UNCERTAINTY SHOCKS ARE AGGREGATE DEMAND SHOCKS

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Abstract. We study the macroeconomic effects of uncertainty shocks in a DSGE model with labor search frictions and sticky prices. In contrast to a real business cycle model, the model with search frictions implies that uncertainty shocks reduce potential output, because a job match represents a long-term employment relation and heightened uncertainty reduces the value of a match. In the sticky-price equilibrium, an uncertainty shock—regardless of its source—consistently acts like an aggregate demand shock because it raises unemployment and lowers inflation. We present empirical evidence—based on a vector autoregression model and using a few alternative measures of uncertainty—that supports the theory's prediction that uncertainty shocks are aggregate demand shocks.

I. Introduction

Since the Great Recession, there has been a rapidly growing literature—led by the influential work of Bloom (2009)—that studies the macroeconomic effects of uncertainty shocks. Most of the studies focus on the effects of uncertainty on real economic activity such as investment and output. Less is known about the joint effects of uncertainty on inflation and unemployment, and thus about the trade-off that policymakers may face in an environment of heightened uncertainty.

In this paper, we provide a theoretical framework and some empirical evidence to show that uncertainty shocks consistently act like aggregate demand shocks, which raise unemployment and lower inflation. This finding suggests that uncertainty presents no trade-off between

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stabilizing output and inflation. Indeed, policymakers react to an increase in uncertainty by lowering the nominal interest rate both in our model and in the data.

To study the macroeconomic effects of uncertainty, we consider a dynamic stochastic general equilibrium (DSGE) framework that incorporates labor search frictions and nominal rigidities. The model economy is populated by a large number of identical and infinitely lived households. The representative household is a family of workers, some are employed and the others are not. In each period, unemployed workers search for jobs and firms post vacancies at a fixed cost, with a matching technology transforming searching workers and vacancies into new job matches. When a match is formed, a wage is determined from a Nash bargaining game between the new firm and the household. We follow Hall (2005a) and assume that real wages are rigid.

In each period, a fraction of employed workers is exogenously separated from their matches. Thus, aggregate employment in a given period is the sum of the number of workers that survive separation and the number of new matches formed.[1]

To introduce nominal rigidities, we follow Blanchard and Galí (2010) and assume that there is a retail sector, in which a large number of retailers produce differentiated retail products using the homogenous intermediate good produced by firms as input. While the intermediate good market is perfectly competitive, the retail goods market is monopolistically competitive. The final consumption good is a Dixit-Stiglitz composite of the differentiated retail products. Each retailer sets a price for its own product subject to a price adjustment cost (Rotemberg, 1982). The retailer takes the price index and the demand schedule for its product as given. Monetary policy follows a feedback interest rate rule (i.e., a Taylor rule), under which the nominal interest rate reacts to deviations of inflation from a target and also to fluctuations in output gap.

In this model, we consider three broad types of uncertainty related to preferences, technology, and fiscal policy. We show that, in contrast to a standard real business cycle (RBC) model, uncertainty shocks are always contractionary in the flexible-price equilibrium. In the RBC framework, a rise in uncertainty is expansionary because it triggers an increase in the household's willingness to work as the marginal utility of consumption rises (Gilchrist and Williams, 2005; Basu and Bundick, 2011). In contrast, in a model with search frictions, positive uncertainty shocks lower potential output. Because of the long-term nature of employment relations in the presence of search frictions, firms are reluctant to hire new workers when the level of uncertainty rises. Therefore, heightened uncertainty lowers the expected

[1]The type of search friction that we consider here takes its root from the original contributions by Diamond (1982) and Mortensen and Pissarides (1994).

value of a filled vacancy. Firms respond by posting fewer vacancies, leading to a decline in the job finding rate and an increase in the unemployment rate.

Our main result is that, once embedded in a model with price rigidities, an uncertainty shock—regardless of its source—not just raises unemployment, but also lowers inflation. In this sense, an uncertainty shock acts like a negative aggregate demand shock. Under the Taylor rule, the monetary authority reacts to the rise in the output gap and the fall in inflation by lowering the nominal interest rate. Our results thus suggest that, even when uncertainty shocks can have "supply-side" effects that lower potential output (i.e., aggregate output in the flexible-price equilibrium), which *ceteris paribus* could be inflationary, the demand effects of uncertainty shocks dominate, so that elevated uncertainty leads to a large negative output gap, a rise in unemployment, and a fall in inflation.

In our model, the macroeconomic effects of uncertainty shocks are amplified through movements in the relative price of intermediate goods, which corresponds to the inverse of the markup in the retail sector. With sticky prices, an uncertainty shock that lowers aggregate demand also lowers the relative price of intermediate goods. The decline in the relative price reduces the value of a new match, so that the unemployment rate rises. As more searching workers fail to find a job match, the household's income declines further, leading to an even greater fall in aggregate demand, which reinforces the initial decline in the relative price, creating a multiplier effect that amplifies uncertainty shocks to generate large macroeconomic fluctuations. This amplification mechanism is absent in the flexible-price model, since the relative price is constant.

Search frictions provide an additional mechanism for uncertainty shocks to generate large increases in unemployment and large declines in inflation in our model with nominal rigidities. This mechanism reflects the impact of uncertainty shocks on the value of a job match and the shape of the Beveridge curve, which captures the negative relationship between vacancies and unemployment. When the cost of posting a vacancy is very low, which would approximate a frictionless labor market, equilibrium unemployment is determined along a relatively inelastic segment of the Beveridge curve. In this case, a rise in uncertainty lowers the value of a filled vacancy; but for any given decline in posted vacancies, the increase in unemployment is muted. However, when the cost of posting vacancies is high (i.e., when search frictions are more important), a given decline in posted vacancies would be associated with a much larger increase in unemployment, since equilibrium unemployment is determined along a relatively more elastic segment of the Beveridge curve. Thus, in our model, search frictions have important interactions with sticky prices to amplify uncertainty shocks.

Since labor search frictions magnify the declines in aggregate demand, they also magnify the declines in inflation when the level of uncertainty rises. Indeed, a robust feature of our model is that an increase in uncertainty consistently leads to an increase in unemployment and a decline in inflation for a wide range of plausible parameter values.

In the second part of the paper, we also present empirical evidence supporting the main predictions from our theoretical model. To examine the macroeconomic effects of uncertainty shocks in the data, we consider four alternative measures of uncertainty, including the VIX index studied extensively by Bloom (2009), the policy uncertainty index constructed by Baker, Bloom, and Davis (2011), and two new survey-based measures. We estimate a vector autoregression (VAR) model that includes a measure of uncertainty, unemployment, inflation, and a short-term nominal interest rate. A consistent pattern emerges from our empirical exercises: uncertainty raises unemployment and lowers inflation, and policymakers accommodate by lowering the nominal interest rate. Thus, both theory and evidence suggest that uncertainty acts like an aggregate demand shock.

Our emphasis on the demand effects of uncertainty relates to that in Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2011) and Basu and Bundick (2011), who first emphasized the importance of nominal rigidities and the role of markups for the transmission of uncertainty shocks. More specifically, Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2011) focus on fiscal policy uncertainty and find that it can trigger sizable adverse effects on economic activity in a model with price and wage rigidities, particularly in the case of uncertainty about taxes on capital income. Similarly, Basu and Bundick (2011) concentrate on the ability of uncertainty shocks to generate simultaneous declines in real macroeconomic variables.

Our approach complement these previous studies along three dimensions. First, we incorporate labor search frictions in the DSGE model with sticky prices. In our model, long-term employment relations are central for understanding the effects of uncertainty on potential output and equilibrium unemployment and also magnify the contractionary effects of uncertainty under price rigidity. Second, we emphasize the joint effects of uncertainty on real economic activity and inflation. Third, we provide evidence to show that the key prediction of our theory that uncertainty acts like a demand shock is a robust feature of the data. Such evidence, to our knowledge, is new to the literature.

Our work adds to the recent rapidly growing literature that studies the macroeconomic effects of uncertainty shocks in a DSGE framework. For example, Bloom, Floetotto, Jaimovich, Saporta-Eksten, and Terry (2012) study a DSGE model with heterogeneous firms and non-convex adjustment costs in productive inputs. They find that a rise in uncertainty makes firms pause hiring and investment and thus leads to a large drop in economic activity. They focus on real economic activity and abstract from the effects of uncertainty on inflation and monetary policy.

Uncertainty shocks can have important interactions with financial factors (Gilchrist, Sim, and Zakrajsek, 2010; Arellano, Bai, and Kehoe, 2011). In a recent study, Christiano, Motto, and Rostagno (2012) present a DSGE model with a financial accelerator in the spirit of Bernanke, Gertler, and Gilchrist (1999). They find that risk shocks (i.e., changes in the volatility of cross-sectional idiosyncratic uncertainty) play an important role for shaping U.S. business cycles.

Most of these studies of uncertainty shocks abstract from labor search frictions and are not designed to examine the impact of uncertainty shocks on labor market dynamics such as unemployment and job vacancies. An exception is Schaal (2012), who presents a model with labor search frictions and idiosyncratic volatility shocks to study the observation in the Great Recession period that high unemployment was accompanied by high labor productivity. As in other studies discussed here, he focuses on the effects of uncertainty on real activity, not on its interaction with inflation and monetary policy.[2]

In what follows, we present the DSGE model with labor search frictions in Section II, discuss the dynamic effects of uncertainty shocks on unemployment and other macroeconomic variables in the calibrated DSGE model in Section III, present empirical evidence that supports the DSGE model's prediction in Section IV, and provide some concluding remarks in Section V.

II. Uncertainty shocks in a DSGE model with search frictions

In this section, we introduce a stylized DSGE model with two key ingredients: sticky prices and labor market search frictions. We show that incorporating search frictions in the labor market has important implications for understanding the effects of uncertainty shocks on both potential output (i.e., output in the flexible-price equilibrium) and equilibrium unemployment.

The model builds on the basic framework in Blanchard and Galí (2010). We focus on the effects of uncertainty shocks. The economy is populated by a continuum of infinitely lived and identical households with a unit measure. The representative household consists of a continuum of worker members. The household owns a continuum of firms, each of which

[2]The literature suggests that rising uncertainty may hinder irreversible investment and hiring decisions, because it raises the option value of waiting. For partial equilibrium analyses of the real option value theory in the context of uncertainty shocks, see, for example, (Bernanke, 1983) and Bloom (2009). Romer (1990) argues that increases in uncertainty following the stock market crash in 1929 contributed to worsening the Great Depression by substantially reducing demand for consumer durable goods. For empirical evidence on the effects of uncertainty on investment, see, for example, Leahy and Whited (1996) and Guiso and Parigi (1999). For a comprehensive survey of the literature on uncertainty shocks, see Bloom and Fernandez-Villaverde (2012).

uses one worker to produce an intermediate good. In each period, a fraction of the workers are unemployed and they search for a job. Firms post vacancies at a fixed cost. The number of successful matches are produced with a matching technology that transforms searching workers and vacancies into an employment relation. Real wages are determined by Nash bargaining between a searching worker and a hiring firm.

The household consumes a basket of differentiated retail goods, each of which is transformed from the homogeneous intermediate good using a constant-returns technology. Retailers face a perfectly competitive input market (where they purchase the intermediate good) and a monopolistically competitive product market. Each retailer sets a price for its differentiated product, with price adjustments subject to a quadratic cost in the spirit of Rotemberg (1982).

The government finances its spending and transfer payments to unemployed workers by lump-sum taxes. Monetary policy is described by the Taylor rule, under which the nominal interest rate responds to deviations of inflation from a target and of output from its potential.

II.1. **The households.** There is a continuum of infinitely lived and identical households with a unit measure. The representative household consumes and invests a basket of retail goods. The utility function is given by

$$E \sum_{t=0}^{\infty} \beta^t A_t \left(\ln C_t - \chi N_t \right), \tag{1}$$

where $E\left[\cdot\right]$ is an expectation operator, C_t denotes consumption, and N_t denotes the fraction of household members who are employed. The parameter $\beta \in (0,1)$ denotes the subjective discount factor and the parameter χ measures the disutility from working.

The term A_t denotes an intertemporal preference shock. Let $\gamma_{at} \equiv \frac{A_t}{A_{t-1}}$ denote the growth rate of A_t. We assume that γ_{at} follows the stochastic process

$$\ln \gamma_{at} = \rho_a \ln \gamma_{a,t-1} + \sigma_{at} \varepsilon_{at}. \tag{2}$$

The parameter $\rho_a \in (-1,1)$ measures the persistence of the preference shock. The term ε_{at} is an i.i.d. standard normal process. The term σ_{at} is a time-varying standard deviation of the innovation to the preference shock. We interpret it as a preference uncertainty shock. We assume that σ_{at} follows the stationary process

$$\ln \sigma_{at} = (1-\rho_{\sigma_a}) \ln \sigma_a + \rho_{\sigma_a} \ln \sigma_{a,t-1} + \sigma_{\sigma_a} \varepsilon_{\sigma_a,t}, \tag{3}$$

where $\rho_{\sigma_a} \in (-1,1)$ measures the persistence of preference uncertainty, $\varepsilon_{\sigma_a,t}$ denotes the innovation to the preference uncertainty shock and is a standard normal process, and σ_{σ_a} denotes the (constant) standard deviation of the innovation.

The representative household is a family consisting of a continuum of workers with a unit measure. The family chooses consumption C_t and saving B_t to maximize the utility function in (1) subject to the sequence of budget constraints

$$C_t + \frac{B_t}{P_t R_t} = \frac{B_{t-1}}{P_t} + w_t N_t + \phi\left(1 - N_t\right) + d_t - T_t, \quad \forall t \geq 0, \tag{4}$$

where P_t denotes the price level, B_t denotes the household's holdings of a nominal risk-free bond, R_t denotes the nominal interest rate, w_t denotes the real wage rate, ϕ denotes an unemployment benefit, d_t denotes profit income from the household's ownership of intermediate goods producers and of retailers, and T_t denotes lump-sum taxes.

Optimal bond-holding decisions result in the intertemporal Euler equation

$$1 = \mathrm{E}_t \beta \gamma_{a,t+1} \frac{\Lambda_{t+1}}{\Lambda_t} \frac{R_t}{\pi_{t+1}}, \tag{5}$$

where $\Lambda_t = \frac{1}{C_t}$ denotes the marginal utility of consumption and $\pi_t \equiv \frac{P_t}{P_{t-1}}$ denotes the inflation rate.

II.2. **The aggregation sector.** Denote by Y_t the final consumption good, which is a basket of differentiated retail goods. Denote by $Y_t(j)$ a type j retail good for $j \in [0, 1]$. We assume that

$$Y_t = \left(\int_0^1 Y_t(j)^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}}, \tag{6}$$

where $\eta > 1$ denotes the elasticity of substitution between differentiated products.

