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Abstract

Recent events suggest that uncertainty changes play a major role in U.S. labor market fluctuations. This study analyzes the impact of uncertainty shocks on unemployment dynamics. We develop a quantitative version of the Diamond-Mortensen-Pissarides (DMP) model, in which uncertainty shocks hit the economy. Given the significant nonlinearities of the DMP model, we show that the introduction of uncertainty shocks allows this textbook model to account for observed characteristics of the U.S. labor market dynamics, with reasonable values for calibrated parameters.

Keywords: Uncertainty shocks, unemployment dynamics, Search and matching, non-linearities
JEL Classification: E24, E32, J64

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1 Introduction

After the last recession, many economists emphasized the crucial role of uncertainty in shaping labor market outcomes, as it affects core expectations of future economic activity, which is important for investment and employment decisions. Large increases in uncertainty occur in periods of big changes. Macro uncertainty seems to be countercyclical: episodes of high uncertainty are times of low economic activity. These rises in uncertainty can have persistent effects, by affecting expectations that drive long-term commitments, such as hiring decisions, and thus, unemployment dynamics.

We focus on the impact of uncertainty shocks on the aggregate unemployment rate. We show that lower vacancies and employment are characteristics of the economy in case of high variance of marginal returns, that is, when uncertainty increases. To understand this phenomenon, we use the Diamond (1982)-Mortensen (1982)-Pissarides (1985) matching model (DMP model). Although this model has become the dominant framework for analyzing labor market fluctuations, extensive analysis of its non-linearity is relatively recent (see Petrosky-Nadeau and Zhang (2017), Petrosky-Nadeau et al. (2018), Ferraro (2018), (2020) and Adjemian et al. (2021)). Nevertheless, these developments do not take into account that uncertainty can change over the business cycle.[1] Leduc and Liu (2016) bridge this gap by showing that the impact of an uncertainty shock resemble the one of an aggregate demand shock and is reinforced by nominal rigidities. Den Haan et al. (2020) highlight that the wage bargaining process plays a central role in the propagation of those uncertainty shocks.[2] Our contribution is to provide a quantitative assessment of the impact of uncertainty shocks on unemployment dynamics by showing that a purely real model can correctly predict the impact of uncertainty on unemployment when wages are flexible. More precisely, using a quantitative version of the DMP model which considers uncertainty shocks[3], we show that *(i)* uncertainty shocks increase average unemployment rate by 0.15pp and account for 26.83% of unemployment variance, *(ii)* uncertainty *per se* influences agents' decisions, and consequently, magnifies productivity shocks and finally, *(iii)* the model's impulse response function to an uncertainty shock is very close to the one based on the VAR estimation. These findings underline that the DMP model seems to be a suitable framework to account for the U.S. labor market fluctuations, if it takes into account uncertainty shocks.[4]

The remainder of this paper is as follow: Section 2 presents the model, and Section 3 presents its results. Finally, Section 4 concludes this paper.

[1] Sims and Zha (2006) show that a VAR with a time-varying matrix of variance-covariances of shocks has a higher likelihood than a VAR with time-varying autoregressive coefficients. Therefore, the more parsimonious approach is to assume a time-varying volatility for shocks that drive economic fluctuations. We follow this method.

[2] They show analytically that an increase in uncertainty per se, i.e. a potential rise in the variance of shocks than will not materialize, increases unemployment only if wages are not completely rigid.

[3] Following Petrosky-Nadeau and Zhang (2017), we solve the model using a global algorithm that allows for non-linearities and considers that vacancies can hit the zero bound. Following Bloom (2009), the changes in uncertainty are modeled by assuming that the volatility of the firm's productivity follows a two-state Markov process.

[4] Our contribution is part of the new literature on the recessive effects of uncertainty on macroeconomic aggregates (see Bloom (2009),Born and Pfeifer (2014), Fernandez-Villaverde et al. (2015), Baker et al. (2016), Basu and Bundick (2017), Born et al. (2020)). See Fernandez-Villaverde and Guerron-Quintana (2020) for a survey of this literature.

2 Model

The environment includes workers and a representative firm whose only productive input is labor. Workers can be either employed or unemployed. The total mass of individuals is a unit mass. Workers are risk neutral with a time discount factor β.

