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Search Frictions and Evolving Labour Market Dynamics

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Abstract

This paper puts Search Frictions models under novel empirical scrutiny. To capture changing dynamics, we fit a Bayesian time-varying parameter VAR to US labour market data from 1965–2016. Using a DSGE model with Search Frictions, we identify several structural shocks, including a shock to worker bargaining power that we name a wage shock. We argue that the wage shock is a key driver of cyclical variation, explaining a higher proportion the variation of these variables than productivity, demand or job separation shocks. We also document stark differences between empirical and theoretical impulse response functions that cast doubt on the core transmission mechanism of search and matching models.

Keywords: time-varying parameter model, real wages, search frictions,

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

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1 Introduction

Macroeconomic models of the labour market look to explain cyclical, long-run, and secular relationships among key variables; namely unemployment, job vacancies and wages. Search Frictions models are the workhorse of modern labour economics (e.g. Diamond, 1982; Mortensen and Pissarides, 1994; Pissarides, 2000). This framework examines the incentives of firms to post vacancies, how unemployed workers find a job match, and the resulting wage of a successful job match. They provide an explanation for the underlying structural dynamics of the labour market, and historically, are successful in assessing the welfare implications of labour market policies. Their success stems from their ability to match key empirical regularities in the data, such as the negative link between unemployment and vacancies.

In this paper, we subject the Search Frictions framework of labour markets to novel empirical scrutiny. We have three main findings. First, we find evidence of important parameter change; this results in changes in impulse responses for key variables that are difficult to explain using standard theoretical models. Second, we find that a shock to the bargaining power of workers, which to date the literature overlooks, is an important driving force for the business cycle. Third, we argue that the key transmission mechanism implicit in the Search Frictions framework of the labour market, i.e. a strong response of vacancies to shocks, leading to volatile movements in unemployment across the business cycle, does not receive empirical support.

One of the main drawbacks of the Search Frictions framework is the presumption that structural relationships are constant over time. A growing empirical literature using models accounting for parameter and volatility variation within labour markets casts doubt on this (see e.g. Benati and Lubik (2014); Mumtaz and Zanetti (2015); Guglielminetti and Pouraghdam (2017))[1]. We extend on this literature by fitting a time-varying parameter VAR with stochastic volatility (TVP VAR) comprising of US data on productivity, real wages, vacancies, unemployment and inflation from 1965Q1–2016Q4

Following Benati (2014), we identify a non-stationary structural productivity shock that maximises the long-horizon covariance between productivity and real wages. We identify other strcutural shocks through robust sign restrictions, by applying the procedure of Canova and Paustian (2011) to a Dynamic Stochastic General Equilibrium model with Search Frictions (DSGE-SF) similar to Mumtaz and Zanetti (2012). Using this approach, we identify structural job destruction, demand and wage bargaining shocks. We use estimates from our structural TVP VAR to evaluate central features of Search Frictions models of the labour market. We question the focus in the literature on productivity shocks as the primary source of cyclical variation in vacancies and unemployment. We present forecast error variance decompositions from our TVP VAR which show that wage shocks explain a higher proportion of the variation in the vacancy rate and the unemployment rate than productivity shocks, demand shocks, and job separation shocks, throughout our estimation sample. In particular, we observe peaks in the percent share of forecast error variance attributable to wage shocks consistent with business

[1]Benati and Lubik (2014) find variation in the position and slope of the Beveridge Curve over time. Mumtaz and Zanetti (2015) find substantial time-variation in the response of key variables to study the response of key labour market variables to technology shocks. Guglielminetti and Pouraghdam (2017) find marked differences in the job creation process over time.

cycle troughs while the proportion of variance associated with productivity shocks remains relatively stable throughout the sample.

In our next exercise, we examine the core transmission mechanisms of the Search Frictions approach by calibrating a DSGE-SF model to match, on average over the impulse horizon, estimates of the impulse response functions for unemployment with respect to job separations shocks, wage shocks, and demand shocks. If the model is correct, impulse response functions for vacancies and wages from our model calibrations should also match the corresponding empirical impulse response functions. We find that they do not. Specifically in order to match the empirical response of the unemployment rate to shocks, the DSGE-SF model requires a large reduction in vacancies to generate a response of unemployment consistent with the data. In the case of demand and wage shocks, we do not observe this vacancy surge in the data. In addition, the DSGE-SF model suppresses the response of the wage to shocks in order to stimulate vacancy creation. However, the empirical response of wages to separations shocks is always much larger than the simulated response. Meanwhile the empirical response of wages to demand and wage shocks are much larger than the simulated response in the latter part of our sample. Taken together, these results cast further doubt on the empirical validity of Search Frictions models of the labour market[2].

The structure of the remainder of this paper is as follows. Section 2 describes data and outlines the econometric model; Section 3 presents reduced form results. In Section 4, we outline our identification strategy, describe the DSGE-SF model we use to derive sign restrictions and present our structural estimates. Section 5 presents evidence on FEVD decompositions and on the fit between empirical and simulated impulse responses and draws conclusions from these. Section 6 concludes and outlines areas for future research.

2 Data Description and Econometric Model

We use quarterly US data from 1954Q3 to 2016Q4 on productivity, real wages, the vacancy rate, the unemployment rate, and inflation. Our sample is driven by data availability as vacancy data from Barnichon (2010*a*) ends in December 2016. 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[3]. The vacancy rate is the Help Wanted Index in Barnichon (2010*a*) and the unemployment rate is from the Bureau of Labor Statistics (BLS). For inflation, we take the Nonfarm Business Sector: Implicit Price Deflator[4]. We take the natural logarithm of productivity and real wages, and the vacancy and unemployment rates enter the model with no transformation, and inflation is the annual percent change in the Nonfarm Business Sector: Implicit Price Deflator that we compute using annual log-differences[5]. We plot the data in

[2] Models with a role for labour market institutions have also been shown to improve the performance of search frictions models, eg Pissarides (2020), Thomas and Zanetti (2009) and Zanetti (2011)

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

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

[5] We work with a VAR in levels of productivity and real wages because economic theory and empirical evidence suggest they are cointegrated. Estimating a simple bi-variate VAR(2) and conducting Johansen (1992, 1995) tests provides evidence in favour of cointegration. Note that asymptotically, Sims et al. (1990) show working with a VAR in levels accounts for any cointegration between the variables with a unit root. In our case, productivity

Figure 1.

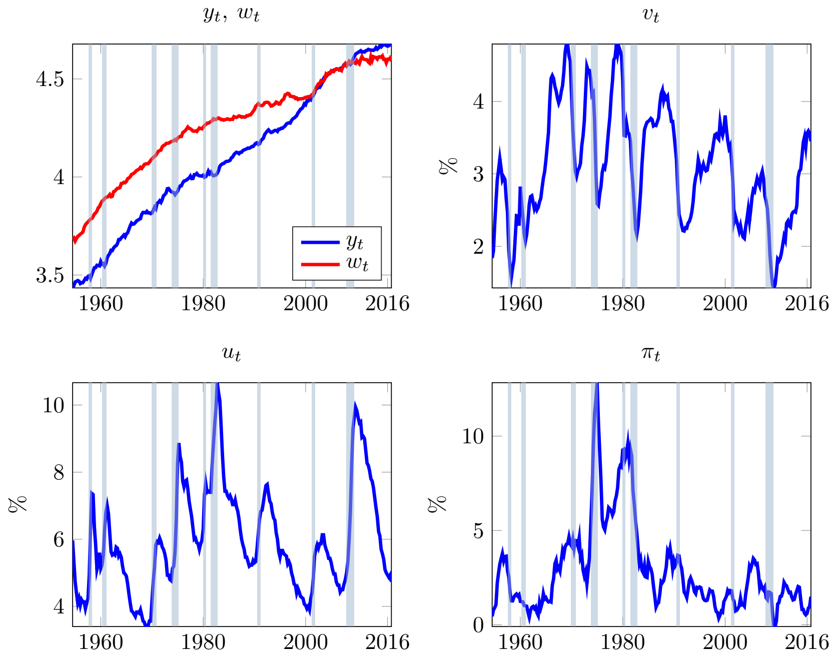

Figure 1: **US Macroeconomic data from 1954Q3 to 2016Q4**
Notes: This figure plots US labour market data from 1954Q3 to 2016Q4. The top left panel plots the log-levels of productivity, y_t, and real wages, w_t; the top right panel plots the vacancy rate, v_t; the bottom left panel plots the unemployment rate, u_t; and the bottom right panel plots the annual inflation rate, π_t. Grey bars indicate NBER recession dates.

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 log-level of labour 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 the inflation rate. $X_t^{'}$ 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 $\gamma_t \equiv [\gamma_{1,t}, : \gamma_{2,t}, ..., : \gamma_{N\cdot(Np+1),t}]'$, where $\gamma_t \backsim N(0, Q_t)$. We consider two different structures for Q_t. In the first case, we set $Q_t = Q$ which we assume is a full matrix containing parameter innovation variances and covariances. This is the standard Primiceri (2005) model. In the second case, we assume Q_t is diagonal and follows a stochastic volatility process which Baumeister and Benati (2013) introduce. Formally, collecting these elements in the vector $q_t \equiv [q_{1,t}, : q_{2,t}, ..., : q_{N\cdot(Np+1),t}]'$, they evolve as geometric random walks

$$\ln q_{i,t} = \ln q_{i,t-1} + \kappa_t \tag{3}$$

and wages contain unit roots and our specification accounts for any long-run relationship present between these variables.

