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Evolving Beveridge Curve Dynamics

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Abstract

We estimate a Bayesian time-varying parameter VAR model to study evolving Beveridge Curve dynamics for the US for 1965-2022. This allows us to test the empirical relevance of different shocks in driving the Beveridge Curve dynamics, as proposed in theoretical literature. We show that demand and wage shocks play an important role in generating movements in unemployment and vacancies, in addition to the productivity and job destruction shocks that are the main focus of the existing literature. We show that the importance of different shocks has varied over time: the productivity shock is dominant from the 1960s to the mid-1990s, but thereafter the wage shock is equally important. And we show that changes in the slope of the aggregate Beveridge Curve reflect changes in the contributions of the different shocks that drive it, so part of the flattening of the aggregate Beveridge Curve in recent years reflects the growing importance of wage shocks.

Keywords: time-varying parameter model, Beveridge Curve, unemployment, vacancies, US labour market

JEL Classification: *E23, E32, J23, J30, J64*

1 Introduction

The Beveridge curve, the inverse relationship between unemployment and vacancies across the business cycle, has played a pivotal role in understanding labour market dynamics. It links equilibrium unemployment to labour market flows and highlights fluctuations in vacancies as a key determinant of cyclical movements of labour market variables. Because of this, the Beveridge Curve is central to policy debates over the functioning and overall efficiency of labour markets.

The large and influential literature on this topic focuses on how economic shocks generate a negative relationship between unemployment and vacancies: the Beveridge Curve. This literature

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analyses the impact of different shocks through the lens of the search and matching model, in which shocks to productivity and job destruction are the main drivers of movements in unemployment and vacancies. We aim to test the empirical relevance of these and other shocks. To do this, we estimate a Time-Varying Parameter VAR model of US labour productivity, unemployment, vacancies, real wages and inflation. We have three main contributions. First, we show that demand and wage shocks play an important role in generating movements in unemployment and vacancies, in addition to the productivity and job destruction shocks that are the main focus of the existing literature. This justifies our inclusion of wages, inflation and output in the VAR in addition to unemployment and vacancies, since this enables us to identify these different shocks. Second, we show that the importance of different shocks has varied over time, justifying our use of a time-varying parameter model. The productivity shock is dominant in the first half of the sample, covering the period from the 1960s to the mid-1990s. But thereafter, the wage shock is as important as the productivity shock. Third, we show that changes in the slope of the aggregate Beveridge Curve in part reflect changes in the contributions of the different shocks that drive it. Movements in unemployment and vacancies across the business cycle are driven by productivity, wage and demand shocks, so the aggregate Beveridge Curve reflects the differing impacts of these shocks. The slope of the Beveridge Curve generated by wage shocks is smaller than the curves generated by productivity and demand shocks: the increasing importance of this shocks therefore implies a flattening of the aggregate Beveridge Curve.

Our finding that the Beveridge Curve reflects the impact of multiple shocks builds on previous theoretical work which has challenged the focus on productivity and job destruction shocks that characterises much of the literature on labour market volatilty. Contributors include Michaillat and Saez (2015) and Ravn and Sterk (2021), who stress the role of aggregate demand shocks, and Drautzburg et al. (2021) and Ellington et al. (2021), who highlight wage shocks[1]. Most of those papers focus on the role of the different shocks through the lens of search and matching models. We contribute to this literature by confronting those theoretical predictions with data and providing a systematic and empirical evaluation of the contribution of the different shocks that have been suggested in the theoretical literature.

Our empirical approach to the Beveridge Curve builds on influential work by Blanchard and Diamond (1989), who analyse the impact of shocks to aggregate activity, reallocation, and labour supply in a VAR model. They find that aggregate activity shocks, which move unemployment and vacancies in the opposite direction, dominate short- and medium-run fluctuations in unemployment[2]. Unlike Blanchard and Diamond (1989), we do not consider reallocation and labour supply

[1] In addition, Hall (2017) expresses scepticism about the ability of productivity shocks alone to account for movements in unemployment across the business cycle.

[2] In a recent paper, Ahn and Rudd (2024) use this approach to investigate linkages between the Phillips Curve and the Beveridge Curve. They identify two job destruction shocks in order to to study different aspects of labour reallocation. They include an aggregate activity shock which, because it increases price inflation on impact, resembles the aggregate demand shock analysed in this paper; they do not identify the type of productivity shock we analyse. They identify a shock to wages; this differs from the wage shock identified in this paper as it is assumed not to affect vacancies on impact.

shocks. However, the job separation shocks we analyse are similar to reallocation shocks. Our work also builds on previous analysis of changes in the slope of the Beveridge Curve. Most prominent in this literature is Benati and Lubik (2014), who estimate a Time-Varying Parameter VAR model for vacancies, unemployment and labour productivity. They identify a permanent productivity shock and two temporary shocks, one which moves unemployment and vacancies in opposite directions, generating the Beveridge Curve, and one that moves them in the same direction, accounting for changes in the position of the curve. A Forecast Error Variance Decomposition (FEVD) shows that the first temporary shock explains almost all movements in the data, consistent with the view that shifts in the Beveridge Curve do not occur at business cycle frequencies. They document changes in the slope of the Beveridge Curve across the business cycle, with a steeper relationship during recessions as the economy moves up the concave curve[3].

Our analysis is based on a structural time-varying parameter VAR model with stochastic volatility (TVP VAR) for productivity, vacancies, unemployment, real wages and inflation for the US, 1954Q3 to 2022Q4[4]. We identify four transitory structural shocks using robust sign restrictions that stem from a DSGE model with search frictions (DSGE-SF) (similar to Mumtaz and Zanetti, 2012), following the procedure in Canova and Paustian (2011). We identify three shocks that move unemployment and vacancies in opposite directions: a productivity shock, an aggregate demand shock, and a wage bargaining power shock. These generate the Beveridge Curve observed at business cycle frequencies. We also identify a shock to job destruction. This shock accounts for longer-term shifts in the Beveridge Curve but plays little role in this paper. Our addition of inflation and real wages to the set of variables used by Blanchard and Diamond (1989) and Benati and Lubik (2014) enables us to identify a richer set of structural shocks than those papers; we essentially decompose the aggregate activity shock of Blanchard and Diamond (1989), and the first temporary shock of Benati and Lubik (2014), into shocks to productivity, aggregate demand and wages. We analyse the impact of the different shocks using impulse response functions and measure the slope of the Beveridge Curve generated by different shocks as the ratio of the impulse response function for vacancies following a shock to the impulse response for unemployment following the same shock.

The structure of the remainder of this paper is as follows. Section 2) describes our data, outlines the econometric model and details our identification strategy. Section 3) presents our results, outlining the varying importance of different shocks and showing the implications for the Beveridge Curve. Section 4) concludes and outlines areas for future research.

[3]Some more recent papers demonstrate a range of different approaches to estimation of the Beveridge Curve, but are less closely related to our work. Klinger and Weber (2016) use an Unobserved Components model for unemployment, vacancies and the job finding rate to decompose Beveridge Curve movements into permanent and transitory components, but, unlike this paper, focus on the permanent component to analyse the Harz reforms to the German labour market. Schuman (2021) uses a VAR comprising employment, unemployment and vacancies to identify a shock to labour supply in addition to the two temporary shocks identified by Benati and Lubik (2014). This shock is used to analyse how migration has shifted the Beveridge Curve in Austria.