Matching. Vacancies V_t meet unemployed workers U_t according to the matching function $G(U_t, V_t) = \frac{U_t V_t}{(U_t^\tau + V_t^\tau)^{1/\tau}}$, with $\tau > 0$. The vacancy filling rate is $q(\theta_t) = \frac{G(U_t,V_t)}{V_t} = (1+\theta_t^\tau)^{-1/\tau} \in (0;1)$, with $\theta_t = \frac{V_t}{U_t}$ the labor market tightness. The law of motion of employment is

$$N_{t+1} = (1-s)N_t + q(\theta_t)V_t \quad \text{with } 0 < s < 1, \text{ and } U_t + N_t = 1. \tag{1}$$

Firms. Firms produce Y_t using CRS technology $Y_t = A_t N_t$ where $a_t \equiv \log(A_t)$ follows an $AR(1)$ process $a_t = \rho a_{t-1} + \sigma_t \epsilon_t$ with $\epsilon_t \sim N(0,1)$ and $0 < \rho < 1$. The volatility $\sigma_t > 0$ follows a two-state Markovian process with $\sigma_t \in \{\sigma_L, \sigma_H\}$, $\Pr(\sigma_{t+1} = \sigma_j | \sigma_t = \sigma_k) = \pi_{j,k}$ and $\sigma_L < \sigma_H$. The unit cost per vacancy is $\kappa_t = \kappa_0 + \kappa_1 q(\theta_t)$, where κ_0 and $\kappa_1 q(\theta_t)$ are respectively the constant and the variable parts of the costs. Taking the wage W_t and $q(\theta_t)$ as given, the firm's decision problem is

$$\max_{V_{t+\tau}, N_{t+\tau+1}} \mathbb{E}_t \left[\sum_{\tau=0}^{\infty} \beta^\tau \left(A_{t+\tau} N_{t+\tau} - W_{t+\tau} N_{t+\tau} - \kappa_{t+\tau} V_{t+\tau} \right) \right]$$

subject to (1) and $V_t \geq 0$. The first-order conditions of the firm's program lead to the following inter-temporal job creation condition[5] and Kuhn-Tucker relations:

$$\frac{\kappa_t}{q(\theta_t)} - \lambda_t = \beta \mathbb{E}_t \left[A_{t+1} - W_{t+1} + (1-s) \left(\frac{\kappa_t}{q(\theta_{t+1})} - \lambda_{t+1} \right) \right] \tag{2}$$

$$q(\theta_t) V_t \geq 0, \quad \lambda_t \geq 0, \quad \text{and} \quad \lambda_t q(\theta_t) V_t = 0 \tag{3}$$

When $\lambda_t = 0$, the equilibrium paths are the same as in the DMP model. When $\lambda_t > 0$, we have $V_t = 0$ and the solution is constrained with $\theta_t = 0$ and $N_{t+1} = (1-s)N_t$ until $N_t > 0$.[6]

Equilibrium. With the Nash-bargained wage $W_t = \eta(A_t + \kappa_t \theta_t) + (1-\eta)b$, the competitive equilibrium is defined by *(i)* the hiring decisions given by Equations (2) and (3), and *(ii)* the employment dynamics (Equation (1)). All labor incomes are consumed as follows ($C_t = W_t N_t + b(1-N_t)$, where unemployment benefits $b(1-N_t)$ are financed by a lump-sum tax paid by all workers) and the goods market equilibrium is $C_t + \kappa_t V_t = A_t N_t$.

[5] The inter-temporal job creation condition is equalizing the marginal costs of hiring at time t to the marginal value of hiring to the firm, which is represented by its marginal benefits of hiring at time $t+1$ discounted to t with the stochastic discount factor β. Intuitively, this marginal cost should be higher in the economy with higher variance as the marginal benefits include the marginal product of labor net of wages.

