi]'\end{aligned}$$

$$\mathbf{H} = \begin{bmatrix} -\theta_l & -\theta_q & +\delta & 1 & 0 & 0 \\ +\beta_l & +\beta_q & 1 & 0 & 0 & 0 \\ 1 & 0 & -\epsilon & +\omega & +\chi_w & \chi_p \\ 0 & 1 & \zeta_c & 0 & 0 & 0 \\ \phi_l & \phi_q & \phi_c & \phi_s & 1 & 0 \\ \psi_l & \psi_q & \psi_c & \psi_s & 0 & 1 \end{bmatrix}. \tag{1}$$

The signs of the parameters in $\mathbf{H}$ represent the sign restrictions that we impose on the model; when an explicit sign is absent, the parameter can be either positive or negative.

We incorporate the extended identification scheme into a Bayesian sign-restricted VAR. The reduced-form model is written as:

$$\mathbf{y}_t = \boldsymbol{\Phi}\mathbf{x}_{t-1} + \boldsymbol{\varepsilon}_t \tag{2}$$

where the reduced form model is related to the structural model as follows:

$$\begin{aligned}\boldsymbol{\Phi} &= \mathbf{HB} &(3)\\ \boldsymbol{\varepsilon}_t &= \mathbf{H}\mathbf{u}_t &(4)\\ \mathbf{D} &= E(\mathbf{u}_t\mathbf{u}_t') &(5)\\ \boldsymbol{\Omega} &= E(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t') = \mathbf{HDH}'. &(6)\end{aligned}$$

We include a constant and eight lags of $\mathbf{y}_t$ in $\mathbf{x}_{t-1}$ to adequately capture the dynamics of $\mathbf{y}_t$. Since the structural shocks are uncorrelated with each other, $\mathbf{D}$ is a diagonal matrix. The reduced-form parameters are estimated from:

$$\begin{aligned}\hat{\boldsymbol{\Phi}}_T &= \left(\sum_{t=1}^{T} \mathbf{y}_t\mathbf{x}_{t-1}'\right)\left(\sum_{t=1}^{T} \mathbf{x}_{t-1}\mathbf{x}_{t-1}'\right)^{-1} \\ \hat{\boldsymbol{\Omega}}_T &= T^{-1}\sum_{t=1}^{T} \hat{\boldsymbol{\varepsilon}}_t\hat{\boldsymbol{\varepsilon}}_t' \\ \hat{\boldsymbol{\varepsilon}}_t &= \mathbf{y}_t - \hat{\boldsymbol{\Phi}}_T\mathbf{x}_{t-1}.\end{aligned}$$

This structural VAR is estimated with a Bayesian method using an algorithm that allows a researcher to impose restrictions directly on parameters in the impact matrix. In their 2015 paper, Baumeister and Hamilton (BH) propose an analytical framework for Bayesian inference in a structural VAR model, along with an estimation algorithm that forms priors incorporating sign and exclusion restrictions on the elements of interest in $\mathbf{H}^{-1}$. In spite of this flexible feature, the algorithm is not always applicable if a researcher has specific priors on parameters in the impact matrix $\mathbf{H}$. One can still form priors on the parameters in $\mathbf{H}^{-1}$ after inverting the impact matrix.[15] However, the priors on $\mathbf{H}$ often become intractable after the matrix is inverted; this is likely to occur when the impact matrix is large, or when the parameters in the impact matrix have complicated functional relationships. So it is more straightforward and convenient to form prior beliefs on the parameters of the impact matrix itself; we therefore modify the BH algorithm in a way that permits us to do so in a flexible manner.[16]

[15] Baumeister and Hamilton (2018) illustrate such cases.
[16] Details are in the online appendix.

Our full sample period runs from January 1967 to December 2023. The large swings in many series during the pandemic can distort model estimates that include such observations. We interpret the pandemic-induced swings as resulting from large transitory shocks that had no material effect on the underlying dynamics of the economy, and so use the model parameters estimated from the pre-pandemic period (January 1967 to December 2019) to compute historical decompositions over the pandemic period (January 2020 to December 2023). In other words, the historical decompositions are extended through the pandemic period by using the pre-pandemic parameter values to back out the implied structural innovations and their propagation dynamics. This approach is in line with several recent studies that consider how to deal with the pandemic period in time-series models (Lenza and Primiceri, 2020; Ng, 2021; Cascaldi-Garcia, 2022), and we use it throughout the paper.[17]

2.3. Prior specification

The priors and sign restrictions on the structural parameters of the impact matrix $\mathbf{H}$ are summarized in Table 3.[18] If a parameter contributes to $\mathbf{H}$ with a specific sign, we impose that sign restriction (column [5]); "NA" indicates that no restriction is imposed. We characterize the prior for each structural parameter with a Student t distribution whose mode is close to the corresponding calibrated value in Blanchard and Diamond (1989) or to a value from more-recent related research, as noted in column [7].[19] For most of the parameters, the scale parameter is set to 0.3 and 3 degrees of freedom are used (as Baumeister and Hamilton, 2022 note, this represents a fairly weak prior belief). Column [6] reports the 65% and 90% ranges of the prior distribution for the corresponding parameter.

We highlight a departure from BD's calibration. The slope of the structural Beveridge curve represents the *cyclical* tradeoff between job vacancies and unemployment that yields the same number of worker-job matches. Assuming a constant-returns-to-scale (CRS) matching function, the slope is determined by the matching elasticity with respect to vacancies (or unemployment). In this sense, the parameter $-\epsilon$ —the impact response of the unemployment rate to an aggregate activity shock that increases the vacancy rate by one percentage point—captures the tradeoff at the impact of an aggregate activity shock. Without the knowledge of how the tradeoff evolves through the propagation of an aggregate activity shock, our prior belief is that $-\epsilon$ approximates the average cyclical tradeoff between the vacancy rate and unemployment rate, and the prior mode $-\epsilon = -0.8$ implies our prior belief that the matching elasticity with respect to vacancies is 0.45.[20] We allow for considerable uncertainty in this parameter so that our prior distribution well covers the range of estimates documented in existing studies (0.3 to 0.5)—see Pissarides and Petrongolo (2001).[21]

In the rest of this section we focus on the parameters not discussed in BD, specifically the effects of the labor market shocks on wage and price inflation. We assume that an aggregate activity shock that lowers the

[17] We acknowledge a few caveats to this approach. First, our model does not estimate the direct effects of fiscal stimulus or monetary policy during this period. Though these policy shocks can be parsed out into one or multiple structural shocks in the context of our model, a different framework is needed to analyze the extent to which the policy shocks influence the Beveridge and Phillips curves. Second, our model cannot account for the possibility that the pandemic permanently altered the propagation of shocks, leading to systematic changes in impulse responses. Four years of monthly observations are insufficient to infer permanent changes in the propagation of structural shocks, though it might be done using a time-varying parameter model with many more post-pandemic observations. See the online appendix for additional discussion.

[18] The prior distributions suggest that the determinant of $\mathbf{H}$ is predominantly negative but the right tail of the distribution extends to 0.6 and includes zero. However, the probability density within the region $[-0.5, 0.6]$ is only two percent. We therefore do not impose an additional prior that prevents the determinant from becoming zero (as considered in Baumeister and Hamilton, 2018); even so, the posterior distribution of the determinant is nonzero.

[19] We also used the empirical results from this research to calibrate the prior modes for a few parameters. (See the online appendix for a detailed discussion.)

[20] Assume a CRS matching function of the form $H = MU^{(1-\alpha)}V^{\alpha}$, where M represents matching productivity, and U, V, and H denote the number (or share of the labor force) of unemployed workers, vacancies, and worker-job matches. Holding M and H constant to shut down shifts of the structural Beveridge curve and to restrict the $V - U$ trajectory to the iso-match curve, the elasticity α can be approximated by noting that $-\frac{1-\alpha}{\alpha} = \frac{d\log(V)}{d\log(U)} \approx -\frac{1}{\epsilon}$. BD's benchmark calibration, by comparison, implies ϵ equals 1.3, which in turn implies the matching elasticity with respect to vacancies is about 0.6.

[21] According to a more recent study by Berstein et al. (2023), the elasticity with respect to vacancies ranges from 0.15 to 0.70, wider than the range documented by Pissarides and Petrongolo (2001). The 90th percentile interval of our prior distribution corresponds to an elasticity range of [0.2, 0.6].