[4]We de-trend our data to remove the impact of permanent shocks.

2 Data, Econometric Model and Identification

We use quarterly US data from 1954Q3 to 2022Q4 on productivity, real wages, the vacancy rate, the unemployment rate, and inflation. Our measures of US productivity and real wages are Nonfarm Business Sector: Real Output Per Hour of all Persons, and Nonfarm Business Sector: Real Compensation Per Hour[5]. The vacancy rate is the Help Wanted Index in Barnichon (2010) and the unemployment rate is from the Bureau of Labor Statistics (BLS). For inflation, we take the Nonfarm Business Sector: Implicit Price Deflator[6]. We take the natural logarithm of productivity, real wages and the implicit price deflator. We next apply the Hamilton (2018) filter to every variable[7]. The resultant vacancy and unemployment gaps are plotted in the Online Appendix[8].

We work with the following TVP VAR model, with $p = 2$ lags and $N = 5$ variables:

$$Y_t = \beta_{0,t} + \beta_{1,t} Y_{t-1} + \cdots + \beta_{p,t} Y_{t-2} + \epsilon_t \equiv X_t^{'} \theta_t + \epsilon_t \tag{1}$$

where $Y_t \equiv [y_t,\ w_t,\ v_t,\ u_t,\ \pi_t]^{'}$ is a vector of endogenous variables. Here y_t is the filtered value of labour productivity, w_t is the filtered value of real wages, v_t and u_t are the vacancy and unemployment gaps, and π_t is the filtered value of the implicit price deflator. $X_t^{'}$ contains lagged values of Y_t and a constant.

Stacking the VAR's time-varying parameters in the vector θ_t, they evolve as a driftless random walk

$$\theta_t = \theta_{t-1} + \gamma_t \tag{2}$$

with $\gamma_t \equiv [\gamma_{1,t}, : \gamma_{2,t}, ..., : \gamma_{N\cdot(Np+1),t}]'$. We consider two specifications for the variance of γ_t. The first case is where $\gamma_t \backsim N(0, Q)$, with Q is a full matrix containing parameter innovation variances and covariances (Primiceri (2005)). The second is where $\gamma_t \backsim N(0, Q_t)$ with Q_t being a diagonal matrix where such diagonal elements of Q_t follow independent log-stochastic volatility processes as in Baumeister and Benati (2013). Bayesian DIC statistics suggest that the Primiceri (2005) model fits our data best and we proceed in this case. Results using the specification in Baumeister and Benati (2013) have the same conclusions as we report here and are available upon request.

The innovations in (1) follow $\epsilon_t \backsim N(0, \Omega_t)$. Ω_t is the time–varying covariance matrix which is factored as

$$\Omega_t = A_t^{-1} H_t (A_t^{-1})^{'} \tag{3}$$

with A_t being a lower triangular matrix with ones along the main diagonal, and the elements

[5] Both series are available from the Federal Reserve Bank of St. Louis (FRED) database with codes OPHNFB and COMPRNFB for productivity and wages respectively.

[6] Also from the FRED database with code: IPDNBS.

[7] The use of this filter implies that we analyse the unemployment and vacancy gaps.

[8] We note the very high values of the unemployment gap in the second and third quarters of 2020, at the height of the Covid-19 pandemic, as well as the large negative value of the unemployment gap, and the very high value of the vacancy gap in 2021-22.

below the diagonal contain the contemporaneous relations. H_t is a diagonal matrix containing the stochastic volatility innovations. Collecting the diagonal elements of H_t and the non-unit non-zero elements of A_t in the vectors $h_t \equiv [h_{1,t}, : h_{2,t}, ..., h_{N,t}]'$, $\alpha_t \equiv [\alpha_{21,t}, : \alpha_{31,t}, \ldots, \alpha_{NN-1,t}]'$ respectively, they evolve as

$$\ln h_{i,t} = \ln h_{i,t-1} + \eta_t \quad (4)$$

$$\alpha_t = \alpha_{t-1} + \zeta_t \quad (5)$$

where $\eta_t \backsim N(0, Z_h)$, and $\zeta_t \backsim N(0, S)$. The innovations in the model are jointly Normal, and the structural shocks, ψ_t are such that $\epsilon_t \equiv A_t^{-1} H_t^{\frac{1}{2}} \psi_t$. Similar to Primiceri (2005), S is a block diagonal matrix; this implies the non-zero and non-unit elements of A_t evolve independently. The specification of the priors of our model are similar to Baumeister and Benati (2013). To calibrate the initial conditions of the model, we use the point estimates of the coefficients and covariance matrix from a time-invariant VAR model using the first 10 years of data. Therefore the estimation sample of our results span 1964Q2–2022Q4. We estimate the model using Bayesian methods allowing for 20,000 runs of the Gibbs sampler. Upon discarding the initial 10,000 iterations as burn-in, we sample every 10^{th} draw to reduce autocorrelation which leaves 1000 draws from the posterior distribution. Details of our prior specification, and an outline of the posterior simulation algorithm as well as estimates of the total prediction variation of our model, the stochastic volatilities of each variable and the reduced form correlations between our variables are available upon request..

Our empirical results contain COVID-19 pandemic. Estimation of the TVP-VAR models uses Kalman filters and hence conditional on the full-sample. Naturally, this brings into question the robustness of our results in light of the pandemic. Existing studies propose various ways to account for this period. Lenza and Primiceri (2022) show how one can estimate linear VAR models that account for outliers throughout this period by re-scaling the residual covariance matrix if one wishes to utilise such models for forecasting. The former also indicate that dropping the observations may be acceptable for parameter estimation; Schorfheide and Song (2021); Baumeister and Hamilton (2023) use such a strategy for identification purposes. Carriero et al. (2022) suggest a method to allow for persistent and transitory changes in a VAR with stochastic volatility to handle outliers. Their analysis shows superior fit throughout the pandemic relative to competing models and that forecasts are at least as good as conventional stochastic volatility models. To the best of our knowledge at the time of writing, there are no approaches that allow one to account for parameter evolution throughout the pandemic. Therefore in light of the existing literature we explore the sensitivity of our results to the pandemic similar to Schorfheide and Song (2021); Baumeister and Hamilton (2023). Specifically, we adopt two approaches. First, we estimate the TVP VAR until 2020Q1 thus omitting the pandemic and also all observations from 2022. Second, we omit observations from 2020Q1–2021Q4 from the sample, and so pool data from 1951Q1–2019Q4 and 2022Q1–2022Q4. Results from these alternatives deliver qualitatively similar results to those we present in the main text; and are available upon request.

Our strategy for identifying structural shocks follows Canova and Paustian (2011) and Mumtaz and Zanetti (2015). We simulate a theoretical model using a range of alternative calibrations, based on randomly sampling parameter values within a specified range, constructing a distribution of impulse responses of our endogenous variables to a variety of shocks. We identify structural shocks for which the sign of the impulse responses on impact is unambiguous across this distribution. In this way, we ensure that our identifying sign restrictions are credible, robust to alternative calibrations of the structural parameters. Our identifying restrictions are based on a standard New Keynesian DSGE model without capital but with search frictions in the labour market, similar to Faia (2008), Krause and Lubik (2007), Blanchard and Gali (2010), Mumtaz and Zanetti (2012) and others. Details of our procedure and the model used are contained in the Online Appendix.