[6] The competitive equilibrium is solved using a projection algorithm that accounts for transitions between the two regimes of the economy, as well as for fluctuations within each regime. For more details see the appendix E

2.1 Calibration

Parameters coming from external information: $\chi = \{\beta, \rho, s, \pi_{HH}, \pi_{LH}\}$. The time discount factor β is equal to 0.9954 to match the mean discount rate in international data 5.73% per annum. The persistence of the productivity ρ is set to $0.95^{1/3}$ following Petrosky-Nadeau et al. (2018). The separation rate is 0.025, which is the mean value of the US job separation rate data constructed by Adjemian et al. (2021). Following Bloom (2009), we set *(i)* $\pi_{L,H} = \frac{1}{36}$ as the uncertainty shock is to be expected every three years, *(ii)* $\pi_{H,H} = 0.71$, which represent the average two-month half-life of an uncertainty shock, and *(iii)* $\sigma_H = 2 \times \sigma_L$.

Estimated parameters and targeted moments. Table 1 shows that the model is able to reproduce the observed volatility of the U.S. labor market with parameter values which exclude extreme calibrations. This result reconciles the DMP model with the stylized facts summarized by the second order moments. The flow value of unemployment benefits (b) is close to the Shimer

Parameters: Θ	Values	Moments	Data	Model
Flow value of unemployment benefits b	0.4	$\mathbb{E}[jfr]$	40.89%	40.86%
Worker's bargaining power η	0.44	$\mathbb{E}[ur]$	5.8%	6.2%
Elasticity of matching function τ	0.8	$\mathbb{V}[ur]$	1.75×10^{-4}	1.64×10^{-4}
Proportional cost of posting a vacancy κ_0	0.6	$\mathbb{V}[jfr]$	3.46×10^{-3}	3.6×10^{-3}
Fixed cost of posting a vacancy κ_1	0.5	$\mathbb{E}[ur \cdot ur_{-1}]$	0.9992	0.9836
Low standard deviation σ_L	0.053	$\mathbb{E}[jfr \cdot jfrr_{-1}]$	0.9974	0.92019

Table 1: **Model's Calibration and Target and Simulated Moments.** Targeted moments are $m_{US,T} = \{\mathbb{E}[ur], \mathbb{E}[jfr], \mathbb{V}[ur], \mathbb{V}[jfr], \mathbb{E}[ur \cdot ur_{-1}], \mathbb{E}[jsr \cdot jsr_{-1}]\}$, where ur denotes the unemployment rate and jfr the job finding rate. The moments $\mathbb{E}[x \cdot x_{-1}]$ for $x = ur, jfr$ represent the auto-correlation. $\Theta = \{\eta, b, \tau, \kappa_0, \kappa_1, \sigma_L\}$ is the solution of $\min [m(\Theta, \chi) - m_{US,T}]' \, Id \, [m(\Theta, \chi) - m_{US,T}]$, where $m(\Theta, \chi)$ and $m_{US,T}$ denote respectively the vectors of simulated and targeted moments. As we do not perform an estimation, the weight matrix is the identity matrix (Id). Data: see appendix A.

(2005)'s calibration.[7] Our value of bargaining power (η) is close to the mean bargaining power found in the literature (*i.e* 0.5) and larger than the one used by Hagendorn and Manovskii (2008). The elasticity of the matching function is between the value used by Petrosky-Nadeau and Zhang (2017) (0.407) and the one obtained by Den Haan et al. (2000) (1.27). The parameters of the function cost of posting a vacancy (κ_0, κ_1) are in the range of the estimates provided by Merz and Yashiv (2007). Finally, the standard deviation of the uncertainty shocks in the regime of low variance (σ_L) is lower value than the ones estimated by Bloom (2009), which is between 0.1 and 0.44.[8]

[7] Thus, our value is much lower than the calibration chosen by Robin (2011) (close to 0.86), and it is also lower than the estimates of Hall and Milgrom (2008) (close to 0.70), Christiano et al. (2016) or Petrosky-Nadeau et al. (2018) (0.88 - 0.85) and the extreme calibration proposed by Hagendorn and Manovskii (2008) (close to 0.95). It is also lower than the estimation provided by Adjemian et al. (2021).

[8] Appendix G provides a sensitivity analysis on these parameter choices.