Table 3: Priors for the structural parameters

[1]	[2] Prior mode	[3] Scale	[4] d.f.	[5] Sign in **H**	[6] 65(90) % range	[7] Sources and empirical grounds
Panel A. *Job-loss reallocation shock*						
θ_l	0.5	0.3	3	–	[0.28,0.86]([0.11,1.24])	Blanchard and Diamond (1989)
β_l	0.1	0.2	5	+	[0.07,0.37]([0.02,0.56])	Blanchard and Diamond (1989), Foroni et al. (2018)
ϕ_l	-0.2	0.3	3	NA	[-0.53,0.13]([-0.91,0.51])	Authors' calibration
ψ_l	-0.2	0.3	3	NA	[-0.53,0.13]([-0.91,0.51])	Authors' calibration
Panel B. *Quits reallocation shock*						
θ_q	0.9	0.3	3	–	[0.60,1.24]([0.33,1.62])	Blanchard and Diamond (1989)
β_q	0.2	0.3	3	+	[0.12,0.62]([0.04,1.02])	Blanchard and Diamond (1989)
ϕ_q	0.2	0.3	3	NA	[-0.13,0.53]([-0.51,0.91])	Authors' calibration
ψ_q	0.2	0.3	3	NA	[-0.13,0.53]([-0.51,0.91])	Authors' calibration
Panel C. *Aggregate activity shock*						
δ	0.4	0.3	3	+	[0.21,0.77]([0.08,1.16])	Blanchard and Diamond (1989)
ϵ	0.8	0.3	3	–	[0.52,1.14]([0.26,1.52])	Blanchard and Diamond (1989), Pissarides and Petrongolo (2001)
ζ_c	0.01	0.3	3	NA	[-0.32,0.34]([-0.70,0.72])	Ahn (2023), author's calibration
ϕ_c	0.5	0.3	3	NA	[0.17,0.83]([-0.21,1.21])	Galí and Gambetti (2020), Ahn et al. (2020)
ψ_c	0.3	0.3	3	NA	[-0.03,0.63]([-0.41,1.00])	Hazell et al. (2022), Fitzgerald et al. (2024), Barnichon and Mesters (2021)
Panel D. *Labor supply shock*						
ω	0.2	0.3	3	+	[0.12,0.62]([0.04,1.02])	Blanchard and Diamond (1989), Foroni et al. (2018)
ϕ_s	-0.1	0.3	3	NA	[-0.43,0.23]([-0.81,0.61])	Foroni et al. (2018)
ψ_s	-0.1	0.3	3	NA	[-0.43,0.23]([-0.81,0.61])	Foroni et al. (2018)
Panel E. *Own shocks to wages and prices*						
χ_w	0.1	0.3	3	+	[0.09,0.57]([0.03,0.97])	Foroni et al. (2018), Galí et al. (2012)
χ_p	0.05	0.2	2	NA	[-0.19,0.29]([-0.53,0.63])	Galí et al. (2012)

Notes: This table summarizes the prior distributions of the structural parameters. "d.f." stands for degrees of freedom. "NA" stands for not applicable.

unemployment rate by approximately 1 percentage point (pp) likely increases price inflation by about 0.3 pp (the mode of ψ_c) and wage inflation by 0.5 pp (the mode of ϕ_c).[22] The prior distributions of these parameters cover the range of estimates found in previous studies; without sign restrictions, these prior distributions extend into the negative region, allowing for the possibility that the slope of the Phillips curve can be zero.[23]

We assign smaller absolute values to the prior modes of the parameters that capture the effects of other labor-market shocks on inflation, reflecting our prior that aggregate activity shocks are likely to be the main source of the observed tradeoff between inflation and real activity. In addition, with limited evidence as to the differential effect of these structural shocks on wages and prices, we apply the same priors to both types

[22]The prior distribution of ϵ implies that an aggregate activity shock that increases the vacancy rate by one percentage point lowers the unemployment rate of job losers by 0.9 percentage point—the prior mean. Since this magnitude is sufficiently close to 1 given the uncertainty surrounding this parameter, we consider the impact of the aggregate activity shock on the unemployment rate to be approximately one percentage point.

[23]Furlanetto and Lepetit (2024) provide a comprehensive survey of estimated Phillips curve slopes; the prior distribution of ψ_c encompasses the range of estimates reported there. For the price Phillips curve, Barnichon and Mesters (2020) report a slope value of -0.24 and Smith et al. (2023) give estimates ranging from -0.25 to -0.29. Fitzgerald et al. (2024) finds that the empirical estimate of the slope based on MSA data is -0.33, whereas the structural model-implied slopes are -0.28 for prices and -0.87 for wages over 1977–2017, and -0.21 and -0.60, respectively, over 1999–2015. However, Hazell et al. (2022) find a slope estimate very close to zero. For the wage Phillips curve, Galí and Gambetti (2020) find slope estimates that range from -0.7 to -0.2 during the sample period 1964–2017, with a preferred estimate of about -0.5, and Ahn et al. (2020) estimate wage Phillips curve slopes that range from -0.63 to -0.37 over 1990–2019 using a variety of compensation measures.

of inflation. To characterize the inflationary effect of a quits reallocation shock that raises the unemployment rate of job leavers by 1 pp, we set the prior modes of ϕ_q and ψ_q to 0.2. To reflect the negative effect on wages and prices of a job-loss reallocation shock that raises the unemployment rate of job losers by 1 pp (see Davis and Wachter, 2011), we set the prior modes of ϕ_l and ψ_l to –0.2.[24] The inflationary effect of a labor-supply shock that raises the labor force participation rate by 1 pp and the unemployment rate of job losers by 0.2 pp—the prior mode of ω—is assumed to be even closer to zero, with the prior modes of ϕ_s and ψ_s set to -0.1. The prior mode of ω falls between the values from Blanchard and Diamond (1989) and Foroni et al. (2018), and we allow for enough uncertainty such that the prior distribution encompasses the range of parameters considered and estimated by both studies. The prior modes of ϕ_s and ψ_s are also in line with the impulse responses found by Foroni et al. (2018).

Finally, we assume that own shocks to wages have small positive impact effects on the unemployment rate of job losers (χ_w). Interpreting these shocks as reflecting changes in wage bargaining power and wage markups, we set the prior mode of χ_w to 0.1, which broadly aligns with the effect on the unemployment rate of a wage-bargaining shock (Foroni et al., 2018) or a wage mark-up shock (Galí et al., 2012).[25] Since price-specific shocks can have positive or negative effects on unemployment, we assign a smaller prior mode for χ_p and use a lower degree of freedom (2), and a smaller scale parameter (0.2) to allow for a sufficient degree of uncertainty, while preventing unreasonably large positive or negative values.

3. Estimation Results: Impulse Responses and Historical Decompositions

3.1. Impulse responses

Figure 1 reports the impulse responses for each variable following each structural shock.[26] (In the panel titles, "$x < y$" denotes the effect of shock y on variable x.) The first column reports the impulse responses following a job-loss reallocation shock.[27] This shock raises the vacancy rate (first row) and has persistent positive effects on the unemployment rate of job losers (second row). The shock lowers the unemployment rate of job quitters for a few months after impact, but the statistical significance of the response declines rapidly (third row). The job-loss reallocation shock lowers wage growth persistently (fourth row); the shock's effects on market-based core inflation are negative for about two years but are only statistically significant for a little over a year (fifth row).

The second column reports the impulse responses following a quits reallocation shock. This shock also persistently raises the vacancy rate (first row) and the unemployment rate of job quitters (third row). The shock lowers the unemployment rate of job losers, but the effects are not statistically significant (second row).[28] The quits reallocation shock results in a statistically significant increase in AHE growth and price inflation (fourth and fifth rows), which is noticeably different from the effects of a job-loss reallocation shock. The effects of a quits-reallocation shock on wage and price changes are what we would expect to see if the reallocation shock led to an increase in the NCRU.

The third column reports the impulse responses that follow an aggregate activity shock. This shock has persistent effects on most of the variables: The aggregate activity shock raises the vacancy rate, AHE growth, and price inflation, and lowers the unemployment rate of job losers. These effects are statistically significant for some time. In particular, the responses of the vacancy rate and the unemployment rate of job losers peak

[24]These magnitudes broadly align with regression-based evidence using the on-the-job search rate and the employment rate of bad matches recovered from Faccini and Melosi (2023). (Details on the regression-based calibration are in the online appendix.)

