European University Institute

DEPARTMENT OF ECONOMICS

Uncertainty and the Macroeconomy

Dario Bonciani

Thesis submitted for assessment with a view to obtaining the degree of Doctor of Economics of the European University Institute

Florence, 01 June 2018

European University Institute
Department of Economics

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Statement of inclusion of previous work (if applicable):

I confirm that chapter 1 was the result of previous study I undertook at the Kiel Institute for the World Economy and was jointly co-authored with Björn Van Roye. I contributed 50% of the work. The chapter draws upon an earlier article "Uncertainty shocks, banking frictions and economic activity" I published in 2016 in the Journal of Economic Dynamics and Control

Signature and Date:

Dario Bonciani
21/05/2018

"It's tough to make predictions, especially about the future."

Yogi Berra

EUROPEAN UNIVERSITY INSTITUTE

Abstract

Department of Economics

Doctor of Philosophy

Uncertainty and the Macroeconomy

by Dario BONCIANI

In this thesis, I study from various angles how uncertainty affects macroeconomic activity.

Chapter 1 investigates the effects of uncertainty shocks on economic activity in the euro area by means of a Dynamic Stochastic General Equilibrium (DSGE) model with heterogenous agents and a stylized banking sector. We show that frictions in credit supply amplify the effects of uncertainty shocks on economic activity. This amplification channel stems mainly from the stickiness in bank loan rates. This stickiness reduces the effectiveness in the transmission mechanism of monetary policy.

In chapter 2, I provide empirical evidence that uncertainty shocks have strong asymmetric effects on economic activity depending on the phase of the business cycle. In particular, the impulse responses estimated with the local projection method on a smooth-transition model show that in recessions uncertainty shocks strongly dampen economic activity. In an expansion, the effects are reversed, and uncertainty shocks have positive macroeconomic effects. One possible explanation is that during expansions uncertainty fosters investments and economic activity through the "growth options" channel, while in recessions it reduces investments via the "wait-and-see" channel.

In chapter 3, I show that shocks to macroeconomic uncertainty negatively affect economic activity both in the short- and in the long-run. In a New Keynesian model with endogenous-growth through investment in R&D, volatility shocks have negative effects in the short-term because of precautionary savings, lower propensity to undertake risky investments and rising markups, and in the long-run because of the fall in R&D investment. The presence of long-run fluctuations in consumption makes agents more risk-averse, which strongly amplifies the effects of uncertainty shocks.

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I also would like to thank my friends Vinzenz and Tim who made my years in Florence extremely pleasant and helped me get through the difficult times of my PhD. Thanks also to Piero, Andrea, Matthijs, Patrick, Richard, Irene and Valentino for their friendship and allowing me to break free from thinking about research from time to time. Thanks to my friends and co-authors Andrea and Martino for the good times at the ECB. I am also indebted to my co-author Björn for his contribution to my first chapter and for his positive attitude, which helped in getting our work published.

Last and most importantly, I would like to thank my parents, Adolfo and Andrea, and my girlfriend, Catalina. Without them, their love, endless support and patience, I honestly would have never managed to get through the ups and downs of my PhD.

Contents

List of Figures

List of Tables

To my wonderful family

Chapter 1

Uncertainty shocks, Banking Frictions and Economic Activity

(joint with Björn Van Roye)

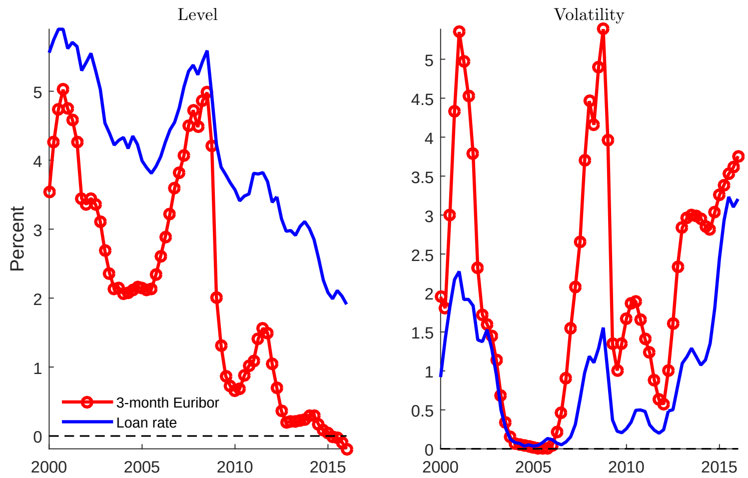
Keywords: Uncertainty Shocks, Financial frictions, Stochastic Volatility, Perturbation Methods, Third-order approximation.
JEL classification: E32, E52.