3 How Do Uncertainty Shocks Affect Unemployment Fluctuations?

Impact of Uncertainty Shocks on Labor Market Moments. Table 2 compares moments generated by the baseline economy and the one without uncertainty.[9] For a given set of draw of innovations ϵ_t and given our calibration of the shocks on the stochastic variance, the two AR(1) processes of a_t (with and without stochastic variance) will have the same variance if and only if the standard deviation of the innovations of the AR(1) process of a_t without stochastic variance is equal to 0.06. With this calibration, the results are attributed to uncertainty alone, and not to a lower unconditional variance of the productivity shock in an economy without stochastic variance.

Moments	$\mathbb{E}[ur]$	$\mathbb{E}[jfr]$	$\mathbb{V}[ur]$	$\mathbb{V}[jfr]$	$\mathbb{E}[ur \cdot ur_{-1}]$	$\mathbb{E}[jfr \cdot jfrr_{-1}]$
Baseline	6.28%	40.86%	1.6×10^{-4}	3.6×10^{-3}	0.9837	0.9202
No uncertainty shocks	6.13%	41.21%	1.2×10^{-4}	3.5×10^{-3}	0.9819	0.9203
Δ	+0.15pp	-0.5pp	73.17%	97%	-	-

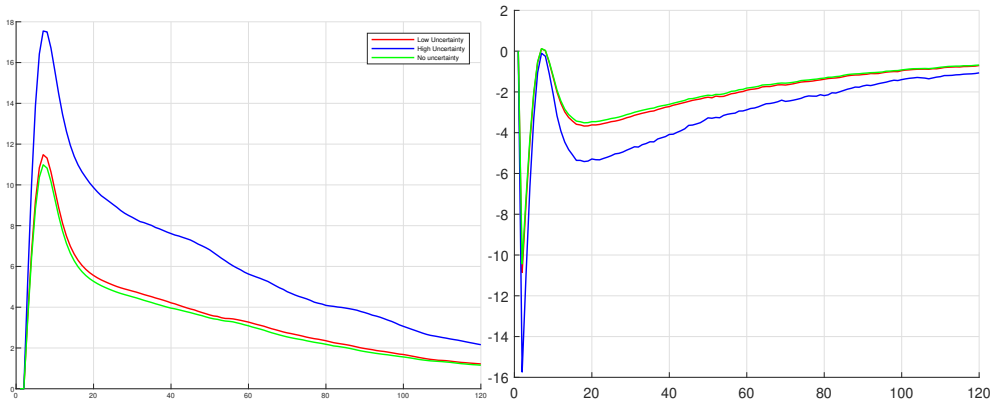
Table 2: **Model's Decomposition.** "Baseline": complete model; "No uncertainty shocks": model where $\sigma_t = \widetilde{\sigma}$, $\forall t$ and with $\widetilde{\sigma} = 0.06$ and $\rho = 0.95^{1/3}$, ensuring that the two economies have an exogenous shock of the same variance. In the two first columns, Δ measures the gaps between the economy with "No uncertainty shocks" and the "baseline" economy in percentage points (pp). In columns 3 and 4, Δ measures the share in the variance of the "baseline" explained by the economy with "No uncertainty shocks."

Table 2 shows that uncertainty shocks reduce the average job finding rate (-0.5pp), and thus increase the average unemployment rate (+0.15pp, i.e. an increase of +2.44% of $\mathbb{E}[ur]$). In fact, uncertainty shocks damp the firms' response to productivity changes, leading to a lower labor tightness and thus a lower job finding rate. As it is shown in Hairault et al. (2010), the labor market tightness is a convex function of productivity. Therefore, the free entry condition is satisfied for greater variations in job creation in booms than in recessions. This tends to increase the average job finding rate in the fluctuating economy, but less when fluctuations also contain uncertainty shocks. Beyond the effects on averages, uncertainty shocks increase the variance of the job finding rates, which also increases the average unemployment rate.[10] As uncertainty shocks only slightly increase the variance of the job finding rate (+3%), this channel contribute weakly to the increase in the average unemployment rate. Table 2 also shows that uncertainty shocks increase the variance of unemployment rate; this source of uncertainty explains 26.83% of this variance. This underlines that uncertainty shocks play a significant role in U.S. labor market dynamics.[11] Finally, Table 2 shows that the auto-correlation of unemployment and job finding rates are not sensitive to the introduction of uncertainty shocks.

