Search Frictions and Evolving Labour Market Dynamics

Michael Ellington*  Chris Martin†  Bingsong Wang‡
University of Liverpool  University of Bath  University of Warwick
August 14, 2020

Abstract
This paper puts Search Frictions models under novel empirical scrutiny and tests their ability to match empirical observations. To capture changing dynamics, we fit an extended Bayesian time-varying parameter VAR to US labour market data from 1962–2016. Our results show significant and important parameter change that is difficult to explain using standard theoretical models. We find that the key transmission mechanism in the Search Frictions model, a strong response of vacancies to productivity shocks, is not present in the data. This raises issues for the extensive debate on unemployment volatility. Our analysis uncovers that a shock to the cost of vacancy creation contributes substantially to the variation in labour market variables; and that these results hold for more sophisticated New Keynesian DSGE models.

Keywords: time-varying parameter model, real wages, search frictions,
JEL Classification: E23, E32, J23, J30, J64

Acknowledgements
We would like to thank Gary Koop and Marco Fogoni for their insightful comments. We are also grateful to seminar participants at: The University of Bath; Brunel University; Durham University; The University of Strathclyde; the 12th International Conference on Computational and Financial Econometrics held at the University of Pisa in December 2018; and the Spanish Association of International Economics and Finance meeting held in Granada in June 2019. Declarations of interest: none.

* m.ellington@liverpool.ac.uk; Management School, University of Liverpool, Liverpool L69 7ZH UK.
† c.i.martin@bath.ac.uk; Department of Economics, University of Bath, Bath BA2 7AY UK.
‡ b.wang.9@warwick.ac.uk; Department of Economics, University of Warwick, Coventry CV4 7AL, UK.
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 and matching models, developed by Diamond (1982), Mortensen and Pissarides (1994) and Pissarides (2000), are the workhorse of modern labour economics. 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 also 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 model to novel empirical scrutiny and document several weaknesses. First, we find evidence of significant and important parameter change; this results in changes in impulse responses for key variables that are difficult to explain using standard theoretical models. Second, the key transmission mechanism embedded in the Search Frictions model, a strong response of vacancies to productivity shocks, leading to volatile movements in unemployment across the business cycle, does not receive support through the lens of the productivity shocks identified using a time-varying parameter VAR with stochastic volatility.

In addition, we argue that a shock to the cost of posting a vacancy, explains a substantial portion of the variance of unemployment, vacancies and wages. This shock, which has not to date been much discussed in the literature, is more important than productivity or job separation shocks in driving the data. We find that the Search Frictions model cannot explain the impact of this shock, as the estimated impact on wages is much stronger than the model would imply. We also conjecture that our results are not specific to the Search Frictions model, but also apply to a New Keynesian DSGE model with Search Frictions. That model introduces a wider menu of shocks, but these simulated responses to these additional shocks are also unable to match our estimated responses.

One of the main drawbacks of the search and matching approach is that structural relationships are assumed to be constant throughout 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))\(^1\). These empirical models do not include the real wage in their specifications. We build on this literature by fitting a time-varying parameter VAR model (TVP VAR) comprising unemployment, vacancies, the real wage and productivity to US labour market data from 1952–2016.

We then use estimates from the TVP VAR to evaluate the central features of models with Search Frictions in the labour market. Specifically, we assess the ability of the standard Search Frictions model of Diamond (1982), Mortensen and Pissarides (1994) and Pissarides (2000) to

match our empirical results. To do this, we calibrate a simple Search Frictions model so that it matches the estimated impulse response of unemployment to a productivity shock. If the model is consistent with the data, it should also match the estimated responses of vacancies and wages to the same shock. Our results provide striking evidence in favour of changes in key labour market transmission mechanisms that are difficult to explain in the traditional Search Frictions model. In particular, during the first half of our sample, the response of unemployment and vacancies become larger, with no change in the behaviour of wages. Contrastingly, in the latter half of our sample, there are periods when the response of wages becomes persistent and highly sensitive, with no change in the responses of unemployment and vacancies.

Our evidence is pertinent to the extensive debate on unemployment volatility. Shimer (2005) calibrates a Search Frictions model with Nash wage bargaining and shows that it is unable to replicate the large volatility of unemployment in the data. His conjecture is that this is due to the response of wages to shocks dampening vacancy creation. In response, a large literature (eg, Hall (2005), Hagedorn and Manovskii (2008) and Hall and Milgrom (2008)) develops alternative models that reduce the impact of labour market conditions on the wage and allows the impact of the shock to largely fall on vacancy creation. This enables the model to generate a large volatility of unemployment. These models have two testable features. First, a productivity shock leads to a large surge in vacancy creation and hence a reduction in unemployment. Second, since a stronger response of unemployment requires a more stable wage rate, a negative correlation between unemployment volatility and wage volatility arises.

The empirical analysis we conduct suggests neither of the above receives empirical support. More specifically, we uncover that the relatively stronger response of vacancies to productivity shocks during the first half compared to the latter half of our sample is due to changing shock sizes. At no point do we observe the large surge of vacancy creation as the Shimer hypothesis indicates. Furthermore, our empirical estimates permit a direct test on the correlation between unemployment and wage variability using time-varying volatilities. These indicate that the negative link between unemployment volatility and wage volatility is present only during the 1970s and 1980s; with strong positive correlations in the other decades.

Another key finding from our empirical work is the economic importance of vacancy cost shocks. A summary on the economic importance of structural shocks is as follows: First productivity shocks explain 20-40% of the volatility in key labour variables. Second job separation shocks explain no more than 10-20% of the variance in our variables. The current literature stresses the importance of productivity and job separations shocks in driving the business cycle in Search Frictions models. Our evidence suggests that these shocks explain, at best, half of the overall variation in US labour market variables throughout our sample. Our analysis reveals that a shock to the cost of vacancy creation is more important than these shocks. It explains

---

Ljungqvist and Sargent (2017) argue that the ability of Search Frictions models to generate a large volatility of unemployment requires the resources devoted to vacancy creation to be relatively small (a low “fundamental surplus”). This argument implies that a large surge in vacancies following a productivity shock is central to Search Frictions models. But it also implies that some types of Search Frictions model do not require a negative relationship between unemployment and wage volatility in order to generate unemployment volatility, as other factors, for example costs of acquiring credit (Wasmer and Weil (2004)), can also lead to a small fundamental surplus. But in the absence of these other factors, the negative relationship is necessary for the generation of a large unemployment volatility.
around 40-60% of the variance of unemployment, vacancies and wages. Thereby indicating that 
this is an important, and neglected, source of movements in key labour market variables. Our 
calibrations also show that the Search Frictions model is unable to match our empirical results. 
In particular, the response of wages to this shock is much larger than implied by the Search 
Frictions model.

