# Revisiting Real Wage Rigidity

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**Abstract**

In this paper, we provide empirical evidence that real wage rigidity is not a major cause of unemployment volatility. We argue that there is a disconnect between the theoretical and empirical literatures on this topic. While theoretical studies define real wage rigidity as the response of wages to changes in unemployment following productivity shocks, the empirical literature measures real wage rigidity as the estimated semi-elasticity of wages with respect to unemployment, averaged over all shocks. We show that averaging over shocks gives a biased measure of real wage rigidity, as the impact of other shocks confounds the response to productivity shocks. Our results indicate that the estimated semi-elasticity with respect to productivity shocks is twice as large as the estimated semi-elasticity averaged over all shocks. This implies that one cannot attribute unemployment volatility to real wage rigidity.

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

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

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# 1 Introduction

The link between unemployment and real wages is central to debates on business cycles. The real wage rigidity hypothesis is a leading candidate to explain the lack of movement in real wages relative to unemployment which prior studies show is evident within the data. New Keynesian DSGE models widely use real wage rigidity, including models using labour market frictions (e.g. Gertler and Trigari, 2009; Blanchard and Gali, 2010; Gertler et al., 2020). Real wage rigidity also appears in the new generation of heterogeneous agent New Keynesian (HANK) models (e.g. Broer et al., 2020), as well as the Diamond-Mortensen-Pissarides models of equilibrium unemployment to account for the volatility of unemployment and vacancies (see e.g. Shimer, 2005; Hall, 2005; Christiano et al., 2015).

In this paper, we argue that there is a disconnect between the theoretical and empirical literatures on real wage rigidity. The empirical literature uses a regression approach to estimate the semi-elasticities of real wages with respect to unemployment (see e.g. Pissarides, 2009; Gertler et al., 2020), with a stronger response of wages to unemployment implying lower values of real wage rigidity[1]. There are alternative approaches to real wage rigidity in the theoretical literature[2]. In this paper, we use the inverse of the semi-elasticity of real wages with respect to unemployment, since this allows us to compare measures of rigidity across the empirical and theoretical literatures. The theoretical literature assigns a prominent role to productivity shocks in driving business cycle fluctuations, focusing on the role of real wage rigidity in generating a large volatility of unemployment in response to productivity shocks. The disconnect arises because the semi-elasticities estimated in the empirical literature reflects the impact of all shocks, not just productivity shocks. This implies that evidence from the empirical literature cannot currently be used to inform the debate in the theoretical literature. In order to address this, one requires an empirical estimate of the semi-elasticity of real wages with respect to unemployment in response to different shocks, especially productivity shocks.

In this paper, we provide this. We present estimates of the semi-elasticities of real wages with respect to unemployment in response to productivity and other shocks. We find that the estimated semi-elasticity in response to productivity shocks is large. This implies a lower value of real wage rigidity thereby suggesting a lack of support for the real wage rigidity hypothesis. We show that the measure used in the current literature overstates the degree of real wage rigidity because it confounds the impact of productivity shocks by averaging over all identified shocks, including

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[1] The value of this semi-elasticity is controversial. Much of the debate concerns which measure of wages one should use. In the data, the response of average wages to unemployment is small, suggesting a high degree of real wage rigidity. Skeptics argue that it is more appropriate to use the wages of newly hired workers, since these wages are more relevant for job creation. Many studies, including Pissarides (2009), find that the wages of new hires are more flexible than the wages of incumbent workers. This suggests a low degree of wage rigidity. Gertler et al. (2020) challenges this view and argues that the relevant margin of adjustment is the wages of workers newly hired from unemployment, rather than the wages of all new hires. The latter includes the wages of workers upgrading to a better job match. After controlling for these composition effects, they find that the wages of new hires are no more cyclical than those of existing workers.

[2] As discussed by Hall (2005) and Christoffel and Linzert (2010), among others.

shocks that move real wages and unemployment in the same direction. By correcting for this confounding effect, we show that the underlying response of real wages relative to unemployment following productivity shocks is much larger than the values used in the current empirical literature.