Table 1: **Contemporaneous Impact of Short-run Shocks on Labour Market Variables**
Notes: This table shows the contemporaneous sign restrictions imposed on variable $x = \{y_t, v_t, u_t, w_t\}$ to a productivity shock, ψ_t^{P}; a job separation shock, ψ_t^{J}; a shock to workers bargaining power, ψ_t^{W}; and a demand shock, ψ_t^{D}, respectively. y_t is the log-level of productivity; w_t is the log-level of real wages; v_t is the vacancy rate; u_t is the unemployment rate; and π_t is inflation. x denotes no restriction.

	y_t	w_t	v_t	u_t	π_t
ψ_t^{P}	+	+	+	−	−
ψ_t^{J}	x	−	+	+	x
ψ_t^{W}	x	+	−	+	x
ψ_t^{D}	x	+	+	−	+

We identify four temporary structural shocks within our empirical model as in Table 1). We identify: a productivity shock, ψ_t^{P}; a job separation shock, ψ_t^{J}; a shock to workers' bargaining power, ψ_t^{W}; and a demand shock ψ_t^{D}. The productivity shock increases productivity, wages and vacancies, while reducing unemployment and inflation. The demand shock increases wages, inflation and vacancies but reduces unemployment; we are agnostic as to its impact on productivity. The job separation shock increases unemployment and vacancies, thus shifting out the Beveridge Curve. It also reduces wages; we are agnostic about its impact on productivity and inflation. The shock to wage bargaining increases wages and unemployment but reduces vacancies; we are again agnostic about its impact on productivity and inflation. As noted above, the positive relationship between wages and unemployment implied by this shock is important for our results.

3 Results and Analysis

3.1 The empirical relevance of the four structural shocks

Figure 1) shows the contribution of each of the four structural shocks to the Forecast Error Variance Decomposition for vacancies and unemployment. This shows that demand and wage shocks play an important role in generating movements in unemployment and vacancies, in addition to the productivity and job destruction shocks that are the main focus of the existing literature. This

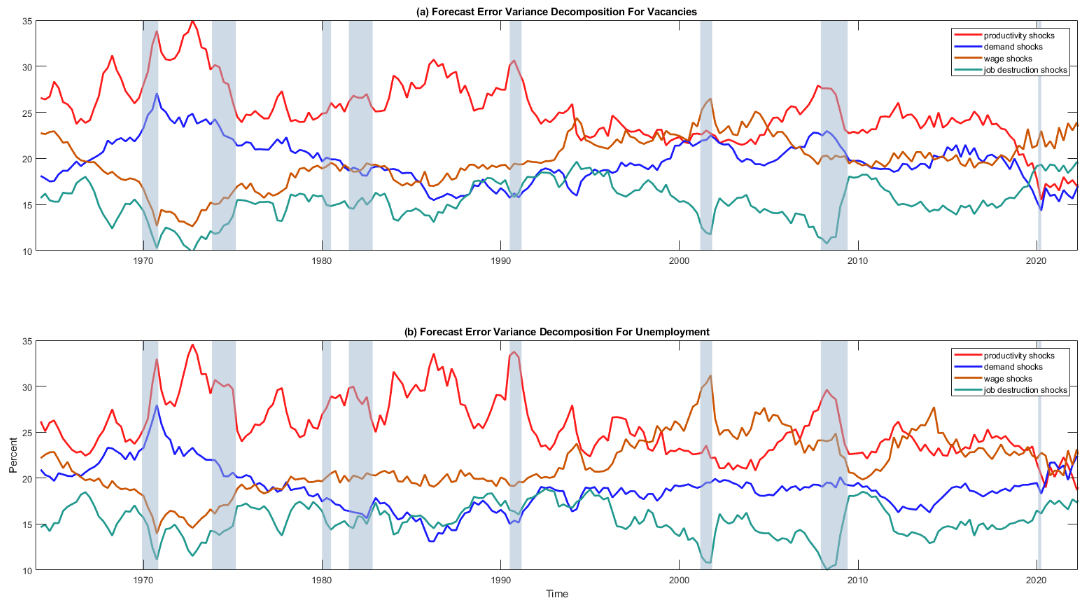

Figure 1: **Forecast Error Variance Decomposition for Vacancies and Unemployment**

justifies our inclusion of wages, inflation and output in the VAR in addition to unemployment and vacancies, since this enables us to identify these different shocks. In addition, the importance of different shocks has varied over time, justifying our use of a time-varying parameter model and suggesting that changes in the Beveridge Curve may in part reflect changes in the contributions of the different shocks that drive it. The productivity shock was dominant for both vacancies and unemployment in the first half of the sample, covering the period from the 1960s to the mid-1990s. But thereafter, the wage shock is as important as the productivity shock, especially for unemployment. The demand shocks consistently explains 20-25% of the variances of unemployment and vacancies, but is never dominant. The job destruction shock never explains more than 20% of the variance.

The upper panel of Figure 2) shows the impact of productivity shocks on the unemployment and vacancy gaps[9]. In the Online Appendix, we present this information as a scatter plot, giving a different perspective on the impact of shocks. We note that the productivity shock is closer to the data on unemployment and vacancy gaps in the 1970s and during the pre-2007 Great Moderation, explaining a larger part of the movements in these variables in those periods. This supports the view that the relationship between labour productivity and unemployment is contingent and time-

[9] The unemployment gap predicted by our model can be written as $\hat{u}_t = \sum_{j \in \{\mathrm{P,D,W,J}\}} \sum_{k=0}^{K} \phi_{t-k,t}^{u,j} \psi_{t-k}^{j}$, where ψ^j are the shocks defined in the previous section and $\phi_t^{u,j}$ is the impulse response of the unemployment gap, on impact, following a structural shock; we use $K = 40$. Given this, a natural measure of the impact of structural shock j on the unemployment gap is $\omega_t^{u,j} = \sum_{k=0}^{K} \phi_{t-k,t}^{u,j} \psi_{t-k}^{j}$, with a corresponding measure for the vacancy gap. The upper panel of Figure 2) plots these measures for the productivity shock; the lower panel plots the corresponding measures for the wage shock.

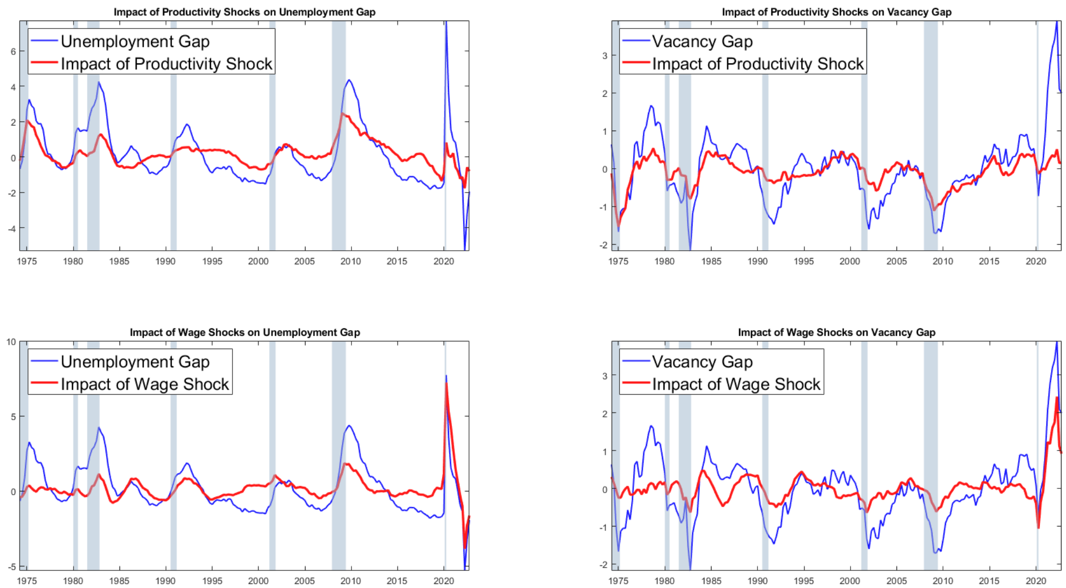

Figure 2: **The Impact of Productivity and Wage Shocks on Vacancies and Unemployment**