[9] To study the effect of different shocks on the economy, we start by simulating an artificial data in continuous state space 5000 times. For each draw of a sequence for ϵ_t, a Markov chain gives the transitions from a regime to the other. To eliminate the initial conditions, which are arbitrary, we simulate the economy 8000 times, and do not consider the 3000 first observations, thereby, preventing the influence of the initial state on the results.

[10] Hairault et al. (2010) show $\mathbb{E}[ur]$ is an increasing function of $\mathbb{V}[jfr]$: $\mathbb{E}ur \approx ur + ur(1-ur)^2 \left(\frac{\mathbb{V}jfr}{\mathbb{E}jfr}\right)^2$ using the steady state value of unemployment rate $\mathbb{E}ur = \mathbb{E}\frac{s}{s+jfr}$ with s a constant separation rate.

[11] See Appendix I for an analysis of alternative modelling of stochastic variance and their impact on this decomposition.



(a) Unemployment Rate (b) Job Vacancies

Figure 1: **Impact of a negative ϵ-shock conditionally to be initially in each regime $\sigma = \sigma_L, \sigma_H$ and in an economy without uncertainty shocks.** The sizes of the shocks are σ_L or σ_H, according to the regime at the initial period. For the economy without uncertainty, the magnitude of the shock is σ_L. The red lines represent the dynamics in the regime where $\sigma = \sigma_L$. The blue lines display the dynamics in the regime where $\sigma = \sigma_H$. The green lines correspond to the dynamics of the economy without uncertainty shocks. We report only the median of the IRF distribution.

Impact of TFP Shocks. In the baseline economy, two sets of IRFs to an innovation ϵ must be distinguished (interaction between shocks and uncertainty): the first is conditional to an ϵ-shock that occurs in the regime where $\sigma = \sigma_L$, and the second is conditional to a ϵ-shock that occurs in the regime where $\sigma = \sigma_H$.[12] Figure 1 compares the IRFs conditionally to the uncertainty perceived by the agents.[13]

When agents know that there are no uncertainty shocks (the variance is constant over time and set at its lowest level), the magnitude of the impact of ϵ shock is the lowest, then illustrating the low volatility generated by the standard DMP model.

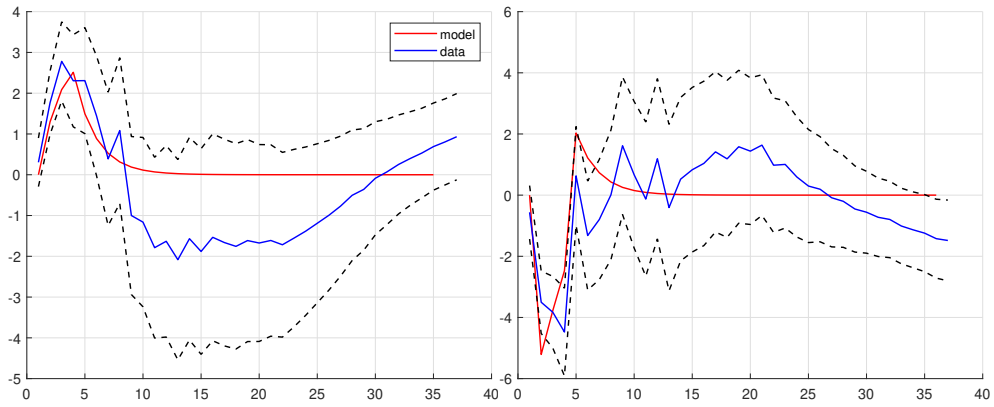
Even if the initial condition is in the regime where the variance is low (and at the same level than in an economy without uncertainty shocks), when agents know that there are uncertainty shocks, that is, the economy can become more risky, they are more reactive to a productivity shock than in an economy without uncertainty shocks. The red lines (ϵ-shock conditionally to be the regime where $\sigma = \sigma_L$) of all Figure 1's panels display an IRF having a larger magnitude than the green lines (without uncertainty shocks). Hence, uncertainty *per se* magnifies the impact of shocks. When uncertainty shocks matter, expectations integrate the possibility to switch in the regime where the variance is high, leading the entrepreneurs to be more sensitive to fluctuations.