We postulate that the results and conclusions we report within this paper are also applicable 
to New Keynesian DSGE models with Search Frictions in labour markets (see e.g. Thomas 
(2008), Blanchard and Gali (2010) and Ravenna and Walsh (2011). In these models, shocks to 
aggregate demand and monetary policy have the same impact on our variables as a productivity 
shock, as they can also increase vacancies and wages and reduce unemployment. We therefore 
simulate the impact of aggregate demand and monetary policy shocks in a New Keynesian 
DSGE model with labour market Search Frictions, and compare these responses to our empirical 
impulse responses. We find simulations are unable to not match our empirical estimates. As 
a result, the inability of the Search Frictions model to match our empirical impulse response 
functions also applies to the New Keynesian DSGE model.

The immediate implications of this paper for policy makers and researchers are twofold: 
first, the stark change in unemployment volatility suggests that business cycles are increasingly 
affecting those in current employment. The implication here is a shift in policy focus toward 
stabilising their incomes. Our analysis demonstrates that policymakers should focus on costs of 
vacancy creation in order to understand key variation in key labour market indicators. Second, 
in light of the inability of Search Frictions in macroeconomic models to reconcile empirical ob-
servations, we may need to refine key characteristics of the labour market in order to understand 
structural change.

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 
explain how we identify structural shocks and present our structural estimates. Section 5 
outlines our theoretical Search Frictions model, present our results on the fit between estimated 
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 1952 to 2016, a period that contains 10 NBER recessions, en-
suring that we are able to detect business cycle effects. Our choice of sample is entirely driven 
by available data, since the vacancy data in Barnichon (2010a) ends in December 2016. Our 
measure of US productivity is constructed by dividing data on GDP, drawn from the Federal 
Reserve Bank of St. Louis database, by a measure of total hours worked collected by the Bureau 
of Labor Statistics (BLS); see Hall (2007) for a discussion of why output per worker hour is 
the appropriate measure of productivity in this context. We use data on unemployment, again 
collected by the BLS. For vacancies, we use the composite Help Wanted index proposed by Bar-
nichon (2010a). For real wages, we take the logarithmic difference between the “Compensation 
Per Hour of the Nonfarm Business Sector” taken from the FRED Economic Database, and the
US Consumer Price Index \(^3\). Labour productivity and real wages are converted into annual growth rates as 100 multiplied by the logarithmic difference of each respective series. We plot our US labour market data in Figure 1.

This study works with the following TVP VAR model with \(p = 2\) lags and \(N = 4\) variables:

\[
Y_t = \beta_{0,t} + \beta_{1,t}Y_{t-1} + \cdots + \beta_{p,t}Y_{t-2} + \epsilon_t \equiv X_t'\theta_t + \epsilon_t
\]  
(1)

where \(Y_t \equiv [y_t, v_t, u_t, w_t]'\) is a vector of endogenous variables. Here \(y_t\) is labour productivity, \(v_t\) is the vacancy rate, \(u_t\) is the unemployment rate, and \(w_t\) is real wages. \(X_t'\) contains lagged values of \(Y_t\) and a constant. The VAR’s time-varying parameters are collected in \(\theta_t\) and evolve as

\[
p(\theta_t|\theta_{t-1}, Q_t) = I(\theta_t) f(\theta_t|\theta_{t-1}, Q_t)
\]  
(2)

where \(I(\theta_t)\) is an indicator function that rejects unstable draws, thereby imposing a stability constraint on the VAR where, conditional on the roots of the VAR polynomial lying outside the unit circle, \(f(\theta_t|\theta_{t-1}, Q_t)\) follows a random walk. Adding an indicator function that rejects draws for the coefficient matrices in every truncates and renormalises the prior. This stability constraint imposes a belief, a priori, that explosive representations of the model are implausible.

\[
\theta_t = \theta_{t-1} + \gamma_t
\]  
(3)

with \(\gamma_t \equiv \{\gamma_{1,t} \cdots \gamma_{N,(Np+1),t}\}'\), where \(\gamma_t \sim N(0, Q_t)\). \(Q_t\) is diagonal, and collecting these elements in the vector \(q_t \equiv [q_{1,t} \cdots q_{N,(Np+1),t}]'\), they evolve as geometric random walks

\[
\ln q_{i,t} = \ln q_{i,t-1} + \kappa_t
\]  
(4)

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

\[
\Omega_t = A_t^{-1}H_t(A_t^{-1})'
\]  
(5)

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 \(h_t \equiv [h_{1,t} \cdots h_{N,t}]'\), \(\alpha_t \equiv [\alpha_{21,t} \cdots \alpha_{31,t} \cdots \alpha_{NN-1,t}]'\) respectively, they evolve as

\[
\ln h_{i,t} = \ln h_{i,t-1} + \eta_t
\]  
(6)

\[
\alpha_t = \alpha_{t-1} + \zeta_t
\]  
(7)

\(^3\)We have also computed an alternative wage series in by using “Compensation of Employees, Received: Wages and Salary Disbursements”, scaled by labour force participation. Specifically, we use series A576RC1 (“Compensation of Employees, Received: Wages and Salary Disbursements”), taken from the FRED Economic Database and scaled by the labour force participation, series CLF16OV. Real wages are then constructed as the logarithmic difference between this and the Consumer Price Index.
where $\eta_t \sim N(0, Z_h)$, and $\zeta_t \sim N(0, S)$. The innovations in the model are jointly Normal, and the structural shocks, $\psi_t$ 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 that implies the non-zero and non-unit elements of $A_t$ evolve independently. The prior specification of our model are similar to Baumeister and Benati (2013). To calibrate the initial conditions of the model, we use the point estimates of a time-invariant VAR model estimated using the first 10 years of data. 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. Details of our prior specification, and an outline of the posterior simulation algorithm is provided in the Online Appendix.

![Figure 1: US Macroeconomic data from 1952 to 2016](image)

Notes: This figure plots quarterly growth rates of US macroeconomic data from 1952Q1–2016Q4. The top left panel plots the annual growth rate of labour productivity, $y_t$; 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 growth rate of real wages, $w_t$. Grey bars indicate NBER recession dates.