varying, consistent with the argument in Hall (2017) that unemployment does not track closely movements of productivity in US data. The lower panel shows the impact of wage shocks. Wage shocks are more prominent during the Great Moderation and especially in the post-2020 pandemic period. They are less important during the Great Recession. Our evidence on the importance of wage shocks in driving the Beveridge curve dynamics is new to the literature[10].

The upper panel of Figure 3) shows the impact of demand shocks on the unemployment and vacancy gaps. The empirical literature has largely ignored the impact of aggregate demand shocks on Beveridge curve dynamics. The main exception to this is Michaillat and Saez (2015), who use a comparison of theoretical and empirical moments to argue that aggregate demand shocks are more important than productivity shocks. Our work builds on this by directly estimating the impact of shocks, finding that the importance of aggregate demand and productivity shocks is roughly similar. The lower panel of Figures 3) shows the impact of job destruction shocks. The impact of this shock is more muted than for other shocks, in line with the literature that stresses the role of these shocks in accounting for lower frequency periodic shifts in the Beveridge Curve (eg Blanchard and Diamond (1989), Elsby et al. (2015) and Barlevy et al. (2023)).

[10]In this paper, we are agnostic about the origins of wage shocks. In search frictions models, wage shocks could reflect shocks to worker wage bargaining power, to the opportunity cost of employment or to the value placed on leisure relative to consumption. For example, the importance of wage shocks in the Covid-19 pandemic may be due to a fall in labour force participation, due either to more generous benefits, a fear of infection or disruption of the supply chains that raised the bargaining power of workers. In either case, the shock will increase wages.

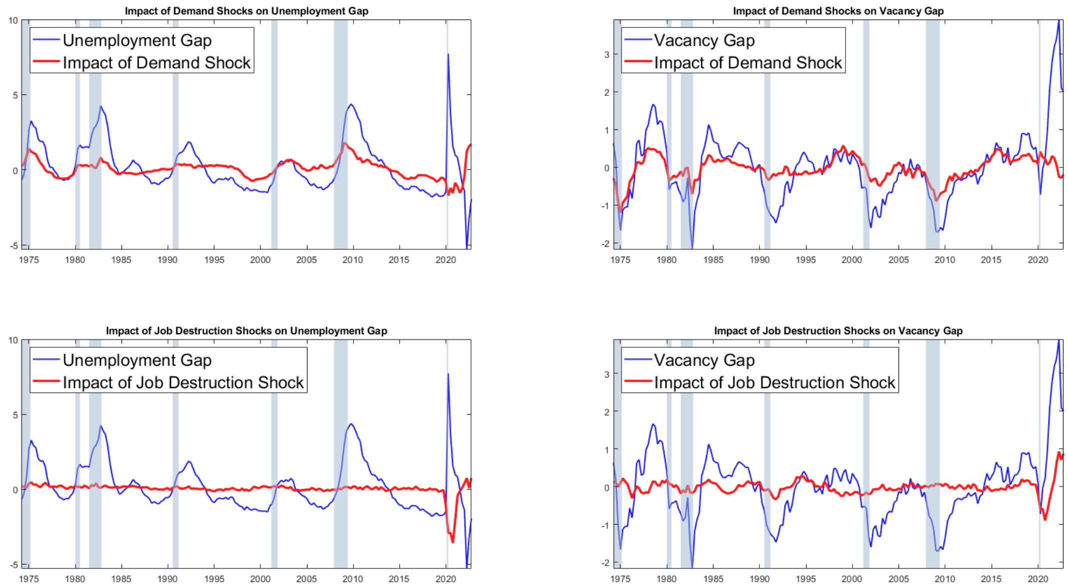

Figure 3: **The Impact of Demand and Job Destruction Shocks on Vacancies and Unemployment**

3.2 The slope of the Beveridge Curve

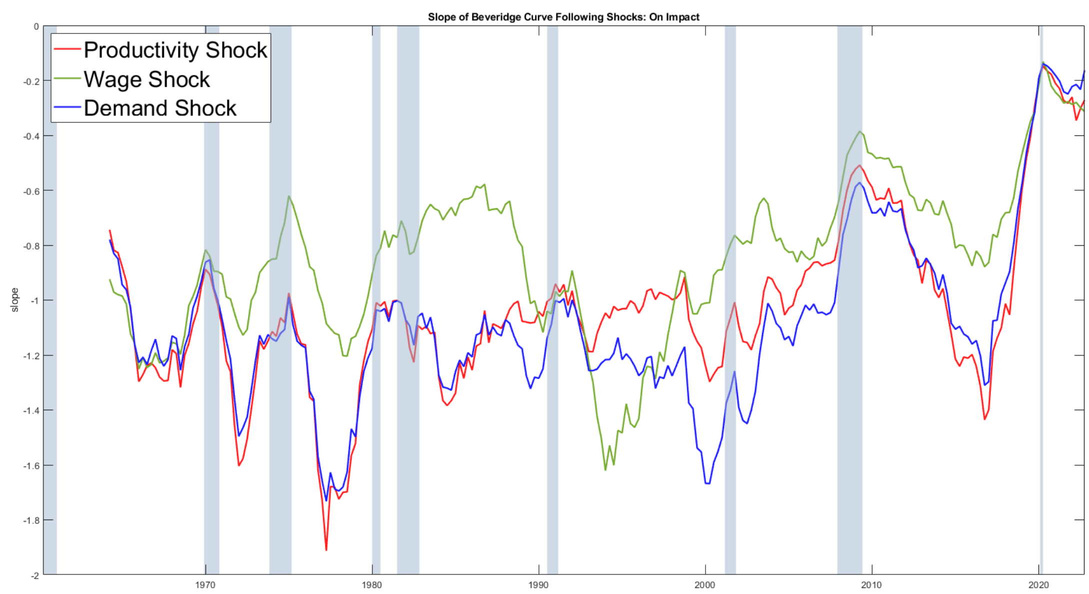

Figure 4: **The Slope of the Beveridge Curve Generated by Productivity, Demand and Wage Shocks, 1965-2022**