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

$$\Omega_t = A_t^{-1} H_t (A_t^{-1})' \tag{4}$$

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

$$\begin{aligned} \ln h_{i,t} &= \ln h_{i,t-1} + \eta_t & (5) \\ \alpha_t &= \alpha_{t-1} + \zeta_t & (6) \end{aligned}$$

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 1965Q2–2016Q4. 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 are in the Online Appendix.

3 Reduced Form Results

As we discuss above, we consider two different structures on the covariance matrix of parameter innovations within the TVP VAR model. We conduct a model selection exercise of our TVP VAR specifications, whilst also benchmarking against various alternatives. We use the Bayesian deviance information criterion (DIC) proposed in Spiegelhalter et al. (2002). The DIC consists of two terms, one evaluating the fit of the model, and the other a penalty term for model complexity. Specifically, the DIC is given by

$$\mathrm{DIC} = \bar{\mathrm{D}} + \mathrm{pD} \tag{7}$$

where $\bar{\mathrm{D}} = -2\mathbb{E}(\ln \mathrm{L}(\mathbf{\Lambda}_i))$, the measure of fit, is equal to minus two times the expected value of the log likelihood evaluated over the draws of the MCMC, and $\mathrm{pD} = \bar{\mathrm{D}} + 2\ln \mathrm{L}(\mathbb{E}(\mathbf{\Lambda}_i))$, is the measure of model complexity; with $\ln \mathrm{L}(\mathbb{E}(\mathbf{\Lambda}_i))$ being the log likelihood evaluated at the posterior mean of parameter draws. The lower the DIC, the better the model fit. For time-varying coefficient VARs with stochastic volatility, the DIC is estimated using a particle filter to deal with the non-linear interaction of the stochastic volatilities (Mumtaz and Sunder-

Plassmann, 2013). The simpler models we include in this exercise are a conventional Bayesian VAR and a time-varying coefficient VAR with constant covariance matrix[6].

Table 1: **Bayesian DIC Statistics for Competing VAR Models**
Notes: This table reports the DIC statistics from a battery of competing Bayesian VAR models. We also report: i) the measure of fit, $\bar{\mathrm{D}} = -2\mathbb{E}(\ln \mathrm{L}(\boldsymbol{\Lambda}_i))$, which is minus two times the expected value of the log likelihood evaluated over the draws of the MCMC; and ii) the penalty term, $\mathrm{pD} = \bar{\mathrm{D}} + 2\ln \mathrm{L}(\mathbb{E}(\boldsymbol{\Lambda}_i))$, which is the log likelihood evaluation at the posterior mean of parameter draws. The row highlighted in bold font indicates the model with the lowest DIC, and therefore the model that best fits the data.

Model	DIC	$\bar{\mathrm{D}}$	pD
TVP VAR (Baumeister and Benati, 2013)	-2248.83	-2647.06	398.23
TVP VAR (Primiceri, 2005)	**-4161.71**	**-4450.18**	**288.46**
TVP VAR with constant covariance matrix	-1631.49	-1784.77	153.28
Linear BVAR	-1737.83	-1790.99	53.16

Table 1 reports the estimated DIC statistics, measures of fit $\bar{\mathrm{D}}$, and penalty terms pD, for competing models. Overall, we can see that the TVP VAR model of Primiceri (2005) provides the lowest DIC relative to the TVP VAR of Baumeister and Benati (2013) and restricted variants. This model also provides the highest value of $\bar{\mathrm{D}}$ which means that even though there is a relatively high value of pD, the DIC statistic remains far lower than alternatives we consider. Therefore we proceed by reporting results using the TVP VAR model of Primiceri (2005)[7].

The upper panel of Figure 2 plots the posterior median and 80% highest posterior density intervals for the logarithmic determinant of the time-varying covariance matrices. As in Guglielminetti and Pouraghdam (2017), this proxies total prediction variation in the model, and tracks the amount of 'noise hitting the system'. This increases gradually from the mid-1960s before peaking during the mid 1970s recession. It then falls gradually from the early 1980s that corresponds with the Volcker disinflation and Great Moderation. Since the burst of the dot-com bubble in 2001, total prediction variation is on a gradual upward trend.

Now looking at the lower panel of Figure 2, we see similar behaviour from the stochastic volatilities. In particular, productivity, unemployment and inflation follow a similar downward trend from the mid 1970s. The volatilities of productivity and the unemployment rate flatten off but still exhibit declines to the end of the sample, meanwhile the volatility of inflation increases following the 2001 recession. The volatility of the vacancy rate appears to exhibit peaks during recessions throughout the sample apart from the 2008 recession. Finally, the volatility of real wages increases throughout the sample. We can see that there is a gradual upward trend until

[6]These models use standard priors in the literature. In particular, BVARs use a Minnesota prior on the coefficients, models with constant covariance matrices have inverse-Wishart priors (see e.g. Koop and Korobilis (2010)), and those with time-varying parameters use analogous priors to the time-varying coefficient VAR models as outlined in the Appendix. Note also, we choose restricted variants of the TVP VAR as we do not wish to presume that periods of economic boom and recession can be represented by just two (or possibly three) sets of parameters; like regime-switching models impose. Finally we do not consider BVARs with stochastic volatility or a full time-varying covariance matrix as the purpose of our study is to track changing relationships within the labour market allowing for both changes in coefficients, as well as volatilities and covariances. Note the DIC statistics do indicate these models better fit the data, and this is down to a lower penalty term, pD, and a marginally higher value of $\bar{\mathrm{D}}$.

[7]Available on request are results from the TVP VAR following Baumeister and Benati (2013), note they are qualitatively similar to those we show in the main text.

the 2001 recession, then until the end of the sample the volatility of wages surges rapidly relative to the beginning of the sample[8].

In Figure 3, we report the time-varying pairwise correlations between our variables. As we can see, the model reproduces the switch from negative to positive correlation between productivity and the unemployment rate during the early 1980s (Barnichon, 2010*b*). Note that we also see a switch from positive to negative correlation (from posterior median estimates) between productivity and the vacancy rate following the recession in the early 1990s. The model implies a positive correlation between productivity and wages, and a negative correlation between productivity and inflation.

The posterior median and 80% posterior credible intervals of the correlation between wages and vacancies fluctuate around zero throughout the sample with gradual increases from 2001 until the end of the sample. We can also see that the correlation between real wages and unemployment is never significant. The correlation between real wages and inflation is negative until around 1998 with marginal significance before trending upwards and losing significance. The overall lack of statistically credible correlation between real wages and the other labour market variables suggests that labour market conditions may not have had a strong impact on the real wage. It also suggests that the increase in wage volatility since 1980s has been independent of the other variables and so the Search Frictions framework may be unable to explain this increased volatility.

The Beveridge Curve correlation between vacancies and unemployment is negative throughout the sample with this negative relationship being significant until around 2006. We can also see that the magnitude varies substantially with the strongest links appearing around the mid 1960s to the mid 1980s. Then the correlation rises and fluctuates around -0.5 until 2006. During the 2008 recession the Beveridge Curve correlation hits zero, before gradually declining until the end of the sample. The gradual rise in correlation from the mid-1980s could suggest that the impact of productivity shocks for labour market dynamics are becoming less important.

Our results suggest that the correlations between vacancies and inflation and between unemployment and inflation are marginal throughout the sample. The correlation between vacancies and inflation is negative until the early 1990s before turning positive from posterior median estimates. We see the opposite change in sign happen for the correlation between unemployment and inflation. It is positive until the early 1980s before turning negative thereafter.

4 Structural Analysis

In this section we present results from structural anaysis of our model. Our identification strategy 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

[8]Other studies also examine the stochastic volatilities of labour market variables. However, they have with different specifications of the VAR. Our estimate of overall model volatility and the volatility of vacancies is similar to Guglielminetti and Pouraghdam (2017). The stochastic volatility of unemployment from our model is more stable than Mumtaz and Zanetti (2015); and prior work does not consider productivity and real wages.