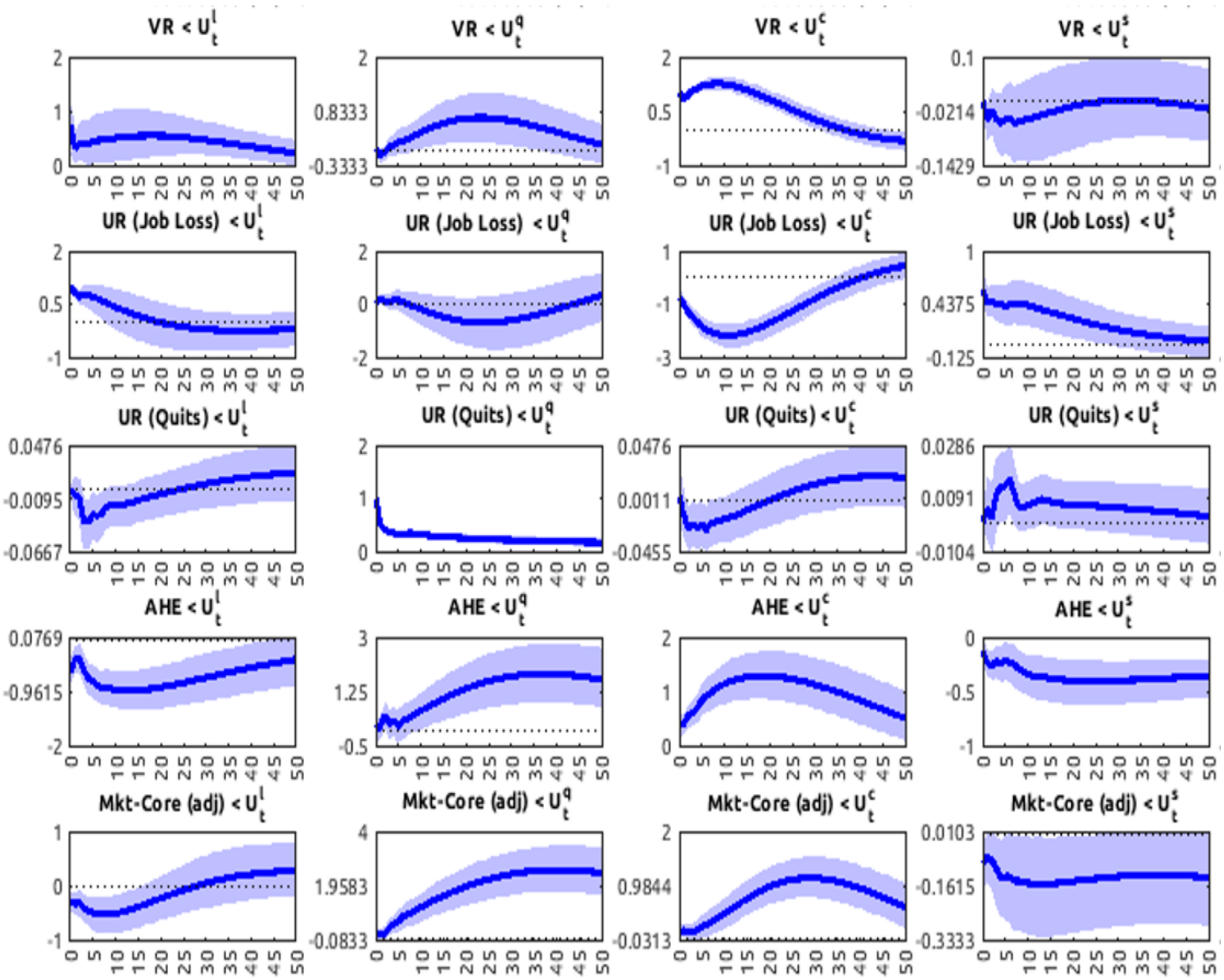
[25]Foroni et al. (2018) find that a 1% rise in real wages due to a wage-bargaining shock raises unemployment by 0.1 pp, while Galí et al. (2012) show that a wage mark-up shock of the same magnitude increases unemployment by 0.2 pp.

[26]The posterior distributions of all structural parameters are reported in the online appendix.

[27]The online appendix reports the full set of impulse responses for all six variables.

[28]In Faccini and Melosi (2023), general-equilibrium effects reduce unemployment after an on-the-job search shock (which is similar to our quits reallocation shock). This largely aligns with our findings: While our quits reallocation shock initially raises the unemployment rate among job quitters without affecting the unemployment rate of job losers, it subsequently lowers the unemployment rate of job losers, although the effect is statistically insignificant. (Note that the analysis in Faccini and Melosi (2023) focuses on employment-to-employment flows, where workers switch jobs without experiencing any period of unemployment.)

Figure 1: Impulse responses



Notes: This figure displays the estimated impulse responses from our baseline system (X-axis: number of months after the shock hits; Y-axis: the magnitude of the response). The posterior median is shown as a solid line; the dotted lines indicate zero; the shaded area gives the 68 percent posterior credible set; and $x < y$ indicates the effect of shock y on variable x. *VR* : the vacancy rate; *UR (Job Loss)* : the unemployment rate of job losers and entrants to the labor force; *UR (Quits)* : the unemployment rate of job quitters; *AHE* : Change in average hourly earnings; *Mkt-Core(adj)* : Market-based core PCE price inflation (adjusted for effects of Nixon-era price controls). U_t^l: job-loss reallocation shock; U_t^q: job-quits reallocation shock; U_t^c: aggregate activity shock; U_t^s: labor supply shock.

approximately one year after the shock and remain statistically significant for about 2.5 to 3 years. Those of wage and price inflation peak at around 1.5 and 2 years, respectively, and remain statistically significant for 3 to 4 years after the shock. The response of wage inflation is a little faster and larger than that of price inflation; this result is consistent with the wage Phillips curve's being steeper than the price Phillips curve.

The fourth column reports the impulse responses following a labor supply shock. This shock raises both unemployment rates, consistent with increased labor-force attachment and an increased number of job seekers drawn into the labor force. However, the effects are statistically significant for the unemployment rate of job losers (second row) but not for job leavers (third row). Effects of labor supply shocks on the vacancy rate are not statistically significant (first row). A labor supply shock lowers wage inflation (fourth row); it also lowers market-based core inflation (fifth row). Though these effects are statistically significant, the statistical significance of labor-supply shock's inflationary effects is not as strong as that of the other shocks.

All told, the four labor-market shocks have unique and distinguishable effects on the joint dynamics of the unemployment and vacancy rates, as well as on wage and price inflation.[29]

3.2. Historical decompositions for the pre-Covid period

We use historical decompositions to obtain the contributions of each structural shock to variations in the data.[30]

Figure 2 reports the historical decomposition of the vacancy rate (first row), the unemployment rates of job losers and quitters (second and third rows, respectively), AHE growth (fourth row), and market-based core inflation (fifth row) by each structural labor-market shock from September 1967 to December 2019. The aggregate activity shock is the main source of variations in the vacancy rate (row 1, column 3) and the unemployment rate of job losers (row 2, column 3), in line with Abraham and Katz (1986).

During the Great Recession, the job-loss reallocation and labor-supply shocks were particularly important for the NCRU.[31] Job-loss reallocation shocks raise the unemployment rate of job losers by about three-quarters of a percentage point during the Great Recession (row 2, column 1); the labor supply shock raises the unemployment rate of job losers by half of a percentage point during this period (row 2, column 4). The sum of these magnitudes is broadly in line with the increase in the short-term natural rate that the Congressional Budget Office (CBO) and Federal Reserve Board staff identified during this episode. In this context, the rise in the unemployment rate from the job-loss reallocation shocks likely represents increased reallocational frictions, including mismatch between workers and jobs, while the portion driven by labor supply shocks might reflect the effect of the extended unemployment insurance (UI) benefits that were put in place during this period.[32] If so, the portion of the unemployment rate driven by job-loss reallocation and labor supply shocks would represent a change in structural unemployment (and so the NCRU) over this period.

The structural labor market shocks also affect wage and price inflation. The aggregate activity shock accounts for some cyclical variation in wage and price inflation (row 4, column 3; row 5, column 3). It is also noteworthy that quits reallocation shocks are important contributors to wage and price inflation from the 1970s to the 1990s and after the Great Recession (row 4, column 2; row 5, column 2). This finding aligns with Faccini and Melosi (2023), who argue that a shock to the propensity to search on the job—similar to our quits reallocation shock—creates a positive link between job quits and price inflation, with the low and stable price inflation following the Great Recession driven by reduced quits reallocation.[33]

3.3. Historical decompositions for the pandemic period

Figure 3 reports the historical decompositions from our model for the period January 2020 to December 2023, with the values for December 2019 normalized to zero.[34] In contrast to earlier periods, both the

[29]The online appendix presents a number of robustness checks, including imposing a positive impact effect of the labor supply shock on the vacancy rate, excluding labor force entrants from the unemployment rate, and using an alternative measure of inflation. Overall, our main results remain robust to these modifications.

[30]A VAR model decomposes the value of $\mathbf{y_t}$ into the component attributable to structural shocks (or reduced-form forecast errors) since the start of the sample and the forecast for date t formed on the basis of initial conditions at time 0 (Hamilton, 2025). The first term is called the stochastic component, and a historical decomposition refers to the cumulative historical contribution of structural shocks to this component of $\mathbf{y_t}$. The second term, obtained from dynamic forecasts based solely on the initial conditions and parameters of the VAR model, can exhibit highly persistent movements if the VAR includes variables with high persistence (Giannone et al., 2018). Because we are interested in the contributions of the structural shocks to cyclical dynamics, we focus on these shocks' contributions when reporting the historical decompositions.