Figure 4) shows the slopes of the Beveridge Curves generated by productivity, demand and wage shocks, given by $\sigma_t^j = \frac{\phi_t^{v,j}}{\phi_t^{u,j}}$ for $j \in \{\mathrm{P}, \mathrm{W}, \mathrm{D}\}$, where $\phi_t^{u,j}$ is the impulse response of unemployment, on impact, following shock j and $\phi_t^{v,j}$ is the corresponding impulse response of vacancies. Four things clearly stand out. First, the slope of the Beveridge Curve generated by productivity shocks is more similar to that generated by demand shocks (correlation=0.924) than that generated by wage shocks (correlation=0.635). This is consistent with the baseline search frictions model, since productivity and demand shocks both affect the creation of a surplus from a job match, whereas a wage shock affects the division of the surplus between worker and firm. Second, the Beveridge Curve generated by wage shocks is flatter than that generated by productivity and demand shocks, apart from a period in the 1990s. Broadly speaking, this is because vacancies are more responsive to productivity and demand shocks than to wage shocks. unemployment is more responsive to productivity and demand shocks than to wage shocks. Third, the divergence in the slopes is large during periods of boom and shrinks drastically during slumps. Fourth, there is some evidence of a flattening in the slope of all three Beveridge Curves in recent years. This pattern develops during the Great Moderation, disappears during the Great Recession and then re-appears in the run-up to the 2020 Covid-19 Pandemic.

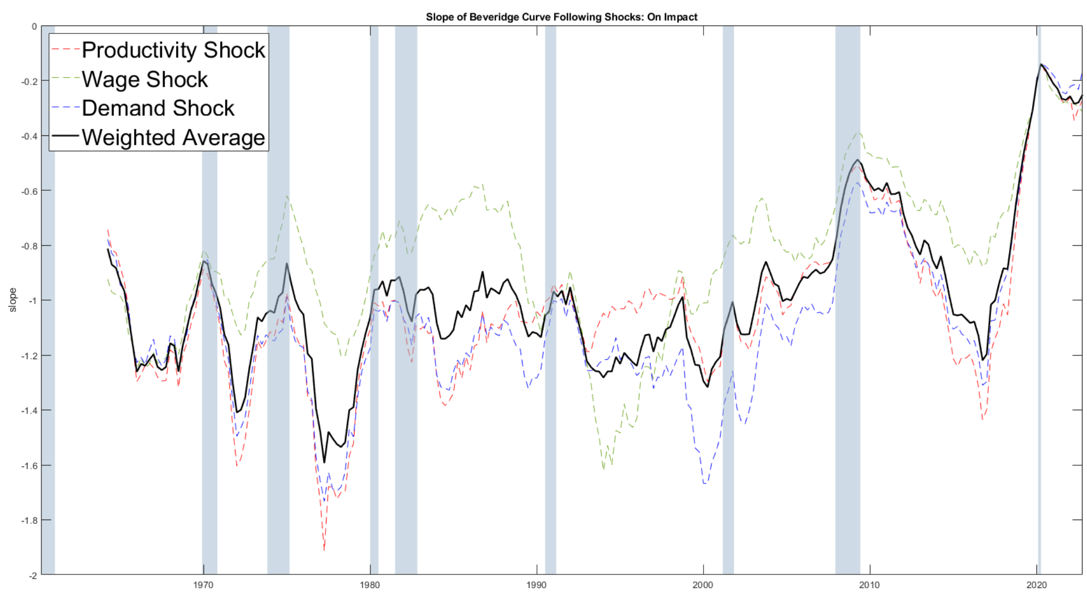

Figure 5: **The Slope of the Aggregate Beveridge Curve, 1965-2022**

Figure 5) shows the slope of the Beveridge Curve generated as the weighted average of the three Beveridge Curves in Figure 4), where the weights are the relative weights of the three shocks in Figure 1), so Figure 5) plots $\sigma_t = \sum_{\mathrm{j} \in \{\mathrm{P,W,D}\}} \omega_t^j \sigma_t^j$, where $\omega_t^j = \frac{\nu_t^j}{\sum_{\mathrm{k} \in \{\mathrm{P,W,D}\}} \nu_t^k}$ and ν_t^j is the share of shock j in generating the forecast error variance decomposition for unemployment at time t. This corresponds to the Beveridge Curve analysed in the existing literature. The slope of this average

Beveridge Curve is more stable than the slopes of the underlying Beveridge Curves that constitute it. There is evidence of a flattening of the average Beveridge Curve during the Great Moderation and in the period before the Covid-19 Pandemic. This reflects the increasing importance of the wage shock in generating movements in unemployment and vacancies over the past two decades and the tendency of the individual Beveridge Curves to flatten over this period.

4 Concluding Remarks

In this paper, we examine the empirical relevance of different shocks in driving the Beveridge curve dynamics, as proposed in theoretical literature. We argue that the Beveridge Curve represents the impact of multiple shocks: in addition to the productivity and job destruction shocks that are typically analysed in the literature, we show the wage and demand shocks are also important. We further show that the importance of these shocks has varied over time, with the productivity shock being dominant in the first half of the sample, but with the wage shock becoming as important during the latter part of the sample. Since different shocks generate different relationships between unemployment and vacancies, the aggregate Beveridge Curve reflects the differing impacts of these shocks. In particular, the slope of the Beveridge Curve generated by wage shocks is smaller than the curves generated by productivity and demand shocks: the increasing importance of this shocks therefore implies a flattening of the aggregate Beveridge Curve.

Our work suggests possible directions for future research. Our current definition of wage shocks is quite broad. To gain a more nuanced understanding, future research could investigate the role of worker preferences, the generosity of benefits packages and disruptions to supply chains in driving Beveridge Curve dynamics, as these factors could potentially strengthen worker bargaining power, leading to positive co-movement between wages and unemployment. Our work shows some evidence of a flattening in the slope of the Beveridge Curves in recent years. More work needs to be done to study whether this is a long-term trend and whether structural changes might also play a role.

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Evolving Beveridge Curve Dynamics
Online Appendix

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1 Online Appendix

1.1 Data

Figure 1 shows the unemployment and vacancy gaps for 1975 to 2022, used in our analysis.

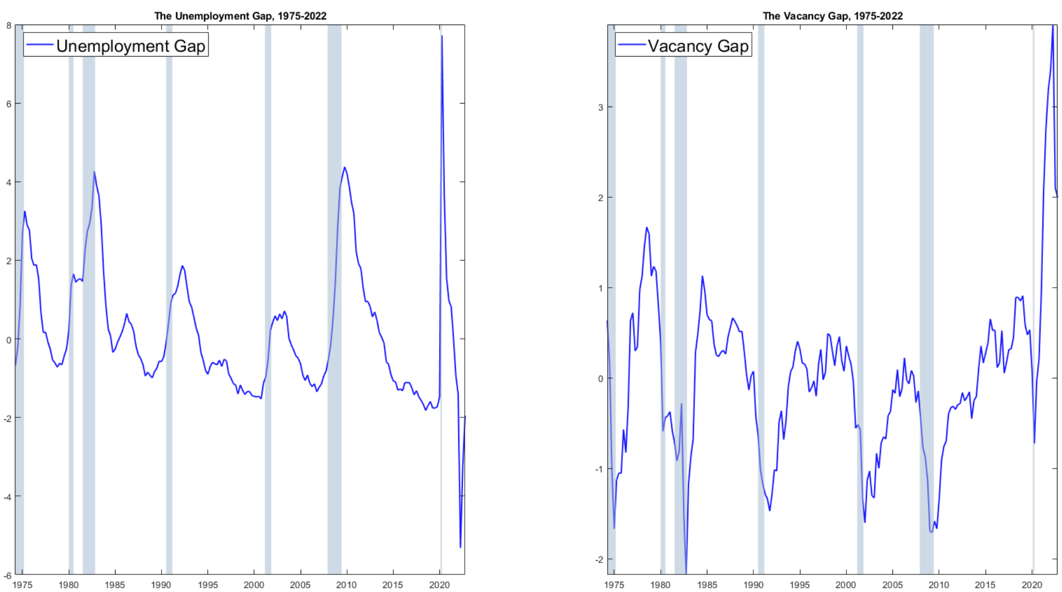

Figure 1: **The Unemployment and Vacancy Gaps, 1975 to 2022**
Notes: Grey bars indicate NBER recession dates. All variables have been filtered using the Hamilton (2018) filter.