3 Reduced Form Results

Before presenting empirical results, it is necessary to evaluate the fit of our baseline model. 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

$$DIC = \bar{D} + pD$$ (8)
where \( \bar{D} = -2\mathbb{E}(\ln L(A_i)) \), the measure of fit, is equal to minus two multiplied by the expected value of the log likelihood evaluated over the draws of the MCMC, and \( pD = \bar{D} + 2\ln L(E(A_i)) \), is the measure of model complexity; with \( \ln L(E(A_i)) \) 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 that evaluates the likelihood function to deal with the non-linear interaction of the stochastic volatilities (Mumtaz and Sunder-Plassmann, 2013). Restricted variants of the time-varying coefficient models include: a conventional Bayesian VAR; a time-invariant coefficient VAR with stochastic volatility; and a time-varying coefficient VAR with constant covariance matrix.\(^4\)

Table 1 reports the estimated DIC statistics, for competing models. It is clear that our time-varying coefficient VAR model with stochastic volatility fit the data best; relative to restricted variants. Based on these results, we proceed by reporting results from our TVP VAR model.\(^6\)

Table 1: Bayesian DIC Statistics for Competing VAR Models

Notes: This table reports the DIC statistics from a battery of competing Bayesian VAR models. The row highlighted in bold font indicates the model with the lowest DIC, and therefore the model that best fits the data.

<table>
<thead>
<tr>
<th>Model</th>
<th>DIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>TVP VAR time-varying covariance matrix</td>
<td>67.66</td>
</tr>
<tr>
<td>TVP VAR constant covariance matrix</td>
<td>807.42</td>
</tr>
<tr>
<td>Bayesian VAR stochastic volatility</td>
<td>411.5</td>
</tr>
<tr>
<td>Linear Bayesian VAR</td>
<td>865.53</td>
</tr>
</tbody>
</table>

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 is characterised as the amount of ‘noise hitting the system’. This increases from the mid-1960s to a peak in the early 1980s. It then falls sharply before rising again in recent years. This pattern is reflected in the stochastic volatilities of US labour market variables, presented in the lower panel of Figure 2. The volatilities of productivity growth and vacancies fall in the early 1980s and account for the fall in the overall volatility in our model in that period. By contrast, the volatility of wages is gradually increasing throughout our sample, especially in the post-2008 period; this accounts for the increase in the estimated overall volatility in recent years.\(^7\)

\(^4\)These models were all estimated with standard priors within the literature. In particular, BVARs were estimated with a Minnesota prior on the coefficients, models with constant covariance matrices were assumed to have inverse-Wishart priors (see e.g. Koop and Korobilis (2010)), and those with time-varying parameters or stochastic volatility were estimated using analogous priors to the time-varying coefficient VAR models as outlined in the Appendix.

\(^5\)We choose restricted variants of our extended 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.

\(^6\)Available on request are results from estimated rolling VAR models. The dynamics of reduced form results from these simple rolling VARs are consistent with those provided in the main text.

\(^7\)Reduced form volatilities have been investigated in the previous literature, although with different specifications of the VAR. Our estimate of overall model volatility and the volatility of vacancies is similar to Guglielminetti and Pouraghdam (2017). Our estimated volatility of unemployment is more stable than Mumtaz and Zanetti (2015). The previous literature has not modelled wages or productivity growth.
Figure 2: Total Prediction Variation, $\ln|\Omega_t|$, and Stochastic Volatilities of US Labour Market Variables from 1962 to 2016

Notes: The upper panel plots the posterior median, and 80% posterior credible intervals of logarithmic determinant of the time-varying reduced-form covariance matrices, $\ln|\Omega_t|$, from 1962Q1–2016Q4. The lower panel plots the posterior median, and 80% posterior credible intervals of the reduced-from stochastic volatility innovations of labour productivity growth, $y_t$ (top left panel); the vacancy rate, $v_t$ (top right panel); the unemployment rate, $u_t$ (bottom left panel); and real wage growth, $w_t$ (bottom right panel) from 1962Q1–2016Q4. Grey bars indicate NBER recession dates.
In Figure 3, we report the time-varying pairwise correlations between our variables. Note that our model is able to reproduce the switch in the correlation between productivity growth and unemployment growth from negative to positive in the early-1980s that was first shown by Barnichon (2010). By contrast, there is no switch in the correlation between productivity growth and vacancies growth. The Beveridge Curve correlation between vacancies and unemployment is negative throughout our sample; yet varies markedly. In particular the Beveridge Curve correlation is highly negative in late 1960s to the early 1980s, but substantially muted thereafter. This switch in correlation may indicate that productivity shocks are not a major driving force of labour market dynamics, since these shocks imply a negative relationship between productivity and unemployment. The correlations between wages and the other variables in the model are small and never significant. The lack of correlation between the real wage and the other 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.

Figure 3: Reduced-form correlations from 1962 to 2016
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. \( \hat{\rho}_{i,t,j} \) denotes the model implied correlation of variable \( i \) and \( j \) at time \( t \) respectively. \( y_t, v_t, u_t, w_t \) denote labour productivity growth, the vacancy rate, the unemployment rate, and real wage growth, respectively. Grey bars indicate NBER recession dates.
4 Structural Analysis

We partially identify the structural model using contemporaneous sign restrictions following a variant of Algorithm 1 in Arias et al. (2018). Following Arias et al. (2018) and Rubio-Ramirez et al. (2010), the time-varying structural impact matrix, $A_{0,t}$, is calculated in the following manner. Given the current state of the economy, take the eigenvalue-eigenvector decomposition of the VAR’s time-varying covariance matrix at time $t$, $\Omega_t = P_t D_t P_t'$. Draw an $N \times N$ matrix $K$ from the $N(0,1)$ distribution and compute the QR decomposition of $K$, normalising the elements of the diagonal matrix $R$ to be positive; the matrix $Q$ is a matrix whose columns are orthogonal to one another. The time-varying structural impact matrix is computed as $A_{0,t} = P_t D_t^{1/2} Q'$. Given $A_{0,t}$, compute the reduced-form innovations using $\epsilon_t = A_{0,t} \psi_t$, where $\psi_t$ contains the structural shocks obtained by drawing from a standard Normal distribution. Further details on generalised impulse response computation are in the Online Appendix.