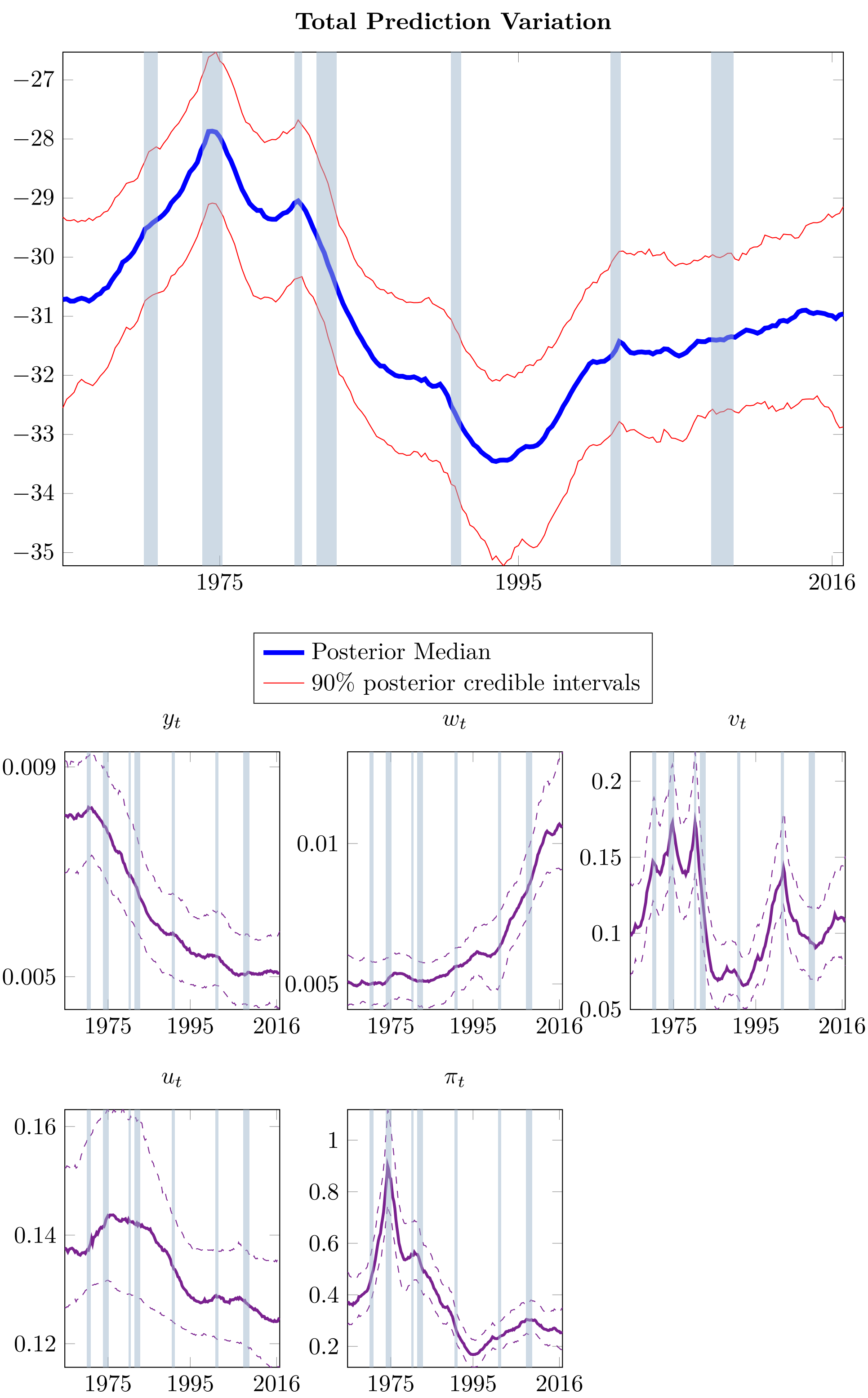

Figure 2: **Total Prediction Variation, $\ln|\Omega_{t|T}|$, and Stochastic Volatilities of US Labour Market Variables from 1964Q3 to 2016Q4**

Notes: The upper panel plots the posterior median, and 80% posterior credible intervals of logarithmic determinant of the time-varying reduced-form covariance matrices, $\ln|\Omega_{t|T}|$, from 1964Q3–2016Q4. The lower panel plots the posterior median, and 80% posterior credible intervals of the reduced-from stochastic volatility innovations of productivity, y_t (top left panel); real wages, w_t (top middle panel); the vacancy rate, v_t (top right panel); the unemployment rate, u_t (bottom left panel); and inflation, π_t (bottom middle panel) from 1964Q3–2016Q4. Grey bars indicate NBER recession dates.

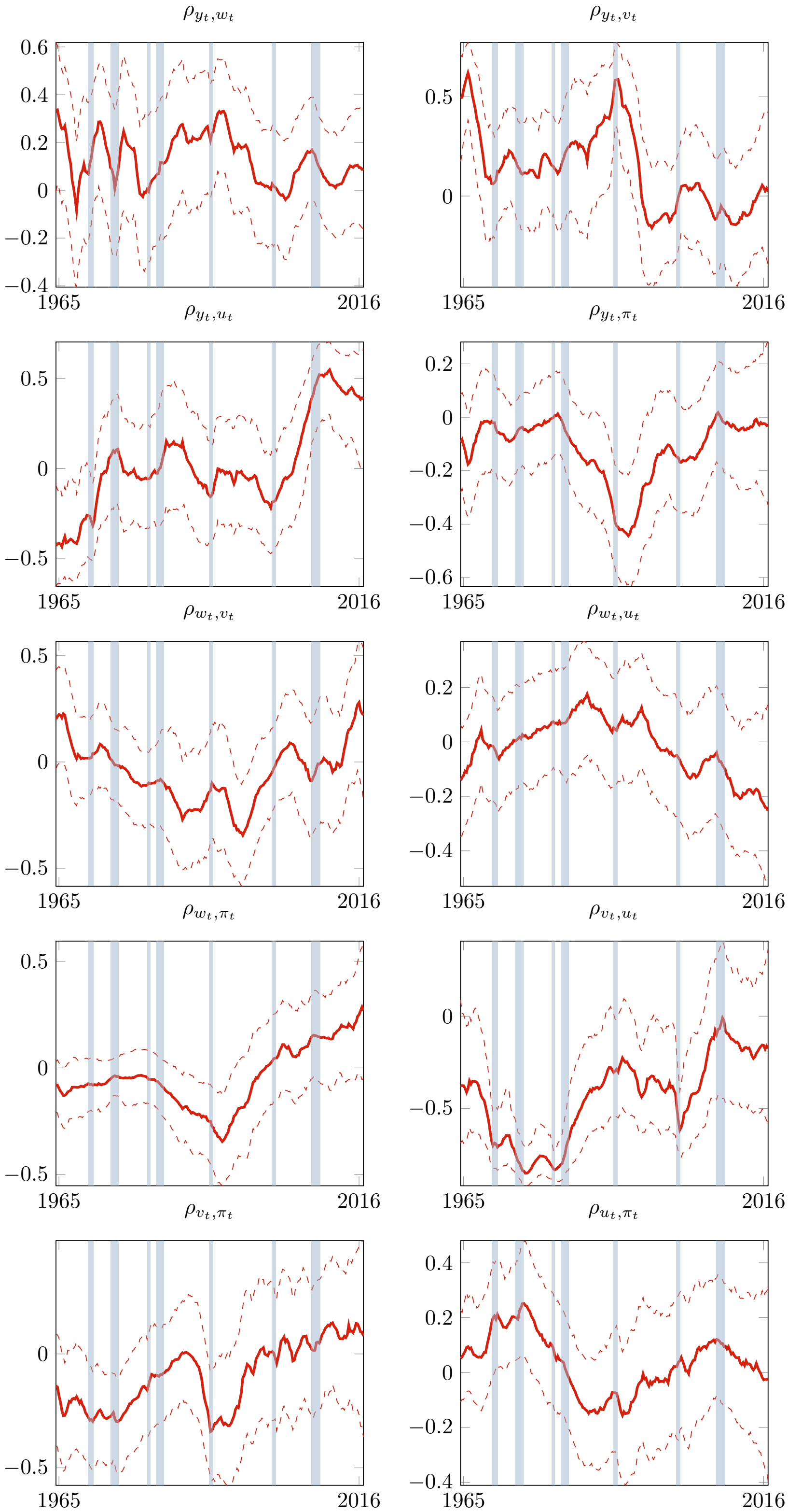

Figure 3: **Reduced-form correlations from 1964Q3 to 2016Q4**
Notes: This figure plots the posterior median, and 80% posterior credible intervals of the reduced-from model implied correlations of variables within the TVP VAR model from 1962Q1–2016Q4. $\hat{\rho}_{i_t,j_t}$ denotes the model implied correlation of variable i and j at time t respectively. y_t, w_t v_t, u_t, π_t denote productivity, real wages, the vacancy rate, the unemployment rate, and inflation, respectively. Grey bars indicate NBER recession dates.

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.

Table 2: **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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

We summarise the model and structural parameters in the upper panel of Table 2. 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 2.

We analyse the impact of four structural shocks. We include a demand shock, ϵ_t^D. We also include a shock to worker relative bargaining 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 also include a permanent productivity shock, assuming $A_t = e^{\epsilon_t^P}$, where ϵ_t^P is a non-stationary random walk. We do not identify the supply shock through sign restrictions, as it is identified as those values that maximise the long-run covariance between productivity and wages. Rather, we include this shock in our simulations to facilitate our evaluation of the Search Frictions model, below.

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[9]. 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 $\kappa = 0.2$[10]

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.

[9] Hagedorn and Manovskii (2008) assume $b = 0.955$, combined with a low value for worker bargaining power. Parameter configurations consistent with this give impulse responses with the same signs as in Table 4.

[10] In other simulations, we show that different values for this parameter give impulse responses with the signs reported in Table 4.