1.2 Econometric Methodology

Our prior specification involves estimating a Bayesian fixed coefficient VAR (BVAR) model over the training sample. The priors imposed on this BVAR model combine the traditional Minnesota prior of Doan et al. (1984) and Litterman (1986) on the coefficient matrices with an inverse-Wishart prior on the BVAR's covariance matrix. In our specification, the prior mean on the coefficient matrix sets all elements equal zero, except those corresponding to the own first lag of each dependent variable which are set to 0.9. This imposes the prior belief that our variables exhibit persistence whilst simultaneously ensuring shrinkage of the other VAR coefficients to zero. The prior variance of the coefficient matrix is set similar to Litterman (1986). Our prior for the BVAR's covariance matrix follows an inverse-Wishart distribution with the prior scale matrix and degrees of freedom set to an N-dimensional identity matrix and 1+N respectively.

We estimate the BVAR using a standard Gibbs sampler. For the sake of brevity, we do not explicitly outline our algorithm since it is well documented; see e.g. Koop and Korobilis (2010). Our alternative prior specification essentially replaces the conventional Cogley and Sargent (2005) prior with the posterior means from the draws of an estimated BVAR over the training sample

$$\bar{\theta}_{\text{BVAR}} = \frac{1}{M}\sum_{i=1}^{M}\theta_i, \tag{1}$$

$$\overline{\text{V}(\theta)}_{\text{BVAR}} = \frac{1}{M}\sum_{i=1}^{M}\text{V}(\theta_i), \tag{2}$$

$$\bar{\Sigma}_{\text{BVAR}} = \frac{1}{M}\sum_{i=1}^{M}\Sigma_i \tag{3}$$

respectively. Here M denotes the number of saved draws from the estimated BVAR which we set to 20,000. θ_i and $\text{V}(\theta_i)$ denote the ith draw of the coefficient matrix and the variance of the coefficient matrix respectively. Σ_i denotes the ith draw of the BVAR's covariance matrix. From these estimates, the initial conditions of the time-varying coefficient models, θ_0, a_0, h_0 are Normal and independent of one another, and the distributions of the hyperparameters. We set

$$\theta_0 \backsim N\left[\bar{\theta}_{\text{BVAR}},\ 4\cdot\overline{\text{V}(\theta)}_{\text{BVAR}}\right] \tag{4}$$

for α_0, h_0, let $\bar{\Sigma}_{\text{BVAR}}$ be the estimated covariance matrix of the residuals from the time–invariant BVAR. Let C be the lower–triangular Choleski factor such that $CC' = \bar{\Sigma}_{\text{BVAR}}$. The prior for the stochastic volatilities are

$$\ln h_0 \backsim N(\ln \mu_0, 10 \times I_5) \tag{5}$$

where μ_0 collects the logarithms of the squared elements along the diagonal of C. Each column of C is divided by the corresponding element on the diagonal; call this matrix $\tilde{C}$. The prior for the contemporaneous relations is

$$\alpha_0 \backsim N\left[\tilde{\alpha}_0,\ \tilde{V}(\tilde{\alpha}_0)\right] \tag{6}$$

with $\tilde{\alpha}_0 \equiv [\tilde{\alpha}_{0,11}, \tilde{\alpha}_{0,21}, \ldots, \tilde{\alpha}_{0,51}]'$ which is a vector collecting all the elements below the diagonal of

$\tilde{C}^{-1}$. $\tilde{V}(\tilde{\alpha}_0)$ is diagonal with each element equal to 10 times the absolute value of the corresponding element of $\tilde{\alpha}_0$. This is an arbitrary prior but correctly scales the variance of each element of α_0 to account for their respective magnitudes.

For the time-varying coefficient model assuming $Q_t = Q$, we set Q to follow an inverse Wishart distribution.

$$Q \backsim IW(\underline{Q}^{-1}, \mathrm{T}_0) \tag{7}$$

where $\underline{Q} = (1 + \dim(\theta_t)) \cdot \overline{\mathrm{V}}(\bar{\theta}_{\mathrm{BVAR}}) \cdot 3.4 \times 10^{-4}$. The prior degrees of freedom, $(1 + \dim(\theta_t))$, are the minimum allowed for the prior to be proper. Our choice of scaling parameter of 3.4×10^{-4} is consistent with Cogley and Sargent (2005). We have also estimated our models using different priors, we allowed for a more restrictive scaling parameter of 1.0×10^{-4} and have also set the degrees of freedom to be the length of the training sample; in our case this is 80. The scaling parameter essentially sets the amount of drift within the θ matrices.

With regards to the hyperparameters under the assumption $Q_t = Q_t$, the diagonal elements of Q_t follow a geometric random walk, let $C_{\overline{\mathrm{V}(\bar{\theta}_{\mathrm{BVAR}})}}$ be the lower-triangular Choleski factor such that $C_{\overline{\mathrm{V}(\bar{\theta}_{\mathrm{BVAR}})}} C'_{\overline{\mathrm{V}(\bar{\theta}_{\mathrm{BVAR}})}} = 3.4 \times 10^{-4} \overline{\mathrm{V}(\bar{\theta}_{\mathrm{BVAR}})}$. We then set

$$\ln q_0 \backsim N\left[\ln \mu_{q_0,0}, 10 \times I_{\dim(\theta_t)}\right] \tag{8}$$

with $\ln \mu_{q_0,0}$ collecting the logarithmic squared diagonal elements of $3.4 \times 10^{-4} \overline{\bar{\theta}_{\mathrm{BVAR}})}$. The variances of these stochastic volatility innovations follow an inverse-Gamma distribution for the elements of Z_q,

$$Z_{q,i,i} \backsim IG(\frac{10^{-4}}{2}, \frac{1}{2}) \tag{9}$$

The blocks of S are also assumed to follow inverse–Wishart distributions with prior degrees of freedom equal to the minimum allowed (i.e. $1 + \dim(S_i)$).