1.1 Introduction

The macroeconomic effects of uncertainty on economic activity is a prevalent topic in both economic policy and academic research. Policymakers and economists have repeatedly claimed that high macroeconomic uncertainty among investors hinders economic recovery. While there has been a rapidly growing literature on the macroeconomic effects of uncertainty shocks, led by the seminal paper by Bloom (2009), there has been relatively little research on the effects of uncertainty shocks under financial frictions. In particular, the existing literature has not yet explained the relationship between uncertainty shocks and frictional banking markets. This paper tries to fill this gap by investigating the effects of uncertainty shocks when banks operate in monopolistic competition and there is an imperfect pass-through of the central bank's policy rate to the loan rate. The importance of monopolistic competition in the banking sector has been extensively documented in the microeconomic literature (see for instance Degryse and Ongena, 2007). In addition, there is vast empirical evidence on the imperfect pass-through of the monetary policy rate to the retail loan rates (see for instance: Kobayashi, 2008; Gerali et al., 2010; Paries et al., 2011; Gambacorta and Signoretti, 2014). In fact, the loan rates to non-financial corporations in the euro area exhibit a much more persistent behaviour than the short-term money market rates (Figure 1.1).

The relationship between macroeconomic uncertainty shocks and economic activity

Figure 1.1: *Level and volatility of 5-year loan rate and 3-month Euribor*



NOTES: Interest rate volatilities are estimated using a GARCH(1,1) model.

is widely analyzed in academic research. Economic theory provides a comprehensive framework in which higher uncertainty affects economic activity through irreversible investments, convex marginal revenues and precautionary savings (Leland, 1968; Hartman, 1976; Bernanke, 1983; Abel, 1983; Kimball, 1990). While almost all academic research papers find significant negative effects of uncertainty shocks on key economic variables in a partial equilibrium setup, the effects in a general equilibrium are more disputed. While Bachmann and Bayer (2013) claim there are no significant effects of uncertainty shocks in general equilibrium, Basu and Bundick (2017) claim that there are, given that prices are sticky and the central bank is constrained by the zero lower bound. Born and Pfeifer (2014) analyze the contribution of monetary and fiscal policy uncertainty shocks in the United States during the Great Recession. They show that while policy uncertainty can be found in the data, it is unlikely to have played a large role in driving business cycle fluctuations. They find even smaller effects of uncertainty shocks to total factor productivity (TFP). Leduc and Liu (2016) study the macroeconomic effects of uncertainty shocks in a DSGE model with labor search frictions and sticky prices. They show that uncertainty shocks act like aggregate demand shocks as they increase unemployment and reduce inflation.

While there is a broad literature on the effects of uncertainty shocks, few researchers have analyzed their impact under financial frictions. Gilchrist et al. (2014) show, both empirically and theoretically, how time-varying uncertainty interacts with financial market frictions in dampening economic fluctuations. Using a standard bond-contracting framework, they find that an increase in uncertainty is beneficial to equity holders while it is costly for bondholders since uncertainty shocks lead to an increase in the cost of capital and ultimately to declining investment. In addition, decreasing credit supply hinders efficient capital reallocation which leads to a further decrease in TFP. Christiano et al. (2014) apply a DSGE model incorporating the financial accelerator mechanism originally proposed by Bernanke et al. (1999) (BGG) and estimate it for the U.S. economy. They find that risk shocks (i.e., changes in the volatility of cross-sectional idiosyncratic uncertainty) play an important role in shaping U.S. business cycles. While Christiano et al. (2014) exclusively consider idiosyncratic uncertainty shocks, Balke et al. (2013) also investigate the effects of macroeconomic uncertainty shocks under credit frictions. Using a model with agency costs, they show that the financial accelerator amplifies the contractionary effects under price stickiness. In equal measure, Cesa-Bianchi and Fernandez-Corugedo (2013) show that credit frictions amplify the negative impact of uncertainty shocks on output, investment, and consumption. In addition, they find that micro uncertainty shocks seem to be quantitatively more important than macro uncertainty shocks.