Table 2 presents our sign restrictions. We identify: a productivity shock, $\psi_{t}^{\text{Prod}}$; a job separation shock, $\psi_{t}^{\text{JS}}$; and a vacancy cost shock, $\psi_{t}^{\gamma}$.

Table 2: Contemporaneous Impact of Identified Shocks on Labour Market Variables

<table>
<thead>
<tr>
<th></th>
<th>$y_t$</th>
<th>$v_t$</th>
<th>$u_t$</th>
<th>$w_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\psi_{t}^{\text{Prod}}$</td>
<td>$\geq$</td>
<td>$\geq$</td>
<td>$\leq$</td>
<td>$\geq$</td>
</tr>
<tr>
<td>$\psi_{t}^{\text{JS}}$</td>
<td>$x$</td>
<td>$\geq$</td>
<td>$\geq$</td>
<td>$\leq$</td>
</tr>
<tr>
<td>$\psi_{t}^{\gamma}$</td>
<td>$x$</td>
<td>$\leq$</td>
<td>$\geq$</td>
<td>$\geq$</td>
</tr>
</tbody>
</table>

These restrictions are consistent with a simple Search Frictions model. A positive productivity shock increases the value of a productive job match; this leads firms to post increased vacancies. This results in more job matches and so unemployment falls; therefore the wage increases. A positive shock to the job separation rate will shift out the Beveridge Curve, increasing unemployment and vacancies. It will also reduce the surplus from a job match as the match is more likely to dissolve; this leads to a lower real wage. We interpret the third shock as a shock to the cost of posting a vacancy. A positive shock to the cost of posting a vacancy will reduce vacancy posting, leading to an increase in unemployment. The effect on the wage is ambiguous. There are offsetting effects on the real wage, since the reduction in labour market tightness reduces the wage but the raises the cost if hiring a replacement worker, increasing the surplus from a filled job match. Using standard calibrations of structural parameters, the second effect dominates which leads us to impose an increase in wages on impact.

---

8As we discuss below, a New Keynesian DSGE model with Search Frictions in the labour market would imply similar restrictions, although with a richer menu of structural shocks

9The most widely-used forms of wage determination in the literature are either worker-firm Nash bargaining or the alternating offer bargaining protocol of Hall and Milgrom (2008). In either case, a positive productivity shock will increase the wage.

10Shocks to the opportunity cost of employment, or to the bargaining power of workers in a model with Nash bargaining over wages, will have similar effects.
Figure 4 presents structural shock volatility. We can see that the volatilities of productivity and vacancy cost shocks are larger than the volatility of job separation shocks. Their evolution also tracks the evolution of the Total Prediction Variation more closely. More notably, we observe a break in the volatility of productivity and vacancy cost shocks from the early 1980s. This is consistent with the reduction in the stochastic volatilities of unemployment and vacancies in Figure 2. Over the past two decades, the volatility of job separation shock is slowly rising, whilst the volatility of productivity and vacancy cost shock volatility are relatively flat.

Figure 4: Volatility of Structural Productivity and Job Separation Shocks from 1962 to 2016
Notes: This figure plots the posterior median and 80% equal-tailed point-wise posterior probability bands for the volatility of identified productivity and job separations shocks from 1962Q1–2016Q4. Grey bars indicate NBER recession dates.

Figures 5, 6 and 7 report impulse response functions of US labour market variables with respect to a one standard deviation productivity shock; job separations shock; and vacancy cost shock respectively. The top four quadrants in each figure present the posterior median response of variables throughout time and over a 20 quarter horizon. The bottom four quadrants allow us to assess the statistical credibility of shocks by plotting the posterior median and 80% posterior credible intervals of the response of variables to shocks 1 quarter following impact. We normalise impulse response functions for productivity shocks to cause a 1% rise in labour productivity on impact. We normalise the impulse response functions of job separations shocks and vacancy
cost shocks to cause the unemployment rate to rise by 1% on impact respectively.

Overall, it is clear that there is marked time-variation in the response of all variables to these shocks. Four main findings emerge from these graphs. First, the cyclical responses of unemployment and vacancies to all shocks are more prominent in the earlier years of our sample. Productivity shocks during the 1970s and 1980s have notably stronger impacts on unemployment and vacancy rates during recessionary periods in these decades. Then, coherent with the Great Moderation, unemployment and vacancies become more resilient to these shocks with no clear cyclical pattern. Second, unemployment and vacancies exhibit a relatively high degree of persistence to all shocks. This is particularly prominent for job separation and vacancy cost shocks which, from posterior median estimates lasts around 15 quarters. However, in terms of absolute magnitude it is clear that the unemployment rate is more sensitive to productivity and vacancy cost shocks relative to the vacancy rate. Third, wages become more sensitive to all shocks from the Great Moderation to the end of our sample. Comparing the response of wages in 1962 and 2016, we see that the impact response almost doubles for all shocks. Fourth, there is a loose relationship between wages and other labour market variables. For example, in the earlier part of our sample, there are marked increases in the impulse response of unemployment and vacancies to productivity shocks but no change in the impulse response of wages. By contrast, in the latter part of our sample, there is a large and sustained increase in the impulse response of wages but no changes in the impulse response of unemployment and vacancies. This loose relationship corresponds well with the correlations we report in Figure 3.

In this section, we present novel results on the interactions between wages and unemployment across the business cycle and how these interactions have evolved over time. These findings pose fresh challenges for theoretical models. In the next section, we consider whether existing models can explain these new results.
Figure 5: Impulse Response Functions with Respect to a Productivity Shock from 1962 to 2016

Notes: The top four quadrants this figure plot the posterior median generalised impulse response functions of US labour market data with respect to a one standard deviation productivity shock from 1962Q1 to 2016Q4. $y_t$, $v_t$, $u_t$, $w_t$ denote the response of labour productivity growth, the vacancy rate, the unemployment rate, and real wage growth respectively. Impulse responses are computed for a 20 quarter horizon and normalised such that the shock causes labour productivity to increase by 1%. The bottom four quadrants of this figure report the posterior median and 80% equal-tailed point-wise posterior probability bands for the responses, at a 1 quarter horizon, of US labour market data with respect to a one standard deviation productivity shock from 1962Q1 to 2016Q4. $y_t$, $v_t$, $u_t$, $w_t$ denote the response of labour productivity growth, the vacancy rate, the unemployment rate, and real wage growth respectively. Grey bars indicate NBER recession dates.
Figure 6: Impulse Response Functions with Respect to a Job Separation Shock from 1962 to 2016