If the ϵ-shock occurs when the economy is in a regime where $\sigma = \sigma_H$, the magnitude of the IFRs are the largest (the blue lines in Figure 1). Indeed, in the case of a recession, it is more likely that

[12] To compute these IRFs in nonlinear economies, we draw $n \in N$ sequences for $\{\epsilon_{n,t}\}_{t=0}^{T}$, and we apply a shock of standard error magnitude to their first points. Using the difference with a simulation without shocks on the first point, we deduce the impact of a shock for a particular draw $n \in N$. We then characterize the distribution of the IRF over the N draws.

[13] See the appendix F for an analysis of the asymmetrical of negative vs.positive TFP shocks.

entrepreneurs choose the option of delaying their hires, waiting for uncertainty to dissipate. This precautionary behavior then leads to unemployment rising sharply.



(a) UR (b) VR

Figure 2: **Uncertainty Shock.** The red lines display the model's IFR. The blue lines are the IRF based on the VAR presented in appendix B. The dashed lines represent the confidence bands at 95% of the VAR IRF.

Uncertainty Shock: Are Model IRFs Close to the VAR Estimates? The impact of uncertainty shock is measured by a rise in the variance of business-conditions, which is modeled by a shock on the variance of productivity.

Panel (a) of Figure 2 shows that unemployment increases by 2.51% three months after an uncertainty shock. This replicates closely the IFR of the VAR. Panel (b) of Figure 2 shows that uncertainty shock increases the number of unopened vacancies. This result comes from the asymmetric adjustments of wages that are exacerbated when uncertainty is large.[14] In the DMP model, the large increase in the labor market tightness pushes up real wages during booms, and thus reduces firms' profits and the incentives to hire. On the contrary, wage reductions are bounded in recessions, because the flow value of unemployment benefit is constant. Therefore, on average over time, the firm's job value is more affected by wages increases than wages reductions. This phenomena is magnified when uncertainty is large because fluctuations become larger, whereas the lower bound for real wage does not change. Hence, with respect to the regime with low variance, the one with a large variance would have less vacancies and thus more unemployment.[15] Hence, this over-identifying "test" suggests that the non-linear version of the DMP model could be a good framework to account for U.S. labor market fluctuations.

[14] In Appendix H, we show that forward-looking wages play an important role in shaping this results, as suggested in Den Haan et al. (2020).

[15] Den Haan et al. (2000) show that a rigid wage implies that job values are insensitive to uncertainty changes in a DMP model. Therefore, the wage channel is crucial in explaining the impact of uncertainty on unemployment.

4 Conclusion

Business cycles are not as regular as suggested by the analyses of the framework of the DSGE models. In particular, crises often accompany an increase in uncertainty. This can have a significant impact on the labor market, as hiring is a risky decision that entrepreneurs have to make in the presence of fixed costs. In this study, we propose an extension of the Diamond-Mortensen-Pissarides model, which allows taking into account the variations of uncertainty observed during the business cycle (changes in the variance of macroeconomic shocks).

In this context, we show that uncertainty shocks explain 26.83% of the variance in unemployment. We obtain these results with a calibration of structural parameters such as unemployment benefits or bargaining power, very close to the ones reported by the OECD, and therefore, far from the extreme calibrations chosen to allow the linearized version of DMP model to match the U.S. labor market fluctuations. Therefore, these results highlight the importance of nonlinearities coupled with uncertainty shocks in explaining the dynamics of U.S. unemployment. An over-identification test, based on the ability of our model to reproduce the IRF of unemployment to an uncertainty shock estimated by a VAR model, shows that our theoretical framework is fairly close to the stylized facts of the U.S. labor market.

References

Adjemian, S., Karame, F. and Langot, F. (2021), Nonlinearities and workers' heterogeneity in unemployment dynamics, working paper 14822, IZA.

Baker, S., Bloom, N. and Davis, S. (2016), 'Measuring Economic Policy Uncertainty', *The Quarterly Journal of Economics* **131**, 1593–1636.

Barnichon, R. (2010), 'Building a composite help-wanted index', *Economic Letter* **109**(3), 175–178.

Basu, S. and Bundick, B. (2017), 'Uncertainty shocks in a model of effective demand', *Econometrica* **85**(3), 937–958.