This strand of literature using DSGE models based on the financial accelerator mechanism focuses only on frictions that characterize the demand side of the financial sector. In this paper, in contrast, we show that supply-side constraints in the financial sector also play an important role in amplifying the effects of uncertainty shocks. Accounting for sticky retail interest rates determines an imperfect pass-through of the central bank interest rate to the private sector. The transmission mechanism of the monetary policy is hence weakened and less effective in offsetting the dampening effects of the uncertainty shock. Our paper is most closely related to Basu and Bundick (2017), Christiano et al. (2014), and Balke et al. (2013). While Basu and Bundick (2017) use a standard New Keynesian model to show the effects of aggregate uncertainty, we assume that entrepreneurs are credit constrained and that lending is implemented through an imperfectly competitive banking sector.

Our contribution is threefold: first, we provide an empirical motivation for the study of uncertainty shocks. Therefore, we estimate a small Vector Autoregressive (VAR) model and show that higher uncertainty reduces main macroeconomic aggregates in the euro area. We show that the imperfect pass-through of the monetary policy rate to the loan rates is an important empirical feature for the transmission of uncertainty shocks. Second, we analyze the effects of uncertainty shocks on business cycle fluctuations using a Dynamic Stochastic General Equilibrium (DSGE) model which incorporates nominal rigidities and financial frictions. We build a multi-sector model featuring credit frictions and borrowing constraints for entrepreneurs as in Iacoviello (2005) and price rigidities as in Rotemberg (1982). Moreover, the model is augmented by a stylized banking sector inspired by Gerali et al. (2010). The main results of our analysis are that frictions in the banking sector considerably amplify the negative effects of uncertainty shocks on economic activity and make uncertainty shocks more persistent than otherwise. Third, we show that the effects of uncertainty shocks are strongly amplified, when considering non-linearities.

The rest of the paper is organized as follows. In section 1.2 we present empirical evidence of the effects of uncertainty shocks on economic activity by estimating a small VAR model for the euro area. In section 1.3 we present the DSGE model with borrowing constrained entrepreneurs and a monopolistically competitive banking sector. In section 1.4 we describe the solution method and simulate the model deriving the main channel through which overall uncertainty transmits via the banking sector to the real economy and drives business cycle fluctuations. Finally, we present concluding remarks in section 1.5.

1.2 Empirical evidence

In order to provide evidence on the relevance of uncertainty shocks on economic fluctuations in the euro area, we estimate a small VAR model and assess both impulse responses and variance decompositions with orthogonalised shocks to macroeconomic uncertainty. As a proxy for aggregate macroeconomic uncertainty, we use an index that is derived from the volatility of financial market variables in the euro area. In particular, we use the VSTOXX which provides a measure of market expectations of short-term up to long-term volatility based on the Euro Stoxx 50 options prices.[1]

Furthermore, we collect data for industrial production, inflation, the money market rate (3-month Euribor) and the loan rate to non-financial corporations from the ECB Statistical Data Warehouse. A detailed description of the data can be found in the appendix. We estimate the model with monthly data over a sample from 2000M1 until 2016M4. The VAR model has the following form:

$$AY_t = B_1 Y_{t-1} + \cdots + B_p Y_{t-p} + \epsilon_t, \quad \text{where} \quad \epsilon_t \sim \mathcal{N}(0, \Sigma), \tag{1.1}$$

where $Y_t = [VOL_t \ \Delta IP_t \ \pi_t \ r_t \ r_t^b]'$ is a vector consisting of the following variables: the logarithm of the VSTOXX (VOL_t), the logarithm of industrial production (IP_t), the 3-month Euribor rate (r_t) and the loan rate r_t^b. The operator Δ represents the year-on-year difference ($x_t - x_{t-12}$). $B_1, \ldots, B_p$ are $(q \times q)$ autoregressive matrices and Σ is the $(q \times q)$ variance-covariance matrix. We choose a lag-length of 2 based on the Akaike and the Bayesian Information Criteria (AIC and BIC).

In our baseline model, we choose recursive identifying restrictions (a lower triangular

[1] Basu and Bundick (2017) use a similar implied volatility index for the United States (VIX) in order to identify the uncertainty shock.

Cholesky identification), ordering the uncertainty index first, such that on impact shocks to the uncertainty index affect the other variables. Conversely, we assume that uncertainty is on impact not affected by shocks to the other endogenous variables. This ordering has been widely used in the literature (e.g., Bloom, 2009; Baker et al., 2016).[2]

The impulse responses to a VSTOXX shock are depicted in Figure 1.2. The blue solid lines are the median responses of the endogenous variables to one-standard-deviation increase in the innovations to uncertainty, while the shaded areas represent 95 percent confidence bands. According to the VAR model, uncertainty shocks have a substantial negative effect on industrial production. Similarly to Leduc and Liu (2016) and Basu and Bundick (2017), we find that uncertainty shocks act like aggregate demand shocks, with declining economic activity and prices.