In order to do this, we depart from the regression approach used by the existing literature to measure real wage rigidity. We estimate a structural time-varying parameter VAR model with stochastic volatility (TVP VAR) in order to track temporal evolutions in the relationships among US productivity, real wages, vacancies, the unemployment rate, and inflation. We identify four transitory structural shocks using robust sign restrictions that stem from a DSGE model with search frictions (DSGE-SF) (similar to Mumtaz and Zanetti, 2012) following the procedure in Canova and Paustian (2011). We calculate the semi-elasticities of real wages with respect to unemployment for: a productivity shock; an aggregate demand shock; a job destruction shock; and a wage bargaining power shock. The latter is crucial to our analysis since it moves unemployment and wages in the same direction. The impact of the wage bargaining power shock in the data reduces the average semi-elasticity, thereby making this a biased estimate of the response of real wages to unemployment following productivity shocks. Evidence on the importance of this shock is in, among others, Fujita and Ramey (2007), Pizzinelli et al. (2020), Drautzburg et al. (2021) and Ellington et al. (2021). Our results quantify the size of the bias. We calculate the average semi-elasticity of real wages with respect to unemployment, averaging over all shocks. This is consistent with the existing literature; and coherent with substantial real wage rigidity. But the semi-elasticity with respect to productivity shocks is over twice as large, implying that the degree of real wage rigidity in response to productivity shocks, the focus of the theoretical literature, is far smaller than the values this literature widely uses.

Our paper proceeds as follows. Section 2) describes our data and outlines our econometric model. Section 3) contains our structural analysis, including our strategy for identifying structural shocks and our estimates of the semi-elasticities of real wages to unemployment following different shocks. Finally, in Section 4) we conclude and consider options for future work.

## 2 Data and Econometric Model

We use quarterly US data from 1954Q3 to 2019Q4 on productivity, real wages, the vacancy rate, the unemployment rate, and inflation[3]. 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[4]. The vacancy rate is the Help Wanted Index in Barnichon (2010) and the unemployment rate is from the Bureau of Labor Statistics (BLS). For inflation, we take the Nonfarm Business Sector: Implicit Price Deflator[5]. We take the natural logarithm of productivity, real wages and the implicit price deflator before applying the Hamilton (2018) filter to every variable.

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[3] We end our sample in 2019, to avoid the turbulence of the Covid-19 pandemic.

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

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

These data are plotted in the Online Appendix.

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

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

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

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

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

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

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

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

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

$$\begin{aligned} \ln h_{i,t} &= \ln h_{i,t-1} + \eta_t & (4) \\ \alpha_t &= \alpha_{t-1} + \zeta_t & (5) \end{aligned}$$

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, $\psi_t$ 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; this implies the non-zero and non-unit elements of $A_t$ evolve independently. The specification of the priors of our model are similar to Baumeister and Benati (2013). To calibrate the initial conditions of the model, we use the point estimates of the coefficients and covariance matrix from a time-invariant VAR model using the first 10 years of data. Therefore the estimation sample of our results span 1964Q2–2019Q4. 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 10th draw to reduce autocorrelation which leaves 1000 draws from the posterior distribution. The Online Appendix contains details of our prior specification, and an outline of the posterior simulation algorithm as well as estimates of the total prediction variation of our model, the stochastic volatilities of each variable and the reduced form correlations between our variables.

## 3 Structural Analysis

In this section we outline structural identification and analysis 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 of the impulse responses on impact is unambiguous across this distribution. In this way, we ensure that our identifying sign restrictions are credible, robust to alternative calibrations of the structural parameters. Our identifying restrictions are based on a standard New Keynesian DSGE model without capital but with search frictions in the labour market, similar to Faia (2008), Krause and Lubik (2007), Blanchard and Gali (2010), Mumtaz and Zanetti (2012) and others. Details of our procedure and the model used are contained in the Online Appendix[6].

Table 1: **Contemporaneous Impact of Short-run Shocks on Labour Market Variables**
Notes: This table shows the contemporaneous sign restrictions imposed on variable $x = \{y_t,\ v_t,\ u_t,\ w_t\}$ to a productivity shock, $\psi_t^{\text{Prod}}$; a job separation shock, $\psi_t^{\text{JS}}$; a shock to workers bargaining power, $\psi_t^{\text{W}}$; and a demand shock, $\psi_t^{\text{D}}$, 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 $\pi_t$ is inflation. x denotes no restriction.