We present these results in Table 3, where + indicates that all values for the impulse response on impact within the credible range were positive, − indicates that all values for the impulse response on impact within the credible range were negative, and ? indicates that the credible range for the impulse response on impact included zero[11]. Our simulations show that positive values of the job separations shock lead to increases in unemployment, vacancies and inflation and a reduction in the wage. Positive values of the bargaining power shock lead to increases in unemployment and the wage and to reductions in vacancies. The response of inflation on impact is negative; but the response becomes positive in the following period, indicating that identification based on the sign of this response may not be secure. Positive values of the the demand shock lead to increases in inflation, vacancies and wages and to a reduction in unemployment.

Table 3: **Impulse Responses on Impact Based on Simulations**
Notes: + indicates that all values for the impulse response on impact within the credible range were positive, − indicates that all values for the impulse response on impact within the credible range were negative, and ? indicates that the credible range for the impulse response on impact included zero. Plots of the impulse responses are shown in the Online Appendix, with further details of our procedure.

	wages	vacancies	unemployment	inflation
job destruction	-	+	+	+
wage shock	+	-	+	?
demand	+	+	-	+

Based on these results[12] , we identify four structural shocks within our empirical model as in Table 4. We identify: a permanent productivity shock, ψ_t^{Prod} and therefore impose no impact sign restrictions; a job separation shock, ψ_t^{JS}[13]; a wage shock that reflects a shock to workers' bargaining power, ψ_t^{W}; and a demand shock ψ_t^{D}.

Table 4: **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 permanent productivity shock, ψ_t^{Prod} which we identify following Benati (2014), this shock maximises the long-run covariance between productivity and wages; a job separation shock, ψ_t^{JS} ; 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^{Prod}	x	x	x	x	x
ψ_t^{JS}	x	−	+	+	x
ψ_t^{W}	x	+	−	+	+
ψ_t^{D}	x	+	+	−	+

[11]Plots of the impulse responses from which Table 3 is derived are contained in the Online Appendix.

[12]In an extension of our analysis, we also analysed the impact of additional shocks, comprising shocks to (i) the discount factor; (ii) the efficiency of job matching; (iii) opportunity cost and (iv) vacancy costs. We find that a shock to the opportunity cost implies the same signs for the impulse responses on impact. In section 5) below we discuss why we prefer to interprt this shock as one to worker bargaining power. Full details of the extended model and the results of simulations of this are contained in the online appendix

[13]The importance of this shock has been highlighted by Fujita and Ramey (2007) and Theodoridis and Zanetti (2020).

We now discuss the empirical procedure that allow us to map to the (partial) structural model from our reduced-form TVP VAR. Our identification scheme combines the procedure in Benati (2014) with algorithm 1 in Arias et al. (2018). The procedure in Benati (2014) modifies the maximum fraction of forecast error variance strategy in Uhlig (2004). We use this algorithm to identify productivity shocks as those that maximise the long-horizon covariance between productivity and real wages.

For each draw of the posterior distribution at time t, we compute the time varying covariance matrix Ω_t. We then take its eigenvalue-eigenvector decomposition such that $\Omega_t = P_t D_t P_t'$. The candidate structural impact matrix, $A_{0,t}$ is given by $A_{0,t} = P_t D_t^{\frac{1}{2}}$. We then specify an orthonormal matrix Q which is the product of all available rotation matrices $R_i(\vartheta, \mathrm{K})$

$$\mathrm{Q} = \prod_{\mathrm{K}=2}^{N} \prod_{i=1}^{N-\mathrm{K}-1} R_i(\vartheta, \mathrm{K}) \tag{8}$$

where $2 \leq \mathrm{K} \leq N$ is the dimension of the square sub-matrix along the diagonal of $R_i(\vartheta, \mathrm{K})$, with N=5 being the number of variables in the system. We then search over the parameter space for the specific values in ϑ (i.e. the rotation angles) that maximise the long-horizon covariance between productivity and real wages. We perform the maximisation using the MATLAB routine `fminsearch.m` for random initial conditions. We then compute $A_{0,t}^* = A_{0,t}\mathrm{Q}'$. This provides us with the permanent productivity shock in the first column of $A_{0,t}^*$. Now using the latter steps in algorithm 1 of Arias et al. (2018), we search the remaining columns of $A_{0,t}^*$ for those that satisfy the sign restrictions for our job separation and vacancy cost shock and insert accordingly. If the sign restrictions are not met, we go back to identification of the permanent productivity shock. Once we have a structural impact matrix from each draw of the posterior and every time period, we compute impulse response functions and forecast error variance decompositions assuming parameters remain constant over the impulse (forecast error) horizon.

Figure 4 presents estimates of the volatilities of our structural shocks. The permanent productivity shock exhibits a gradual downward trend throughout the estimation sample. However, we can see that it rises throughout the 1980s until the mid-1990s before declining gradually toward the end of the sample. Turning our attention to the volatility of the job separation shock, this remains relatively stable in the first half of our sample. Then, from the 1990s until the end of our sample the volatility is increasing gradually until the end of 2016. The volatility of the wage shock appears relatively stable throughout the estimation sample with peaks occurring in conjunction with recessions. Finally concerning demand shocks, we see a clear reduction in volatility in the early 1980s as with the volatility of the productivity shock. Adding to this, there is clear evidence of cyclical behaviour with peaks in volatilities coinciding with all recessionary periods apart from the 2008 recession.

In Figures 5–8, we report impulse response functions of US labour market variables with respect to one standard deviation: productivity shocks; job separations shocks; wage shocks; and demand shocks, respectively. The top five plots in each figure present the posterior median response of variables throughout time on the x-axis, at a 40 quarter horizon on the y-axis, with the magnitude of the response on the z-axis. The bottom five plots show the posterior median response of variables 1-quarter following impact. We normalise impulse response functions to generate a 1% rise/fall in the unemployment rate as per Canova and Paustian (2011) robust sign restriction in Table 4[14].

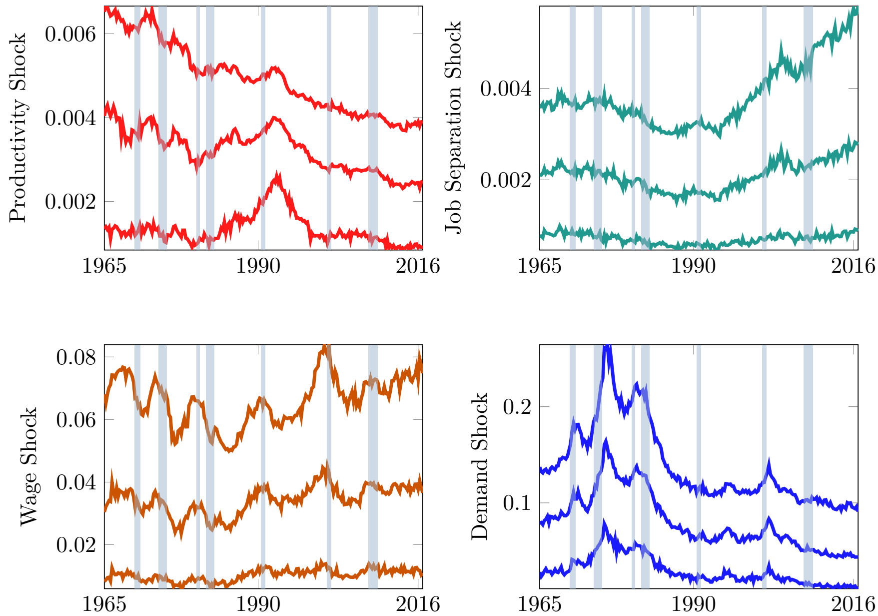

Figure 4: **Volatility of Structural Shocks from 1965 to 2016**
Notes: This figure plots the posterior median and 68% equal-tailed point-wise posterior probability bands for the volatility of identified structural shocks from 1965Q1–2016Q4. The top-left quadrant reports the volatility of the permanent productivity shock, the top-right quadrant reports the volatility of the job separations shocks. The bottom-left and bottom-right quadrants report the volatilities of the wage and demand shock respectively. Grey bars indicate NBER recession dates.

Considering permanent productivity shocks in Figure 5, we can see that there is considerable time-variation in the response of labour market variables. Notably, the response of productivity and wages is stronger from 1965–1995, then both variables become more resilient to these shocks until the end of the sample. Looking at the response of unemployment and vacancies, the respective peaks and troughs are strongest during the 1970s, and again throughout the mid-1990s to early 2000s. The response of inflation changes sign and switches from negative during the first 10 years of our estimation sample, to positive thereafter.

We now examine the impulse response functions of labour market variables with respect to shocks we identify pertinent to the labour market. These are job separations shocks in Figure 6 and wage shocks in Figure 7. Five main findings emerge from these graphs. First, there is marked time-variation in the response of all variables to these shocks. Second, we observe surges in the response of vacancies and unemployment with respect to job separations shocks during recessions. However, the response of the vacancy rate declines throughout our sample, whereas the response of the unemployment rate rises. What we can see is that during the Great Moderation the response of both variables seems to plateau which indicates a resilience to these shocks relative to the 1970s and 1980s.