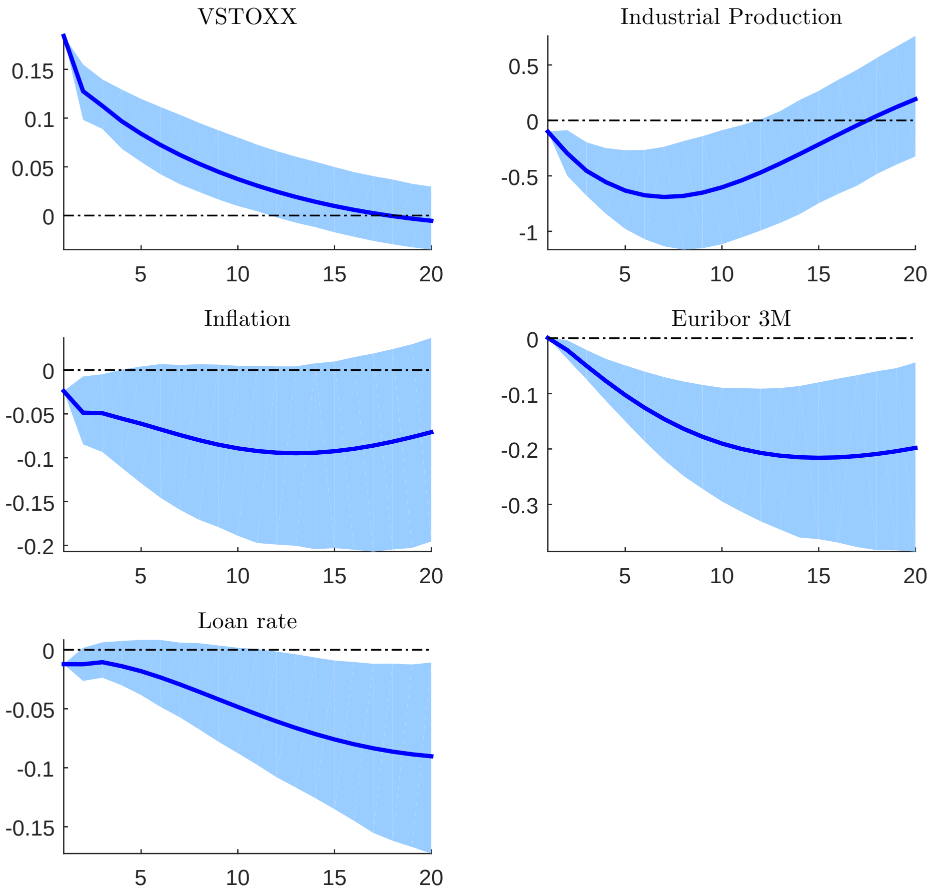
Industrial production and inflation decline by about 0.7 and 1 percent respectively. The results are in line with other empirical studies about the effects of uncertainty for other countries.[3]

Monetary policy reacts to lower inflation and lower economic activity by reducing the short-interest rate. However, the reduction in money-market rates is not fully passed through to the loan rate. While the money-market rate is 0.2 percent lower after one year, the loan rate only declines by 0.05 percent. In order to quantify the role of this imperfect pass-through in the transmission of uncertainty shocks, we construct hypothetical impulse responses, holding the loan rate fixed at all forecast horizons. This approach is similar to the methodology used by Bachmann and Sims (2012) to understand the role of confidence in the transmission of government spending shocks. Figure 1.3 displays the impulse in the baseline scenario (blue line) and in the hypothetical scenario (red circled line). In the latter case, the effect of uncertainty shocks on economic activity is much weaker. While industrial production falls by more than 0.6 percent after 7 months in the baseline model, it only declines by 0.4 percent when keeping the loan rate fixed. Accordingly, also monetary policy reacts less aggressively to an uncertainty shock in the hypothetical exercise.

[2] As a robustness exercise, we test for an alternative ordering of the variables. More specifically, when the uncertainty index is ordered last. In addition, we estimate Bayesian VARs with alternative prior distributions. Results can be found in the appendix (section A.2) The results do not substantially differ from the ones reported here.