| | $y_t$ | $w_t$ | $v_t$ | $u_t$ | $\pi_t$ |
|---|---|---|---|---|---|
| $\psi_t^{\text{Prod}}$ | $+$ | $+$ | $+$ | $-$ | $-$ |
| $\psi_t^{\text{JS}}$ | x | $-$ | $+$ | $+$ | x |
| $\psi_t^{\text{W}}$ | x | $+$ | $-$ | $+$ | x |
| $\psi_t^{\text{D}}$ | x | $+$ | $+$ | $-$ | $+$ |

We identify four temporary structural shocks within our empirical model as in Table 1). We identify: a productivity shock, $\psi_t^{\text{Prod}}$; a job separation shock, $\psi_t^{\text{JS}}$; a shock to workers' bargaining power, $\psi_t^{\text{W}}$; and a demand shock $\psi_t^{\text{D}}$. The productivity shock increases productivity, wages and vacancies, while reducing unemployment and inflation. The demand shock increases wages, inflation and vacancies but reduces unemployment; we are agnostic as to its impact on productivity. The job separation shock increases unemployment and vacancies, thus shifting out the Beveridge Curve.

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[6] This approach is similar to Ellington et al. (2021). That paper works with permanent productivity shocks and focuses on structural change in the labour market. By contrast, this paper addresses issues around real wage rigidity using a model that, in line with the literature, examines responses to temporary productivity shocks.

It also reduces wages; we are agnostic about its impact on productivity and inflation. The shock to wage bargaining increases wages and unemployment but reduces vacancies; we are again agnostic about its impact on productivity and inflation. As noted above, the positive relationship between wages and unemployment implied by this shock is important for our results.

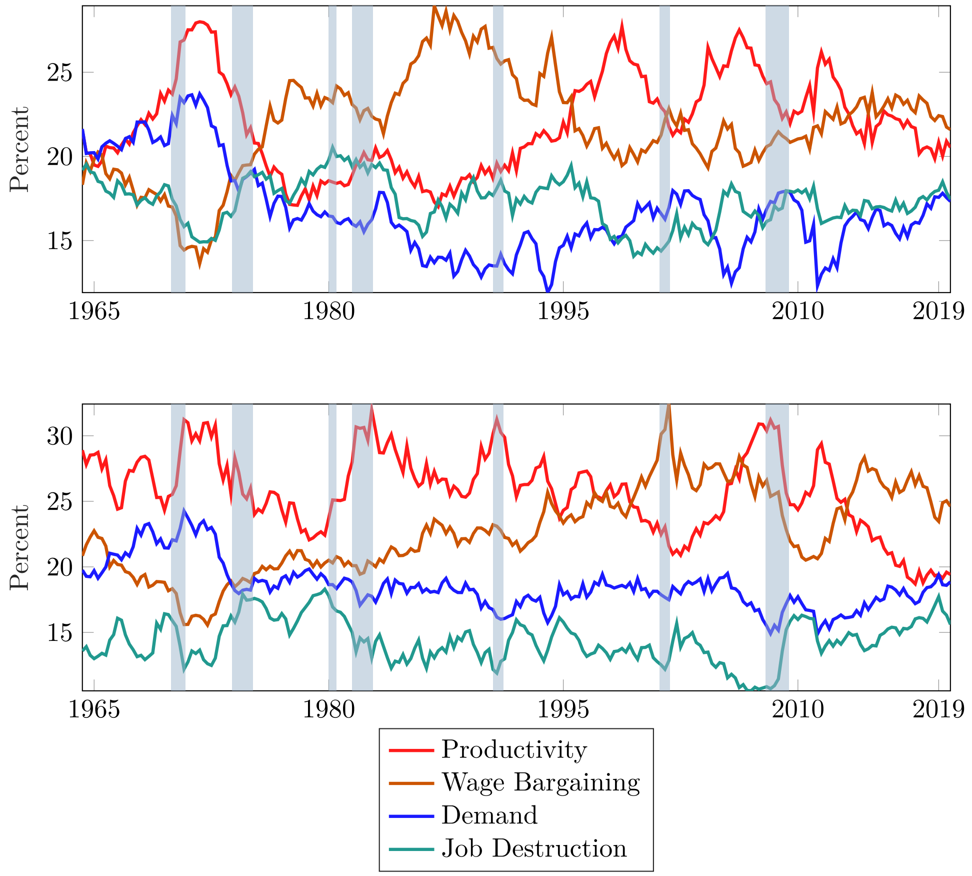

Figure 1: **Variance Decomposition of the One-Period Ahead Forecast Error Variances of Wages and Unemployment**
Notes: This figure plots the contribution of (i) productivity shocks (red); (ii) wage bargaining power shocks (brown); (iii) demand shocks (blue) and (iv) job destruction shocks (green) in explaining the volatility of the one-period ahead forecast error variances of wages (top panel) and unemployment (lower panel) across our sample.