Expenditure minimizing implies that demand for a type j retail good is inversely related to the relative price, with the demand schedule given by

$$Y_t^d(j) = \left(\frac{P_t(j)}{P_t} \right)^{-\eta} Y_t, \tag{7}$$

where $Y_t^d(j)$ and $P_t(j)$ denote the demand for and the price of retail good of type j, respectively. The price index P_t is related to the individual prices $P_t(j)$ through the relation

$$P_t = \left(\int_0^1 P_t(j)^{\frac{1}{1-\eta}} \right)^{1-\eta}. \tag{8}$$

II.3. **The retail goods producers.** There is a continuum of retail goods producers, each producing a differentiated product using a homogeneous intermediate good as input. The production function of retail good of type $j \in [0, 1]$ is given by

$$Y_t(j) = X_t(j), \tag{9}$$

where $X_t(j)$ is the input of intermediate goods used by retailer j and $Y_t(j)$ is the output. The retail goods producers are price takers in the input market and monopolistic competitors in the product markets, where they set prices for their products, taking as given the demand schedule in equation (7) and the price index in equation(8).

Price adjustments are subject to the quadratic cost

$$\frac{\Omega_p}{2}\left(\frac{P_t(j)}{\pi P_{t-1}(j)}-1\right)^2 Y_t, \tag{10}$$

where the parameter $\Omega_p \geq 0$ measures the cost of price adjustments and π denotes the steady-state inflation rate. Here, we assume that price adjustment costs are in units of aggregate output.

A retail firm that produces good j solves the profit-maximizing problem

$$\max_{P_t(j)} \quad \mathrm{E}_t \sum_{i=0}^{\infty} \frac{\beta^i \Lambda_{t+i} A_{t+i}}{\Lambda_t A_t}\left[\left(\frac{P_{t+i}(j)}{P_{t+i}}-q_{t+i}\right) Y_{t+i}^d(j)-\frac{\Omega_p}{2}\left(\frac{P_{t+i}(j)}{\pi P_{t+i-1}(j)}-1\right)^2 Y_{t+i}\right], \tag{11}$$

where q_{t+i} denotes the relative price of intermediate goods in period $t+i$. The optimal price-setting decision implies that, in a symmetric equilibrium with $P_t(j) = P_t$ for all j, we have

$$q_t = \frac{\eta-1}{\eta} + \frac{\Omega_p}{\eta}\left[\frac{\pi_t}{\pi}\left(\frac{\pi_t}{\pi}-1\right) - \mathrm{E}_t \frac{\beta \gamma_{a,t+1} \Lambda_{t+1}}{\Lambda_t} \frac{Y_{t+1}}{Y_t} \frac{\pi_{t+1}}{\pi}\left(\frac{\pi_{t+1}}{\pi}-1\right)\right]. \tag{12}$$

Absent price adjustment costs (i.e., $\Omega_p = 0$), the optimal pricing rule implies that real marginal cost q_t equals the inverse of the steady-state markup.

II.4. **The Labor Market.** In the beginning of period t, there are u_t unemployed workers searching for jobs and there are v_t vacancies posted by firms. The matching technology is described by the Cobb-Douglas function

$$m_t = \mu u_t^{\alpha} v_t^{1-\alpha}, \tag{13}$$

where m_t denotes the number of successful matches and the parameter $\alpha \in (0,1)$ denotes the elasticity of job matches with respect to the number of searching workers. The term μ scales the matching efficiency.

The probability that an open vacancy is matched with a searching worker (or the job filling rate) is given by

$$q_t^v = \frac{m_t}{v_t}. \tag{14}$$

The probability that an unemployed and searching worker is matched with an open vacancy (or the job finding rate) is given by

$$q_t^u = \frac{m_t}{u_t}. \tag{15}$$

In the beginning of period t, there are N_{t-1} workers. A fraction ρ of these workers lose their jobs. Thus, the number of workers who survive the job separation is $(1-\rho)N_{t-1}$. At the same time, m_t new matches are formed. Following the timing assumption in Blanchard and Galí (2010), we assume that new hires start working in the period they are hired. Thus, aggregate employment in period t evolves according to

$$N_t = (1 - \rho) N_{t-1} + m_t. \tag{16}$$

With a fraction ρ of employed workers separated from their jobs, the number of unemployed workers searching for jobs in period t is given by

$$u_t = 1 - (1 - \rho) N_{t-1}. \tag{17}$$

Following Blanchard and Galí (2010), we assume full participation and define the unemployment rate as the fraction of the population who are left without a job after hiring takes place in period t. Thus, the unemployment rate is given by

$$U_t = u_t - m_t = 1 - N_t. \tag{18}$$

II.5. **The firms (intermediate good producers).** A firm can produce only if it can successfully match with a worker. The production function for a firm with one worker is given by

$$x_t = Z_t,$$

where x_t is output and Z_t is an aggregate technology shock. The technology shock follows the stochastic process

$$\ln Z_t = (1 - \rho_z) \ln Z + \rho_z \ln Z_{t-1} + \sigma_{zt} \varepsilon_{zt}. \tag{19}$$

The parameter $\rho_z \in (-1, 1)$ measures the persistence of the technology shock. The term ε_{zt} is an i.i.d. innovation to the technology shock and is a standard normal process. The term σ_{zt} is a time-varying standard deviation of the innovation and we interpret it as a technology uncertainty shock. We assume that the technology uncertainty shock follows the stationary stochastic process

$$\ln \sigma_{zt} = (1 - \rho_{\sigma_z}) \ln \sigma_z + \rho_{\sigma_z} \ln \sigma_{z,t-1} + \sigma_{\sigma_z} \varepsilon_{\sigma_z,t}, \tag{20}$$

where the parameter $\rho_{\sigma_z} \in (-1, 1)$ measures the persistence of the technology uncertainty, the term $\varepsilon_{\sigma_z,t}$ denotes the innovation to the technology uncertainty and is a standard normal process, and the parameter $\sigma_{\sigma_z} > 0$ is the standard deviation of the innovation.

If a firm finds a match, it obtains a flow profit in the current period after paying the worker. In the next period, if the match survives (with probability $1 - \rho$), the firm continues; if the match breaks down (with probability ρ), the firm posts a new job vacancy at a fixed cost κ, with the value V_{t+1}. The value of a firm with a match is therefore given by the Bellman equation

$$J_t^F = q_t Z_t - w_t + E_t \frac{\beta \gamma_{a,t+1} \Lambda_{t+1}}{\Lambda_t} \left[(1 - \rho) J_{t+1}^F + \rho V_{t+1} \right]. \tag{21}$$

If the firm posts a new vacancy in period t, it costs κ units of final goods. The vacancy can be filled with probability q_t^v, in which case the firm obtains the value of the match. Otherwise, the vacancy remains unfilled and the firm goes into the next period with the value V_{t+1}. Thus, the value of an open vacancy is given by

$$V_t = -\kappa + q_t^v J_t^F + E_t \frac{\beta \gamma_{a,t+1} \Lambda_{t+1}}{\Lambda_t} (1 - q_t^v) V_{t+1}.$$

Free entry implies that $V_t = 0$, so that

$$\kappa = q_t^v J_t^F. \tag{22}$$

Substituting equation (22) into equation (21), we obtain

$$\frac{\kappa}{q_t^v} = q_t Z_t - w_t + E_t \frac{\beta \gamma_{a,t+1} \Lambda_{t+1}}{\Lambda_t} (1 - \rho) \frac{\kappa}{q_{t+1}^v}. \tag{23}$$

II.6. **Workers' value functions.** If a worker is employed, he obtains an after-tax wage income and suffers a utility cost for working in period t. In period $t+1$, the match is dissolved with probability ρ and the separated worker can find a new match with probability q_{t+1}^u. Thus, with probability $\rho(1 - q_{t+1}^u)$, the worker who gets separated does not find a new job in period $t+1$ and thus enters the unemployment pool. Otherwise, the worker continues to be employed. The (marginal) value of an employed worker therefore satisfies the Bellman equation

$$J_t^W = w_t - \frac{\chi}{\Lambda_t} + E_t \frac{\beta \gamma_{a,t+1} \Lambda_{t+1}}{\Lambda_t} \left\{ \left[1 - \rho(1 - q_{t+1}^u)\right] J_{t+1}^W + \rho(1 - q_{t+1}^u) J_{t+1}^U \right\}, \tag{24}$$

where J_t^U denotes the value of an unemployed household member. If a worker is currently unemployed, then he obtains an unemployment benefit and can find a new job in period $t+1$ with probability q_{t+1}^u. Otherwise, he stays unemployed in that period. The value of an unemployed worker thus satisfies the Bellman equation

$$J_t^U = \phi + E_t \frac{\beta \gamma_{a,t+1} \Lambda_{t+1}}{\Lambda_t} \left[q_{t+1}^u J_{t+1}^W + (1 - q_{t+1}^u) J_{t+1}^U \right]. \tag{25}$$

II.7. **The Nash bargaining wage.** Firms and workers bargain over wages. The Nash bargaining problem is given by

$$\max_{w_t} \quad \left(J_t^W - J_t^U\right)^b \left(J_t^F\right)^{1-b}, \tag{26}$$

where $b \in (0,1)$ represents the bargaining weight for workers.

Define the total surplus as

$$S_t = J_t^F + J_t^W - J_t^U. \tag{27}$$

Then the bargaining solution is given by

$$J_t^F = (1 - b) S_t, \quad J_t^W - J_t^U = b S_t. \tag{28}$$

It then follows from equations (24) and (25) that

$$bS_t = w_t^N - \phi - \frac{\chi}{\Lambda_t} + E_t \frac{\beta \gamma_{a,t+1} \Lambda_{t+1}}{\Lambda_t} \left[(1-\rho) \left(1 - q_{t+1}^u\right) bS_{t+1} \right]. \tag{29}$$

Given the bargaining surplus S_t, which itself is proportional to firm value J_t^F (see the bargaining solution (28)), this last equation determines the Nash bargaining wage w_t^N.

If equilibrium real wage equals the Nash bargaining wage, then we can solve out an explicit expression for the Nash wage. Specifically, we use equations (22), (28), and (29) and impose $w_t = w_t^N$ to obtain

$$w_t^N = (1-b) \left[\frac{\chi}{\Lambda_t} + \phi \right] + b \left[q_t Z_t + \beta(1-\rho) E_t \frac{\beta \gamma_{a,t+1} \Lambda_{t+1}}{\Lambda_t} \frac{\kappa v_{t+1}}{u_{t+1}} \right]. \tag{30}$$

In this case, the Nash bargaining wage is a weighted average of the worker's reservation value and the firm's productive value of a job match. By forming a match, the worker incurs a utility cost of working and foregoes unemployment benefits. By employing a worker, the firm receives the marginal product from labor in the current period and saves the vacancy cost from the next period.

II.8. **Wage Rigidity.** In general, however, equilibrium real wage may be different from the Nash bargaining solution. Indeed, Hall (2005b) points out that real wage rigidity is important to generate empirically reasonable volatilities of vacancies and unemployment.

There are several ways to formalize real wage rigidity (Hall, 2005a; Gertler and Trigari, 2009; Blanchard and Galí, 2010). We follow the literature and consider real wage rigidity by assuming that the real wage is a geometrically weighted average of the Nash bargaining wage and the last-period realized wage. In particular, we consider the wage rule

$$w_t = w_{t-1}^{\gamma} (w_t^N)^{1-\gamma}, \tag{31}$$

where $\gamma \in (0,1)$ represents the degree of real wage rigidity.[3]

II.9. **Government policy.** The government finances exogenous spending G_t and unemployment benefit payments ϕ through lump-sum taxes. We assume that the government balances the budget in each period so that

$$G_t + \phi(1 - N_t) = T_t \tag{32}$$

We assume that the ration of government spending to output $g_t \equiv \frac{G_t}{Y_t}$ follows the stationary stochastic process

$$\ln g_t = (1-\rho_g) \ln g + \rho_g \ln g_{t-1} + \sigma_g \varepsilon_{gt}, \tag{33}$$

[3]We have examined other wage rules as those in Blanchard and Galí (2010) and we find that our results do not depend on the particular form of the wage rule.

where $\rho_g \in (-1, 1)$ is the persistence parameter, the innovation ε_{gt} is an i.i.d. standard normal process, and σ_g is the time-varying standard deviation of the innovation. We interpret σ_{gt} as an uncertainty shock to government spending.

The government spending uncertainty shock follows the stationary stochastic process

$$\ln \sigma_{gt} = (1 - \rho_{\sigma_g}) \ln \sigma_g + \rho_{\sigma_g} \ln \sigma_{g,t-1} + \sigma_{\sigma_g} \varepsilon_{\sigma_g,t}, \tag{34}$$

where the parameter $\rho_{\sigma_g} \in (-1, 1)$ measures the persistence of the uncertainty shock to government spending, the term $\varepsilon_{\sigma_g,t}$ denotes the innovation to the uncertainty shock and is a standard normal process, and the parameter $\sigma_{\sigma_g} > 0$ is the standard deviation of the innovation.

The government conducts monetary policy by following the Taylor rule

$$R_t = r\pi^* \left(\frac{\pi_t}{\pi^*}\right)^{\phi_\pi} \left(\frac{Y_t}{Y}\right)^{\phi_y}, \tag{35}$$

where the parameter ϕ_π determines the aggressiveness of monetary policy against deviations of inflation from the target π^* and ϕ_y determines the extent to which monetary policy accommodates output fluctuations. The parameter r denotes the steady-state real interest rate (i.e., $r = \frac{R}{\pi}$).

II.10. **Search equilibrium.** In a search equilibrium, the markets for bonds, capital, final consumption goods, and intermediate goods all clear.

Since the aggregate supply of the nominal bond is zero, the bond market-clearing condition implies that

$$B_t = 0. \tag{36}$$

Goods market clearing implies the aggregate resource constraint

$$C_t + \kappa v_t + \frac{\Omega_p}{2} \left(\frac{\pi_t}{\pi} - 1\right)^2 Y_t + G_t = Y_t, \tag{37}$$

where Y_t denotes aggregate output of final goods.

Intermediate goods market clearing implies that

$$Y_t = Z_t N_t. \tag{38}$$

III. Economic implications from the DSGE model

To examine the macroeconomic effects of uncertainty shocks in our DSGE model, we calibrate the model parameters and simulate the model to examine impulse responses of macroeconomic variables to a few alternative sources of uncertainty shocks. We focus on the responses of unemployment, inflation, and the nominal interest rate following an uncertainty shock.

III.1. **Calibration.** We calibrate the structural parameters to match several steady-state observations. For those structural parameters that do not affect the model's steady state, we calibrate their values to be consistent with other empirical studies in the literature. The structural parameters to be calibrated include β, the subjective discount factor; χ, the disutility of working parameter; η, the elasticity of substitution between differentiated retail products; α, the elasticity of matching with respect to searching workers; μ, the matching efficiency parameter; ρ, the job separation rate; ϕ, the flow unemployment benefits (in final consumption units); κ, the fixed cost of positing vacancies; b, the Nash bargaining weight; Ω_p, the price adjustment cost parameter; π, the steady-state inflation rate (or inflation target); ϕ_π, the Taylor-rule coefficient for inflation; and ϕ_y, the Taylor-rule coefficient for output. In addition, we need to calibrate the parameters in the shock processes. The calibrated values of the model parameters are summarized in Table 1.