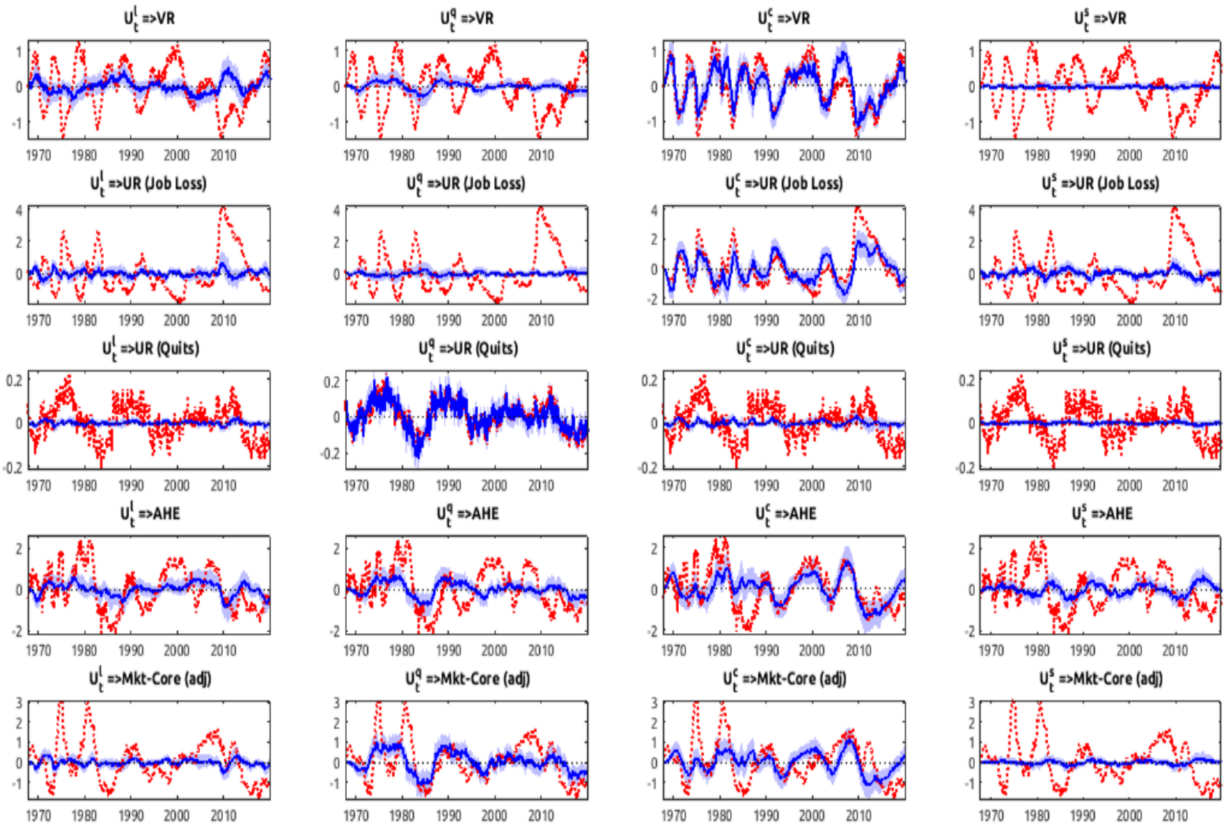
[31]Relative to these shocks, the quits reallocation shock's contribution to overall unemployment rate fluctuations is muted. The quits reallocation shock is the primary driver of the unemployment rate of job quitters, but this category represents a small share of the overall unemployment pool.

[32]The extended UI benefits likely have motivated long-term unemployed individuals to continue their job searches, thereby raising the unemployment rate.

[33]Note that although the quits reallocation shock is identified from the unemployment rate of job quitters, it likely also captures job-to-job transitions and could therefore have sizable effects on wage and price inflation. The congruence of our results with Faccini and Melosi (2023) is notable inasmuch as our estimation methodology is very different to that paper (which uses a relatively tightly parameterized DSGE model to identify the inflationary effects of a change in on-the-job search).

[34]Recall that the parameter values that we use come from a model whose estimation period ends in 2019.

Figure 2: Historical decompositions: pre-pandemic



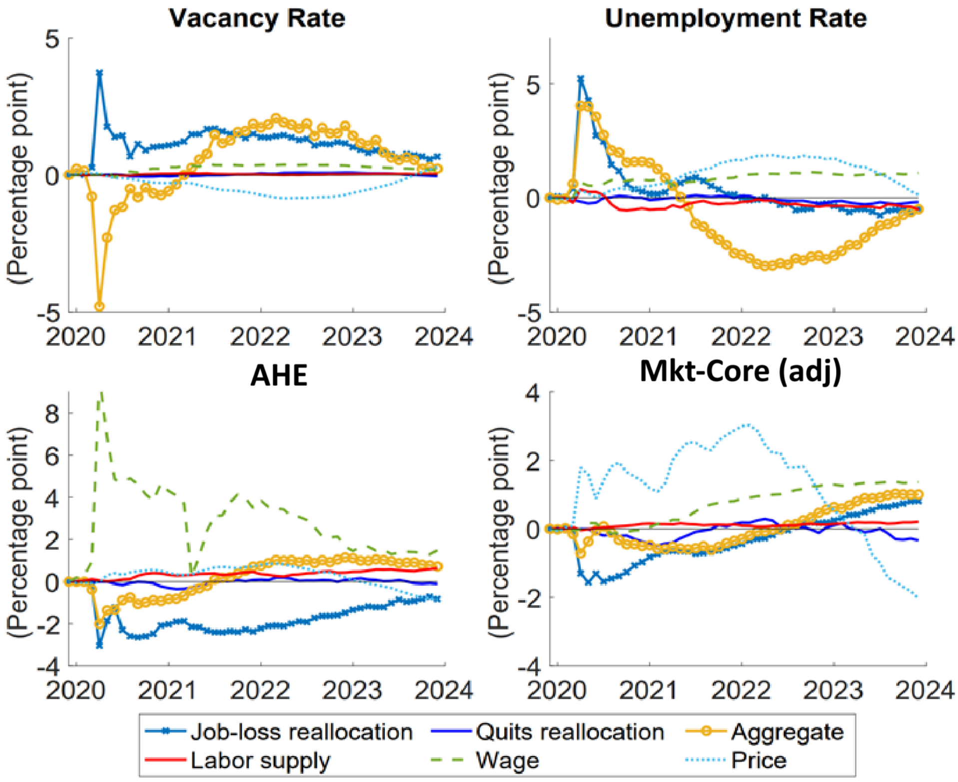
Notes : This figure displays the posterior medians of the historical decompositions of the variables in our VAR system prior to the Covid-19 pandemic (X-axis: calendar month; Y-axis: the magnitude of variations in the endogenous variable). The shaded area gives the 68 percent posterior credible set. The blue lines are the portions of the data that are explained by each shock. The red lines represent the sum of the historical decompositions for a given variable. *VR* : the vacancy rate; *UR (Job Loss)* : the unemployment rate of job losers and entrants to the labor force; *UR (Quits)* : the unemployment rate of job quitters; *AHE* : Change in average hourly earnings; *Mkt-Core(adj)* : Market-based core PCE price inflation (adjusted for effects of Nixon-era price controls). U_t^l: job-loss reallocation shock; U_t^q: job-quits reallocation shock; U_t^c: aggregate activity shock; U_t^s: labor supply shock.

aggregate activity shock *and* the job-loss reallocation shock make important contributions to the dramatic swings in the labor market variables and wage and price inflation seen during this period.

The job-loss reallocation shocks (light-blue line with markers) cause the unemployment rate (upper-right panel) and the vacancy rate (upper-left panel) to rise sharply in April 2020 and to then decline rapidly over the second half of that year. This positive effect of the reallocation shocks on job postings is consistent with Barrero et al. (2021) and also with Haltiwanger (2021), who shows that new business formation spiked in the early phase of the pandemic. Hence, the job-loss reallocation shock might be raising the number of unemployed job losers in some sectors or firms, while at the same time creating new job vacancies elsewhere. From the second half of 2020, both the job-loss reallocation and aggregate activity shocks contribute to a persistent increase in the vacancy rate. The duration of the effect of the job-loss shocks is again consistent with Barrero et al. (2021), who conclude that the pandemic acted like a *persistent* reallocation shock. This observation suggests that the job-loss reallocation shock led to a rise in the NCRU.