Notes: The top four quadrants of this figure plots the posterior median generalised impulse response functions of US labour market data with respect to a one standard deviation job separation shock from 1962Q1 to 2016Q4. $y_t$, $v_t$, $u_t$, $w_t$ denote the response of labour productivity growth, the vacancy rate, the unemployment rate, and real wage growth respectively. Impulse responses are computed for a 20 quarter horizon and normalised such that the shock causes unemployment to increase by 1%. The bottom four quadrants of this figure report the posterior median and 80% equal-tailed point-wise posterior probability bands for the responses, at a 1 quarter horizon, of US labour market data with respect to a one standard deviation job separation shock from 1962Q1 to 2016Q4. $y_t$, $v_t$, $u_t$, $w_t$ denote the response of labour productivity growth, the vacancy rate, the unemployment rate, and real wage growth respectively. Grey bars indicate NBER recession dates.
Figure 7: Impulse Response Functions with Respect to a Vacancy Cost Shock from 1962 to 2016
Notes: The top four quadrants this figure plot the posterior median generalised impulse response functions of US labour market data with respect to a one standard deviation vacancy cost shock from 1962Q1 to 2016Q4. $y_t$, $v_t$, $u_t$, $w_t$ denote the response of labour productivity growth, the vacancy rate, the unemployment rate, and real wage growth respectively. Impulse responses are computed for a 20 quarter horizon and normalised such that the shock causes labour productivity to increase by 1%. The bottom four quadrants of this figure report the posterior median and 80% equal-tailed point-wise posterior probability bands for the responses, at a 1 quarter horizon, of US labour market data with respect to a one standard deviation productivity shock from 1962Q1 to 2016Q4. $y_t$, $v_t$, $u_t$, $w_t$ denote the response of labour productivity growth, the vacancy rate, the unemployment rate, and real wage growth respectively. Grey bars indicate NBER recession dates.
5 Can Theory Match the Evidence?

We now turn to theory in order to examine whether a standard Search Frictions model is consistent with our empirical findings. We focus on the ability of the Search Frictions model to match three things. First, our finding that unemployment is more responsive to productivity and vacancy cost shocks than are vacancies. Second, the growing response of wages to a productivity and vacancy cost shocks, with little change in the responses of unemployment and vacancies, that we observe in the latter part of our sample. Third, the strong response of unemployment to vacancy cost shocks. As we discuss below, these findings pose significant challenges to the amplification mechanism embedded in the Search Frictions model.

To do this, we compare our empirical impulse responses at different dates with simulated impulse responses from a simple Search Frictions model. We focus on the impulse responses in 1974Q2 and 2008Q4. These dates correspond to similar points on the business cycle and the differences between the empirical impulse responses at these dates captures the marked changes in the impulse responses for wages and the relatively mild changes in the impulse responses for vacancies and unemployment in the second half of our sample as documented in Figures 5 and 7. To generate simulated impulse responses, we first calibrate a standard Search Frictions model so that the simulated impulse responses for unemployment following a productivity shock and a vacancy cost shock match the corresponding estimated impulse response function in 1974Q2. Using this, we investigate whether this calibrated model can also match the estimated impulse responses for vacancies and wages in 1974Q2. We then recalibrate the model to match the estimated impulse response function for unemployment in 2008Q4; using this, we assess whether the re-calibration enables the theoretical model to match changes in estimated impulse responses for wages.

Before reporting those results, we briefly outline our Search Frictions model and explain our calibration strategy. Our simple Search Frictions model is as follows. Aggregate hiring is determined by the matching function

\[ h_t = mu^\alpha v_1^{1-\alpha}, \]

where \( h \) is the number of workers hired, \( u \) is unemployment and \( v \) are vacancies. \( m \) and \( \alpha \) are parameters characterising the matching function. Labour market tightness is \( \theta_t = v_t u_t \). Existing job matches dissolve at the end of the period with exogenous but time-varying probability \( \tau_t \); we assume that \( \tau_t = \tau e^{\varepsilon_t} \) where \( \varepsilon_t \) is distributed as \( N(0, \sigma^2_\tau) \). There is a continuum of identical workers on the unit interval. If unemployed, an individual finds a job and is employed in the next period with endogenous probability \( f = \frac{h}{u} \). If employed, a worker earns \( w \); if unemployed, they receive the opportunity cost of employment \( z \). There is a continuum of identical firms on the unit interval. Each firm can hire up to one worker and a firm with an employed worker produces \( y_t = s_t \); where \( s_t = e^{\varepsilon_t} \); we assume \( \varepsilon_t = \rho^\tau \varepsilon_{t-1} + \eta^\tau_t \) where \( \eta^\tau_t \) is distributed as \( N(0, \sigma^2_\tau) \). Firms must pay a real cost of \( \gamma_t \) to post a vacancy, where where \( \gamma_t = \gamma e^{\varepsilon_t} \); we assume \( \varepsilon_t = \rho^\gamma \varepsilon_{t-1} + \eta^\gamma_t \) where \( \eta^\gamma_t \) is distributed as \( N(0, \sigma^2_\gamma) \). Vacancies are then filled at the start of the next period with endogenous probability \( q = \frac{h}{v} \). Wages are set through worker-firm Nash bargaining. The cost of hiring a worker is \( \lambda_t = \gamma_t \frac{(1+r)}{q_t} - \frac{(1-\tau_t)}{E[q_{t+1}]} \)

The model may be written in three simple relations; the evolution of unemployment given by

\[ 1 - u_t = (1 - \tau_t)(1 - u_{t-1}) + h_t \]
the job creation condition

\[ y_t = w_t + \lambda_t \]  

(10)

and the wage

\[ w_t = (1 - \phi)z + \phi(y_t + \gamma \theta_t) \]  

(11)

We summarise parameter values for calibration in Table 3. We normalize a time period to be one month. We set \( r = 0.004 \), equivalent to an annual discount rate of 5%. We calibrate the average monthly job separation rate as \( \tau = 0.033 \). For the matching function, we set \( \alpha = 0.5 \); this is consistent with the range of estimates obtained by Petrongolo and Pissarides (2001). The opportunity cost of employment is \( z = 0.66 \); this is slightly below the value used by Hall and Milgrom (2008) \( (z = 0.71) \) but is close to the mid-point of the range of alternative estimates based on alternative specifications of the flow value of non-work reported by Chodorow-Reich and Karabarbounis (2016), from \( z = 0.47 \) to \( z = 0.96 \). Worker bargaining power is set as \( \phi = 0.6 \).