Figure 1) shows the forecast error variance decompositions of wages and unemployment that emerge from our structural estimates. Movements in wages and unemployment across our sample reflect the impact of all the shocks, with no single shock accounting for more than 35% of the variance of unemployment and more than 30% of the variance of wages. Productivity and wage bargaining shocks make the largest contribution to explaining the volatility of both variables across our sample. Productivity shocks have the strongest impact on unemployment until around 2000. Thereafter, wage bargaining shocks become more prominent. Productivity shocks have the strongest impact on wages until 1975 and in 1995-2010. Wage bargaining shocks make a larger contribution in 1975-1995; the two shocks have roughly equal importance in recent years. The relative importance of the shock to worker wage bargaining power in Figure 1) is consistent with evidence in Fujita and Ramey (2007), Pizzinelli et al. (2020), Drautzburg et al. (2021) and Ellington et al. (2021)[7].

Using our structural estimates, we estimate impulse response functions for wages and unemployment in response to each of the structural shocks, for every data point in our sample and for each of $K$ periods after the incidence of the shock as

$$\zeta^{\mathrm{w,s}}_{t+k,t} = \frac{\partial log w_{t+k}}{\partial \psi^{\mathrm{s}}_t} \tag{6}$$

and

$$\zeta^{\mathrm{u,s}}_{t+k,t} = \frac{\partial u_{t+k}}{\partial \psi^{\mathrm{s}}_t} \tag{7}$$

for $\mathrm{s} \in \{\mathrm{Prod}, \mathrm{JS}, \mathrm{W}, \mathrm{D}\}$ and for $k = 1, ...., K$. From these, we construct estimates of semi-elasticities of wages with respect to unemployment, for all four structural shocks as[8]

$$se^{\mathrm{s}}_{t+k,t} = \frac{\zeta^{\mathrm{w,s}}_{t+k,t}}{\zeta^{\mathrm{u,s}}_{t+k,t}} \tag{8}$$

for $\mathrm{s} \in \{\mathrm{Prod}, \mathrm{JS}, \mathrm{W}, \mathrm{D}\}$

To compare our estimates to the existing literature, we calculate a weighted average of the four semi-elasticities as

$$\bar{se}_{t+k,t} = \sum_{\mathrm{s} \in \{\mathrm{Prod,JS,W,D}\}} \phi^{s}_{t+k,t} se^{\mathrm{s}}_{t+k,t} \tag{9}$$

where $\phi^{s}_{t+k,t}$ is the share of shock $s$ in the Forecast Error Variance Decomposition, as shown in Figure 1), so that a shock that explains a larger share of the FEVD has a larger weight. The average value of this statistic across our sample corresponds to the point estimate of the semi-elasticity of wages with respect to unemployment in the existing literature, and so allow us to compare our estimates with previous results.

Table 2 contains sample averages of the estimated average semi-elasticity and the estimated semi-elasticities with respect to our four structural shocks, for different values of $k$. Several features are worth noting. First, our estimates of the average value semi-elasticity, $\bar{se}$, are within the range of estimates in the existing literature. Our average semi-elasticity lies between $-1.259$ and $-0.613$, depending on the value of $k$. By comparison, Gertler et al. (2020) estimate a continuing worker semi-elasticity of $-0.46$; the same semi-elasticities are estimated as $-0.6$ in Bils (1985) and as $-2.6$ in Barlevy (2001). Second, underlying the average semi-elasticity are very different responses to different shocks. In particular, our estimates of semi-elasticities in response to productivity shocks are substantially larger than the average semi-elasticity. For example, our estimates of

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[7] For example, Drautzburg et al. (2021) find that bargaining power shocks account for 28% of aggregate fluctuations. This is consistent with the evidence we present in Figure 1).