$$S_1 \backsim IW(\underline{S}_1^{-1}, 2) \tag{10}$$
$$S_2 \backsim IW(\underline{S}_2^{-1}, 3) \tag{11}$$
$$S_3 \backsim IW(\underline{S}_3^{-1}, 4) \tag{12}$$
$$S_4 \backsim IW(\underline{S}_4^{-1}, 5) \tag{13}$$

we set S_1, S_2, S_3 in accordance with $\tilde{\alpha}_0$ such that $\underline{S}_1 = 10^{-3} \times |\tilde{\alpha}_{0,21}|$, $\underline{S}_2 = 10^{-3} \times \mathrm{diag}([|\tilde{\alpha}_{0,31}|, |\tilde{\alpha}_{0,32}|]')$, $\underline{S}_3 = 10^{-3} \times$ diag$([|\tilde{\alpha}_{0,41}|, |\tilde{\alpha}_{0,42}|, |\tilde{\alpha}_{0,43}|]')$, $\underline{S}_4 = 10^{-3} \times$ diag$([|\tilde{\alpha}_{0,51}|, |\tilde{\alpha}_{0,52}|, |\tilde{\alpha}_{0,53}|, |\tilde{\alpha}_{0,54}|]')$. This calibration is consistent with setting S_1, S_2, S_3, S_4 to 10^{-4} times the corresponding diagonal block of $\tilde{V}(\tilde{\alpha}_0)$. The variances for the stochastic volatility innovations, as in Cogley and Sargent (2005), follow an inverse–Gamma distribution for the elements of W,

$$W_{i,i} \backsim IG(\frac{10^{-4}}{2},\ \frac{1}{2}) \tag{14}$$

In order to simulate the posterior distribution of the hyperparameters and states, conditional on the data, we implement the following MCMC that combines elements from Primiceri (2005) and Cogley and Sargent (2005).

1) *Draw elements of* θ_t Conditional on Y^T, α^T and H^T, the observation equation (1) is linear with Gaussian innovations with a known covariance matrix. Factoring the density of θ_t, $p(\theta_t)$ in the following manner

$$p(\theta^T|y^T, A^T, H^T, V) = p(\theta_T|Y^T, A^T, H^T, V) \prod_{t=1}^{T-1} p(\theta_t|\theta_{t+1}, Y^t, A^T, H^T, V) \tag{15}$$

the Kalman filter recursions pin down the first element on the right hand side of the above in the following manner: $p(\theta_T|Y^T, A^T, H^T, V) \backsim N(\theta_T, P_T)$, P_T is the precision matrix of θ_T from the Kalman filter. The remaining elements in the factorisation are obtained via backward recursions as in Cogley and Sargent (2005). Since θ_t is conditionally Normal

$$\theta_{t|t+1} = P_{t|t}P_{t+1|t}^{-1}(\theta_{t+1} - \theta_t) \tag{16}$$

$$P_{t|t+1} = P_{t|t} - P_{t|t}P_{t+1|t}^{-1}P_{t|t} \tag{17}$$

which yields, for every t from $T-1$ to 1, the remaining elements in the observation equation (1). More precisely, the backward recursion begins with a draw, $\tilde{\theta}_T$ from $N(\theta_T,\ P_T)$. Conditional on $\tilde{\theta}_T$, the above produces $\theta_{T-1|T}$ and $P_{T-1|T}$. This permits drawing $\tilde{\theta}_{T-1}$ from $N(\theta_{T-1|T},\ P_{T-1|T})$ until t=1.

2) *Drawing elements of* α_t Conditional on Y^T, θ^T and H^T we follow Primiceri (2005) and note that (1) can be written as

$$A_t\tilde{Y}_t \equiv A_t(Y_t - X_t^{'}\theta_t) = A_t\epsilon_t \equiv \psi_t \tag{18}$$

$$Var(\psi_t) = H_t \tag{19}$$

with $\tilde{Y}_t \equiv [\tilde{Y}_{1,t},\ \tilde{Y}_{2,t},\ \tilde{Y}_{3,t},\ \tilde{Y}_{4,t}]'$ and

$$\tilde{Y}_{1,t} = \psi_{1,t} \tag{20}$$

$$\tilde{Y}_{2,t} = -\alpha_{21,t}\tilde{Y}_{1,t} + \psi_{2,t} \tag{21}$$

$$\tilde{Y}_{3,t} = -\alpha_{31,t}\tilde{Y}_{1,t} - \alpha_{32,t}\tilde{Y}_{2,t} + \psi_{3,t} \tag{22}$$

$$\tilde{Y}_{4,t} = -\alpha_{41,t}\tilde{Y}_{1,t} - \alpha_{42,t}\tilde{Y}_{2,t} - \alpha_{43,t}\tilde{Y}_{3,t} + \psi_{4,t} \tag{23}$$

These observation equations and the state equation permit drawing the elements of α_t equation by equation using the same algorithm as above; assuming S is block diagonal.

3) *Drawing elements of* H_t Conditional on Y^T, θ^T and α^T, the orthogonal innovations u_t, $Var(\psi_t) = H_t$ are observable. Following Jacquier et al. (2002) the stochastic volatilities, $h_{i,t}$'s, are sampled element by element; Cogley and Sargent (2005) provide details in Appendix B.2.5 of their paper.

4) *Drawing the hyperparameters* Conditional on Y^T, θ^T, H_t and α^T, the innovations in θ_t, α_t and $h_{i,t}$'s are observable, which allows one to draw the elements of $Q_t = Q$, S_1, S_2, S_3 and the $W_{i,i}$.

Note that for the model allowing for stochastic volatility in the innovation variances of the time-varying coefficients, Q_t being a diagonal matrix, we add an extra block into the MCMC algorithm.

3*a*) *Drawing the elements of* Q_t Conditional on θ_t, the innovations $\kappa_t = \theta_t - \theta_{t-1}$, with $\mathrm{Var}(\kappa_t) = Q_t$ are observable. Therefore we sample the diagonal elements of Q_t applying the Jacquier et al. (2002) algorithm element by element. Following this, we can then sample the $Z_{q,i,i}$ from the inverse-Gamma distribution in step 4 of the above algorithm.

1.3 Strategy for Identification of Structural Shocks

In this section we outline our identification strategy, which follows Canova and Paustian (2011) and Mumtaz and Zanetti (2015). We simulate a theoretical model using a range of alternative calibrations, based on randomly sampling parameter values within a specified range, constructing a distribution of impulse responses of our endogenous variables to a variety of shocks. We identify structural shocks for which the sign of the impulse responses on impact is unambiguous across this distribution. In this way, we ensure that our identifying sign restrictions are credible, robust to alternative calibrations of the structural parameters. Our identifying restrictions are based on a standard New Keynesian DSGE model without capital but with search frictions in the labour market, similar to Mumtaz and Zanetti (2012) and others.

We summarise the model and structural parameters in the upper panel of Table 1. Equations (T.1)–(T.6) outline the structure of the labour market. Equation T.1 defines the sum of employment (N) and unemployment (u) as the labour force, which is normalised to 1. Equation T.2 outlines employment dynamics and relates employment to hires (h). Equation T.3 defines labour market tightness (θ) as the ratio of vacancies (v) to unemployment. T.4 contains a standard constant returns matching function, while T.5 and T.6 define the vacancy filling rate (q) and the job finding rate (f) respectively. Equation T.7 contains the production function. T.8 defines the marginal cost of hiring labour. Equation T.9 gives the wage, where we have assumed simple Nash bargaining. Equation T.10 defines marginal cost, while T.11 relates price to marginal cost. Equation T.12 is the Euler equation; a summary of these values are in the lower panel of Table 1.