Third, the vacancy rate and the unemployment rate exhibit a relatively high degree of

[14] We refrain from presenting error bands because they are wide and this makes it difficult to examine variation in the responses over time. However, we note that the response of real wages and the vacancy rate are significant for the job separation shock and that real wages, the vacancy rate, unemployment and inflation are significant for the wage shock. These results are available on request.

persistence to both labour market shocks. From posterior median estimates the impact of these shocks lasts around 20 quarters. However, in absolute magnitude the peak in unemployment surpasses the trough in vacancies in response to a wage shock. Fourth, wages become more sensitive to both shocks throughout the sample. Looking at the response of real wages to job separations shocks, we can see that the contraction in wages gets larger from 1965 until the mid-2000s before declining until the end of the sample. In comparing the response of real wages to a wage shock in 1965Q1 and 2016Q4, we see that the 1-quarter response doubles. Fifth, the sensitivity of real wages, vacancies and unemployment in response to wage shocks increase throughout the sample. This indicates that key labour market variables become more responsive to this shock.

In Figure 8, we examine the impact of demand shocks. Again, we find time-variation in the response of labour market variables. In particular, the sensitivity of productivity and wages are increasing throughout the sample. The 1-quarter response of productivity in 2016 is around -2%, however we observe a positive response in 1965. Looking at wages, the response in 2016 is double that of 1965. The sensitivity of vacancies to demand shocks is largest during from 1965–1985, and again in the early 2000s. Looking at the response of unemployment we can see that this becomes more resilient to these shocks throughout the estimation sample. The response of inflation to demand shocks fluctuates around a 2% rise throughout the sample.

In the Online Appendix, we analyse an extension of our model that includes additional shocks, to the opportunity cost of employment (b), the cost of posting a vacancy (κ), the efficiency of job matching (m) and the discount factor (β). As shown in the Appendix, the impact of an opportunity cost shock is the same as a bargaining power shock. Although, as discussed below, we feel that the evidence in Figure 9 favours the interpretation of ψ_t^{W} as a bargaining power shock. Shocks to the discount factor have the same impact as a demand shock, so one might think of ψ_t^{D} as a composite shock that also reflects these.

5 Implications

In this section, we posit that our results challenge the current literature using the Search Frictions model to analyse movements in the labour market across the business cycle. We make two main arguments. First, we present Forecast Variance Error Decompositions (FEVDs) which show that wage shocks explain a higher proportion of unemployment and vacancy rate variation in our sample relative to productivity, demand and job separations shocks. The Search Frictions literature predominantly focuses on productivity shocks as the main driver of the business cycle, and to a lesser extent demand and job separation shocks. However, our analysis suggests that the literature overlooks the key role of wage shocks. Second, we argue that key mechanisms implicit in the Search Frictions model of the labour market receive little empirical support. In particular, our estimates of the response of vacancies to wage shocks and demand shocks are too weak to be consistent with the responses of unemployment to these shocks that we observe in the data. Adding to this, the responses of wages to wage shocks and demand shocks are too strong to be consistent with the empirical responses of unemployment.

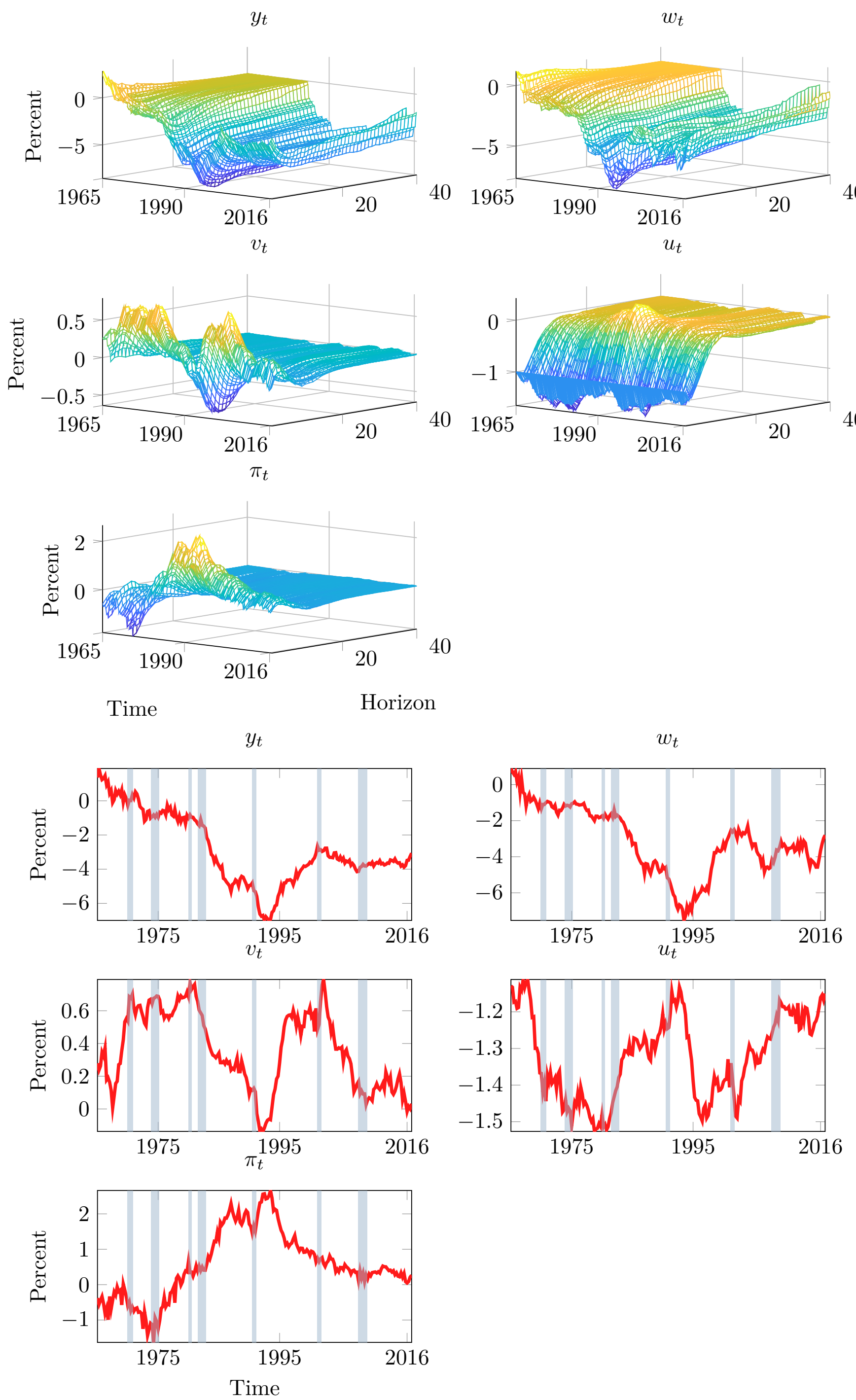

Figure 5: **Impulse Response Functions with Respect to a Productivity Shock from 1965 to 2016**

Notes: The top five plots this figure plot the posterior median impulse response functions of US labour market data with respect to a one standard deviation productivity shock from 1965Q1 to 2016Q4. y_t, w_t, v_t, u_t, π_t denote the response of: the log-level of labour productivity; the log-level of real wages; the vacancy rate; the unemployment rate; and the inflation rate respectively. Impulse responses span a 40 quarter horizon and normalised such that the shock causes the unemployment rate to fall by 1%. The bottom five plots report the posterior median responses, at a 1 quarter horizon, of US labour market data with respect to a one standard deviation productivity shock from 1965Q1 to 2016Q4. y_t, w_t, v_t, u_t, π_t denote the response of: the log-level of labour productivity; the log-level of real wages; the vacancy rate; the unemployment rate; and the inflation rate respectively. Grey bars indicate NBER recession dates.