[8] Our approach is similar to Barnichon and Mesters (2019), who estimate a "Phillips Multiplier" showing the cumulated response of inflation to a demand shock relative to the cumulated response of unemployment, ie $PM = \frac{\sum_{k=0}^{K} \zeta^{\pi,\mathrm{D}}_{t+k,t}}{\sum_{k=0}^{K} \zeta^{u,\mathrm{D}}_{t+k,t}}$

semi-elasticities with respect to productivity shocks are $-2.416$ for $k = 0$ and $-2.165$ for $k = 1$. These are approximately twice as large as the corresponding average semi-elasticities. Third, the weak average response of wages to unemployment stems from a strong positive semi-elasticity of wages with respect to unemployment following shocks to wage bargaining power. Finally, the estimated semi-elasticity in response to job destruction shocks is more volatile than the responses to other structural shocks. The impact of this on our results is limited, since shocks to job destruction explain much less of the variation in unemployment and wages than do productivity and wage bargaining power shocks.

Table 2: **Sample Averages of Semi-Elasticities of Wages With Respect to Unemployment**
Notes: This table presents estimated semi-elasticities of real wages with respect to unemployment, calculated as the ratios of the estimated impulse response functions as in (8), for different values of $k$ and averaged across 1964Q2–2019Q4. The first row shows the value of $\bar{se}_{t+k,t}$, calculated using (9). The second row shows the value of $se^{\text{PROD}}_{t+k,t}$, calculated using (8). The other rows show the values of $se^{\text{W}}_{t+k,t}$, $se^{\text{D}}_{t+k,t}$ and $se^{\text{JS}}_{t+k,t}$, also calculated using (8).

| | $k = 0$ | $k = 1$ | $k = 2$ | $k = 4$ |
|---|---|---|---|---|
| $\bar{se}$ | $-1.259$ | $-1.025$ | $-0.818$ | $-0.613$ |
| $se^{\text{PROD}}$ | $-2.416$ | $-2.165$ | $-1.598$ | $-1.031$ |
| $se^{\text{W}}$ | 2.273 | 1.808 | 1.848 | 1.020 |
| $se^{\text{D}}$ | $-2.2207$ | $-1.531$ | $-1.406$ | $-1.289$ |
| $se^{\text{JS}}$ | $-3.387$ | 0.020 | 0.632 | $-0.182$ |

Summarising these results, we note that our average semi-elasiticities are in line with the existing literature. As such, they show a weak response of wages to unemployment which indicates substantial real wage rigidity. However, as we show above, these results are misleading, because of the influence of the strong positive response of wages to unemployment following shocks to worker wage bargaining power. The object of interest to the theoretical literature is the response of wages to unemployment following productivity shocks. As shown in Figure 2), we find this to be far larger than the average semi-elasticity. Overall, this implies that the degree of real wage rigidity in response to productivity shocks, the focus of the theoretical literature, is much smaller than the values the empirical literature widely use[9].

Our approach enables us to go beyond the literature by examining movements in semi-elasticities over time. Figure 2) shows estimates of the semi-elasticity of wages with respect to unemployment following productivity shocks and the semi-elasticity of wages with respect to unemployment wage averaged over shocks. Table 3) shows the average values of these semi-elasticies for the periods 1964Q2-1979Q4; 1980Q1-2008Q4 and post-2008. We note that the average semi-elasticity has remained stable over time. This suggests that the existing literature would find no evidence of changes to wage rigidity over time. By contrast, the absolute value of the semi-elasticity in response to productivity shocks has risen across our sample. This implies that the degree of real wage rigidity

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[9] As further evidence against wage rigidity, we note that the estimated semi-elasticities in Table 2) decline as $k$ increases; this reflects the fact that real wages respond more quickly than unemployment to shocks.

has fallen throughout our sample.