Bloom, N. (2009), 'The Impact of Uncertainty Shocks', *Econometrica* **77**, 623–685.

Born, B., Muller, G. and Pfeifer, J. (2020), Uncertainty shocks in currency unions, CEPR Discussion Papers 15579.

Born, B. and Pfeifer, J. (2014), 'Risk matters: the real effects of volatility shocks: Comment', *American Economic Review* **104**(12), 4231–4239.

Christiano, L., Eichenbaum, M. and Trabandt, M. (2016), 'Unemployment and business cycles', *Econometrica* **84**(4), 1523–1569.

Den Haan, W., Ramey, G. and Watson, J. (2000), 'Job destruction and propagation of shocks', *American Economic Review* **90**(3), 482–498.

Den Haan, W., Rendahl, P. and Freund, L. (2020), Volatile Hiring: Uncertainty In Search And Matching Models, CEPR 14630.

Diamond, P. (1982), 'Wage determination and efficiency in search equilibrium', *Review of Economic Studies* **49**, 217–227.

Fernandez-Villaverde, J. and Guerron-Quintana, P. (2020), Uncertainty Shocks and Business Cycle Research, Technical report, Penn University.

Fernandez-Villaverde, J., Guerron-Quintana, P., Kuester, K. and Rubio-Ramirez, J. (2015), 'Fiscal volatility shocks and economic activity', *Amercian Economic Review* **105**(11), 3352–3384.

Ferraro, D. (2018), 'The Asymmetric Cyclical Behavior of the U.S. Labor Market', *Review of Economic Dynamics* **30**, 145–162.

Ferraro, D. (2020), 'Fast Rises, Slow Declines: Asymmetric Unemployment Dynamics with Matching Frictions', *Journal of Money, Credit and Banking* **Forthcoming**.

Hagendorn, M. and Manovskii, I. (2008), 'The cyclical behavior of equilibrium unemployment and vacancies revisited', *American Economic Review* **98**(4), 1692–1706.

Hairault, J.-O., Langot, F. and Osotimehin, S. (2010), 'Matching frictions, unemployment dynamics and the cost of business cycles', *Review of Economic Dynamics* **13**(4), 759–779.

Hall, R. E. and Milgrom, P. R. (2008), 'The limited influence of unemployment on the wage bargain', *American Economic Review* **98**(4), 1653–1674.

Leduc, S. and Liu, Z. (2016), 'Uncertainty Shocks are Aggregate Demand Shocks', *Journal of Monetary Economics* **82**, 20–35.

Lise, J. and Robin, J.-M. (2017), 'The macro-dynamics of sorting between workers and firms', *American Economic Review* **107**(4), 1104–1135.

Merz, M. and Yashiv, E. (2007), 'Labor and the Market Value of the Firm', *The American Economic Review* **97**, 1419–1431.

Mortensen, D. (1982), The matching process as a noncooperative bargaining game, *in* J. J. McCall, ed., 'The Economics of Information and Uncertainty', University of Chicago Press.

Petrosky-Nadeau, N. and Zhang, L. (2017), 'Solving the dmp model accurately', *Quantitative Economics* **8**, 611–650.

Petrosky-Nadeau, N., Zhang, L. and Kuehn, L. (2018), 'Endogenous disasters', *American Economic Review* **108**, 2212–2245.

Pissarides, C. (1985), 'Short-run dynamics of unemployment, vacancies, and real wages', *American Economic Review* **75**, 676–690.

Pissarides, C. (2009), 'The unemployment volatility puzzle: Is wage stickiness the answer?', *Econometrica* **77**(5), 1339–1369.

Robin, J.-M. (2011), 'On the dynamics of unemployment and wage distributions', *Econometrica* **79**(5), 1327–1355.

Rouwenhorst, K. (1995), Asset pricing implications of equilibrium business cycle models, *in* T. Cooley, ed., 'Frontiers of Business Cycle Research', Princeton University Press, pp. 294–330.

Shimer, R. (2005), 'The cyclical behavior of equilibrium unemployment and vacancies', *American Economic Review* **95**(1), 25–49.

Sims, C. and Zha, T. (2006), 'Were There Regime Switches in U.S. Monetary Policy?', *American Economic Review* **96**, 54–81.