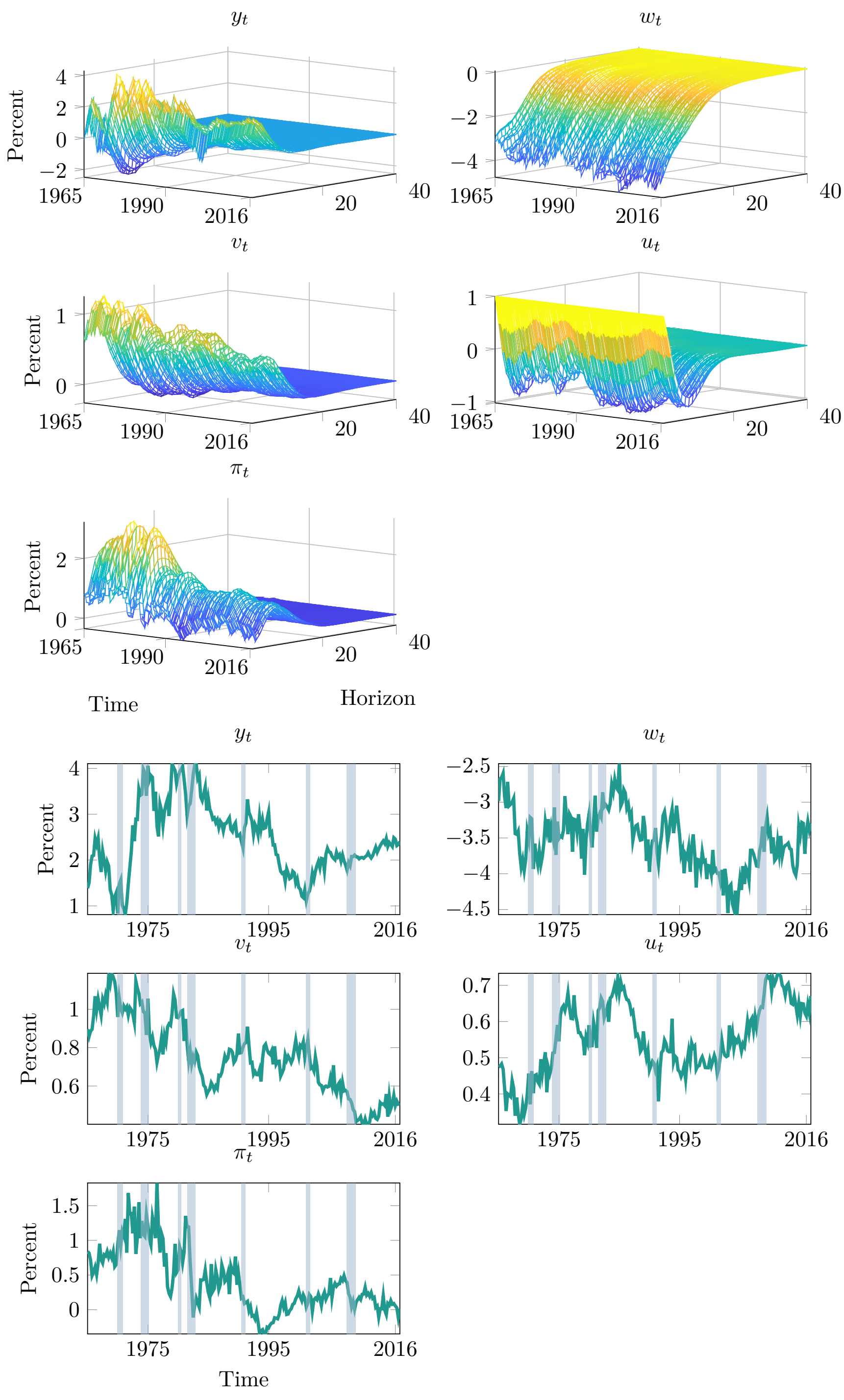

Figure 6: **Impulse Response Functions with Respect to a Job Separation Shock from 1965 to 2016**

Notes: The top five plots this figure plot the posterior median impulse response functions of US labour market data with respect to a one standard deviation job separations shock from 1965Q1 to 2016Q4. y_t, w_t, v_t, u_t, π_t denote the response of: the log-level of labour productivity; the log-level of real wages; the vacancy rate; the unemployment rate; and the inflation rate respectively. Impulse responses span a 40 quarter horizon and normalised such that the shock causes the unemployment rate to rise by 1%. The bottom five plots report the posterior median responses, at a 1 quarter horizon, of US labour market data with respect to a one standard deviation job separation shock from 1965Q1 to 2016Q4. y_t, w_t, v_t, u_t, π_t denote the response of: the log-level of labour productivity; the log-level of real wages; the vacancy rate; the unemployment rate; and the inflation rate respectively. Grey bars indicate NBER recession dates.

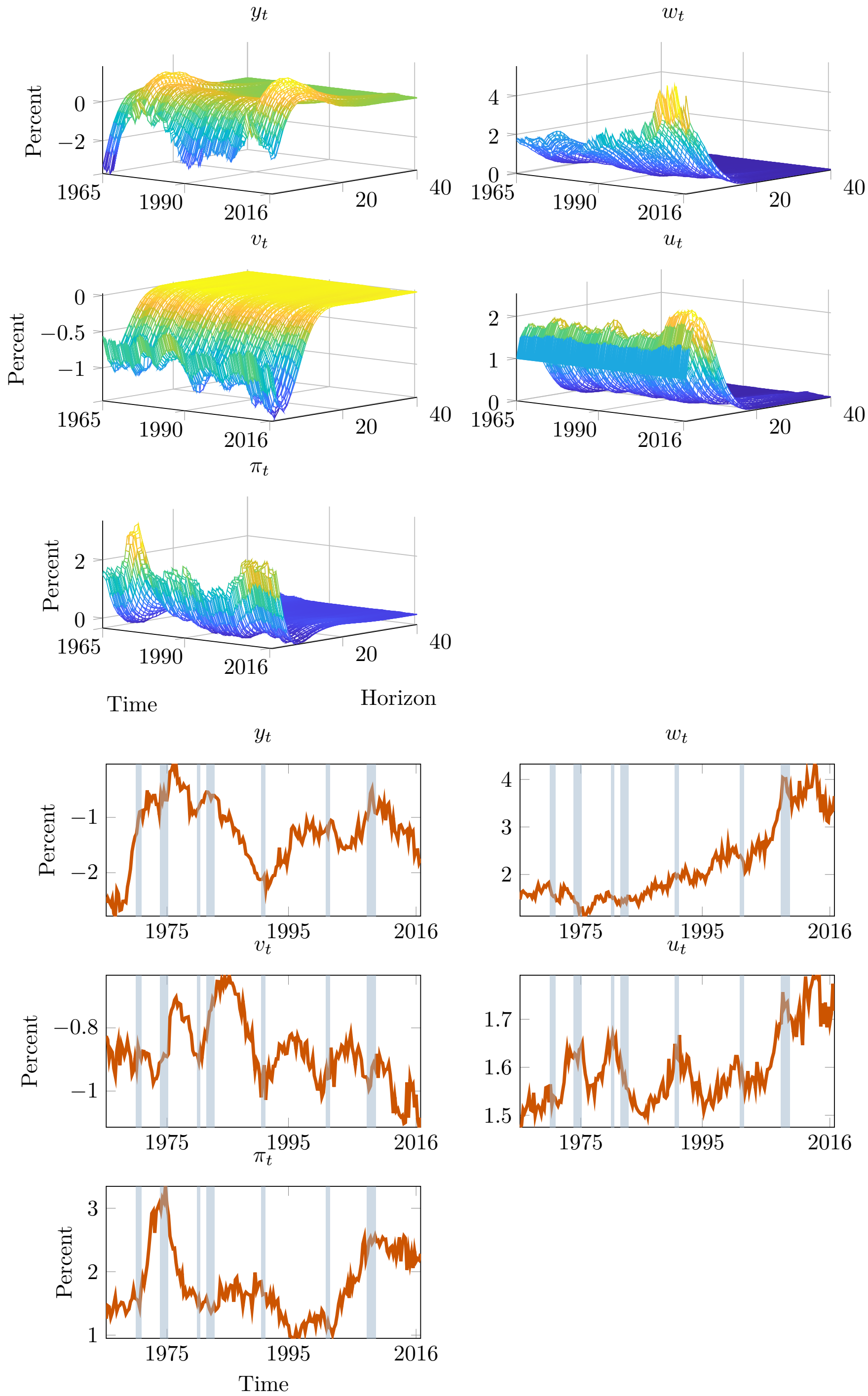

Figure 7: **Impulse Response Functions with Respect to a Wage Shock from 1965 to 2016**

Notes: The top five plots this figure plot the posterior median impulse response functions of US labour market data with respect to a one standard deviation wage shock from 1965Q1 to 2016Q4. $y_t, w_t, v_t, u_t, \pi_t$ denote the response of: the log-level of labour productivity; the log-level of real wages; the vacancy rate; the unemployment rate; and the inflation rate respectively. Impulse responses span a 40 quarter horizon and normalised such that the shock causes the unemployment rate to rise by 1%. The bottom five plots report the posterior median responses, at a 1 quarter horizon, of US labour market data with respect to a one standard deviation wage shock from 1965Q1 to 2016Q4. y_t, w_t, v_t, u_t, π_t denote the response of: the log-level of labour productivity; the log-level of real wages; the vacancy rate; the unemployment rate; and the inflation rate respectively. Grey bars indicate NBER recession dates.