We set $\beta = 0.99$, so that the model implies a steady-state real interest rate of 4 percent per annual. We set $\eta = 10$ so that the average markup is about 10 percent, in line with the estimates obtained by Basu and Fernald (1997) and others. We set $\alpha = 0.5$ following the literature (Blanchard and Galí, 2010; Gertler and Trigari, 2009). We set $\rho = 0.1$, which is consistent with an average monthly job separation rate of about 3.4 percent as in the Job Openings and Labor Turnover Survey (JOLTS) for the period from 2001 to 2011. Following Hall and Milgrom (2008), we set $\phi = 0.25$ so that the unemployment benefit is about 25 percent of normal earnings. We set $b = 0.5$ following the literature.

We choose the value of the vacancy cost parameter κ so that, in the steady state, the total cost of posting vacancies is about 2 percent of gross output. To assign a value of κ then requires knowledge of the steady-state number of vacancies v and the steady-state level of output Y. We calibrate the value of v such that the steady-state vacancy filling rate is $q^v = 0.7$ and the steady-state unemployment rate U is 6 percent, as in den Haan, Ramey, and Watson (2000). Given the steady-state value of the job separation rate $\rho = 0.1$, we obtain $m = \rho N = 0.094$. Thus, we have $v = \frac{m}{q^v} = \frac{0.094}{0.7} = 0.134$. To obtain a value for Y, we use the aggregate production function that $Y = ZN$ and normalize the level of technology such that $Z = 1$. This procedure yields a calibrated value of $\kappa = 0.14$.

Given the steady-state values of m, u, and v, we use the matching function to obtain an average matching efficiency of $\mu = 0.65$. To obtain a value for χ, we solve the steady-state system so that χ is consistent with an unemployment rate of 6 percent. The process results in $\chi = 0.46$. We set the real wage rigidity parameter to $\gamma = 0.9$.

The price adjustment cost parameter Ω_p and the Taylor-rule parameters ϕ_π and ϕ_y do not affect the model's steady state. We calibrate these parameters to be consistent with empirical studies in the literature. We set $\Omega_p = 112$ so that the slope of the Phillips curve in the model corresponds to that in a Calvo staggered price-setting model with four quarters of price contract duration.For the Taylor rule parameters, we set $\phi_\pi = 1.5$ and $\phi_y = 0.2$. We set $\pi = 1.005$, so that the steady-state inflation rate is about 2 percent per year, corresponding to the Federal Reserve's implicit inflation objective.

The model does not provide information for the parameters in the exogenous shock processes. For purpose of illustration, we normalize the steady-state levels of the shocks such that $\gamma_a = 1$, $Z = 1$. We set $g = 0.2$ so that the steady-state ratio of government spending to aggregate output is about 20 percent. We also normalize the mean values of the uncertainty shocks so that $\sigma_k = 0.01$ for $k \in \{a, z, \tau, g\}$. We set the standard deviation of the innovation to each uncertainty shock to $\sigma_{\sigma_k} = 1$, so that a one standard deviation shock to uncertainty represents a 100 percent increase in the level of uncertainty (i.e., the shock leads to a doubling of the level of uncertainty). The persistence parameters for all shocks, including the level shocks and the uncertainty shocks, are set to $\rho_k = 0.90$ for $k \in \{a, z, g, \sigma_a, \sigma_z, \sigma_g\}$.

III.2. **Macroeconomic effects of uncertainty shocks.** We solve the model using third order approximations around the steady state. We then compute the impulse responses following an uncertainty shock. We consider three different types of uncertainty shocks: (1) preference uncertainty σ_{at}; (2) technology uncertainty σ_{zt}; and (3) fiscal policy uncertainty σ_{gt}.[4] We show that incorporating search frictions renders the transmission mechanism for uncertainty shocks quite different from that of the standard New Keynesian model.

III.2.1. *Potential output effects of uncertainty.* We first consider the effects of uncertainty shocks in the flexible-price version of the DSGE model. We find that the impact of uncertainty shocks on potential output (i.e., output in the model with flexible prices) in the presence of search frictions differs qualitatively from that in the standard RBC model with spot labor markets.

In the standard RBC model, uncertainty shocks are expansionary since heightened uncertainty lowers consumption and thus creates an incentive for households to work harder at any given wage rate (Basu and Bundick, 2011). Thus, the RBC model predicts that heightened uncertainty raises potential output.

The long-term employment relations in our model with search frictions create a different channel for uncertainty shocks to affect potential output. In our model, heightened uncertainty reduces the value of a filled vacancy. Firms thus respond to uncertainty shocks by posting fewer vacancies. As a consequence, the job finding rate declines and the unemployment rate rises.

[4]We have also examined the effects of uncertainty shocks to tax rates and find that the qualitative results are similar to those of government spending uncertainty shocks (not reported).

Figures 1 through **??** display the impulse responses of several macroeconomic variables in the DSGE model with flexible prices following the three types of uncertainty shocks—preference uncertainty, technology uncertainty, and fiscal policy uncertainty. The figures reveal that uncertainty shocks—regardless of the sources—generate a rise in unemployment and a decline in potential output when prices are flexible.

III.2.2. *Aggregate demand effects of uncertainty.* In this section, we show that, with sticky prices, uncertainty shocks unambiguously act like an aggregate demand shock that reduces real activity, raises unemployment, and lowers inflation. Figures 4 through **??** show that, for all three types of uncertainty shocks, uncertainty indeed acts like an aggregate demand shock, once nominal rigidities are introduced.

When prices are sticky, the recessionary effects of uncertainty are amplified through fluctuations in the relative price of intermediate goods (or equivalently, the markup in the retail sector). In the flexible-price equilibrium, the relative price is constant following uncertainty shocks, and thus this amplification channel is absent. When prices are sticky, an increase in the level of uncertainty lowers the demand for both retail goods and intermediate goods. Thus, the relative price of intermediate goods falls, lowering firms' profits and the value of a filled vacancy. A decline in the real wage could have mitigated the fall in profits. But with real wage rigidity, this mitigating effect is absent. Firms respond to the decline in profits and thus the value of a job match by posting fewer vacancies, making it more difficult for searching workers to find a match. Thus, unemployment rises. As more workers are unemployed, the household's income falls, reinforcing the initial decline in aggregate demand and in the relative price, leading to a multiplier that amplifies the effects of uncertainty shocks on macroeconomic activity.

A rise in the level of uncertainty and consequent reduction in aggregate demand not just raise the unemployment rate, but also lower the inflation rate. Under the Taylor rule, the central bank lowers the nominal interest rate to alleviate the contractionary and disinflationary effects of the uncertainty shock. Nonetheless, equilibrium unemployment still rises and equilibrium inflation still falls following a rise in uncertainty.

Comparing Figures 1 through **??** with Figures 4 through **??**, we see that uncertainty shocks generate significant reductions in aggregate demand in the DSGE model with sticky prices but have relatively very small effects on unemployment and other macroeconomic variables with flexible prices. Thus, in this stylized DSGE model, uncertainty shocks do not seem to drive changes in the economy's productive capacity, but they do generate large declines in aggregate demand.

III.3. **The importance of search frictions.** We have shown that positive uncertainty shocks act as negative demand shocks that depresses aggregate activity. This effect is not unique to our model with search frictions and sticky prices. Similar effects have also been found in the standard DSGE model without search frictions (Basu and Bundick, 2011; Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez, 2011). We now illustrate that incorporating search frictions is important not only because it helps generates a decline in potential output following an uncertainty shock (whereas the standard model does not), but also because there are important interactions between search frictions and nominal rigidities that further amplify the aggregate demand effects of uncertainty shocks.

To illustrate this point, we show in Figure 7 the Beveridge curve (BC) and the job creation curve (JCC). The intersection of these two curves determines the equilibrium vacancy rate v and unemployed searching workers u.[5]

The Beveridge curve describes the inverse relation between v and u implied by the matching technology. In particular, the matching function (13) implies that

$$v = \left(\frac{m}{\mu}\right)^{\frac{1}{1-\alpha}} \left(\frac{1}{u}\right)^{\frac{\alpha}{1-\alpha}}. \tag{39}$$

This Beveridge curve relation also reveals that, for any given matching m and the elasticity parameter α, the vacancy rate v is a convex function of the number of searching workers u.

The job creation curve describes the optimal vacancy posting decision in equation (22). It represents a positive relation between v and u for any given firm value J^F and vacancy cost κ. In particular, the JCC is described by the relation

$$v = \left(\frac{\mu J^F}{\kappa}\right)^{\frac{1}{\alpha}} u, \tag{40}$$

where we have used the definition of the vacancy filling rate $q^v = \frac{m}{v}$ and the matching function (13).

First, consider the labor market equilibrium in our benchmark model. Suppose the initial (steady-state) equilibrium is at point A in Figure 7. As we have discussed in the previous section, an increase in uncertainty lowers the value of a job match (i.e., J^F declines) through the aggregate demand channel and real wage rigidities amplify the decline in firm value. Thus, the JCC rotates downward, leading to a new equilibrium at point B, with a lower vacancy rate and a higher unemployment rate.

Now, consider a counterfactual economy with a smaller cost of vacancy posting κ. In such an economy, search frictions are less important than in our benchmark economy. If vacancy

[5]Under the timing of our model, u is the number of unemployed workers who are searching for jobs. Total unemployment is the fraction of searching workers who remain without a job after matching occurs (i.e., $U = u - m$; see equation (18)).

costs are smaller, firms will post more vacancies, implying a higher job finding rate for a searching worker.[6] From equation (40), a lower value of κ implies a higher value of v for any given u. Thus, the job creation curve (the solid black line denoted by JCC') is steeper than that in the benchmark economy (the solid blue line denoted by JCC). Accordingly, the labor-market equilibrium implies a higher vacancy rate and a lower unemployment rate (point A'). When the level of uncertainty increases, the job creation curve rotates downward along the Beveridge curve, reaching the new equilibrium at point B'. As in the benchmark model, the increase in uncertainty lowers the vacancy rate and raises the unemployment rate. But because the Beveridge curve represents a convex relation between v and u, the increase in unemployment in this counterfactual economy with a lower vacancy cost is smaller than that in the benchmark economy.

Since search frictions amplify the effects of uncertainty shocks on aggregate demand, all else equal, inflation is likely to decline by more in our model than in the standard DSGE model without search frictions.[7]

IV. The Macroeconomic Effects of Uncertainty Shocks: Evidence

We now present empirical evidence that supports the predictions of our theoretical model. To examine the macroeconomic effects of uncertainty shocks in the data, we estimate a VAR model that includes a measure of uncertainty and a few macroeconomic variables. VAR models are used in the literature as a main statistical tool to estimate the responses of macroeconomic variables to uncertainty shocks. Examples include Alexopoulos and Cohen (2009), Bloom (2009), Bachmann, Elstner, and Sims (2011), and Baker, Bloom, and Davis (2011). Existing studies focus on the effects of uncertainty on real economic activity such

[6] Our model does not completely nest the standard RBC model with a spot labor market. In the extreme case with $\kappa = 0$, the vacancy-posting decision problem is not well defined.

[7] In a recent study, Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez (2011) report that uncertainty shocks to fiscal policy can cause stagflation in a standard DSGE model with nominal rigidities but without search frictions. They argue that, facing higher levels of uncertainty in demand, firms have a precautionary motive to set a high relative price. Such an upward pricing bias is stronger the higher the degree of nominal rigidities. In our model, this mechanism is also at work. However, since we incorporate search frictions in the DSGE model, the negative aggregate demand effects of uncertainty shocks dominate. Thus, under our calibrated parameters, we find that inflation declines following an increase in the level of uncertainty. In principle, however, one could get a stagflationary effects of uncertainty shocks even in the presence of search frictions. For example, we find that an uncertainty shock leads to a rise in both inflation and unemployment if the price adjustment cost is sufficiently large (equivalent to more than 12 quarters of price-contract duration in the Calvo sense). That size of the price adjustment costs is not supported by empirical evidence (Bils and Klenow, 2004; Nakamura and Steinsson, 2008).

as employment, investment, and output. We focus on the joint effects of uncertainty on unemployment and inflation.

IV.1. **Measures of uncertainty.** We consider four alternative measures of uncertainty, including (1) a measure of perceived uncertainty by consumers from the Michigan Survey of Consumers, (2) a measure of perceived uncertainty by firms from the CBI Industrial Trends Survey in the United Kingdom, (3) the VIX index, which measures the implied volatility of the S&P 500 stock price index, and (4) a measure of economic policy uncertainty recently developed by Baker, Bloom, and Davis (2011).

While the VIX index and policy uncertainty are both standard, the two survey-based measures of uncertainty are new and deserve some explanation. We begin with the consumers' perceived uncertainty constructed from the Michigan Survey.

Each month since 1978, the Michigan Survey has been conducting interviews of about 500 households throughout the United States, asking questions ranging from their perceptions of business conditions to expectations for future movements in prices. More important for our analysis, the survey tallies the fraction of respondents who report that "uncertain future"is a factor that will likely limit their expenditures on durable goods (such as cars) over the next 12 months.[8]

Figure 8 shows the time-series plots of consumers' perceived uncertainty along with the VIX index. Similar to the VIX index, consumers' perceived uncertainty is countercyclical. It rises in recession and falls in expansions. A notable difference between the consumers' perceived uncertainty and financial uncertainty measured by the VIX is that the 1997 East-Asian financial crisis and the 1998 Russian debt crisis led to large spikes in the VIX, but did not seem to have much impact on consumer perceptions of uncertainty.

We follow a similar procedure to construct firms perceived uncertainty from the Confederation of British Industry (CBI) Industrial Trends Survey in the United Kingdom. Each quarter since 1978, the CBI has been surveying a large sample of roughly 1,100 firms in the United Kingdom in each quarter. We measure firms' perceived uncertainty as the fraction of firms that report "uncertainty about demand" as a factor limiting their capital expenditures over the next 12 months.[9]

[8]For instance, the question on vehicle purchases is, "Speaking now of the automobile market–do you think the next 12 months or so will be a good time or a bad time to buy a vehicle, such as a car, pickup, van or sport utility vehicle? Why do you say so?" Reasons related to uncertainty are then compiled. Note that the series is weighted by age, income, region, and sex to be nationally representative.

[9]The question asked by the CBI is, "What factors are likely to limit (wholly or partly) your capital expenditure authorisations over the next twelve months?" Participants can choose "uncertainty about demand" as one of six options. Firms can provide other reasons or choose multiple reasons.

As Figure 9 shows, firms' perceived uncertainty is also countercyclical, but it appears relatively more stable than what is reported by the Michigan survey of consumers. This difference may reflect the fact that U.K. firms are asked about a specific form of uncertainty (i.e., about the demand for their products), whereas no such specificity is attached to the measure of uncertainty in the Michigan survey.