At the onset of the pandemic, negative aggregate activity shocks (yellow line) lowered the vacancy rate

Figure 3: Historical decompositions: pandemic period



Notes : This figure displays the posterior medians of the historical decompositions of the variables in our VAR system during the Covid-19 pandemic (X-axis: calendar month; Y-axis: the magnitude of variations in the endogenous variable). *Vacancy rate*: The vacancy rate; *Unemployment rate*: The unemployment rates of job losers and leavers combined; *AHE*: Change in average hourly earnings; *Mkt-core(adj)*: Market-based core PCE price inflation (adjusted for effects of Nixon-era price controls).

(upper-left panel) but sharply raised the unemployment rate of job losers (upper-right panel); for vacancies, aggregate activity shocks more than offset the positive effects from job-loss reallocation shocks. Positive aggregate activity shocks facilitated a rapid recovery of the vacancy rate and the unemployment rate of job losers in the second half of 2020; from 2021, the aggregate activity shock contributes to a higher vacancy rate and a lower unemployment rate.

During this period of cyclical tightening, aggregate activity shocks acted to reduce the unemployment rate. These shocks pushed the unemployment rate about 2 percentage points lower than its pre-pandemic level (the yellow line in the upper-right panel), suggesting that labor market conditions in that year were tighter than those just before the pandemic.[35]

Meanwhile, job-loss reallocation shocks (light-blue line with markers) and shocks to wage and price inflation (dashed green line and dotted light-blue line, respectively) contributed to raising the unemployment rate. The upward pressure from the wage-specific shock might reflect increased wage growth expectations that were driven by expectations for higher price inflation or an increase in desired wages. In addition, the rise in price inflation (likely reflecting cost-push factors) negatively affected the labor market, increasing unemployment and reducing the vacancy rate, though these effects faded as supply disruptions normalized.

[35] Crump et al. (2024) also find that their estimate of the unemployment rate gap is below its pre-pandemic level in 2022. However, in 2023 our estimate suggests less tightness in the labor market than what these authors find (their estimate for the gap is a few percentage points below its pre-pandemic level).

The job-loss reallocation shock also raised the unemployment rate in 2021, but as this shock unwound it lowered the unemployment rate, leaving the portion of the unemployment rate attributable to job-loss reallocation slightly below its pre-pandemic level by the end of 2023. Primarily led by the job-loss reallocation shock, the boost to the NCRU gradually dissipated from mid-2021 through the recovery period. By the end of 2023, the portion of the unemployment rate reflecting aggregate activity shocks had largely returned to its pre-pandemic level.[36]

The evolution of wage inflation over the pandemic period is dominated by large swings in the contribution of own-shocks (the dashed green line in the lower-left panel), which in turn reflect a rapid change in the composition of employment: In the early phase of the pandemic, job losses were disproportionately concentrated among low-wage workers, which caused measured average wages to rise quickly. The sharp downward movement in wage growth in 2021 is the result of base effects (recall that these are 12-month changes), as the earlier upward spike in wage growth drops out of the 12-month moving window. These composition effects mostly play out by the end of 2022; thereafter, the contribution of these shocks declines steadily. The aggregate activity shocks lower wage inflation in 2020 and 2021, but push it up from 2022–on (yellow line), and the job-loss reallocation shocks put persistent downward pressure on wage growth (light-blue line with markers). These results highlight the important influence that the structural labor market shocks had on the evolution of wage inflation during the pandemic.

Similarly, own-shocks are the dominant force driving price inflation over this period (dotted light-blue line). The importance of the own-shocks reflects the fact that typically only a modest fraction of the variability in price inflation can be explained by developments in the labor market. In this episode, the own-shocks to price inflation likely reflect import price growth and the presence of supply–demand imbalances in product markets. In turn, the own-shocks cause a reduction in inflation from 2022–on that likely captures the gradual resolution of these imbalances. Even so, the influence of some fundamentals is clearly apparent: Aggregate activity (yellow line) puts downward pressure on inflation until 2021; in addition, own-shocks to wage inflation (green dashed line) contribute about 1.5 pp to core inflation by 2023, implying a non-negligible amount of pass-through from wages to prices. The contribution of job-reallocation shocks to price inflation is mostly negative until 2022. However, in 2023 decreased reallocation activity accompanying job losses puts small upward pressure on price inflation.[37]

The behavior of inflation and unemployment during this period therefore reflected a number of structural shocks that induced both movements along and shifts of the Beveridge and Phillips curves. This mix of shocks allowed inflation to decline and the labor market to normalize without a large increase in the unemployment rate.

4. The Anatomy of the Beveridge and Phillips Curves

In this section, we first decompose the movements in the unemployment rate and vacancy rate into portions attributable to each structural shock; we then compute the Phillips correlation conditional on each structural shock.

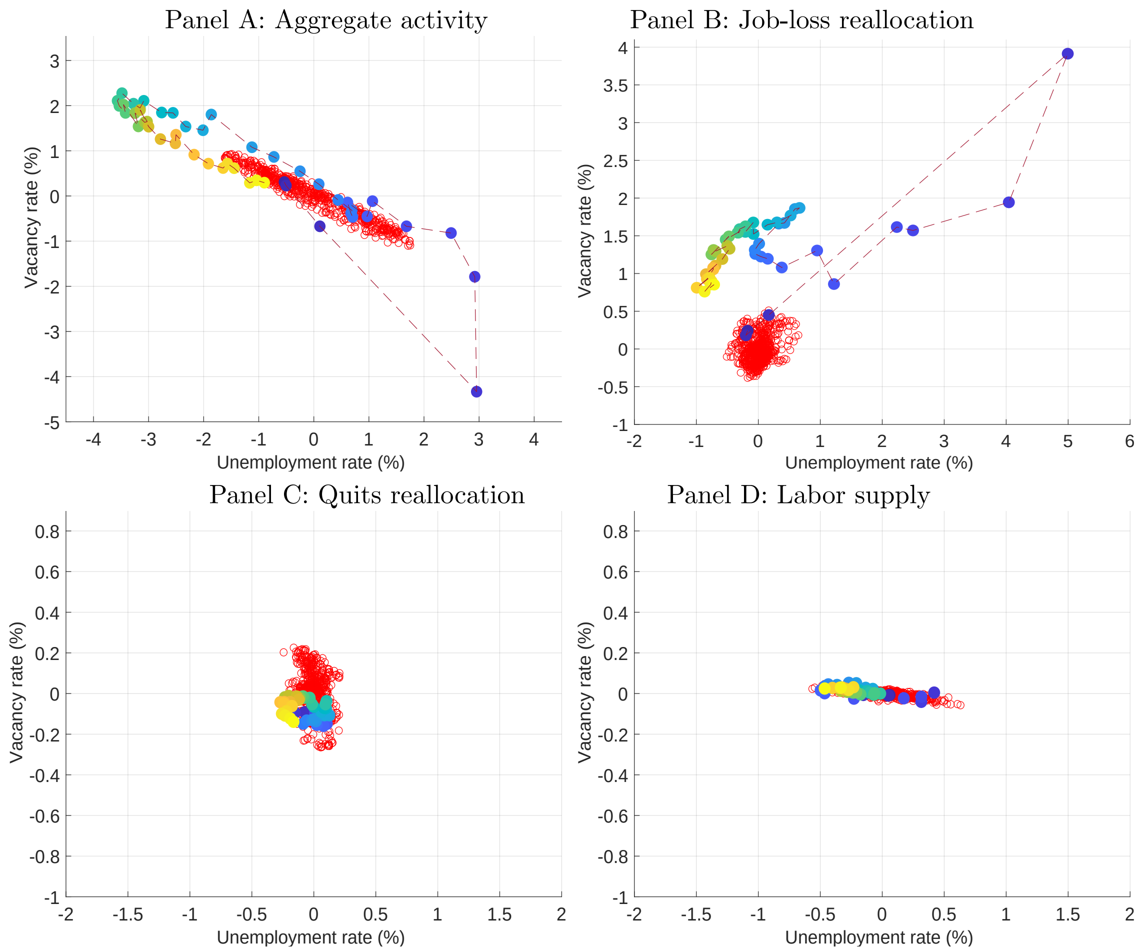
4.1. Structural shocks and the Beveridge curve

An outward shift in the Beveridge curve has often been interpreted as indicating an increase in the NCRU. However, increased unemployment inflows can also shift the curve, making such an interpretation problematic (see Ahn and Crane, 2020 and Barnichon and Figura, 2010). Our empirical decomposition of Beveridge curve dynamics into the contributions of different structural shocks can be used to examine movements of or along the Beveridge curve.

[36] The quits reallocation shocks raise the unemployment rate of job quitters in 2021 (not shown). This result is consistent with the anecdotes of a "Great Resignation" that occurred during the recovery from the pandemic recession; however, the effect on the total unemployment rate is small.

[37] The fact that inflation's decline did not require a sequence of disinflationary activity or job-loss reallocation shocks suggests that labor-market normalization was not a precondition for inflation to come down.