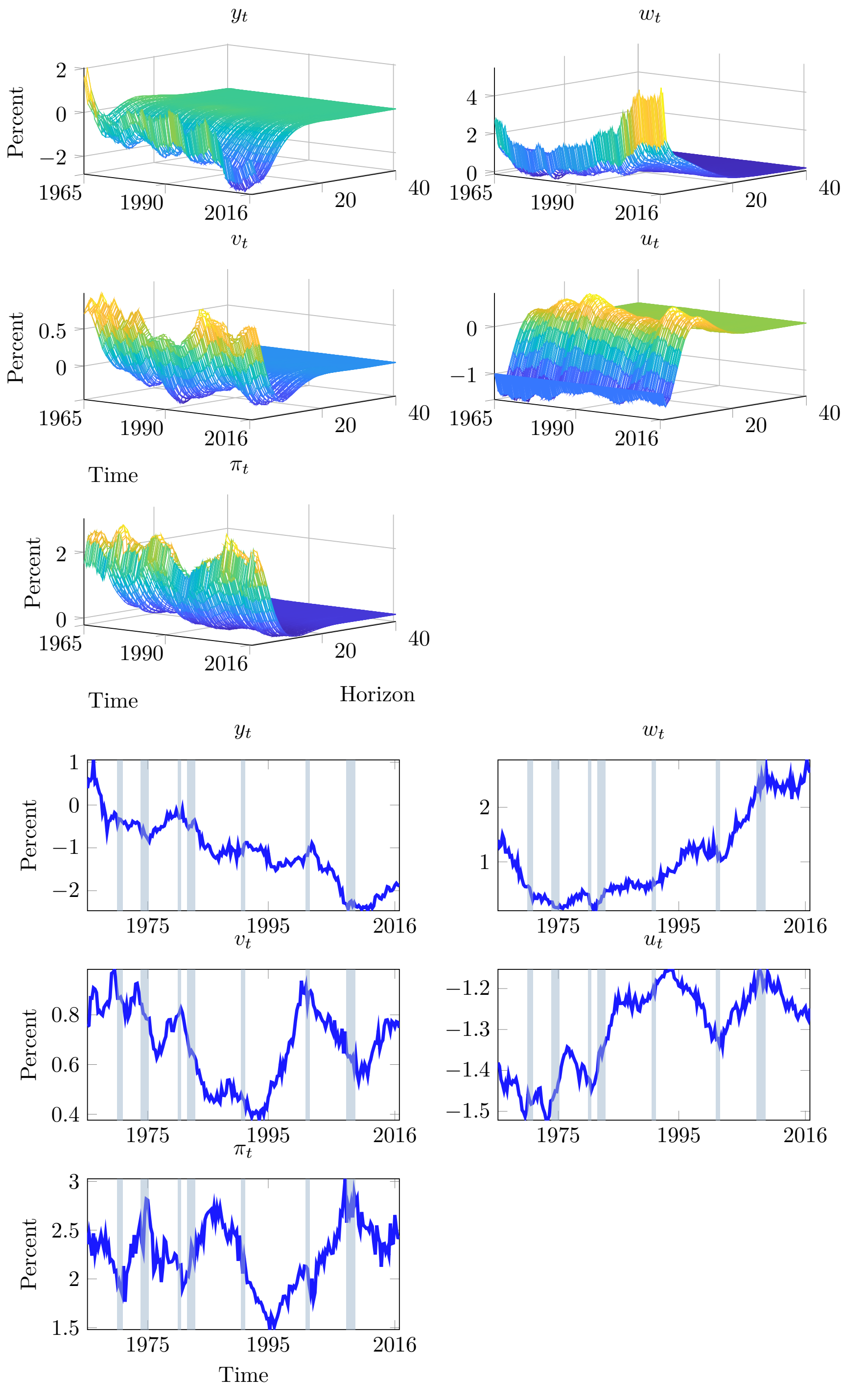

Figure 8: **Impulse Response Functions with Respect to a Demand Shock from 1965 to 2016**

Notes: The top five plots this figure plot the posterior median impulse response functions of US labour market data with respect to a one standard deviation demand shock from 1965Q1 to 2016Q4. y_t, w_t, v_t, u_t, π_t denote the response of: the log-level of labour productivity; the log-level of real wages; the vacancy rate; the unemployment rate; and the inflation rate respectively. Impulse responses span a 40 quarter horizon and normalised such that the shock causes the unemployment rate to rise by 1%. The bottom five plots report the posterior median responses, at a 1 quarter horizon, of US labour market data with respect to a one standard deviation demand shock from 1965Q1 to 2016Q4. y_t, w_t, v_t, u_t, π_t denote the response of: the log-level of labour productivity; the log-level of real wages; the vacancy rate; the unemployment rate; and the inflation rate respectively. Grey bars indicate NBER recession dates.

5.1 Business Cycle Drivers

Considering our first main argument, Figure 9 reports the posterior median estimates of the percent share of the overall forecast error variance of: productivity, y_t; real wages, w_t; the vacancy rate, v_t; the unemployment rate, u_t; and inflation, π_t attributable to productivity shocks, job separation shocks, wage shocks, and demand shocks at a 40-quarter horizon. As a consequence of our identification scheme, permanent productivity shocks explain the majority of variation in labour productivity and real wages. With the exception of the mid 1970s to the mid-1980s, this shock explains around 80% of the variation in productivity and real wages[15].

Wage shocks explain a higher proportion of variation in the vacancy rate and the unemployment rate than productivity, demand and job separation shocks. This shock explains up to 30% of the variation in vacancies and up to 38% of the variation in the unemployment rate across the business cycle; with surges consistent with business cycle troughs. Moreover, the wage shock also helps to account for the rising volatility of wages documented in Figure 2. The impulse response functions with respect to a wage shock in Figure 7 shows that the response of wages to a wage shock has been on an upward trend since the 1970s. Although the importance of the wage push shock falls towards the end of the sample, this shock always explains a higher proportion of unemployment and vacancy rate variation when comparing to other shocks we identify. By contrast, productivity shocks explain less than 20% of the variation in unemployment and vacancies[16], with demand and job separation shocks typically explaining less than this. These findings suggest that analysis of the labour market needs to account for the importance of wage shocks[17]

5.2 Questioning the Mechanism

To examine the mechanisms within the Search Frictions model, we compare our empirical impulse responses with simulated impulse responses from the DSGE-SF model we use to obtain robust sign restrictions. We calibrate the model so that the simulated impulse responses for unemployment following wage shocks, demand shocks, and job separation shocks match, as far as possible, the corresponding empirical impulse response functions; whilst also generating a steady-state unemployment rate matching the observed rate. If the model is a good description of the forces generating the data, the simulated responses of vacancies and wages to these shocks will also match their empirical counterparts. Due to the changes in empirical impulse response functions over time, we repeat this exercise for two different dates; 1974Q2 and 2008Q4. Notably, these dates correspond both correspond to business cycle troughs to reflect the dynamics we document in our empirical results. We summarise the parameter values used in this exercise in

[15] Also note that our structural shocks explain most of the variance in all variables across our sample, it is unlikely that a fifth structural shocks would have a strong impact on our results.

[16] Those findings echo Hall (2017) who argues that the importance of the productivity shock might have been overestimated.

[17] As noted above, our identified wage shock is also consistent with a shock to the opportunity cost of employment (see the online appendix for a more detailed analysis). We prefer to interpret the identified wage shock as a shock to worker bargaining power for two reasons; (i) the reduced contribution of these shocks to variance of unemployment and vacancies towards the end of the sample, seen in Figure 9), is consistent with a decline in unionisation; (ii) the stronger impulse response function of wages with respect to a wage shock in Figure 7 is consistent with the increase in wage volatility in the US between the late 1980s and early 2000s; this is associated with de-unionization and a shift towards performance-pay contracts (Champagne and Kurmann (2013))

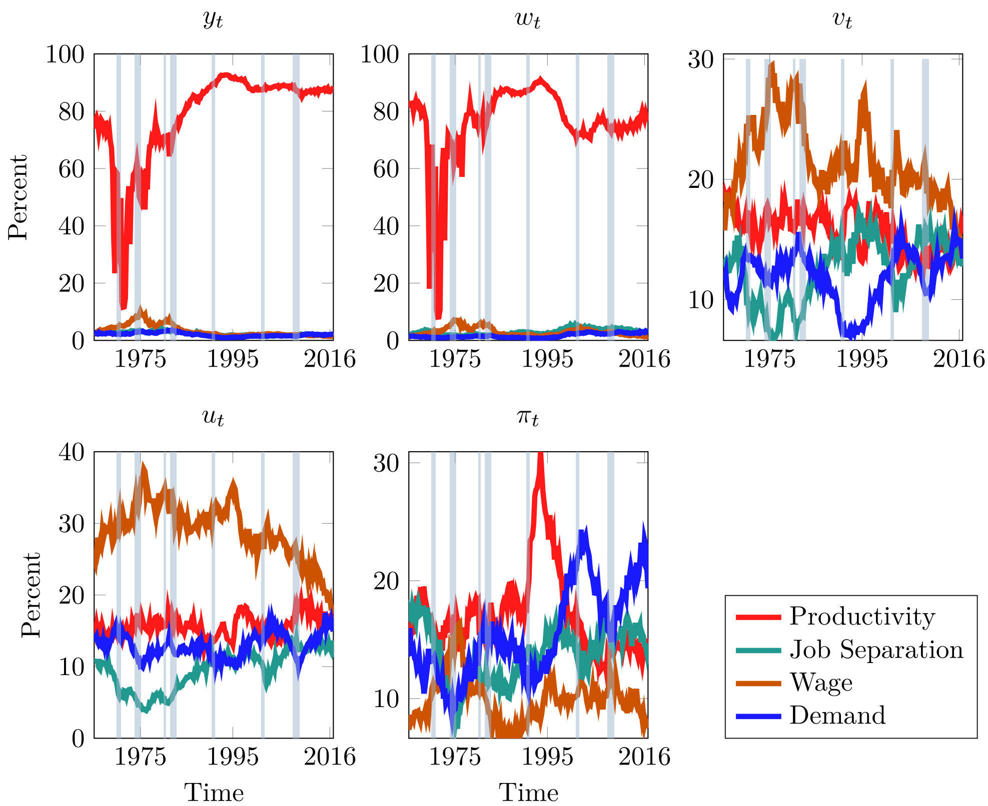

Figure 9: **Forecast Error Variance Decompositions of Labour Productivity, Real Wages, the Vacancy rate, the Unemployment rate, and Inflation from 1965 to 2016**
Notes: This figure plots the posterior median, of the percent share of variance attributable, at a 40 quarter horizon, to productivity shocks (Red line); job separation shocks (Green line); wage shocks (Orange Line) and Demand shocks (Blue line) for: the log-level of productivity, y_t; the log-level of real wages, w_t; the vacancy rate, v_t; the unemployment rate, u_t; and the inflation rate, π_t from 1965Q1–2016Q4. Grey bars indicate NBER recession dates.