IV.2. **Macroeconomic effects of uncertainty shocks: Estimated VAR.** We now examine the macroeconomic effects of uncertainty shocks by estimating a Baysian vector autoregression (BVAR) model with four variables. These variables include a measure of uncertainty, the unemployment rate, the inflation rate measured as the year-over-year change in the consumer price index (CPI), and the three-month Treasury bills rate. The sample ranges from January 1978 to February 2012.Sims and Zha (1998) argue that, if the number of variables included in the VAR model is relatively large, sampling errors can lead to difficulties in estimating error bands for the impulse responses, because the sample is typically short for macroeconomic time series data. They propose using Baysian priors (instead of flat priors) to help improve the estimation of error bands for impulse responses. We follow their approach in our analysis.

Since uncertainty typically rises in recessions and falls in booms, it is challenging to identify shocks to uncertainty. We consider two alternative identification strategies. First, we take advantage of the timing of the survey relative to the release dates of the macroeconomic time series and place the measure of uncertainty first in the Cholesky ordering of the variables in the VAR system (Leduc, Sill, and Stark, 2007; Auerbach and Gorodnichenko, 2012; Leduc and Sill, forthcoming). With this ordering, we implicit assume that uncertainty does not respond to macroeconomic shocks in the impact period, while unemployment, inflation, and the nominal interest rate are allowed to change on impact of an uncertainty shock.

This assumption seems reasonable given the timing of the surveys relative to the timing of macroeconomic data releases. For example, in the Michigan Survey, phone interviews are conducted throughout the month, with most interviews concentrated in the middle of each month, and preliminary results released shortly thereafter. The final results are typically released by the end of the month. When answering questions, survey participants have information about the previous month's unemployment, inflation, and interest rates, but they do have have (complete) information about the current-month macroeconomic conditions because the macroeconomic date have not yet been made public. Hence, our identification strategy uses the fact that when answering questions at time t about their expectations of the future, the information set on which survey participants condition their answers will not include, by construction, the time t realizations of the unemployment rate and the other variables in our VAR.

Similarly, the questionnaires for the CBI survey must be returned by the middle of the first month of each quarter. The design of the survey implies that participants have information about the values of the variables in the VAR for the previous quarter when they filled in the survey, but they do not know those values for the current quarter. We again take advantage of the survey timing to identify uncertainty shocks.

Second, to examine the robustness of our results, we estimate an alternative VAR model with the same four variables but with uncertainty ordered last. While the timing of the survey relative to macroeconomic data releases suggests that survey respondents do not possess complete information about the macroeconomic data in the current period, we cannot rule out that they observe other, possibly higher-frequency variables that give them information about the time t realizations of the variables in the VAR model. By ordering uncertainty last in the VAR model, we allow the measure of uncertainty to respond to contemporaneous macroeconomic shocks in the system. Despite this conservative assumption, we find that the estimated impulse responses of macroeconomic variables to uncertainty shocks are remarkably similar across the two very different identification strategies.

We first look at the transmission of uncertainty shocks in the Unites States using the measure of consumer uncertainty from the Michigan Survey. The sample we analyze goes from January 1978 to November 2011 to match the sample of available data on uncertainty from the Michigan Survey.

Figure 10 presents the impulse responses in the VAR model, in which consumer uncertainty is ordered first. For each variable, the solid line denotes the mean estimate of the impulse response and the dashed lines represent the range of the 90-percent confidence band around the point estimates. The figure shows that an unexpected increase in uncertainty leads to a persistent increase in the unemployment rate, which reaches a peak about 12 months after the shock and remains significantly positive for about three years. Heightened uncertainty also leads to a significant and persistent decline in inflation, with the peak effect also occurring roughly 12 months after the shock.

Figure 11 presents the impulse responses in the VAR model with consumer uncertainty (from the Michigan Survey) ordered last. The responses of the three macroeconomic variables to an uncertainty shock look remarkably similar to those in the baseline VAR with uncertainty ordered first. Under each identification strategy, a positive uncertainty shock acts like a negative aggregate demand shock that raises unemployment and lowers inflation. In response to the recessionary effects of uncertainty shocks, monetary policy reacts by easing the stance of policy and lowering the nominal interest rate.

The aggregate demand effect of uncertainty is not unique to the U.S. economy. It is also present in the U.K. data. Using the measure of firms' perceived uncertainty from the CBI Survey, we examine the effects of uncertainty shocks in a VAR model using UK data on unemployment, inflation, and the three-month nominal interest rate. Since the survey data are quarterly, we convert the unemployment rate, the inflation rate, and the 3-month nominal interest rate from monthly to quarterly frequency by taking the end of quarter observations (e.g., unemployment for the first quarter of 1980 is the unemployment rate in March 1980 and for the second quarter, it is that in June, and so on.). The sample ranges from 1979:Q4 to 2011:Q2. Considering our baseline identification strategy that orders uncertainty first, Figure 14 indicates that unemployment rises and inflation falls in the UK as well following an unanticipated increase in uncertainty. Similar to that in the United States, monetary authority in the United Kingdom reacts to the uncertainty shock by adopting a more accommodative policy, as reflected by the fall in the short-term interest rate.[10]

IV.3. **Robustness.** The finding that uncertainty shocks act like aggregate demand shocks is fairly robust. As we just demonstrated, it holds both for the United States and for the United Kingdom for two different measures of uncertainty that display relatively different time-series properties; and also for two different Cholesky identification restrictions. Moreover, it holds for the other two measures of uncertainty that we consider: the VIX index (Figure 12), and policy uncertainty (Figure 13).

When we expand the VAR model to include additional macroeconomic variables, uncertainty shocks continue to act like a decline in aggregate demand. First, we augment our four-variable VAR with the series on job vacancies constructed by Barnichon (2010), which combines data from JOLTS with the Help-Wanted Index published by the Conference Board. Figure 15 shows that, as predicted by our theoretical model, a rise in uncertainty leads to a decline in vacancies, while the unemployment rate rises and inflation falls. We also consider a 5-variable VAR that includes industrial production (in place of vacancy rates) as an additional control for economic activity. Figure 16 indicates that, in this case, a rise in uncertainty continues to affect the economy like a negative aggregate demand shock, as predicted by theory.

In addition, we have estimated the baseline four-variable VAR model with the sample ending at the end of 2008, before the policy rates in the United States and the United Kingdom hit the zero lower bound. We find that the qualitative results remain unchanged (not reported).[11]

[10]The results are qualitatively similar if we place uncertainty last in the VAR model for the Cholesky identification.

[11]We have also estimated other models that, in addition to the four variables in our baseline VAR model (with consumer uncertainty ordered first), also include (i) consumption of nondurables and services and business fixed investment; (ii) credit spread and stock price index; or (iii) full-time and part-time employment.

IV.4. **Uncertain future or bad economic times?** As shown in Figure 8, consumer uncertainty rises in recessions and falls in booms. A priori, one cannot rule out the possibility that consumer uncertainty from the Michigan survey may reflect the respondents' perceptions of "bad economic times" rather than "uncertain future." To examine to what extent consumer uncertainty might reflect their perceptions of bad economic times, we run two separate experiments.

In the first experiment, we replace the uncertainty measure in the benchmark 4-variable VAR model by the median expected change in income over the next 12 months, which is also taken from the Michigan survey. As can be seen from Figure 17, this variable is highly correlated with the business cycle, rising in good times and falling during economic downturns. We keep the Cholesky ordering of the variables the same as in our benchmark VAR model and we continue to focus on the three macroeconomic variables (unemployment, inflation, and interest rates). Figure 18 shows the impulse responses of the macroeconomic variables to a shock to the expected income measure. A shock to expected income does not appear to drive any significant changes in unemployment, inflation or the nominal interest rate. In contrast, as shown in Figure 10, a shock to our measure of consumer uncertainty leads to large and persistent increases in unemployment and large and persistent declines in inflation.

In the second experiment, we examine to what extent the macroeconomic effects of shocks to consumer uncertainty may reflect the responses to changes in other indicators of economic conditions, such as consumer confidence. For this purpose, we follow a similar approach in Baker, Bloom, and Davis (2011) and estimate a 5-variable VAR model that includes a consumer sentiment index from the University of Michigan survey of consumer sentiment as an additional variable (ordered second in the VAR, immediately after consumer uncertainty). Figure 19 shows the impulse responses of macroeconomic variables following a shock to consumer uncertainty in the 5-variable VAR model with the consumer sentiment index included as a second variable. The figure shows that the macroeconomic effects of uncertainty shocks are qualitatively similar to those estimated from the benchmark VAR. Following an exogenous increase in uncertainty, unemployment rises and inflation and nominal interest rates fall, with these macroeconomic responses statistically significant at the 90 percent level.[12] Thus,

In each case, uncertainty shocks consistently act like an aggregate demand shock that raises unemployment and lowers inflation and the nominal interest rate. Because our model abstracts from these dimension of the data, we do not report these results in the paper. The figures are available upon request.

[12]The consumer sentiment index that we use here is a measure of consumer sentiment about current economic conditions. We have also estimate a 5-variable VAR model by using the consumer sentiment index for expectations. The qualitative results are also very similar to those in the benchmark VAR model.

the macroeconomic effects of consumer uncertainty shocks do not seem to reflect responses of macroeconomic variables to changes in consumer confidence.

These findings suggest that consumers are not confusing an uncertain future with low levels of economic activity and that uncertainty shocks have direct impact on macroeconomic variables.

V. Conclusion

In this paper, we study the macroeconomic effects of uncertainty shocks and show that uncertainty shocks act like aggregate demand shocks both in theory and in the data. We present a DSGE model with search frictions and nominal rigidities. We show that the long-term nature of employment relationships in this framework significantly alters the transmission of uncertainty shocks compared to the standard RBC model or the New Keynesian models built on the RBC framework. When prices are flexible, uncertainty shocks have contractionary effects on potential output in our model. Since a job match represents a long-term employment relation, firms are reluctant to post new vacancies when the level of uncertainty rises. The reduction in vacancy postings lowers the job finding rate and raises the unemployment rate. Thus, unlike the standard RBC model that predicts an expansionary effect of uncertainty shocks on potential output, our model predicts a recessionary effect on potential output. The decline in potential output following uncertainty shocks is important since it implies that, ceteris paribus, uncertainty shocks could be inflationary in an environment with sticky prices to the extent that they lead to a fall in the output gap. However, in the presence of sticky prices in our model with search frictions, uncertainty shocks—regardless of their sources—always act like aggregate demand shocks that raise unemployment and lower inflation.

We have documented robust evidence that supports the theory's predictions. Our estimated VAR models show that an increase in the level of uncertainty leads to a rise in unemployment and declines in inflation and the nominal interest rate. This result is robust to alternative measures of uncertainty, alternative identification strategies, and alternative model specifications. Overall, both theory and evidence suggest that uncertainty shocks are aggregate demand shocks.

To highlight the aggregate demand effects of uncertainty shocks, we have focused on a stylized model that abstracts from some realistic and potentially important features of the actual economy. For example, the model does not have endogenous capital accumulation and is thus not designed to studying the effects of uncertainty shocks on business investment. To the extent that investment adjustments are costly, investors are likely to cut back investment expenditures when they face higher levels of uncertainty. Thus, incorporating endogenous capital accumulation in our model with search frictions may have important implications for the quantitative magnitude of the responses of potential and equilibrium output. However, in light of several recent studies in the literature (Basu and Bundick, 2011; Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez, 2011), incorporating capital accumulation is unlikely to change the qualitative transmission mechanism of uncertainty shocks that we have identified in this paper.

In our model, uncertainty shocks raise equilibrium unemployment by lowering the value of job matches, thus reducing job creation. Meanwhile, we have assumed that the job separation rate is exogenous. Therefore, the responses of equilibrium vacancy and unemployment represent a movement along the downward-sloping Beveridge curve. A more realistic model should incorporate endogenous job separation along the lines of den Haan, Ramey, and Watson (2000) and Walsh (2005), which is likely to further strengthen the aggregate demand effects of uncertainty shocks that we have studied in this paper. This should prove a fruitful avenue that we intend to pursue in future research.

Table 1. Parameter calibration

Parameter	Description	value
	Structural parameters	
β	Household's discount factor	0.99
χ	Scale of disutility of working	0.68
η	Elasticity of substitution between differentiated goods	10
α	Share parameter in matching function	0.50
μ	Matching efficiency	0.65
ρ	Job separation rate	0.10
ϕ	Flow value of unemployment	0.25
κ	Vacancy cost	0.14
b	Nash bargaining weight	0.5
γ	Real wage rigidity	0.9
Ω_p	Price adjustment cost	112
π	Steady-state inflation (or inflation target)	1.005
ϕ_π	Taylor-rule coefficient for inflation	1.5
ϕ_y	Taylor-rule coefficient for output	0.2
	Shock parameters	
γ_a	Average value of preference shock	1
Z	Average value of technology shock	1
g	Average ratio of government spending to output	0.2
ρ_k	Persistence of shock $k \in \{\gamma_a, z, \tau\}$	0.90
σ_k	Mean value of volatility of shock $k \in \{\gamma_a, z, g\}$	0.01
ρ_{σ_k}	Persistence of uncertainty shock σ_{kt}	0.90
σ_{σ_k}	Standard deviation of uncertainty shock σ_{kt}	1

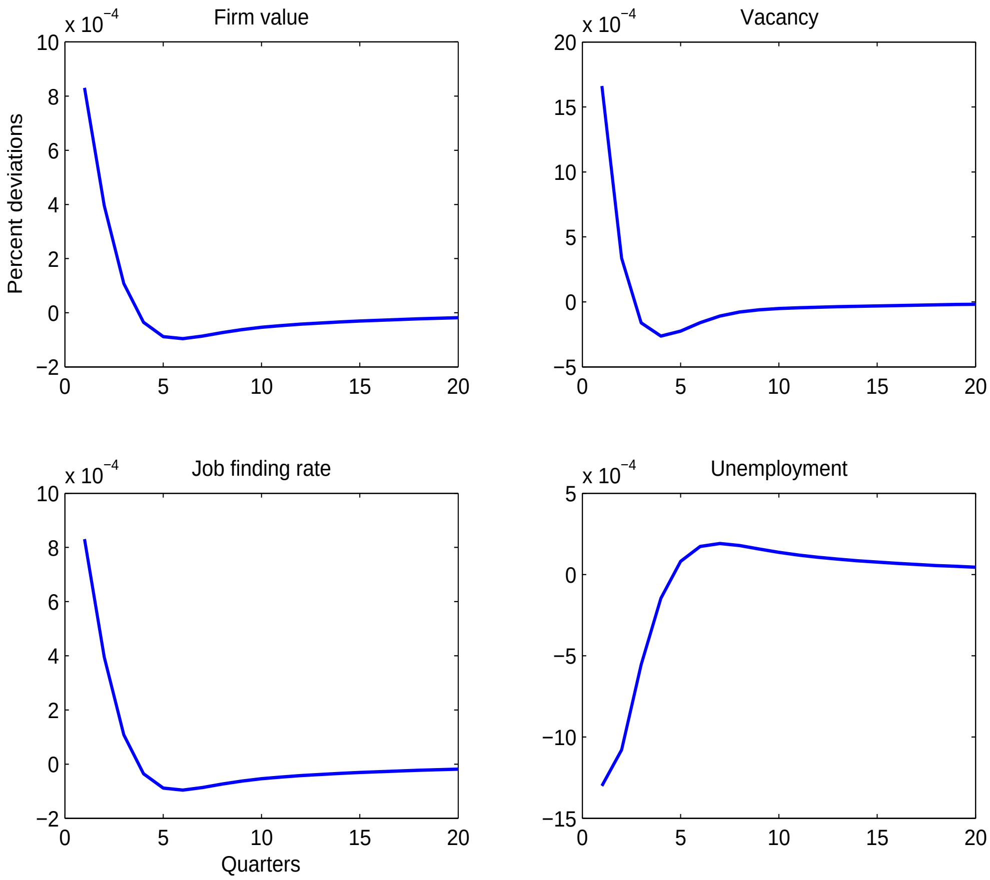

FIGURE 1. Impulse responses of macroeconomic variables to preference uncertainty shock in the DSGE model with flexible prices.