Table 3: Parameter Values for Calibration: The Search Frictions Model

This table reports the values of the calibrations for 1974Q2 and 2008Q4.

<table>
<thead>
<tr>
<th>Parameter Interpretation</th>
<th>1974Q2</th>
<th>2008Q4</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \tau ) Ave separation rate</td>
<td>0.033</td>
<td>0.033</td>
</tr>
<tr>
<td>( r ) Discount rate</td>
<td>0.004</td>
<td>0.004</td>
</tr>
<tr>
<td>( \alpha ) Elasticity of matching function</td>
<td>0.50</td>
<td>0.50</td>
</tr>
<tr>
<td>( b ) Opportunity cost of unemployment</td>
<td>0.66</td>
<td>0.53</td>
</tr>
<tr>
<td>( \gamma ) Vacancy posting cost</td>
<td>0.42</td>
<td>0.33</td>
</tr>
<tr>
<td>( m ) Matching coefficient</td>
<td>0.80</td>
<td>1.00</td>
</tr>
<tr>
<td>( \phi ) Bargaining power</td>
<td>0.60</td>
<td>0.87</td>
</tr>
<tr>
<td>( \rho^s ) Persistence of productivity shock</td>
<td>0.878</td>
<td>0.878</td>
</tr>
<tr>
<td>( \sigma^s ) Volatility of productivity shock</td>
<td>0.004</td>
<td>0.0037</td>
</tr>
<tr>
<td>( \rho^\gamma ) Persistence of vacancy cost shock</td>
<td>0.878</td>
<td>0.878</td>
</tr>
<tr>
<td>( \sigma^\gamma ) Volatility of vacancy cost shock</td>
<td>0.003</td>
<td>0.003</td>
</tr>
</tbody>
</table>

We have two free parameters, \( m \), matching efficiency, and \( \gamma \), the average cost of posting a vacancy. For 1974Q2, we calibrate these so that the steady-state of the model matches the unemployment rate in 1974Q2 and the simulated impulse response for unemployment matches its empirical counterparts; this gives \( m=0.8 \) and \( \gamma = 0.42 \). For 2008Q4, we re-calibrate the efficiency of matching to \( m = 1 \) and the cost of posting a vacancy to \( \gamma = 0.325 \) to match the different unemployment rate and different impulse response for unemployment in that period. We also increase the worker’s bargaining power to \( \phi = 0.87 \) and decrease the opportunity cost of employment to \( z = 0.53 \). Doing so, we increase the response of wages to a productivity shock without dampening the response of unemployment to a productivity shock. We calibrate the the volatility and persistence of the productivity and vacancy cost shocks at each date to match the estimated impulse response of unemployment to these shocks at each date; this gives \( \sigma^s = 1 \) in 1974Q2 and \( \sigma^s = 0.7 \) in 2008Q4. We also find that the calibrating \( \rho^s = 0.878 \), following Shimer (2005), works well for both dates. For the vacancy cost shock, we use \( \sigma^\gamma = 0.3 \) and \( \rho^\gamma = 0.878 \) in both cases.
Figure 8 contains our results. To highlight our arguments, we normalise estimated and simulated impulse responses so that unemployment increases by 1 on impact in response to both shocks. The responses of wages and vacancies therefore show the responses of these variables relative to the response of unemployment.

5.1 Vacancies and Unemployment

We now focus on comparing how well impulse response functions from our Search Frictions model track what we see in the data. We see in our empirical results that unemployment is more responsive than vacancies to productivity and vacancy cost shocks. Figure 8 reveals that the impulse responses of vacancies stemming from our TVP VAR are very different from their simulated counterparts. It is clear that the vacancy rate in response to both shocks, and at both dates, is 10 times larger from our calibrations relative to those from the empirical model. In order to match the impulse response for unemployment in the Search Frictions model, a large surge in vacancies is needed. Ultimately, this finding suggests that the amplification mechanism in the Search Frictions model is absent in the data.

One might argue that this finding reflects the simplicity of the Search Frictions model we use in this exercise. To assess this, we consider two extension of this model; a model with endogenous separations and a model with vacancy dynamics. To model endogenous separations, we use the model in Chapter 2 of Pissarides (2000). Productivity is idiosyncratic, described by a Poisson process with arrival rate $\zeta$. Firms dismiss workers if the productivity of a job match is below a reservation level given by $R = 1 - \frac{\gamma(r + \zeta)}{(1 - \phi)q(\theta)}$. This model enables a productivity shock to affect the inflow to and outflow from unemployment, whereas the simple model used above only allows shocks to affect the outflow. Introducing this additional channel implies that a positive productivity shock reduces the inflow to unemployment through endogenous separations; a smaller surge in vacancies is therefore required to match the empirical impulse response for unemployment\textsuperscript{11}. As a result, the impulse response for vacancies following a productivity shock is therefore more consistent with the estimated response.

However a model with endogenous separations is unable to capture the estimated impulse response functions to a vacancy cost shock. A shock that increases the cost of posting a vacancy will decrease reservation productivity and therefore reduce the endogenous inflow into unemployment\textsuperscript{12}. As a result, a stronger reduction is vacancies is required to match the empirical impulse response for unemployment; this widens the gap between the empirical and simulated impulse response functions for vacancies following a vacancy cost shock.

The empirical impulse response functions for vacancies in Figure 8 display ‘hump-shaped’ responses, similar to that for unemployment. This suggests the presence of stock-flow effects; these arise if not all unfilled vacancies are destroyed at the end of a period. Fujita and Ramey (2007), Leduc and Liu (2016) and Coles and Moghaddasi-Kelishomi (2018) develop models in which some matching opportunities persistent beyond the end of each period, so not all unfilled vacancies are immediately destroyed. This introduces dynamics for vacancies similar to that for

\textsuperscript{11} A positive productivity shock increases labour market tightness and so reduces the vacancy filling rate. This reduces reservation productivity and so reduces the endogenous inflow.

\textsuperscript{12} An increase in vacancy cost will also affect the reservation productivity through the vacancy filling rate. However the direct impact dominates so the reservation productivity will decrease.
unemployment. We calibrate these alternative Search Frictions models to examine whether they provide a better match to our estimated impulse responses; results are available upon request. Our results from alternative calibrations are qualitatively similar to those we present in the main text. Although this approach is better able to capture the initial increase in vacancies following a productivity shock, the match between estimated and simulated responses to a productivity shock is generally worse, while the responses to a job separations shock are no closer\(^{13}\).