We analyse the impact of four structural shocks. We identify a productivity shock, assuming $A_t = e^{\epsilon_t^P}$. We include a demand shock, ϵ_t^D. We also include a shock to worker relative bargaining

Table 1: **Contemporaneous Impact of Short-run Shocks on Labour Market Variables**
Notes: Panel a) of this table shows the theoretical model that we simulate. Panel b) shows the range of parameter values from which we sample in our simulations

a) Model Summary

$$N_t + u_t = 1 \tag{T.1}$$

$$N_t = (1-\tau_t)N_{t-1} + h_{t-1} \tag{T.2}$$

$$\theta_t = \frac{v_t}{u_t} \tag{T.3}$$

$$h_t = m u_t^{\alpha} v_t^{(1-\alpha)} \tag{T.4}$$

$$q_t = m\theta_t^{-\alpha} \tag{T.5}$$

$$f_t = q_t\theta_t \tag{T.6}$$

$$Y_t = A_t N_t \tag{T.7}$$

$$\lambda_t = \frac{\kappa}{q_t} - \beta\mathbb{E}_t\frac{\kappa(1-\tau_{t+1})}{q_{t+1}} \tag{T.8}$$

$$w_t = (1-z_t)b + z_t(A_t + \kappa\theta_t) \tag{T.9}$$

$$mc_t = \frac{w_t + \lambda_t}{A_t} \tag{T.10}$$

$$\frac{P_t^*}{P_t} = \frac{\eta}{1-\eta}\left(1-\beta\omega\right)\mathbb{E}_t\sum_{k=0}^{\infty}\left(\beta\omega\right)^k mc_{t+k} \tag{T.11}$$

$$Y_t^{-\eta} = \beta e^{\epsilon_t^D}\mathbb{E}_t Y_{t+1}^{-\eta}\frac{(1+i_t)}{1+\pi_{t+1}} \tag{T.12}$$

$$(1+i_t) = (1+\pi_t)^{\rho_\pi} \tag{T.13}$$

b) Credible Calibration Ranges

Parameter	Interpretation	Range
β	Discount Factor	0.996
α	Elasticity of Matching wrt Unemployment	0.3 – 0.7
m	Efficiency of Job Matching	0.3 – 1.5
b	Opportunity Cost of Employment	0.4 – 0.8
τ	Rate of Job Destruction	0.087 – 0.104
z	Worker Relative Bargaining Power	0.1 – 0.8
θ_p	Probability Prices Are Fixed	0. – 0.9
ρ_π	Monetary Policy Response to Inflation	1.35 – 2.0
η	Intertemporal Elasticity of Substitution	1
κ	Cost of Vacancy Posting	0.2

power, assuming $z_t = ze^{\epsilon_t^z}$, where ϵ_t^z is a bargaining power shock. And there is a shock to the rate of job destruction, assuming $\tau_t = \tau e^{\epsilon_t^\tau}$, where ϵ_t^τ is a job separations shock. We use impulse response functions to these shocks to impose impact sign restrictions on our structural model.

We specify ranges of values for parameter calibrations and assume that parameters are uniformally distributed within this range. We assume that values of α are uniformally distributed between $0.3-0.7$; this is somewhat wider than the range of credible values suggested by Petrongolo and Pissarides (2001). We also consider a wide range of values for matching efficiency, assuming that values of m are uniformally distributed between $0.3-1.5$. For the rate of job destruction, Hall and Milgrom (2008) use $\tau = 0.03$, while Pissarides (2009) uses $\tau = 0.036$. These calibrations are designed for monthly data, whereas we use a quarterly frequency, consistent with our data. We therefore consider values between $0.087-0.104$. The value of the opportunity cost of employment is also contentious; Shimer (2005) assumes $b = 0.4$, Hall and Milgrom (2008) assume $b = 0.71$. We assume that b is uniformally distributed between 0.4 and 0.8. For the bargaining power of workers, we consider values between $z = 0.1$, so workers have little power to $z = 0.8$, where workers are able to extract most of the surplus from a job match in the form of higher wages. We consider a wide range of values for the probability that prices are fixed, considering values in the range $\theta_\pi = 0$ to $\theta_\pi = 0.9$, encompassing the cases where there is little nominal rigidity and where prices are highly sticky. For the monetary policy response to inflation, we consider values between $\rho_\pi = 1.35$ and $\rho_\pi = 2.0$, encompassing the different estimated values for this parameter in the post-1979 period. We use $\eta = 1$ and set $\kappa = 0.2$. We simulate our model by randomly selecting a set of calibration values from the distributions we outline above. We calculate the steady-state solution for our model implied by this calibration and construct impulse responses from a log linear expansion of the model around this steady-state. We repeat this process 1000 times, building a distribution of impulse responses. We use this to construct the sign restrictions documented in Table 1) of the main paper.

1.4 Scatterplots of the Impact of Shocks on the Unemployment and Vacancy Gaps

Figures 2) and 3) are scatter plots that show the impact of productivity and wage shocks and demand and job destruction shocks, respectively, on the unemployment and vacancy gaps.

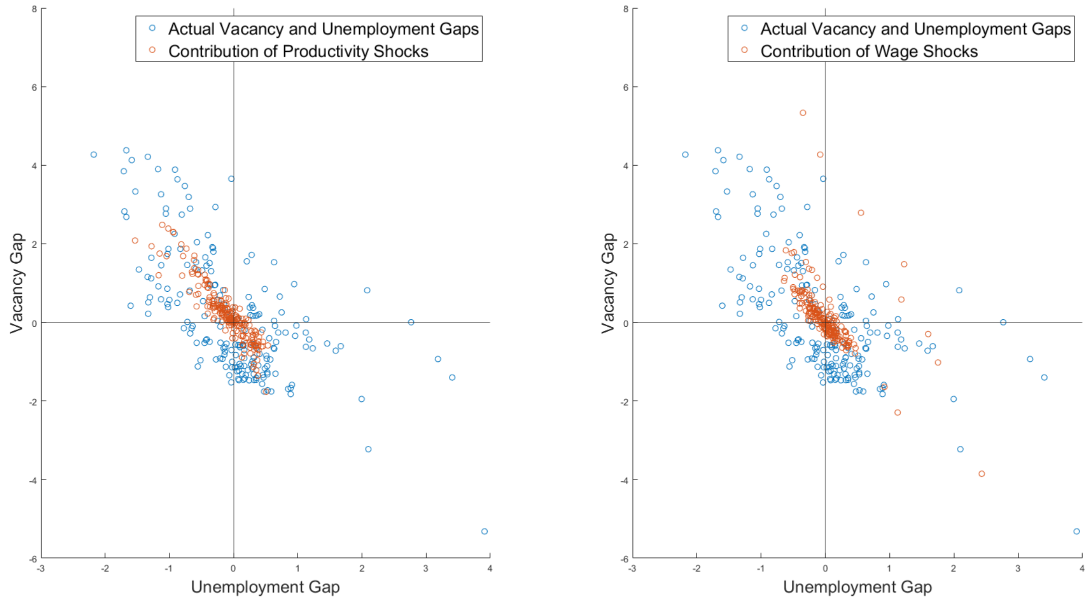

Figure 2: **Scatterplot of Vacancy and Unemployment Gaps, Showing Contribution of Productivity and Wage Shocks, 1965-2022**

Figure 3: **Scatterplot of Vacancy and Unemployment Gaps, Showing Contribution of Demand and Job Destruction Shocks, 1965-2022**

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