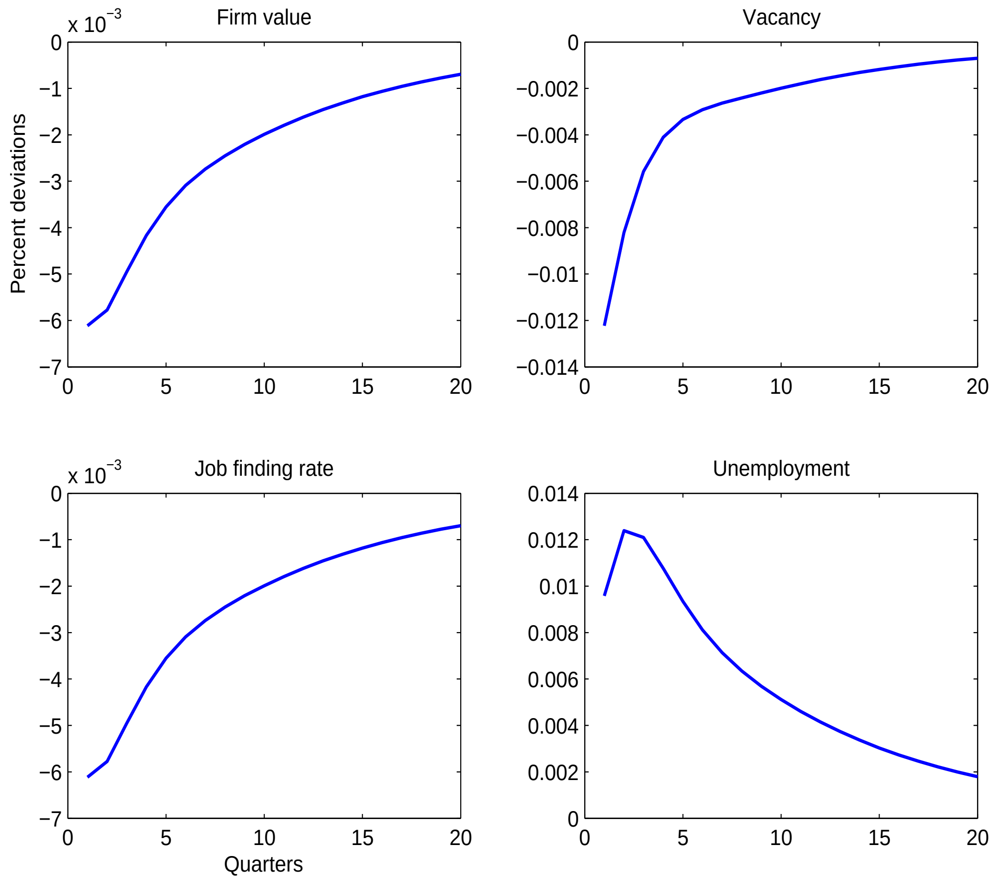

FIGURE 2. Impulse responses of macroeconomic variables to productivity uncertainty shock in the DSGE model with flexible prices.

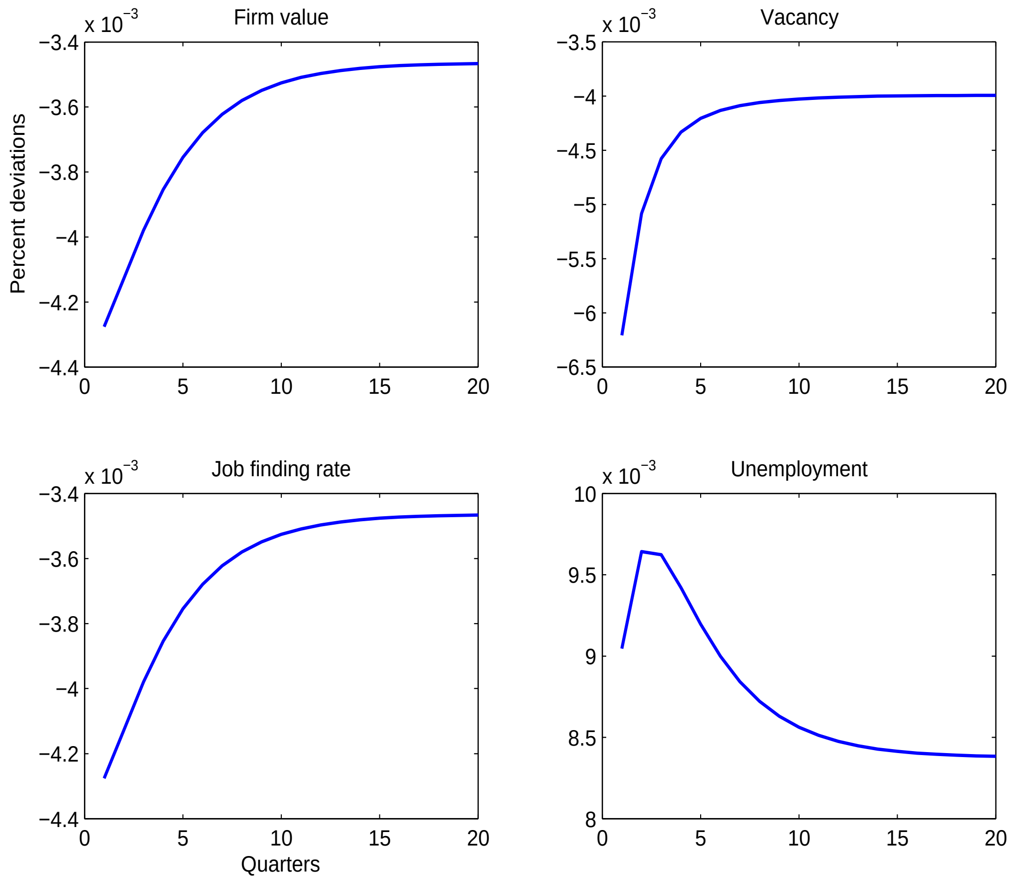

FIGURE 3. Impulse responses of macroeconomic variables to tax uncertainty shock in the DSGE model with flexible prices.

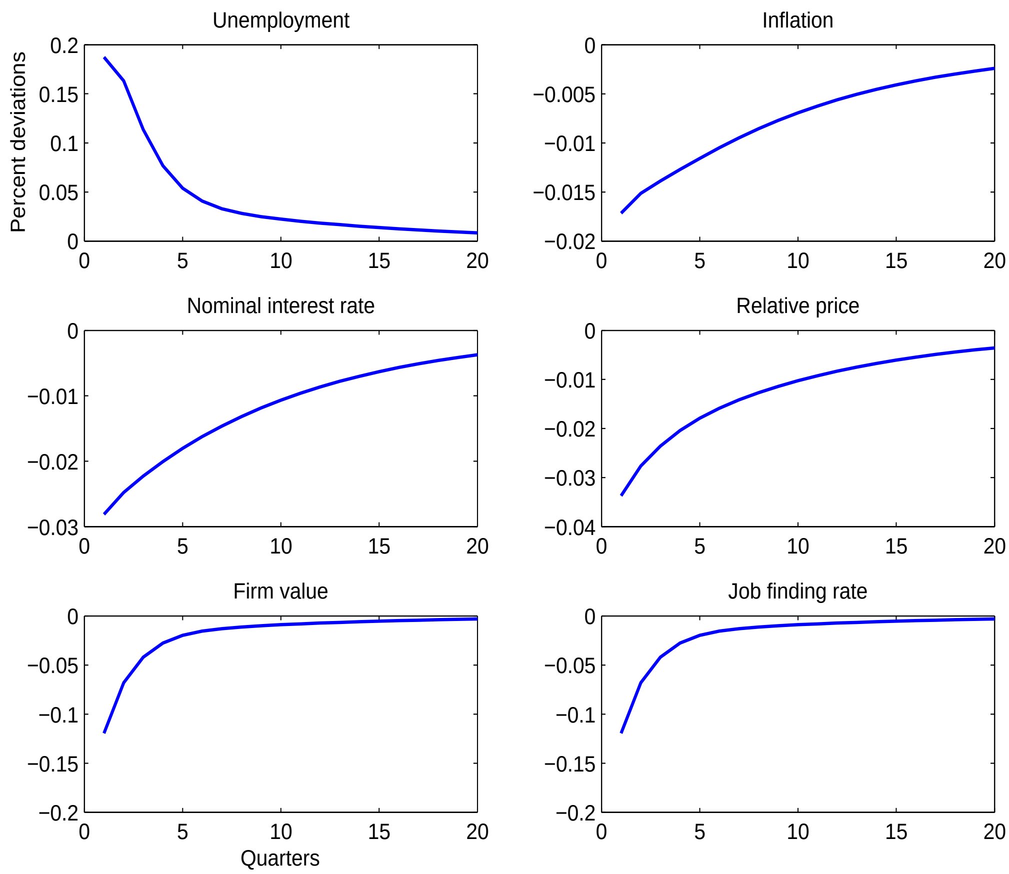

FIGURE 4. Impulse responses of macroeconomic variables to a preference uncertainty shock in the DSGE model with sticky prices.

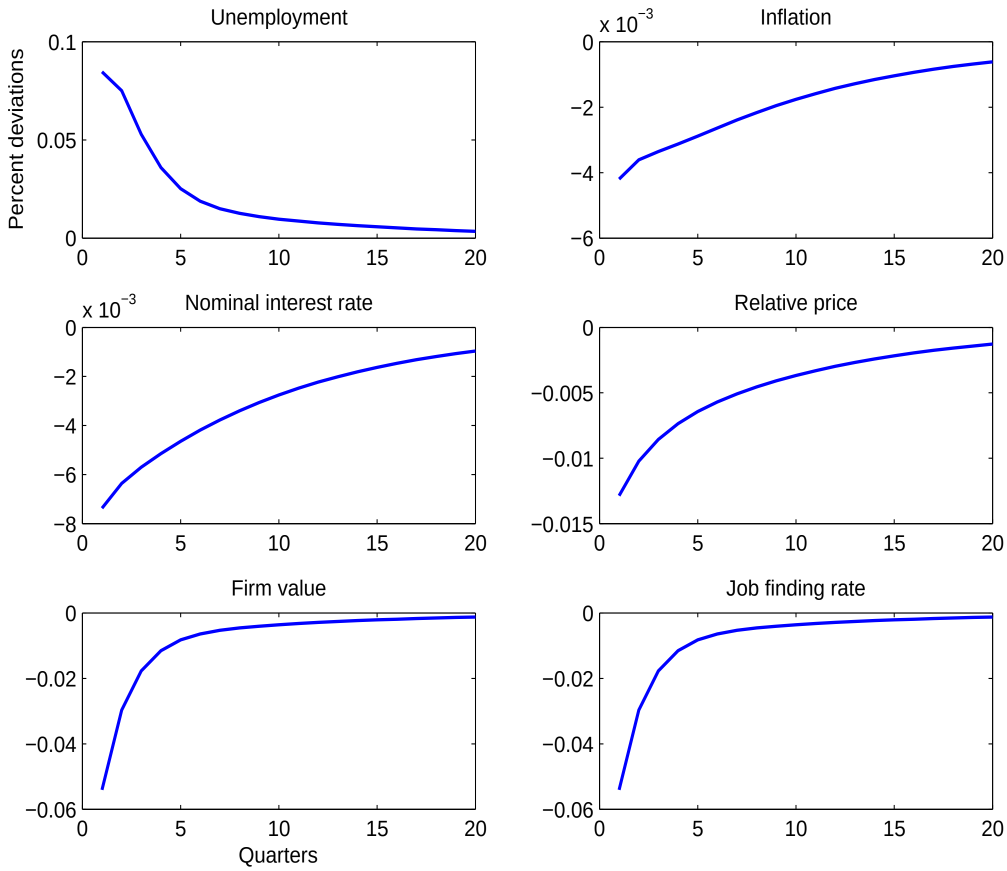

FIGURE 5. Impulse responses of macroeconomic variables to a technology uncertainty shock in the DSGE model with sticky prices.

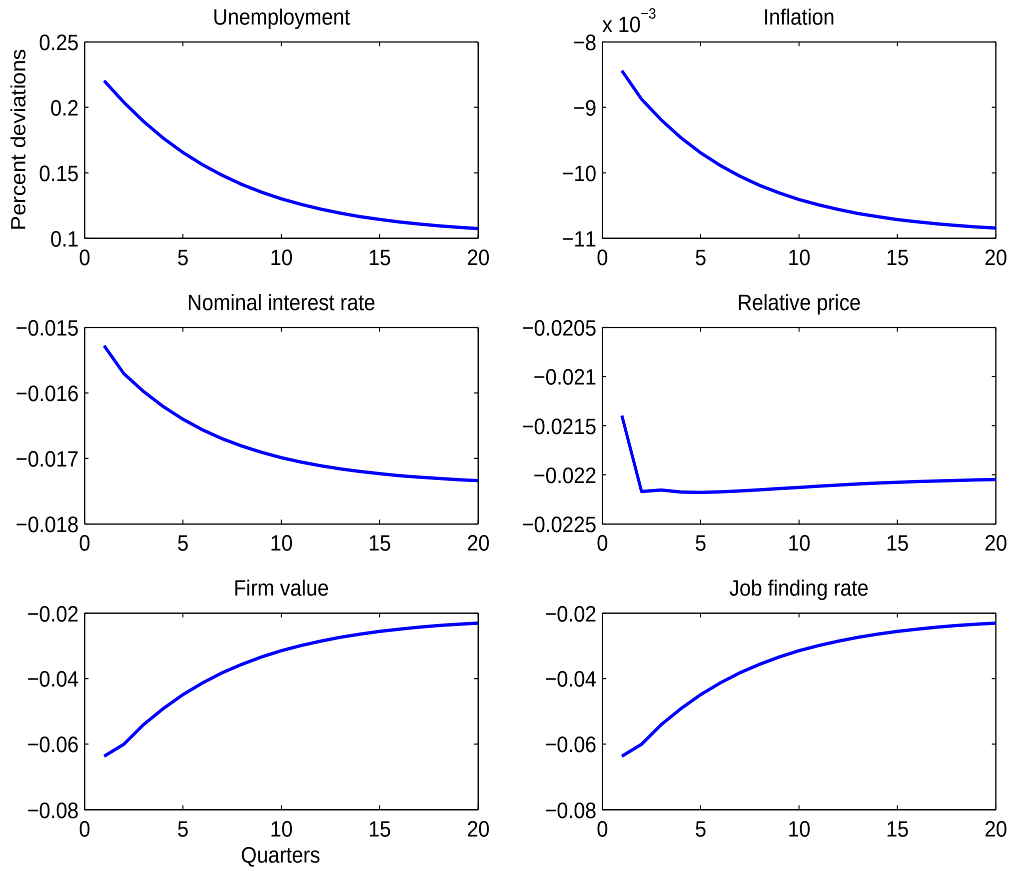

FIGURE 6. Impulse responses of macroeconomic variables to a tax uncertainty shock in the DSGE model with sticky prices.