### 5.2 Wages and Unemployment

Our empirical evidence on the changing relationships between wages and unemployment presents issues for the Search Frictions model. In what follows, we explore three of these. First, the simulated impulse responses of wages to productivity and vacancy cost shocks in Figure 8 differ markedly from estimated responses, especially for vacancy cost shocks. Second, there has been an increasing impulse response of wages to productivity and vacancy cost shocks since 1980s that has occurred without any reduction in the impulse response of unemployment to those shocks. And third, there is a positive correlation between unemployment volatility and wage volatility.

Table 4 documents the correlations between the volatilities of wages and unemployment, in the using the full sample of 1962Q1–2016Q4; between earlier and later halves of the sample in half; and across decades. There is a strong positive correlation between unemployment and wage volatility in most of our sample periods.

**Table 4: Model-Implied Correlations between Unemployment and Wage Volatility**

<table>
<thead>
<tr>
<th>Sample</th>
<th>$\hat{\rho}(\sigma^u_t, \sigma^w_t)$</th>
<th>Sample</th>
<th>$\hat{\rho}(\sigma^u_t, \sigma^w_t)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1962Q1-1969Q4</td>
<td>0.84</td>
<td>1990Q1-1999Q4</td>
<td>0.33</td>
</tr>
<tr>
<td>1970Q1-1979Q4</td>
<td>-0.89</td>
<td>2000Q1-2009Q4</td>
<td>0.97</td>
</tr>
<tr>
<td>1980Q1-1989Q4</td>
<td>-0.91</td>
<td>2010Q1-2016Q4</td>
<td>0.76</td>
</tr>
<tr>
<td>1962Q1-1989Q2</td>
<td>0.11</td>
<td>1989Q3-2016Q4</td>
<td>0.87</td>
</tr>
<tr>
<td>1962Q1-2016Q4</td>
<td>0.34</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 8 shows that the simulated impulse responses of wages to productivity and vacancy cost shocks are unable to match their estimated counterparts, at either date. This is because we calibrate our model to match the estimated impulse response of unemployment to shocks. In order to match the strong estimated response of unemployment to shocks, the model must be calibrated to ensure a strong response of vacancies. This is the source of the vacancy surge discussed above. But the consequence of this calibration is that the response of the wage does not match the estimated response. This issue is especially acute for the impulse response for

\(^{13}\text{Coles and Moghaddasi-Kelishomi (2018) argue that the labour market is largely driven by job separation shocks and the key amplification mechanism embedded in their model is a delayed response of vacancy creation to these shocks. Our estimates are not supportive of a delayed response, as there is a strong response of vacancy creation to job separation within a quarter, although this response does not peak until the second quarter.}\)
Figure 8: Estimated and Simulated Impulse Response Functions for Productivity and Vacancy Cost Shocks: 1974Q2 and 2008Q4

Notes: This figure plots the impulse response function of vacancies, $v_t$; unemployment, $u_t$; and wages, $w_t$ with respect to a productivity shock (LHS plots) and a vacancy cost shock respectively (RHS plots). Solid lines represent the posterior median impulse response functions from the TVP VAR and dashed lines stem from calibrations of our Search Frictions model. All impulse response functions are normalised to generate a 1% increase in unemployment. Panel A uses impulse response functions from the TVP VAR from 1974Q2 and the Search Frictions model uses data during this period for calibration. Panel B uses impulse response functions in 2008Q4 and the Search Frictions model uses data during this period for calibration.
vacancy costs\textsuperscript{14}. We further note that the simulations are not able to explain the increased response of wages; this lack of match is, again, especially marked for vacancy cost shocks.

These findings are important as they relate to the large literature on unemployment volatility puzzle. One of the more prominent proposed solutions to this puzzle is to introduce real wage rigidity. The role of real wage rigidity in amplifying the impact of shocks on unemployment arises because it has a strong and direct impact on resources available for vacancy creation, implied by the job hiring condition in (10). Our results question the role of real wage rigidity as a source of unemployment volatility\textsuperscript{15}. This paper adds two important empirical observations to this debate. First, we find a positive correlation between the volatilities of wages and unemployment across most of our sample period. Second, the paper shows the estimated impulse response of wages to a productivity shock has dramatically increased since early 2000 and is much stronger than its simulated counterpart if the model is calibrated to match the impulse response of unemployment. These findings are hard to reconcile with the view that unemployment volatility is caused by low wage volatility.

Finally, we note that it is also difficult for Search Frictions model to capture the positive correlation between unemployment and wage volatility. One might argue that a positive correlation can be generated by a reduction in the profits of firms. But that would require a reduction in profits across most of our sample period, and especially in the post-1990 period, when the positive correlation is particularly strong. That does not seem plausible. Alternatively, one might argue that changes in structural parameters such as the volatility of productivity can give rise to a positive correlation. But this would require changes in these parameters across our sample period, which also seems unlikely.

5.3 The Importance of Vacancy Cost Shocks

We now address whether vacancy cost shocks exhibit economic importance. Figure 9 shows the posterior median estimate of the percent share of the overall forecast error variance of unemployment, vacancies and wages attributable to productivity, job separation and vacancy creation shocks at a 20 quarter horizon. Note that our structural shocks explain most of the variance in our variables across our sample, and it is unlikely that a fourth structural shocks would have a strong impact on our results. Productivity shocks make the largest contribution to explaining the variance of vacancies in the early part of our sample, explaining 25-35\% of the variance, but have been declining to around 20\% in recent decades. Vacancy costs shocks explain around 25\% of the variance; this contribution is stable across the sample. The contribution of separations shocks is less than 20\% at the start of the same but increases to 25\% in the post-2000 period. Vacancy costs shocks make the largest contribution to the variance

\textsuperscript{14}We consider Nash bargained wage in our simulations. With this, a positive vacancy cost shock increases cost of posting a vacancy but also decreases market tightness. These offsetting effects lead to a small increase in the wage, so the simulated response fails to match the large estimated response. Alternative modes of wage formation are unlikely to resolve this. For example, credible bargaining will lessen the impact of vacancy costs and so widen the gap between simulated and estimated responses.