Figure 4: The anatomy of the Beveridge curve



Notes: This figure displays the posterior medians of the historical decompositions for vacancy and unemployment rate pairs generated by four structural shocks. The red circles denote pre-pandemic observations; pandemic-period observations start as dark-blue dots and end as yellow dots. The X-axis is the portion of the unemployment rate driven by each structural shock (%). The Y-axis is the portion of the vacancy rate driven by each structural shock (%).

Figure 4 displays the estimated portions of the vacancy and unemployment rates driven by each structural shock; the vacancy rate (V) is plotted on the y-axis and the unemployment rate (U) is plotted on the x-axis. The red circles capture the trajectories of V and U for the pre-pandemic period. With a posterior median for $-\epsilon$ of -0.65, the aggregate activity shock and its propagation yield a downward-sloping V–U relation (panel A) that implies a CRS matching function elasticity of 0.40 with respect to vacancies for 1967M9–2019M12, and a similar value (0.36) for the period when JOLTS data are available (2000M12–2019M12).[38] Meanwhile,

[38] Our empirical analogue of the structural Beveridge curve is the V–U trajectory driven by aggregate activity shocks shown in panel A. Assuming a CRS matching function (see footnote 20), the matching elasticity with respect to vacancies α can be recovered from $-\frac{1-\alpha}{\alpha} = \frac{d\log(\hat{V})}{d\log(\hat{U})}$, where $\hat{V}$ and $\hat{U}$ are the portions of the vacancy and unemployment rates driven by aggregate activity shocks. To obtain $\hat{V}$ and $\hat{U}$, we start with the portion of the variable's historical decomposition that is attributable to aggregate activity shocks and add in the variable's sample mean (recall that the historical decompositions are mean-zero). We

job-loss reallocation shocks yield an *upward*-sloping V–U relationship (panel B). By contrast, the quits-reallocation shock plays a limited role in observed V–U movements because job quitters represent a small share of the unemployment pool (panel C). Finally, labor supply shocks move the Beveridge curve sideways (panel D). All told, the structural labor market shocks generate distinct sets of V–U dynamics, suggesting that we should consider the contribution of each shock separately when using the Beveridge curve to evaluate the state of the labor market.

The pandemic period is represented by the solid dots. The effects of the realized shocks in 2020 are captured with the dark-blue dots, the subsequent realizations with lighter blue dots, and the most-recent realizations with yellow dots. The dark-red dashed line traces out the trajectory induced by each shock. Our estimates demonstrate just how unprecedented the pandemic-induced shocks to the labor market actually were. Not only did this period see an extraordinarily large change in aggregate activity (panel A), it also saw a rise in job-loss reallocation that induced an outward shift in the Beveridge curve that was larger and more persistent than anything seen before (panel B). By contrast, the effects of the labor-supply shocks (panel D) were more in line with previous episodes.

Our anatomy of the movements in the Beveridge curve during and after the pandemic directly speaks to the debate over the likelihood of a so-called soft landing in the labor market. Specifically, Blanchard et al. (2022) and Figura and Waller (2022) have expressed diametrically opposed views about the likely evolution of the labor market as the post-pandemic recovery matures. The former argue that the observed movements in vacancies and unemployment during the pandemic indicate that the structural Beveridge curve is flat (in V–U space), and so a reduction in labor demand will lower the vacancy rate but yield a very large increase in the unemployment rate. Meanwhile, Figura and Waller argue that the observed changes in vacancies and unemployment reflected a high number of job separations in the early phase of the pandemic, but that the downward slope of the structural Beveridge curve is steeper than what a simple read of the observed V–U trajectory would indicate, implying that a reduction in job vacancies could occur without a large increase in the unemployment rate.

We can view this debate through the lens of our formal statistical framework. Essentially, what Blanchard et al. and Figura and Waller disagree about is the slope of the structural Beveridge curve—the locus of vacancy and unemployment rates that results from shocks to aggregate activity. However, identifying this slope requires controlling for the effects of other structural shocks. Our decomposition does exactly that, providing a useful way to evaluate the two views. Our estimated matching elasticity with respect to vacancies of 0.40 suggests that the slope of the structural Beveridge curve is indeed steeper than the conjecture by Blanchard et al., broadly aligning with the perspective of Figura and Waller.[39]

Furthermore, our formal statistical approach uncovers the key structural shocks driving the soft landing, which neither paper explicitly identified or estimated. Looking at the historical decomposition in Figure 3, both the job-loss reallocation and aggregate activity shocks exerted comparable amounts of upward pressure on the vacancy rate from the second half of 2021. In other words, the cyclical strength in the vacancy rate was smaller than what a simple read of the data suggested. Therefore, in 2022 and 2023 the decline in the vacancy rate as demand weakened was able to occur without the dramatic rise in the unemployment rate that Blanchard et al. predicted. Also during this period, job-loss reallocation gradually unwound and put modest downward pressure on the unemployment rate; a soft landing with lower inflation was further facilitated because the job-loss reallocation shocks pushed down inflation through 2022. Thereafter, the unwinding of the price-specific shocks over the second half of 2023 put additional downward pressure on the unemployment rate that partly offset the upward pressure from aggregate activity.

Our analysis of this period demonstrates why it is important to consider a full accounting of the underlying structural shocks that affect labor-market outcomes when using the Beveridge curve to assess the current and prospective state of the labor market.

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then regress the log difference of the resulting vacancy series on the log difference of the unemployment series and a constant. The estimated coefficient for the log difference of the unemployment series—a measure of the slope of the structural Beveridge curve—is -1.51 for 1967M9–2019M12 and -1.77 for 2000M12–2019M12, and the estimated constant is close to zero in both cases. (Details are in the online appendix.)

[39] In their 2024 paper, Figura and Waller update their baseline estimate to 0.38.

4.2. Structural shocks and the Phillips curve

Changes in aggregate demand should induce movements along the Phillips curve rather than shifts in the curve. We can therefore get an idea of the slope of the Phillips curve by quantifying the movements in the unemployment rate and inflation that obtain following an aggregate activity shock. As our results demonstrate, one reason to take this approach is that other structural shocks can influence the size and direction of co-movements in the unemployment rate and price inflation that can in turn affect the reduced-form correlation of these variables.

To illustrate this point, we compute the correlation of the unemployment rate and market-based core inflation conditional on each structural shock. Using the impulse responses from the baseline model (Figure 1), we compute the ratio of the cumulative response of price inflation and that of the unemployment rate (we combine both types of unemployment) following each structural shock. We compute the cumulative responses over h periods, so these ratios give the average change in price inflation that is associated with a given change in the unemployment rate through horizon h following a structural shock.[40] For the aggregate activity shock, this ratio can be thought of as a measure of the inflation–unemployment tradeoff—the Phillips curve slope as it is typically defined. We also report analogous estimates for wage growth.

Table 4 reports estimates of these "Phillips ratios" for the four labor market shocks. The aggregate activity shock results in a Phillips ratio of -0.10 for $h = 6$ and -0.15 for $h = 12$, indicating a statistically significant tradeoff between inflation and the unemployment rate (panel C). It is notable that the Phillips ratios are more negative for labor-supply shocks (panel D) and for job-loss reallocation shocks (panel A) than for aggregate activity shocks, implying that these two shocks can generate a larger negative reduced-form Phillips correlation than what the aggregate activity shock induces.[41] Quite differently, a quits reallocation shock induces a positive Phillips ratio (panel B); a rise in unemployment associated with increased quits is actually *inflationary*. The quits reallocation shock can therefore flatten the slope of the reduced-form Phillips curve.

For wage inflation, the Phillips ratios are more negative in response to aggregate activity shocks, job-loss reallocation shocks, and labor-supply shocks compared to their price counterparts. This finding aligns with evidence suggesting that the wage Phillips curve is steeper than the price Phillips curve (e.g., Galí and Gambetti, 2020). An exception is the quits reallocation shock, where the price Phillips ratio is larger than the ratio for wage inflation.[42]

Our estimates suggest that the observed slope of the reduced-form Phillips curve will depend on the incidence and size of the structural labor-market shocks, and hence that the tradeoff between inflation and real activity can be obscured in periods where these other shocks are important. In this context, we can evaluate the contribution of each shock to the reduced-form correlation between price inflation and the unemployment rate by expressing the unconditional correlation as a weighted sum of the contributions of each shock's Phillips ratio. Let U_t denote the aggregate unemployment rate, $U_t \equiv (U_t^l + U_t^q)$. We use the historical decompositions to break down the correlation between the stochastic components of Π_t and U_t, which we denote as $\tilde{\Pi}_t$ and $\tilde{U}_t$, into the contributions of each shock (the stochastic components are the portions of Π_t and U_t that are explained by the structural shocks). Let $\Delta\tilde{\Pi}_{t+\tau}$ denote changes in $\tilde{\Pi}_t$ between $t+\tau-1$ and $t+\tau$, and let $\Delta\tilde{U}_{t+\tau}$ represent changes in $\tilde{U}_t$ between $t+\tau-1$ and $t+\tau$. We denote the

[40]This ratio is conceptually similar to the "Phillips multiplier" of Barnichon and Mesters (2021).