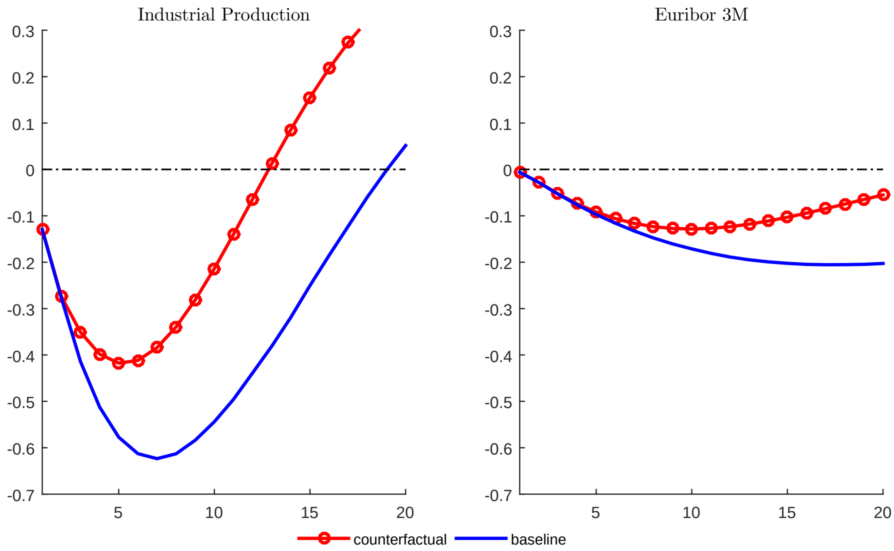
[3] Bloom (2009) and Baker et al. (2016) show in a VAR model that uncertainty leads to a persistent decrease in industrial production in the United States. Denis and Kannan (2013) find persistently negative effects of uncertainty on monthly GDP indicators for the United Kingdom and on economic sentiment indicators.

Figure 1.2: *Impulse responses to a VSTOXX shock*



Notes: The VSTOXX is ordered first. The blue solid lines are responses of the endogenous variables to a standardized increase in the innovations to uncertainty. Shaded areas represent 95 error bands computed as in Sims and Zha (1999).

Figure 1.3: *Isolating the role of the loan rate*



NOTES: The blue solid lines represent impulse responses of industrial production and the Euribor in the baseline model. The red line represents the impulse responses of industrial production and the Euribor in the counterfactual exercise.

Decomposing the forecast error variance of industrial production reinforces the finding that uncertainty shocks are an important driver of economic activity in the euro area. Almost 20 percent of total variation in industrial production can be attributed to VSTOXX shocks.[4] For variations in the Euribor, uncertainty accounts for almost 30 percent after one year. Against this background, further investigation of the theoretical propagators for uncertainty shocks is desirable to shed light on the main transmission channels.

We acknowledge two potential limitations of our empirical analysis that are common to most of the literature on the macroeconomic effects of uncertainty shocks. The first issue is related to the use of the VSTOXX as a proxy for macroeconomic uncertainty. The VSTOXX is a measure of implied volatility of the EURO STOXX 50 index options. These measures of stock market volatility tend to be driven not only by macroeconomic risk but also other factors such as leverage, sentiments and investors' risk aversion (see e.g. Jurado et al., 2015; Bekaert et al., 2013). A second potential issue is related to the identification strategy adopted to analyze the effects of the uncertainty shocks on the endogenous variables in the VAR. In particular the VSTOXX, just like other measures of uncertainty used in the literature, is highly endogenous and may respond contemporaneously to other variables in the VAR. Nevertheless, the

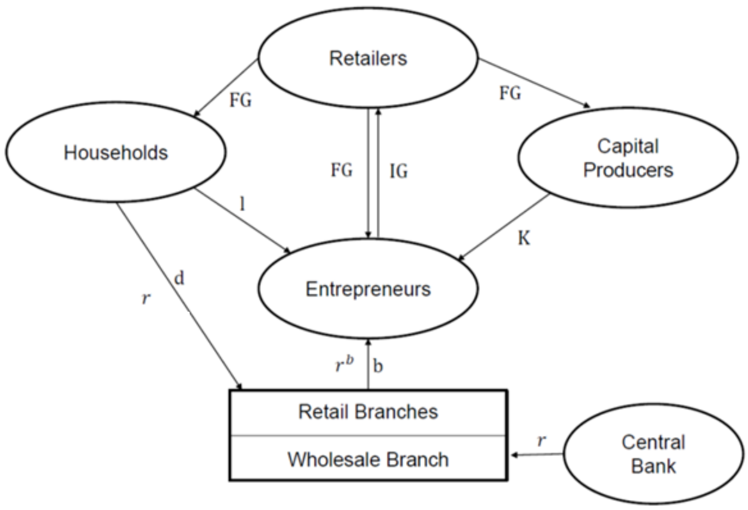
[4]Results for the forecast error variance decomposition can be found in the appendix in section A.1.

recursive identification scheme is widely adopted in the applied literature dealing with uncertainty shocks, and we have decided to align our shock identification in order to better and more easily compare our results with those previously obtained by other authors.