\textsuperscript{15}The current debate is largely centred around the issue of whether the wages of new hires are more cyclical than the aggregate wage (e.g. Pissarides (2009), Haefke et al. (2013) and Gertler et al. (2019)). The logic of this debate is that if the wages of new hires are highly cyclical, then real wage rigidity is not the solution to unemployment volatility puzzle.
of unemployment, explaining around 40-50% across the sample. Productivity shocks explain around 30-40% of the variance in the early part of the sample but then decline in importance. Job separations never explain more than 10-15% of the variance. Vacancy cost shocks also make the largest contribution to explaining the forecast error variance of wages, accounting for 30-40% of the variance across the sample. Productivity and job separations shocks make a smaller contribution, explaining 20-25% of the variance each.

Figure 9: Forecast Error Variance Decompositions of Vacancies, Unemployment and Wage Growth 1962 to 2016
Notes: This figure plots the posterior median, of the percent share of variance attributable, at a 20 quarter horizon, to productivity shocks (Red line); job separation shocks (Green line); and vacancy cost shocks (Blue line) for: the vacancy rate, \( v_t \) (LHS figure); the unemployment rate, \( u_t \) (Central figure); and real wage growth, \( w_t \) (RHS figure) from 1962Q1–2016Q4. Grey bars indicate NBER recession dates.

One might question our interpretation of this shock that we identify as one that moves unemployment and wages in the same direction and moves vacancies in the opposite direction. In our simple Search Frictions model, shocks to the cost of posting vacancies have this affect. However, one can rationalise that shocks to the opportunity cost of employment and to worker bargaining power\(^{16}\). We feel our interpretation is reasonable for two reasons. First, vacancy costs are important in all types of Search Frictions model, unlike the other candidate shocks. A shock to bargaining power is not relevant in a model that does not have Nash wage bargaining, and a shock to the opportunity cost of employment is not relevant in models where this is not an important determinant of wages, for example models with wage posting. Second, one could argue that vacancy cost shocks acts as a proxy for other shocks that are not captured by our simple Search Frictions model. In a richer model, shocks to vacancy costs might reflect shocks to the cost of capital (e.g., Wasmer and Weil (2004), Hagedorn and Manovskii (2008) and Eckstein et al. (2019)) or financial shocks (e.g., Hall (2017) and Eckstein et al. (2019)).

We acknowledge that some may disagree, but for this paper the important question is

\(^{16}\)Other models have alternative shocks that also satisfy this identification. For example, in the Credible Bargaining model of Hall and Milgrom (2008), a shock to the cost of delaying in wage negotiations has the same effect.
whether our interpretation of this shock as a shock to vacancy costs affects our results. To assess this, we simulated the impact of shocks to the opportunity cost of employment and to bargaining power. We followed the same approach as above; we used the calibrations in Table 4 and calibrated the volatilities of these shocks so that the simulated responses matched the estimated responses of unemployment. Our key finding is unchanged; the response of the wage to these shocks is small, similar to the response to a vacancy cost shock. None of the shocks are able to match the large estimated response of wages to this shock. Therefore we posit that our findings are robust to alternative interpretations of this shock.

5.4 Summary

Overall the we provide substantial evidence supporting the view that vacancy costs are more important than productivity shocks in driving movement in the labour market across the business cycle. Since there is little discussion of these shocks in the current literature, we conjecture that further investigation of these shocks may be useful. Our results also imply that the emphasis on productivity shocks in most of the current literature is misplaced. They also suggest that researchers may have been looking in the wrong place for a solution to the unemployment volatility puzzle. This section has also shown that the Search Frictions model cannot match the estimated responses of the labour market to productivity and vacancy cost shocks. This suggests that some important amplification mechanism may be missing in the model.

5.5 The New Keynesian Model With Search Frictions

Naturally one questions whether our results and the implications hold New Keynesian models with search frictions in labour markets (Thomas (2008), Blanchard and Gali (2010) and Ravenna and Walsh (2011)). In comparison to the Search Frictions model, this approach permits a more detailed analysis of aggregate demand. It also introduces a richer set of shocks, including shocks to aggregate demand and monetary policy. The impact of these shocks is similar to the impact of a productivity shock, since they also reduce unemployment and increase vacancies and wages. We therefore simulated the impact of aggregate demand and monetary policy shocks, to investigate whether these shocks can generate impulse responses similar to the estimated impulse responses reported in Section 4 above.

To do this, we use a model similar to Ravenna and Walsh (2011). This model incorporates labour search frictions and Nash bargaining over wages into a simple New Keynesian model. We do not include wage rigidity\textsuperscript{17}. The simulated impact of aggregate demand and monetary policy shocks is similar to the impact of productivity shocks, reported in Figure 8. This result is not surprising, as the New Keynesian model contains essentially the same model of the labour market as the Search Frictions model. As a result, our arguments about the inability of the Search Frictions model to match our estimated impulse response functions also applies to the New Keynesian model.

\textsuperscript{17}The model and simulations results are available on request
6 Concluding Remarks

This paper puts search and matching models, the workhorse of modern labour market marcoeconomics, under novel empirical scrutiny. Using state-of-the-art Bayesian estimation techniques, we fit an extended TVP VAR to US labour market data from 1962–2016. We depart from the existing literature (see e.g. Yashiv (2006); Faccini et al. (2013); Hall (2005); Hagedorn and Manovskii (2008); Lubik (2009)) in two ways. First, we find that the search frictions model overestimates the impact of job creation on the response of unemployment to productivity and vacancy cost shocks. The data rejects the theoretical surge in vacancies in response to those two shocks. Second, it is difficult for Search Frictions models to capture the estimated increasing response of wages to productivity and vacancy cost shocks without dampening the response of unemployment to those shocks. It is also difficult for Search Frictions models to capture the positive correlation between unemployment and wage volatility. These findings question the literature that uses wage rigidity to address the unemployment volatility puzzle. Finally, our analysis highlights the economic importance of shocks to vacancy creation, which have been overlooked in the literature. These play an important role in driving labour market dynamics by explaining around 40-60% of variation in key variables.

Our conclusions hold for: i) alternative transformations of the data; ii) extensions of conventional Search Frictions models; and iii) New Keynesian DSGE models with Search Frictions within the labour market. With this in mind, the main implication of our findings is the call for a refinement of search and matching models in order to match what we observe in the data. We also note for policy makers that the stark change in unemployment volatility suggests that business cycles are increasingly affecting those in current employment. The implication here is a shift in policy focus toward stabilising their incomes. Our analysis demonstrates that policy makers should focus on costs of vacancy creation in order to understand key variation in key labour market indicators.

References