[41]Our prior implies that the aggregate activity shock generates a larger Phillips correlation (in absolute value) at impact than the other shocks. However, the posterior distributions suggest that the other shocks' Phillips correlations are larger, which suggests that the shocks' identification is data-driven. One interpretation of the steeper Phillips ratio for the job-loss reallocation shock is that this type of shock erodes the bargaining power of workers, thereby lowering wage growth and putting downward pressure on price inflation. This sizable negative effect is in line with empirical evidence on the significant and persistent reduction in wages and income of job losers (see Davis and Wachter, 2011).

[42]A possible explanation is that a positive quits reallocation shock could draw low-wage workers into the job seeker pool, leading to a compositional shift that puts downward pressure on measured average hourly earnings. The wage Phillips ratio of the quits reallocation shock, measured using the unemployment rate of job leavers, is larger positive than the estimate with the total unemployment rate but remains statistically insignificant until $h = 12$ (bottom part of panel B).

Table 4: Cumulative wage and price Phillips correlations by structural shock

	Wage Phillips ratio		Price Phillips ratio	
	Median	68% PI	Median	68% PI
A: Job-loss reallocation				
$h = 6$	-0.77	(-1.27, -0.43)	-0.50	(-1.04, -0.20)
$h = 12$	-1.01	(-1.90, -0.49)	-0.56	(-1.39, -0.11)
(Excluding job leavers)				
$h = 6$	-0.76	(-1.23, -0.43)	-0.49	(-1.01, -0.21)
$h = 12$	-1.00	(-1.85, -0.51)	-0.56	(-1.36, -0.13)
B: Quits reallocation				
$h = 6$	0.36	(-0.23, 1.14)	0.65	(0.21, 1.28)
$h = 12$	0.58	(-0.76, 2.50)	1.33	(0.03, 3.63)
(Job leavers)				
$h = 6$	0.45	(-0.27, 1.17)	0.80	(0.27, 1.31)
$h = 12$	0.95	(-0.07, 1.96)	1.76	(0.93, 2.56)
C: Aggregate activity				
$h = 6$	-0.44	(-0.55, -0.32)	-0.10	(-0.20, -0.00)
$h = 12$	-0.47	(-0.59, -0.36)	-0.15	(-0.26, -0.05)
D: Labor supply				
$h = 6$	-0.48	(-0.76, -0.23)	-0.24	(-0.47, -0.05)
$h = 12$	-0.61	(-0.95, -0.32)	-0.30	(-0.63, -0.04)

Notes: This table reports the cumulative dynamic wage and price Phillips correlations conditional on the structural shocks. Panels A, B, C, and D report the wage and price Phillips correlations driven by job-loss reallocation, quits reallocation, aggregate activity, and labor supply shocks. Rows in each panel (h) capture the magnitude of the correlation h months after the shock's impact. PI denotes posterior intervals.

cumulative changes in $\Delta\tilde{\Pi}_{t+\tau}$ and $\Delta\tilde{U}_{t+\tau}$ between t and $t+h$ as $\Delta\tilde{\Pi}_{t,t+h}$ and $\Delta\tilde{U}_{t,t+h}$, respectively:

$$\Delta\tilde{\Pi}_{t,t+h} = \sum_{\tau=1}^{h} \Delta\tilde{\Pi}_{t+\tau}, \qquad \Delta\tilde{U}_{t,t+h} = \sum_{\tau=1}^{h} \Delta\tilde{U}_{t+\tau}.$$

Denoting the portions of $\Delta\tilde{\Pi}_{t,t+h}$ and $\Delta\tilde{U}_{t,t+h}$ attributable to structural shock j as $\Delta\tilde{\Pi}^j_{t,t+h}$ and $\Delta\tilde{U}^j_{t,t+h}$, respectively, lets us write:

$$\frac{\Delta\tilde{\Pi}_{t,t+h}}{\Delta\tilde{U}_{t,t+h}} = \sum_{j=1}^{J} \left(\frac{\Delta\tilde{\Pi}^j_{t,t+h}}{\Delta\tilde{U}^j_{t,t+h}}\right)\left(\frac{\Delta\tilde{U}^j_{t,t+h}}{\Delta\tilde{U}_{t,t+h}}\right) = \sum_{j=1}^{J} c^j_h \left(\frac{\Delta\tilde{U}^j_{t,t+h}}{\Delta\tilde{U}_{t,t+h}}\right) + \epsilon_{t,t+h}, \tag{7}$$

where c^j_h is the Phillips ratio of shock j (for $j = 1,2,\cdots J$, J=6) for horizon h and $\epsilon_{t,t+h}$ is an approximation error.[43] Note that the terms $\Delta\tilde{U}^j_{t,t+h}$ and $\Delta\tilde{U}_{t,t+h}$ in (7) are obtained from the historical decomposition.

If we compute the covariance of both sides of equation (7) with $\Delta\tilde{U}_{t,t+h}$ and divide through by the

[43] Here, $j = 1$ represents the job-loss reallocation shock, $j = 2$ the quits reallocation shock, $j = 3$ the aggregate activity shock, $j = 4$ the labor-supply shock, $j = 5$ the own shock to wage inflation, and $j = 6$ the own shock to price inflation.

variance of $\Delta\tilde{U}_{t,t+h}$, we obtain a decomposition of the Phillips correlation coefficient:

$$\frac{Cov(\Delta\tilde{\Pi}_{t,t+h}, \Delta\tilde{U}_{t,t+h})}{Var(\Delta\tilde{U}_{t,t+h})} = \sum_{j=1}^{J} c_h^j \underbrace{\left(\frac{Cov(\Delta\tilde{U}_{t,t+h}^j, \Delta\tilde{U}_{t,t+h})}{Var(\Delta\tilde{U}_{t,t+h})}\right)}_{\beta_{t,t+h}^j} + \underbrace{\frac{Cov(\epsilon_{t,t+h}, \Delta\tilde{U}_{t,t+h})}{Var(\Delta\tilde{U}_{t,t+h})}}_{e_{t,t+h}} \tag{8}$$

$$= \underbrace{\sum_{j=1}^{4} c_h^j \beta_{t,t+h}^j}_{labor-market} + \underbrace{\sum_{j=5}^{6} c_h^j \beta_{t,t+h}^j + e_{t,t+h}}_{other}, \tag{9}$$

where the term on the left-hand side is the *pseudo-unconditional Phillips correlation.*[44] The term $\beta_{t,t+h}^j$ on the right-hand side of equation (8) captures the contribution of shock j to $\Delta\tilde{U}_{t,t+h}$, and the second term on the right-hand side, $e_{t,t+h}$, is an approximation error. Equation (8) shows that the pseudo-unconditional Phillips correlation approximates the sum of each shock's Phillips ratio weighted by the contribution of each shock to $\Delta\tilde{U}_{t,t+h}$. Focusing on the contributions of labor-market factors, we express the right-hand side of (8) as the sum of the contributions from the four labor-market shocks (the first term) and the remaining components (the second term), as shown in equation (9). We call the first term *the labor-market Phillips ratio.*

Table 5 presents the resulting decompositions. We focus on $h = 12$ because the impulse responses indicate that the effects of aggregate activity shocks on the unemployment rate of job losers (and the total unemployment rate) and the vacancy rate peak approximately 12 months after the shock's impact; hence $h = 12$ is the horizon at which the tradeoff between real activity and price inflation is adequately estimated.[45] The four values in row (1) give c_h^j and columns (d)–(f) report the $\beta_{t,t+h}^j$ estimates for each labor-market shock.[46] The aggregate activity shock (u_t^c) is the main driver of variations in the unemployment rate, while the other shocks' contributions are relatively small and change over time. It is notable that the contribution of the job-loss reallocation shock increases during the pandemic—row (5), column (d). Unlike the other labor-market shocks, the quits reallocation shock makes a small *negative* contribution to changes in the unemployment rate, reflecting its procyclical aspect and the small share of job leavers in total unemployment pool.