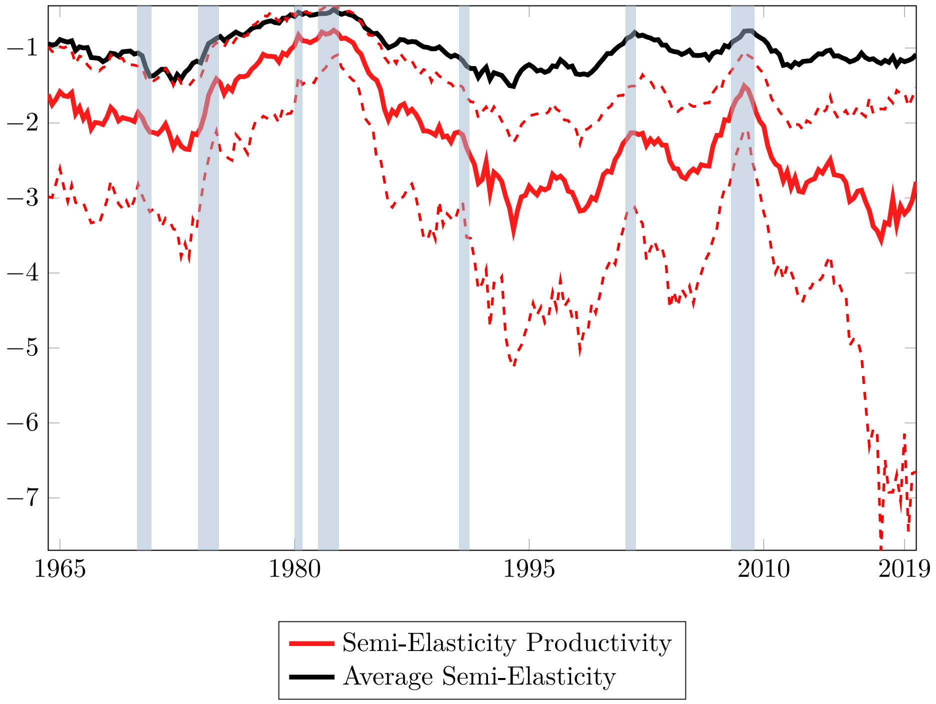

Figure 2: **Variation in Estimated Semi-Elasticities Over Time**
Notes: This figure plots estimated semi-elasticities of real wages with respect to unemployment, calculated as the ratios of the estimated impulse response functions, using $k = 1$. The figure plots (i) the estimated semi-elasticity of wages with respect to unemployment following productivity shocks (red), calculated using (8), with associated credibility bands; (ii) the estimated semi-elasticity of wages with respect to unemployment wage averaged across all shocks (9) (**black**), calculated using (9).

Table 3: **Estimated Sample Averages of Semi-Elasticities of Wages With Respect to Unemployment At Different Dates**
Notes: This table presents estimated semi-elasticities of real wages with respect to unemployment, calculated as the ratios of the estimated impulse response functions as in (8), for $k = 1$ and averaged across 1964Q2-1979Q4; 1980Q1-2008Q4 and 2009Q1-2019Q4. The first row shows the values of $\bar{se}_{t+k,t}$, calculated using (9). The second row shows the values of $se^{\text{PROD}}_{t+k,t}$, calculated using (8).

| | 1964Q2 − 1979Q4 | 1980Q1 − 2008Q4 | 2009Q1 − 2019Q4 |
|---|---|---|---|
| $\bar{se}$ | −1.006 | −1.009 | −1.105 |
| $se^{\text{PROD}}$ | −1.764 | −2.171 | −2.781 |

We explore the robustness of these findings in two ways. First, we use the alternative measure of productivity constructed by Fernald (2014), which adjusts for variations in factor utilisation. Second, we use an alternative empirical identification strategy, which combines the maximum forecast error variance procedure of Uhlig (2004) with our sign restrictions that stem from the theoretical model. This is in a similar vein to Pizzinelli et al. (2020). As the Online Appendix documents, both experiments yield similar conclusions to those we report in the main text. Productivity and wage bargaining shocks account for the majority of wage and unemployment variation with an increasing relative importance of wage bargaining shocks as we move through our sample. The absolute value of the semi-elasticity in response to productivity shocks has risen throughout the sample while the semi-elasticity averaged over all shocks remains relatively stable.

### 3.1 Implications

Our results imply that many arguments in the existing theoretical literature rely on implausibly large values for real wage rigidity, as measured by the responsiveness of real wages to unemployment in the context of productivity shocks. To assess the implications of this, we calibrate a workhorse New Keynesian model with matching frictions in two scenarios. In the first, we calibrate the model in order to match the semi-elasticity of wages with respect to unemployment that is used in the current empirical literature. In the other, we calibrate in order to match the larger value of the semi-elasticity of wages with respect to unemployment that we estimate in this paper. We then calculate key business cycle statistics under these alternative scenarios.