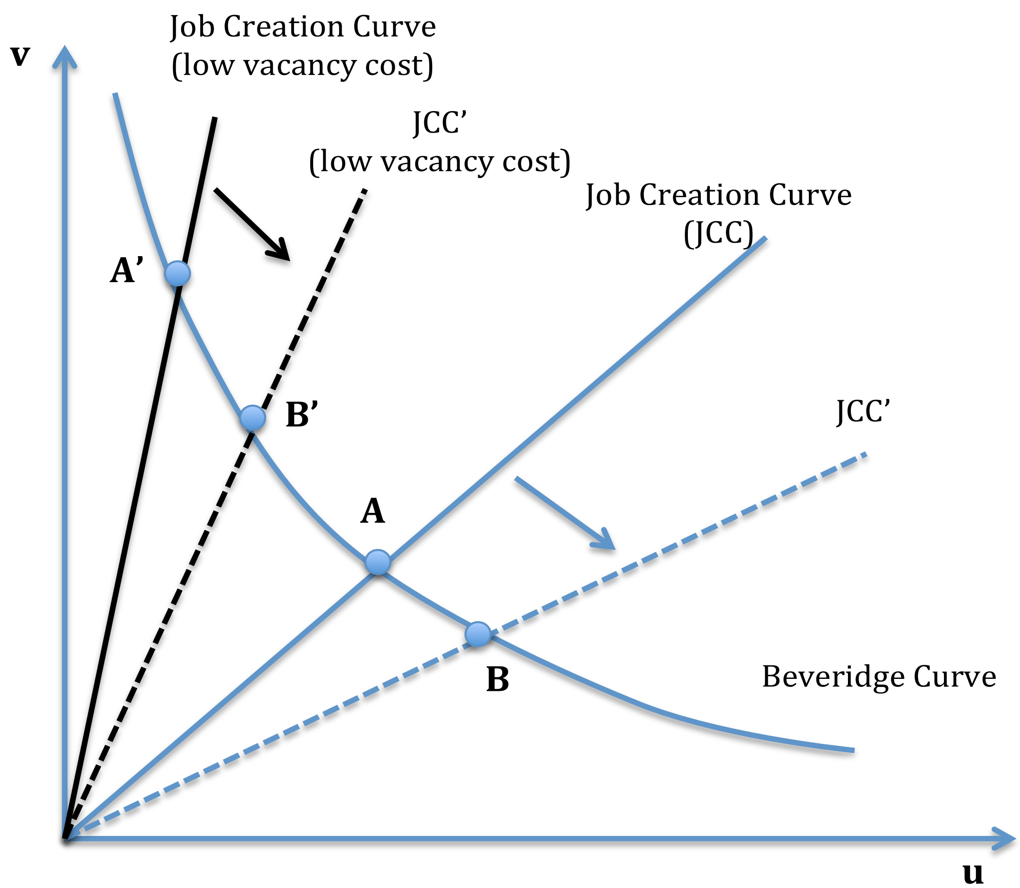

Figure 7. The amplification mechanism through labor market search frictions.

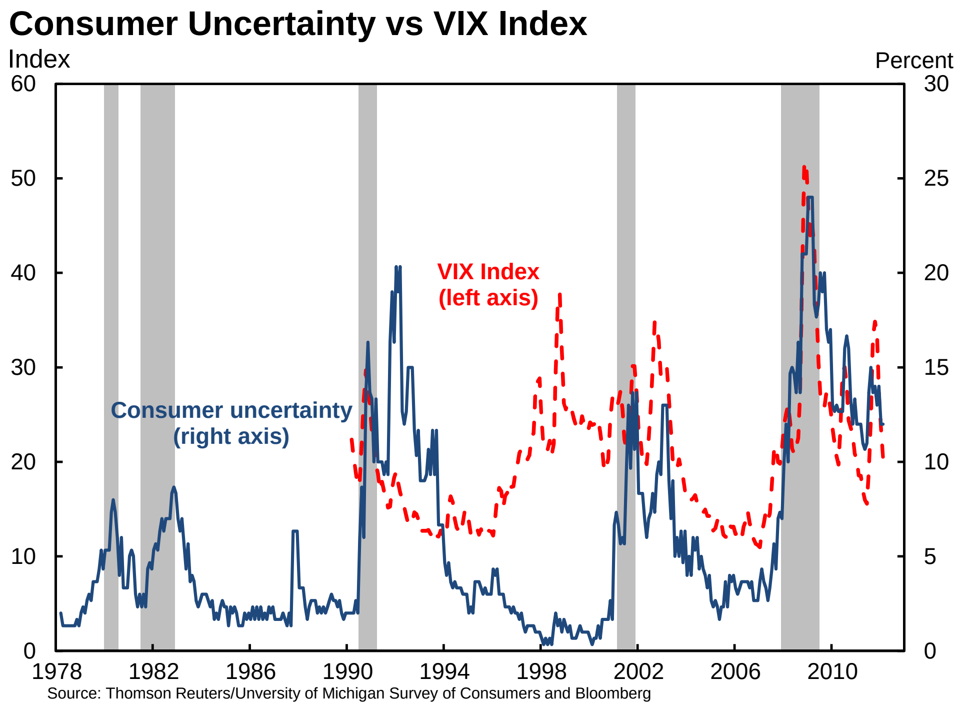

FIGURE 8. Consumers' perceived uncertainty from the Michigan Survey of Consumers in the United States versus the VIX index. The grey shaded areas indicate NBER recession dates in the United States. Data frequencies are monthly. Three-month moving averages are plotted.

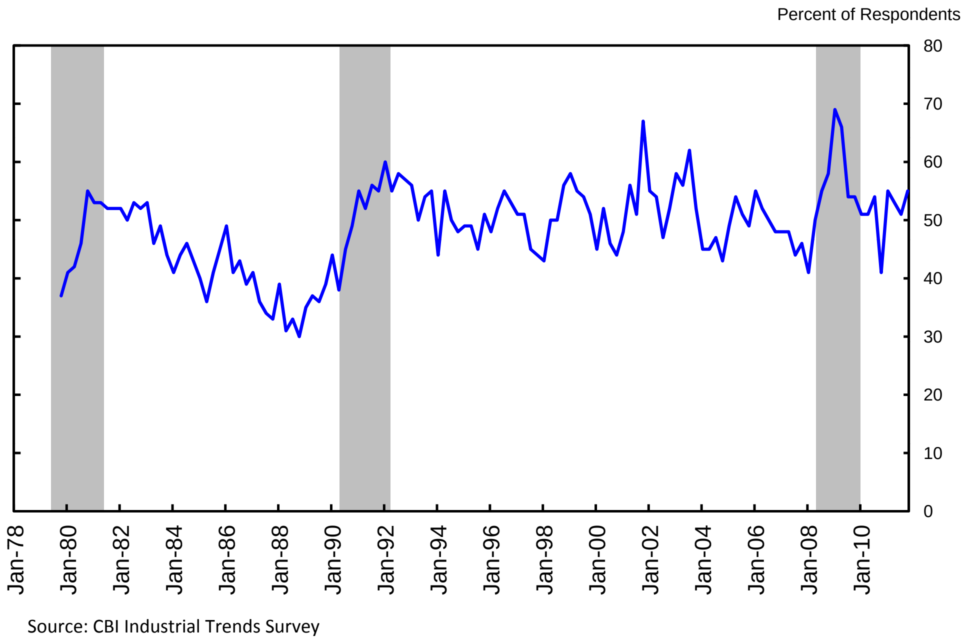

Figure 9. Firms' perceived uncertainty from the CBI Industrial Trends Survey in the United Kingdom. The grey shaded ares indicate recession dates in the United Kingdom. Data frequency is quarterly.

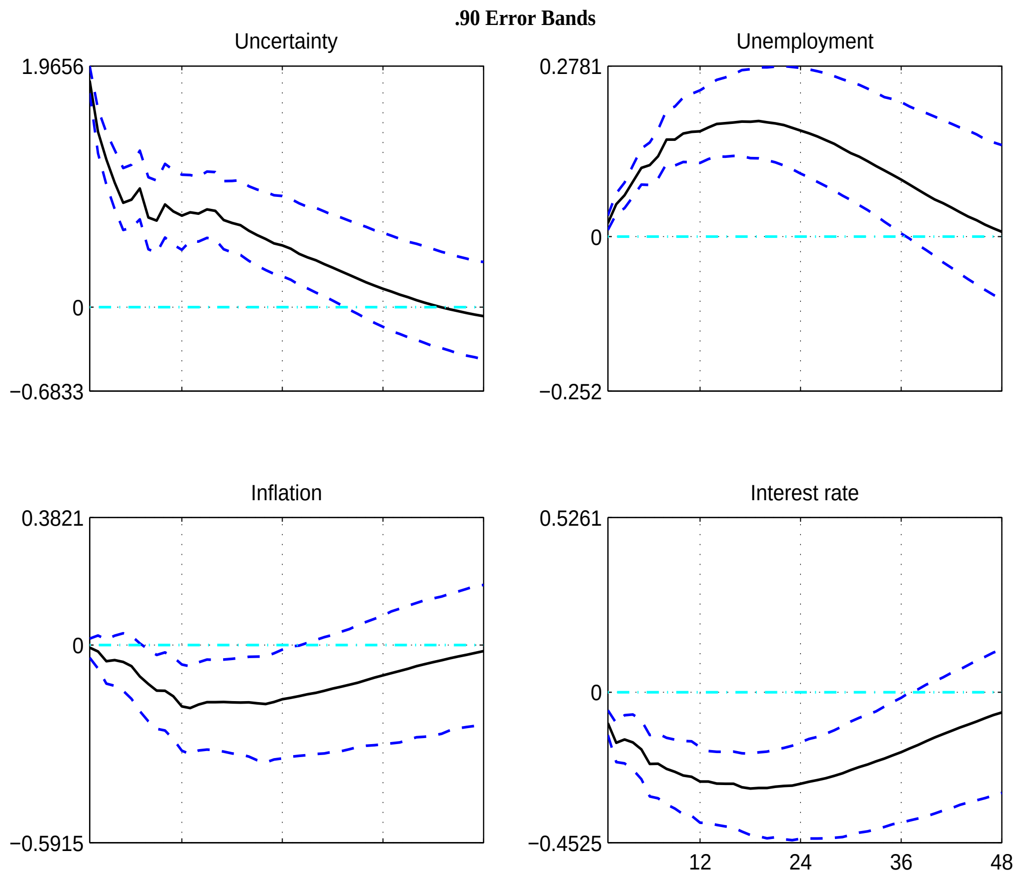

FIGURE 10. The effects of a one-standard deviation shock to perceived uncertainty in the Michigan Survey of Consumers: uncertainty measure ordered first. The solid lines represent median responses of the variables to a one-standard-deviation increase in the innovations to uncertainty. The dashed lines around each solid line represent the 90-percent confidence bands of the estimated median impulse responses.

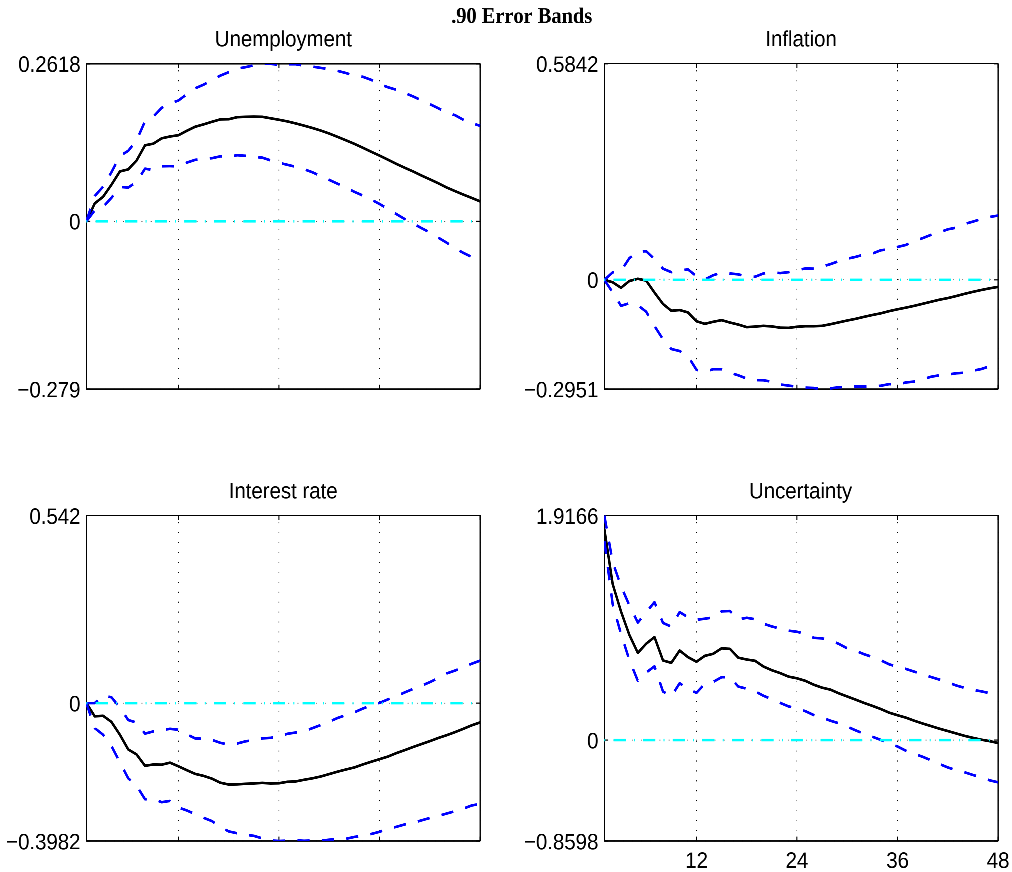

FIGURE 11. The effects of a one-standard deviation shock to perceived uncertainty in the Michigan Survey of Consumers: uncertainty measure ordered last. The solid lines represent median responses of the variables to a one-standard-deviation increase in the innovations to uncertainty. The dashed lines around each solid line represent the 90-percent confidence bands of the estimated median impulse responses.