We compare the labor-market Phillips ratio—the values *not* in parentheses in column (b)—with the pseudo-unconditional correlation—the values in column (a)—for the full sample period and three subsamples. The pseudo-unconditional correlation changes from a small positive value over 1980–1999 to a small negative value over 2000–2019, and both values are statistically insignificant, in line with the flattening of the Phillips curve (e.g., Atkeson and Ohanian, 2001). By contrast, all the estimates of labor-market Phillips ratio are statistically significant and larger negative than the unconditional correlations. Before the pandemic the labor-market Phillips ratio remains stable at around −0.20 with a sample average of −0.24. After adjusting the weights to account for the four labor-market shocks only, the weight-adjusted labor-market Phillips ratios—the values *in* parentheses in column (b)—become more negative, remaining stable at around −0.25 during the pre-pandemic period and with a sample average of −0.29. This apparent difference between the pseudo-unconditional correlation and the labor-market Phillips ratio is shown in column (c); it largely reflects factors that obscure the slope of the Phillips curve such as the prevalence of cost-push shocks during

[44]The pseudo-unconditional correlation differs from the raw correlation, since the former only uses the parts of the variables that are explained by the structural shocks. Supplementing Table 5, note that the raw unconditional correlations are −0.10 (1968–2023); 0.00 (1980–1999); 0.00 (2000–2019); and −0.19 (2000–2023).

[45]In this context, $h = 12$ aligns with the frequency domain considered in previous Phillips curve studies that estimate the price changes that are directly linked to changes in the unemployment rate caused by aggregate demand shocks. In the online appendix, we also report results for $h = 6$ that demonstrate the robustness of the main results.

[46]The sum of the four β coefficients is not equal to one because the weights of the own shocks to wage and price inflation are excluded; including them yields one for each sample period. The posterior median and 68 percent credibility intervals for the $\beta_{t,t+h}^j$ estimates are provided in the online appendix.

Table 5: Decomposition of reduced-form Phillips correlations by structural shock (h=12)

	(a) Reduced	(b) LM	(c) a-b	(d) u_t^l	(e) u_t^q	(f) u_t^c	(g) u_t^s
(1) Phillips ratio				-0.56	1.33	-0.15	-0.30
					(β estimates)		
(2) Total (1968 – 2023)	-0.07 [-0.11,-0.03]	-0.24 (-0.29) [-0.45,-0.08] ([-0.55,-0.10])	0.17	0.24	-0.01	0.60	0.03
(3) 1980 – 1999	0.07 [-0.04,0.19]	-0.18 (-0.25) [-0.35,-0.05] ([-0.48,-0.07])	0.26	0.10	-0.02	0.67	0.01
(4) 2000 – 2019	-0.05 [-0.11,0.02]	-0.19 (-0.24) [-0.33,-0.06] ([-0.44,-0.07])	0.14	0.13	-0.01	0.59	0.10
(5) 2000 – 2023	-0.19 [-0.20,-0.16]	-0.32 (-0.35) [-0.60,-0.12] ([-0.66,-0.13])	0.14	0.38	-0.01	0.57	0.04

Notes: Column (a) reports the pseudo-unconditional correlation. Column (b) presents the labor-market (LM) Phillips ratio: numbers without parentheses are the weight-unadjusted estimates, while those in parentheses are the weight-adjusted estimates. These estimates represent the posterior median. Numbers in square brackets indicate 68% posterior intervals (PI), and those in parentheses are the PI for the weight-adjusted estimates. Column (c) reports the posterior median from column (a) and the weight-unadjusted estimate from column (b). The estimates for row (1) are from Table 4. The β estimates in the right section capture the relative contribution of each structural shock to variations in the unemployment rate. We report estimates based on the posterior median of the historical decomposition.

the earlier period and anchored inflation expectations in the later period. The effects of these obscuring factors change significantly between the two subperiods, and drive the evolution of the pseudo-unconditional correlation. Expanding the sample period to include the pandemic (2000-2023), however, the increased importance of the job-loss reallocation shock resulted in a more negative labor-market Phillips ratio of -0.32 (with a weight-adjusted ratio of -0.35), which in turn caused the reduced-form correlation to become more negative (the -0.19 value in column (a)).

Our analysis carries important implications for the empirical Phillips curve literature. Identifying the Phillips curve slope depends on how effectively we can isolate the portion of inflation that is linked to cyclical changes in the unemployment rate, and how well we can control for other factors that obscure the relationship. Our approach does so by identifying the structural labor-market shock that is relevant for the Phillips curve; specifically, we carefully uncover the portion of the unemployment rate driven by aggregate activity shocks while controlling for shocks that affect the NCRU, such as job-loss and quits reallocation shocks and labor-supply shocks.[47] By bringing this valuable identifying information from the Beveridge curve to bear, our methodology refines the estimate of the Phillips curve slope by specifically identifying the effects of aggregate demand on inflation and the unemployment rate.

The literature on the Phillips curve disagrees on the magnitude of its slope, with estimates ranging from nearly flat (e.g., -0.0062 from Hazell et al., 2022) to steeper values around -0.3 (e.g., -0.24 from Barnichon and Mesters, 2020 and -0.33 from Fitzgerald et al., 2024).[48] Our estimate—the Phillips ratio for aggregate activity shocks—is -0.15, placing it midrange of previous estimates. The difference between our estimate and the steeper estimates from previous studies primarily reflects the effects of the job-loss reallocation and labor-supply shocks, both of which have a more negative Phillips ratio but influence the NCRU. Since existing studies do not account for these labor-market shocks, their estimates are conceptually

[47] Previous studies consider limited variation in the NCRU, relying on trends from statistical filters or cross-sectional fixed effects (e.g., Barnichon and Mesters, 2020; Hazell et al., 2022).

[48] McLeay and Tenreyro (2020) estimate a slope of -0.38 using regional data, similar to Fitzgerald et al. (2024), but McLeay and Tenreyro's sample period (1990–2017) is shorter than that of Fitzgerald et al. (1977–2018). In addition, Smith et al. (2023) find a modest flattening in the slope from -0.29 to -0.25 before and after 2000.

similar to our labor-market Phillips ratios (weight-adjusted or unadjusted), which are in fact steeper than our aggregate-activity Phillips ratio and which also show sub-sample stability in line with Hazell et al. (2022) and Fitzgerald et al. (2024). In this sense, some existing estimates likely overstate the steepness of the structural Phillips curve.[49]

The preceding results show why it is important to distinguish different labor-market shocks when estimating the slope of the Phillips curve. To further illustrate the importance of identifying these shocks, the online appendix reports results from three exercises: (1) estimating the Phillips ratio for the unemployment rate from the generalized impulse responses of the reduced-form VAR; (2) removing sign restrictions from the baseline model; and (3) using the total unemployment rate rather than the two separate types of unemployment. The first two analyses demonstrate that neither the labor market shocks of interest nor the Phillips correlation coefficients for each shock can be reliably recovered without the identification of structural shocks based on the sign restrictions. The third analysis demonstrates the necessity of considering two distinct unemployment rates to identify the quits reallocation shock, whose effects on price and wage inflation are fundamentally different from those of the job-loss reallocation shock.

As a corollary, our analysis implies that the reduced-form Phillips curve over a particular span of time will depend on the composition of the structural shocks that are realized over that period. Depending on that set of realizations, therefore, the slope of the reduced-form Phillips curve can change over time in ways that are unconnected with the actual tradeoff between real activity and inflation. As an illustration, after the pandemic recession the observed rise in price and wage inflation given conventional estimates of product- and labor-market slack led some researchers to conclude that the inflation–activity tradeoff had worsened. Our analysis provides an alternative interpretation: The apparent non-linearity in the reduced-form Phillips curve in recent years might actually reflect the greater size and prevalence of job-loss reallocation shocks that accompanied the unprecedentedly large aggregate activity and price-specific shocks of this period.

5. Conclusion

We have demonstrated that common structural shocks drive the dynamics of inflation and the labor market, leading to a deep connection between the Beveridge and Phillips curves that can be uncovered by analyzing both relations jointly. We find that over time, changes in the size and incidence of different types of structural labor market shocks can alter the reduced-form relationships among vacancies, unemployment, and inflation, highlighting the importance of considering these structural shocks when using observed Beveridge and Phillips relations to evaluate and forecast the state of the economy. As an application, we used our structural accounting to analyze the pandemic recession and recovery, and found that labor reallocation shocks associated with job losses played a critical role in driving labor market dynamics and the steepening of the reduced-form Phillips curve during this period. Hence, the post-pandemic "soft landing" was not the result of an atypically favorable tradeoff between vacancies and unemployment but instead resulted from an interplay of shocks that induced both shifts of and movements along the Beveridge curve.

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[49] Our slope estimate differs from Hazell et al. (2022), who find a near-zero Phillips curve slope. One explanation is that Hazell et al. use the prices of nontradables excluding housing services prices, while we use a measure of inflation that includes housing services prices (defined consistently over time), which are more cyclically sensitive than other PCE price components such as goods prices. Hazell et al. do find that the slope of the Phillips curve becomes approximately four times larger when a measure of shelter rents is included—though that slope is still quite flat.

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