To do this, we adapt the model used to derive credible identifying restrictions in section 3)[10]. In scenario 1), we calibrate the opportunity cost of employment ($b$) and the average value of worker bargaining power ($z$) in order to match a semi-elasticity of wages with respect to productivity shocks of $se^{\text{PROD}} = -0.46$ (the value obtained by Gertler et al. (2020)); in scenario 2), we target a semi-elasticity of $se^{\text{PROD}} = -2.17$ (the value estimated in this paper). The other parameters are the same as those used in our identification exercise. For scenario 1), this implies a high value for the opportunity cost and a small value for bargaining power ($b = 0.71$ and $z = 0.085$). For scenario 2), this implies a lower opportunity cost and much higher bargaining power ($b = 0.4$ and $z = 0.88$).

Table 4: **Simulation Results**

| Parameter | Interpretation | Scenario 1 | Scenario 2 |
|---|---|---|---|
| $\sigma_u$ | Volatility of Unemployment | 0.031 | 0.01 |
| $\sigma_w$ | Volatility of the Wage | 0.014 | 0.02 |
| $\rho_{w,u}$ | Correlation Between Wage and Unemployment | $-0.987$ | -0.983 |
| $\psi_w$ | First-Order Autocorrelation of the Wage | 0.878 | 0.878 |
| $\psi_u$ | First-Order Autocorrelation of unemployment | 0.935 | 0.935 |

Our results are summarised in Table 4). We find similar values for the correlation between wages and unemployment, and for the first-order auto-correlations of wages and unemployment. But the volatility of unemployment, relative to the volatility of wages, is three times larger with scenario 1). Although our simple DSGE model is not designed to replicate the high value of unemployment volatility that is observed in the data, it is clear from this that our finding of a low value for wage rigidity challenges existing models that are able to generate a high value for unemployment volatility.

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[10] The Online Appendix contains details.

To explore this further, we used a calibration similar to that of Hagedorn and Manovskii (2008), a well known paper that is able to generate a large volatility of unemployment. In particular, we set $b = 0.955$ and $z = 0.052$. The resultant semi-elasticity of wages with respect to unemployment is only $se^{\text{PROD}} = -0.05$, much lower than any estimate in the literature. We also used a calibration similar to that of Shimer (2005), whose calibration does not generate a large unemployment volatility. In this case, we set $b = 0.4$ and $z = 0.72$; the resultant semi-elasticity is $se^{\text{PROD}} = -1.56$, which is consistent with existing evidence, although somewhat lower than our estimate. These experiments highlight how our results create a challenge to the theoretical literature, since it is not clear whether any existing model can match the high value of unemployment volatility in the data while also matching the small value for real wage rigidity that we estimate in this paper.

## 4 Conclusions

This paper argues there is a disconnect between the theoretical and empirical literatures on real wage rigidity. The theoretical literature assigns a prominent role to productivity shocks in driving business cycle fluctuations, focusing on the role of real wage rigidity in generating a large volatility of unemployment in response to productivity shocks. The empirical literature uses estimates of the semi-elasticity of wages with respect to unemployment to measure real wage rigidity. We point out that this measure is not specific to productivity shocks because it reflects the impact of the different shocks that drive the economy. The impact of other shocks therefore induce bias into estimates of the object of interest; namely the semi-elasticity of wages with respect to unemployment following a productivity shock. This issue is important since the data reflect the impact of shocks to the wage bargaining power of workers as a main driver of unemployment and wage variation. This shock drives wages and unemployment in the same direction and therefore leads to a semi-elasticity one averages over all shocks that indicates substantial wage rigidity.

Using a structural time-varying parameter VAR with stochastic volatility, we estimate the semi-elasticity of wages with respect to unemployment for four structural shocks, including productivity shocks and wage bargaining power shocks. We find that the semi-elasticity with respect to productivity shocks is twice as large as the semi-elasticity one averages over all shocks. This implies a much lower value for real wage rigidity, providing evidence against the hypothesis that real wage rigidity is a major cause of unemployment volatility.

Although we obtain these results using a specific DSGE model with search frictions, our conclusions about the lack of real wage rigidity in the data are more general and not restricted to this type of model. It is also possible to identify the most important structural shocks in our analysis using a model without search frictions in the labour market. This shows that our results apply in a wider set of models than those considered in this paper.

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