Table 5.

Table 5: **Parameter Values for Calibration: The Search Frictions Model**
This table reports the values of the calibrations for 1974Q2 and 2008Q4.

Parameter	Interpretation	1974Q2	2008Q4
τ	Ave separation rate	0.09	0.09
r	Discount factor	0.99	0.99
α	Elasticity of matching function	0.60	0.60
b	Opportunity cost of unemployment	0.71	0.71
γ	Vacancy posting cost	0.30	0.30
m	Matching coefficient	0.75	0.725
ϕ	Bargaining power	0.25	0.25
θ_p	Probability prices are fixed	0.50	0.50
ρ_π	Monetary policy response to inflation	1.50	1.50
η	Intertemporal elasticity of substitution	1.00	1.00
ρ^z	Persistence of wage push shock	0.90	0.90
σ^z	Volatility of wage push shock	0.09	0.1
ρ^γ	Persistence of demand shock	0.70	0.70
σ^γ	Volatility of demand shock	0.02	0.015
ρ^τ	Persistence of job separation shock	0.733	0.733
σ^τ	Volatility of job separation shock	0.01	0.01

We plot the empirical and theoretical impulse response functions, over a 20 quarter horizon, for real wages (first row), the vacancy rate (middle row), and the unemployment rate (bottom row) in Figure 10. Panels A and B pertain to 1974Q2 and 2008Q4 respectively. The leftmost columns show responses to job separation shocks, while the middle and rightmost columns show responses to wage shocks and demand shocks respectively. First considering job separations shocks, there are clear differences between the estimated and simulated impulse response functions for real wages and vacancies. We note here the stark difference between empirical and theoretical impulse response functions of wages. Calibrations of the DSGE-SF model suggest a small response of wages to job separations shocks, in contrast to the sizeable empirical responses of real wages.

Turning our attention to wage shocks, we can see that the empirical response of real wages is far larger than those from our calibrations; particularly in 2008Q4. Note also that the empirical response of vacancies is smaller than those from our calibrations. The mechanism within the Search Frictions model requires a large reduction in the vacancy rate to generate large increases in unemployment. Now looking at the response of labour market variables to demand shocks, we observe differences between empirical and theoretical responses of real wages and vacancies.

Taken together, these results cast further doubts for the transmission mechanisms inherent within the Search Frictions framework for the labour market. For wage shocks, the underpinning mechanism requires a large reductions in vacancies in order to generate a large rise in unemployment. For demand shocks, our calibration of the DSGE-SF model requires a large surge in vacancy creation to match the empirical reductions in unemployment. However in order to stimulate vacancy creation, the theoretical model suppresses the response of the real wage with respect to the demand shock. This is why we observe notably smaller surges in real wages from the calibrated impulse response functions. The main message from this exercise is that the data does not lend support to the transmission mechanisms inherent within Search Frictions models of the labour market.

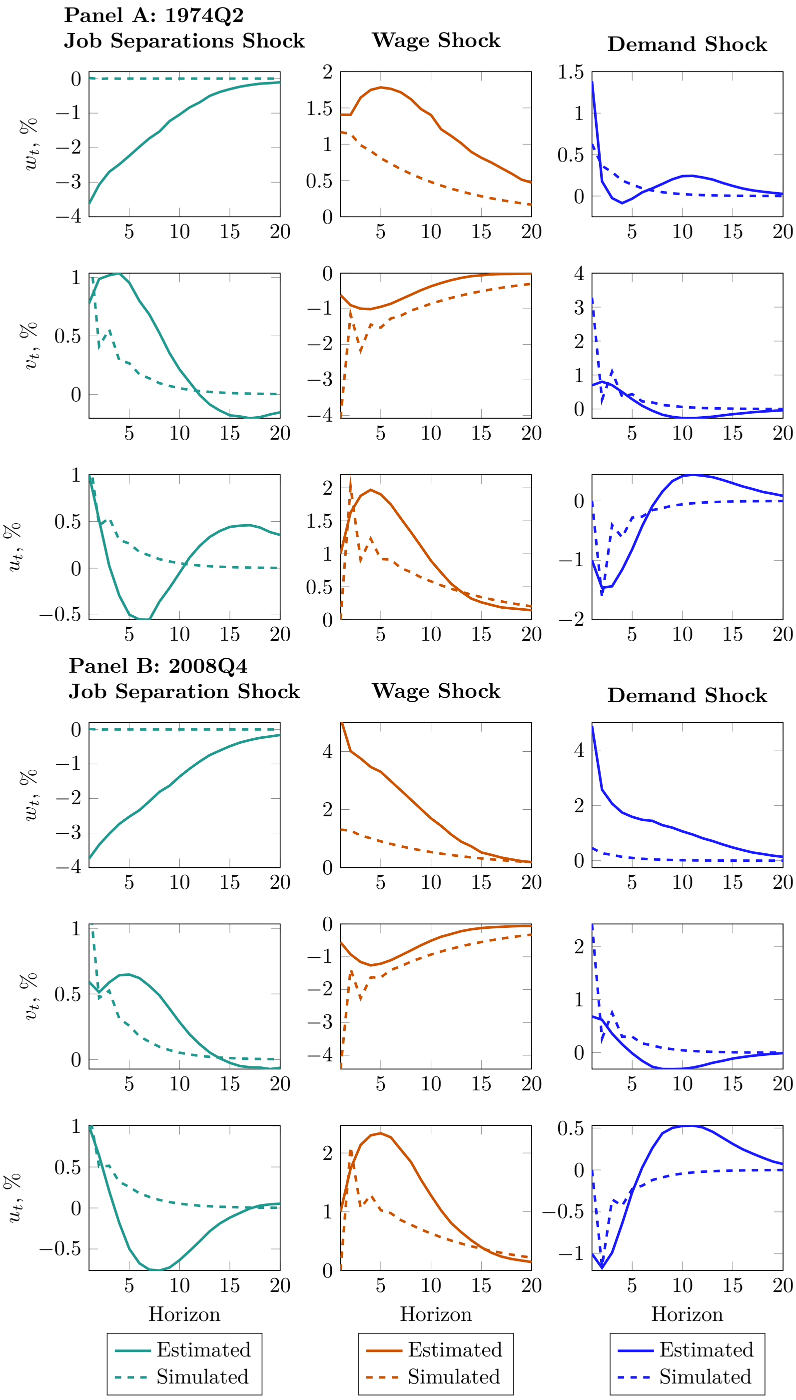

Figure 10: **Empirical and Theoretical Impulse Response functions of Key Labour Market Variables: 1974Q2 and 2008Q4**

Notes: This figure plots the posterior median impulse response functions of: real wages, w_t; the vacancy rate, v_t; and the unemployment rate, u_t with respect to: a job separations shock (Leftmost column); a Wage Shock (Middle middle); and a demand shock (rightmost column). Panel A reports results from estimated impulse response functions in 1974Q2 with simulated impulse response functions calibrated using data from 1974Q2. Panel B shows analogous results, but for 2008Q4.

6 Concluding Remarks

In this paper, we subject the Search Frictions framework of labour markets to novel empirical scrutiny. Our empirical analysis uses time-varying parameter VAR models with stochastic volatility to assess evolving labour market dynamics in the US from 1965 to 2016. Overall, our analysis provides evidence against two main implications of Search Frictions models of the labour market. The first is that productivity shocks drive cyclical variation in key labour market variables. We show that productivity shocks are not the main driver of variation in vacancies and unemployment in the data; a shock to wages accounts for a larger share of the variance of these variables. The second is that a large surge in vacancy creation is required to generate reductions in unemployment that match those observed in the data; and that a suppression in the response of wages is required to stimulate vacancy creation. Contrary to this, our estimates show a large response of real wages as well as of vacancies.

Our work suggests possible directions for future research. Our finding that the data support the importance of shocks to workers' bargaining power, a shock that the current literature overlooks, suggests that analysis of a richer menu of shocks may give a more complete view of the drivers of the business cycle. Our finding that the impact of structural shocks varies over time implies a greater focus on the causes of structural change. We intend to address these issues in future work.

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