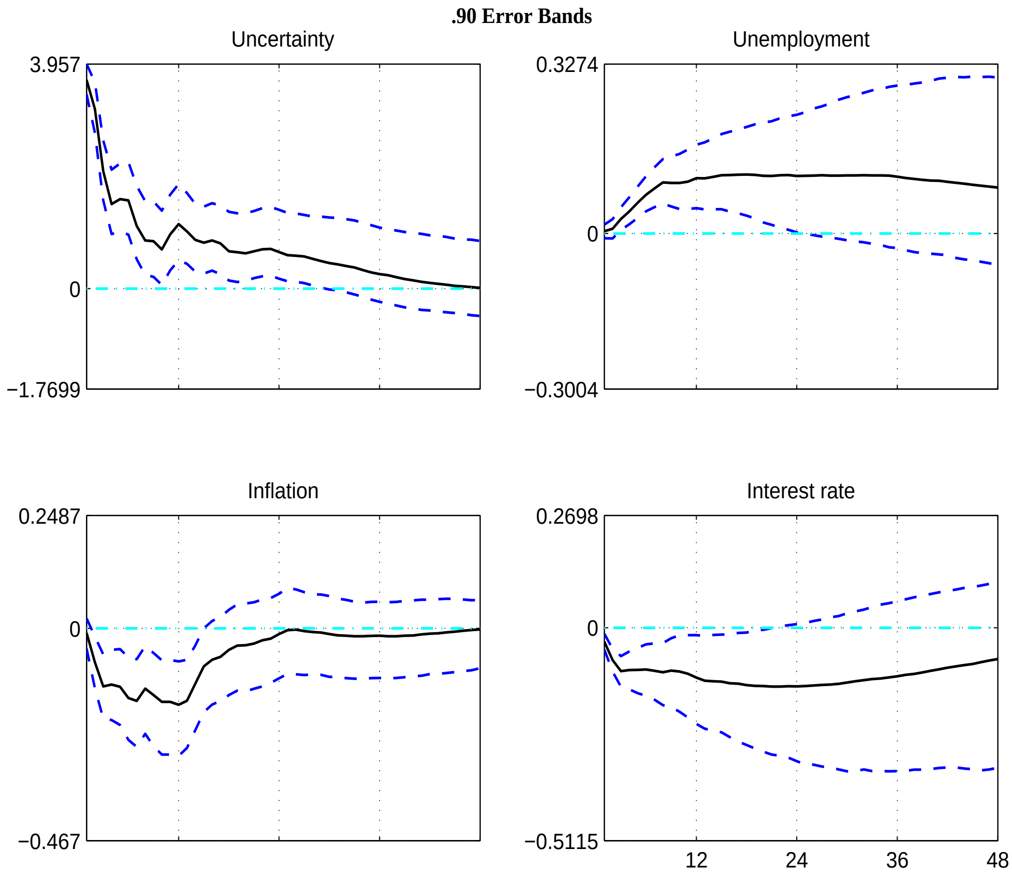

FIGURE 12. The effects of a one-standard deviation shock to the VIX index. The solid lines represent median responses of the variables to a one-standard-deviation increase in the innovations to uncertainty. The dashed lines around each solid line represent the 90-percent confidence bands of the estimated median impulse responses.

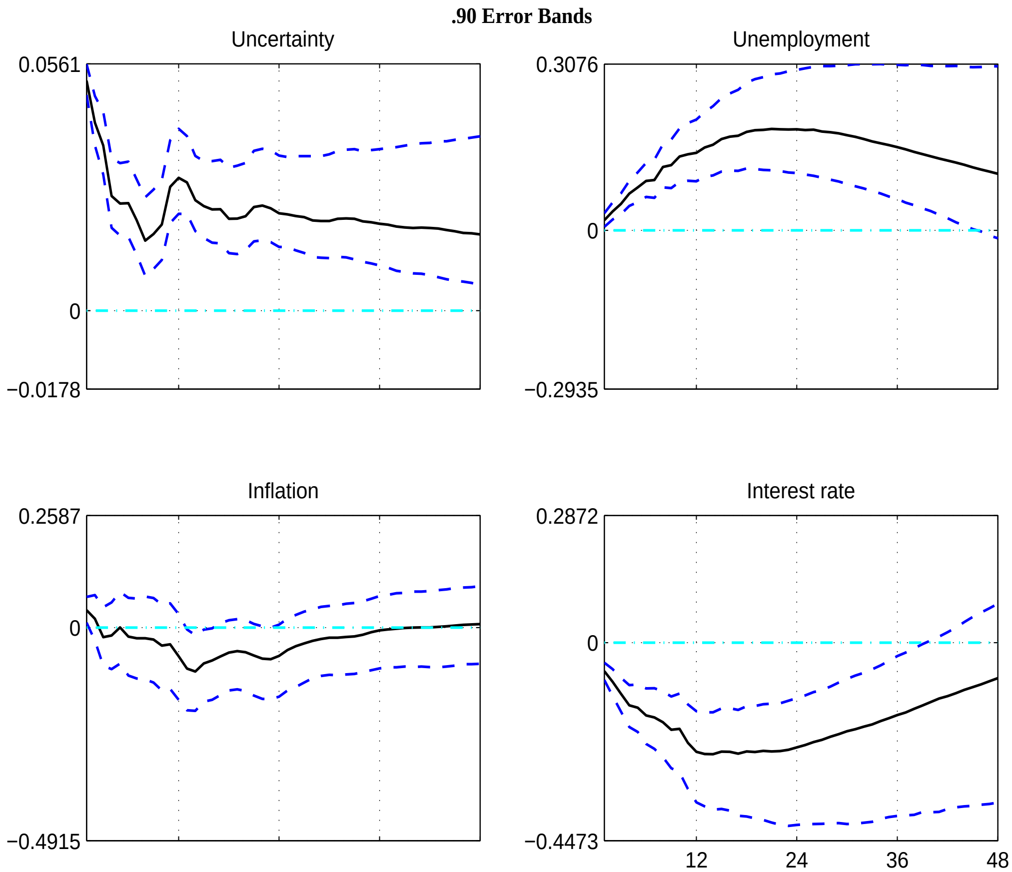

FIGURE 13. The effects of a one-standard deviation shock to policy uncertainty. The solid lines represent median responses of the variables to a one-standard-deviation increase in the innovations to uncertainty. The dashed lines around each solid line represent the 90-percent confidence bands of the estimated median impulse responses.

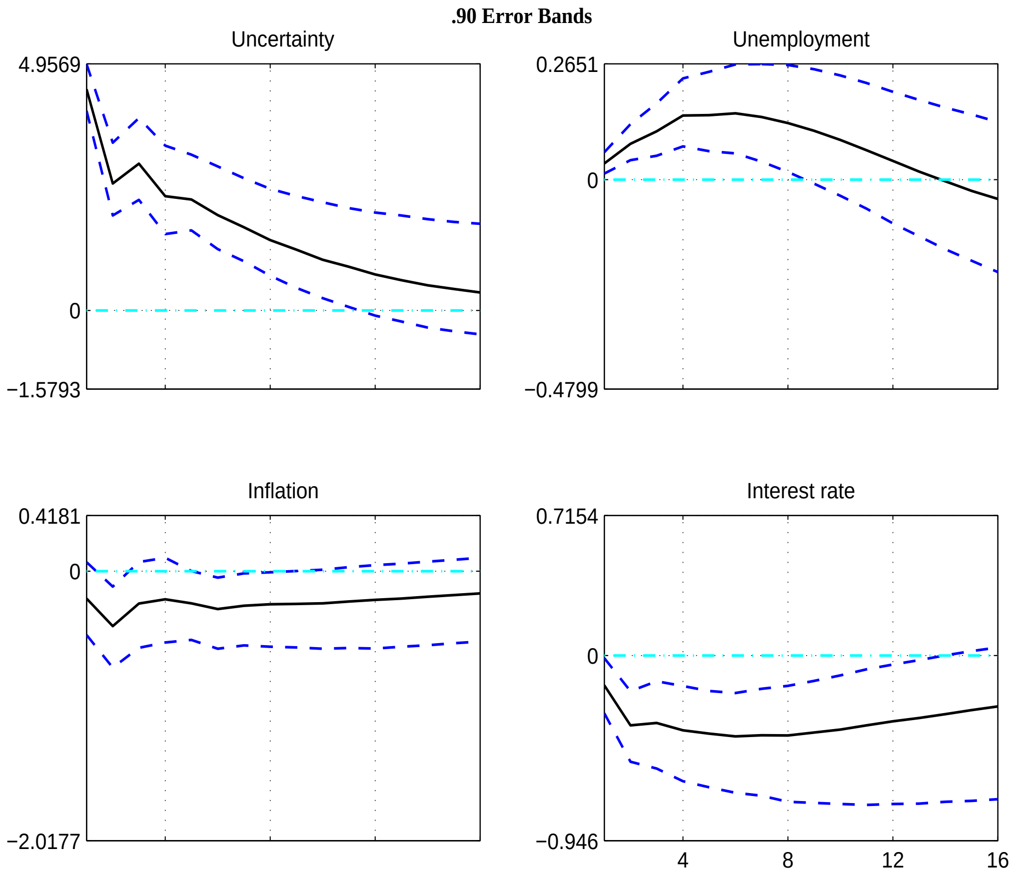

FIGURE 14. The effects of a one-standard deviation shock to perceived uncertainty in the CBI Industrial Trends Survey in the United Kingdom. The solid lines represent median responses of the variables to a one-standard-deviation increase in the innovations to uncertainty. The dashed lines around each solid line represent the 90-percent confidence bands of the estimated median impulse responses.

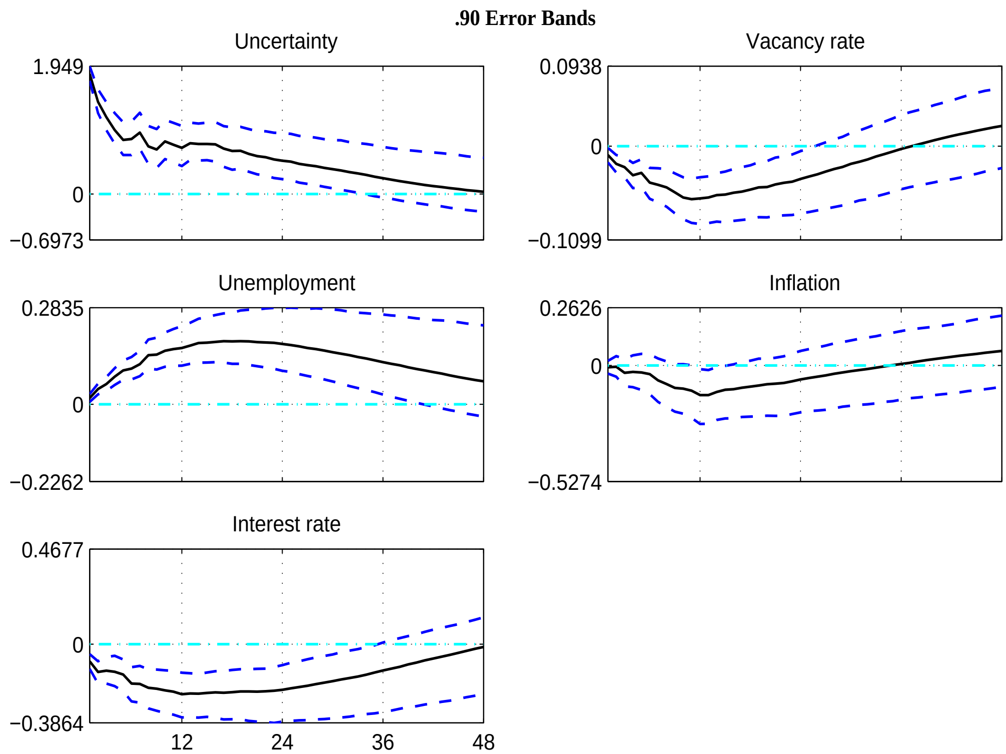

FIGURE 15. The effects of a one-standard deviation shock to perceived uncertainty in the Michigan Survey of Consumers in the VAR model augmented with job vacancy rates. The solid lines represent median responses of the variables to a one-standard-deviation increase in the innovations to uncertainty. The dashed lines around each solid line represent the 90-percent confidence bands of the estimated median impulse responses.

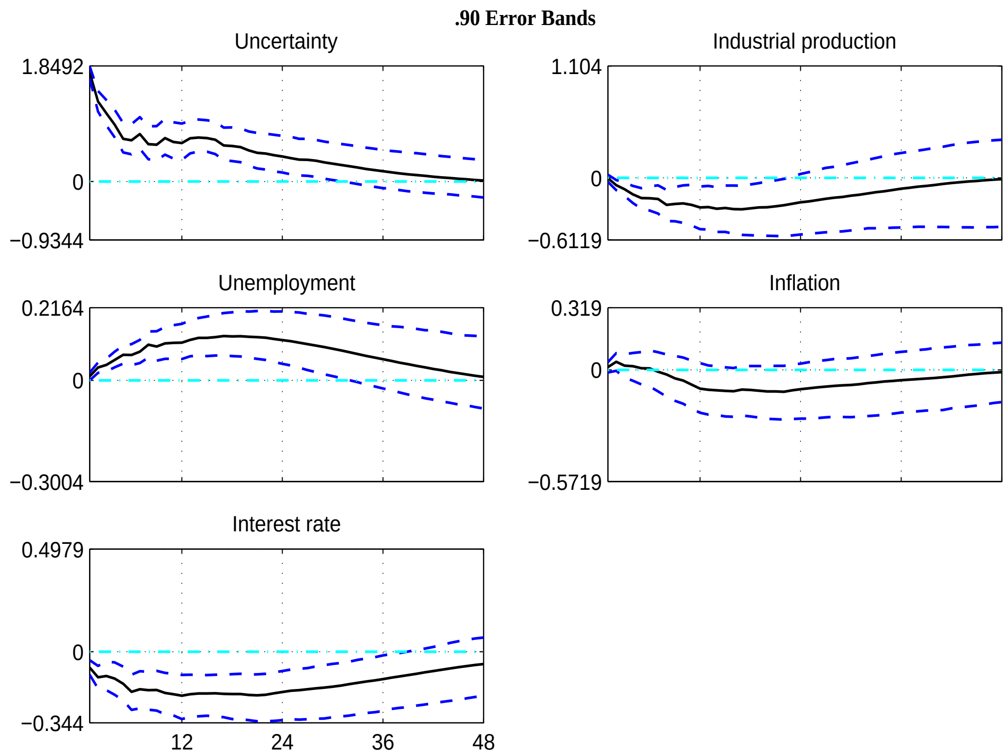

FIGURE 16. The effects of a one-standard deviation shock to perceived uncertainty in the Michigan Survey of Consumers in the VAR model augmented with industrial production. The solid lines represent median responses of the variables to a one-standard-deviation increase in the innovations to uncertainty. The dashed lines around each solid line represent the 90-percent confidence bands of the estimated median impulse responses.

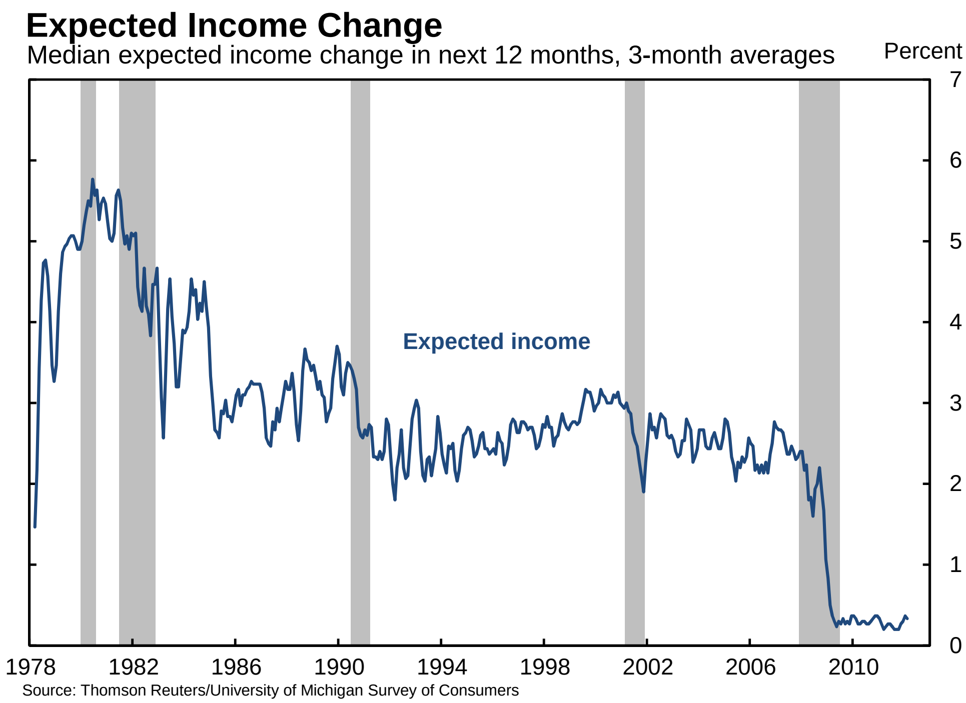

FIGURE 17. Expected income change in the next 12 months from the Thomson Reuters/University of Michigan Survey of Consumers. The grey shaded areas indicate NBER recession dates in the United States. Data frequencies are monthly. Three-month moving averages are plotted.

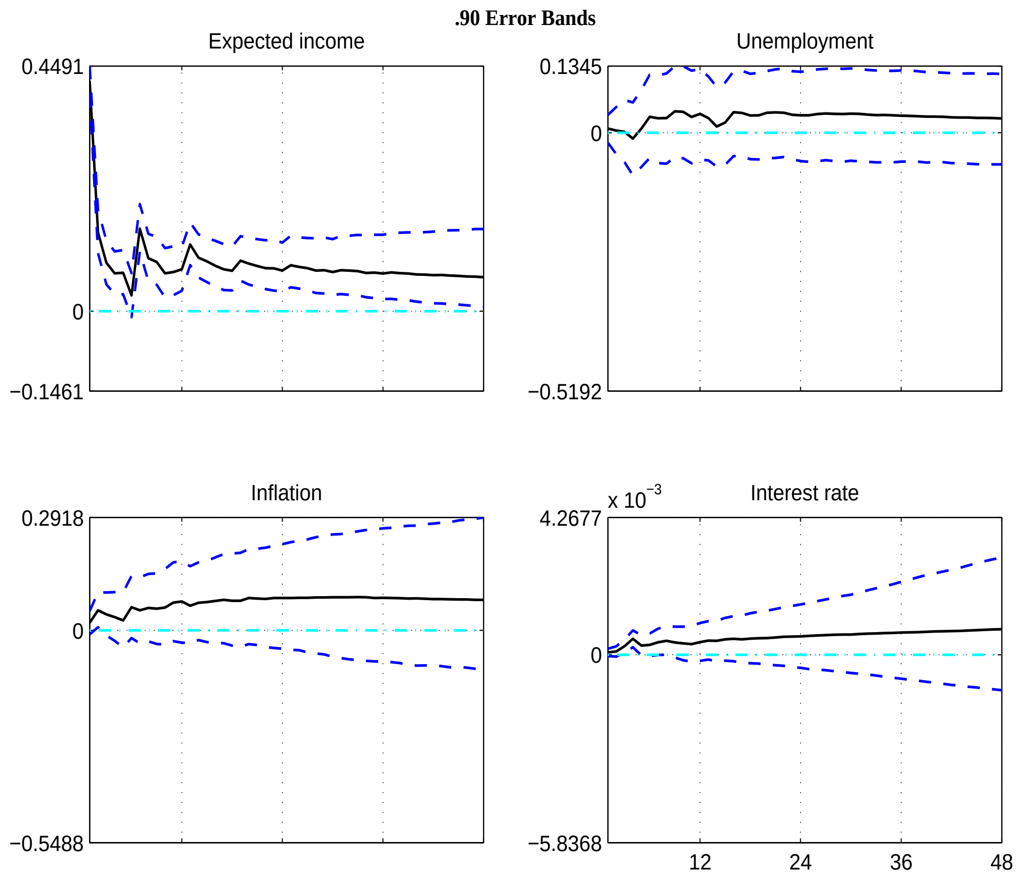

FIGURE 18. The effects of a one-standard deviation shock to median changes in expected income in the Michigan Survey of Consumers. The solid lines represent median responses of the variables to a one-standard-deviation increase in the innovations to median income change. The dashed lines around each solid line represent the 90-percent confidence bands of the estimated median impulse responses.

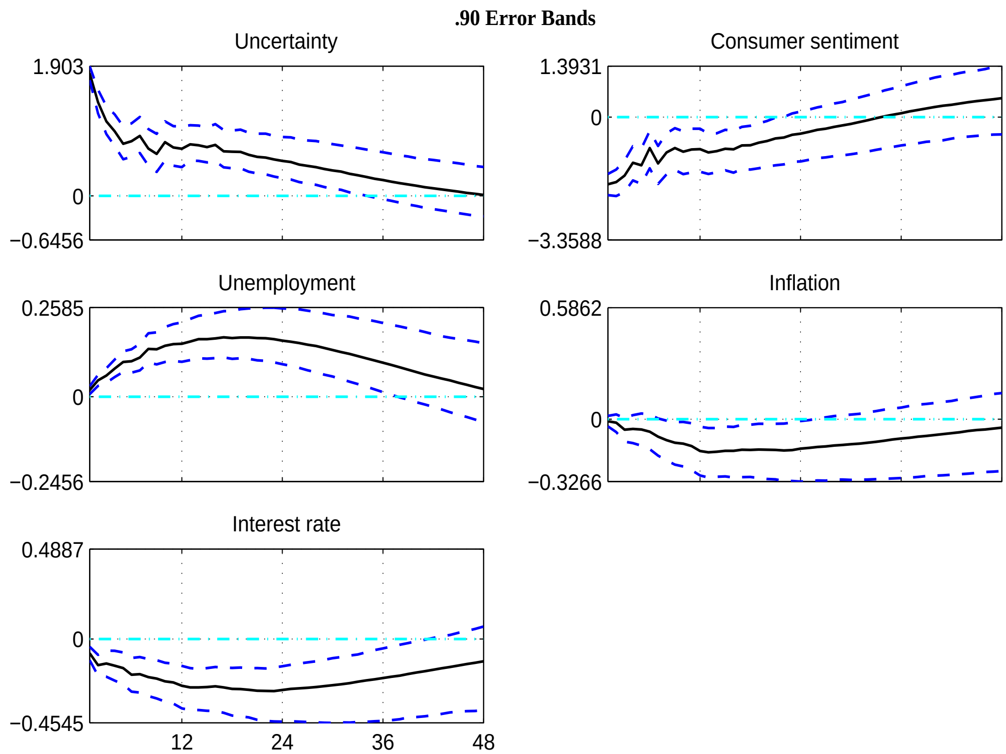

FIGURE 19. The effects of a one-standard deviation shock to consumers' perceived uncertainty from the Michigan Survey in the VAR model augmented with the consumer sentiment index (current conditions). Data frequencies are monthly, from January 1978 to March 2011. The solid lines represent median responses of the variables to a one-standard-deviation increase in the innovations to uncertainty. The dashed lines around each solid line represent the 90-percent confidence bands of the estimated median impulse responses.

References

Alexopoulos, M., and J. Cohen (2009): "Uncertain Times, Uncertain Measures," University of Toronto Department of Economics Working Paper 352.

Arellano, C., Y. Bai, and P. Kehoe (2011): "Financial Markets and Fluctuations in Uncertainty," Federal Reserve Bank of Minneapolis Research Department Staff Report.

Auerbach, A. J., and Y. Gorodnichenko (2012): "Measuring the Output Responses to Fiscal Policy," *American Economic Journal: Economic Policy*, 4, 1–27.

Bachmann, R., S. Elstner, and E. Sims (2011): "Uncertainty and Economic Activity: Evidence from Business Survey Data," University of Michigan Working Paper.

Baker, S. R., N. Bloom, and S. J. Davis (2011): "Measuring Economic Policy Uncertainty," Stanford University Working Paper.

Barnichon, R. (2010): "Building a Composite Help-Wanted Index," *Economic Letters*, 109(3), 175–178.

Basu, S., and B. Bundick (2011): "Uncertainty Shocks in a Model of Effective Demand," Boston College Working Paper.

Basu, S., and J. G. Fernald (1997): "Returns to Scale in U.S. Production: Estimates and Implications," *Journal of Political Economy*, 105(2), 249–283.

Bernanke, B. S. (1983): "Irreversibility, Uncertainty, and Cyclical Investment," *Quarterly Journal of Economics*, 98(1), 85–106.

Bernanke, B. S., M. Gertler, and S. Gilchrist (1999): "The Financial Accelerator in a Quantitative Business Cycle Framework," in *The Handbook of Macroeconomics*, ed. by J. B. Taylor, and M. Woodford, pp. 1341–1393. Elsevier Science B.V., Amsterdam, North Holland.

Bils, M., and P. J. Klenow (2004): "Some Evidence on the Importance of Sticky Prices," *Journal of Political Economy*, 112, 947–985.

Blanchard, O. J., and J. Galí (2010): "Labor Markets and Monetary Policy: A New Keynesian Model with Unemployment," *American Economic Journal: Macroeconomics*, 2, 1–30.

Bloom, N. (2009): "The Impact of Uncertainty Shocks," *Econometrica*, 77(3), 623–685.

Bloom, N., and J. Fernandez-Villaverde (2012): "The Macroeconomics of Uncertainty and Volatility," Unpublished working paper, Stanford University and University of Pennsylvania.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry (2012): "Really Uncertain Business Cycles," NBER Working Paper18245.

Christiano, L., R. Motto, and M. Rostagno (2012): "Risk Shocks," Unpublished manuscript, Northwestern University.

den Haan, W. J., G. Ramey, and J. Watson (2000): "Job Destruction and Propagation of Shocks," *American Economic Review*, 90, 482–498.

Diamond, P. A. (1982): "Aggregate Demand Management in Search Equilibrium," *Journal of Political Economy*, 90(5), 881–894.

Fernández-Villaverde, J., P. Guerrón-Quintana, K. Kuester, and J. Rubio-Ramírez (2011): "Fiscal Volatility Shocks and Economic Activity," University of Pennsylvania Working Paper.

Gertler, M., and A. Trigari (2009): "Unemployment Fluctuations with Staggered Nash Wage Bargaining," *Journal of Political Economy*, 117(1), 38–86.

Gilchrist, S., J. W. Sim, and E. Zakrajsek (2010): "Uncertainty, Financial Frictions, and Investment Dynamics," Boston University Working Paper.

Gilchrist, S., and J. C. Williams (2005): "Investment, Capacity, and Uncertainty: A Putty-Clay Approach," *Review of Economic Dynamics*, 8, 1–27.

Guiso, L., and G. Parigi (1999): "Investment and Demand Uncertainty," *Quarterly Journal of Economics*, 114, 185–227.

Hall, R. E. (2005a): "Employment Fluctuations with Equilibrium Wage Stickiness," *American Economic Review*, 95, 50–65.

——— (2005b): "Employment Fluctuations with Equilibrium Wage Stickiness," *American Economic Review*, 95(1), 50–65.

Hall, R. E., and P. R. Milgrom (2008): "The Limited Influence of Unemployment on the Wage Bargain," *American Economic Review*, 98,(4), 1653–1674.

Leahy, J. V., and T. M. Whited (1996): "The Effect of Uncertainty on Investment: Some Stylized Facts," *Journal of Money, Credit and Banking*, 28(1), 64–83.

Leduc, S., and K. Sill (forthcoming): "Expectations and Economic Fluctuations: An Analysis Using Survey Data," *Review of Economics and Statistics*.

Leduc, S., K. Sill, and T. Stark (2007): "Self-Fulfilling Expectations and the Inflation of the 1970s: Evidence from the Livingston Survey," *Journal of Monetary Economics*, 54(2), 433–459.

Mortensen, D. T., and C. A. Pissarides (1994): "Job Creation and Job Destruction in the Theory of Unemployment," *Review of Economic Studies*, 61(3), 397–415.

Nakamura, E., and J. Steinsson (2008): "Five Facts About Prices: A Reevaluation of Menu Cost Models," *Quarterly Journal of Economics*, 123(4), 1415–1464.

Romer, C. D. (1990): "The Great Crash and the Onset of teh Great Depression," *Quarterly Journal of Economics*, 105(3), 597–624.

Rotemberg, J. J. (1982): "Sticky Prices in the United States," *Journal of Political Economy*, 90(6), 1187–1211.

Schaal, E. (2012): "Uncertainty, Productivity and Unemployment in the Great Recession," Unpublished manuscript, Federal Reserve Bank of Minneapolis.

Sims, C. A., and T. Zha (1998): "Bayesian Methods for Dynamic Multivariate Models," *International Economic Review*, 39(4), 949–968.

Walsh, C. E. (2005): "Labor Market Search, Sticky Prices, and Interest Rate Policies," *Review of Economic Dynamics*, 8, 829–849.

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