1.3 The model

We derive a medium-sized DSGE model based on Iacoviello (2005) and Gerali et al. (2010) that incorporates three different sectors: a non-financial sector, a financial sector and a public sector that is represented by the monetary authority. In particular, the non-financial sector consists of households that maximize their discounted lifetime utility by choosing consumption and labor. They deposit their savings at the banks at the policy rate r. In addition, we assume that households own final-good firms (i.e. retail firms). Entrepreneurs own firms that produce a homogeneous intermediate good by mixing labor services, supplied by the households, and capital that they purchase from capital producers. They sell the intermediate good to retailers, who use it to produce the final consumption good. Entrepreneurs can borrow from the banks at the loan rate r^b. Their ability to borrow is constrained by the value of their stock of physical capital that is used as collateral. Entrepreneurs are furthermore assumed to own the capital producing firms. The financial sector consists of commercial banks that are owned by the households. They operate in a monopolistically competitive environment and therefore have a certain degree of market power. In this way, banks can assert a loan rate to the entrepreneurs that is higher than the policy rate, $r \leq r^b$. Furthermore, we assume that banks pay adjustment costs when changing the retail interest rates. In Figure 1.4 we depict the model economy.

Figure 1.4: *The model economy*



NOTES: FG denotes the final good and IG the intermediate good.

1.3.1 Non-financial sector

We assume two different types of non-financial agents, i.e. households and entrepreneurs. Households are more patient than entrepreneurs and are therefore characterized by a higher intertemporal discount factor (i.e. $\beta_h > \beta_e$). This determines that in equilibrium households will be net lenders and entrepreneurs net borrowers.

Households

Households, indexed by $i \in [0, \omega]$, choose consumption, labor and savings to be deposited at the bank in order to maximize their expected discounted lifetime utility:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta_h^t z_t \left[log(c_{h,t}(i)) - \frac{l_t(i)^{1+\phi}}{1+\phi} \right], \tag{1.2}$$

where $c_{h,t}(i)$ represents the household's individual consumption, $l_t(i)$ are household's individual hours worked and z_t is a preference shock (i.e. a shock to the discount factor). Each representative household maximizes its utility subject to its budget constraint:

$$c_{h,t}(i) + d_t(i) = w_t l_t(i) + \frac{1 + r_{t-1}}{(1 + \pi_t)} d_{t-1}(i) + J_t^R(i) + (1 - \varphi) J_t^B(i). \tag{1.3}$$

The expenditures of the current period consist of consumption and "buying" deposits at the bank. The income stream of the households is decomposed into wage income $(w_t l_t(i))$, real interest payments resulting from last period's deposits made at the bank, deflated by the consumer price inflation $((1 + r_{t-1})/(1 + \pi_t))$, profits of the monopolistically competitive retail sector (J_t^R) and a share $(1 - \varphi)$ of profits, J_t^B, from the monopolistically competitive banking sector which is paid out as dividends.

Entrepreneurs

Entrepreneurs own firms that produce a homogeneous intermediate good. They maximize their lifetime utility given by:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta_e^t \left[\log(c_{e,t}(j)) \right], \tag{1.4}$$

subject to:

$$c_{e,t}(j) + w_t l_t(j) + \frac{1 + r_{t-1}^b}{(1 + \pi_t)} b_{t-1}(j) + q_t^k k_t(j) = \frac{y_t^e(j)}{x_t} + b_t(j) + (1 - \delta) q_t^k k_{t-1}(j),$$

where r_t^b represents the borrowing rate for the entrepreneur and $b_t(j)$ is the total amount borrowed from the bank. $k_t(j)$ is the stock of physical capital, δ its depreciation rate, and q_t^k its price. Ultimately, $1/x_t = P_t^W/P_t$ is the relative price of the intermediate good, such that x_t can be interpreted as the gross markup of the final good over the intermediate good. The firm uses a Cobb-Douglas production function given by:

$$y_t^e(j) = [k_{t-1}(j)]^{\alpha} l_t(j)^{1-\alpha}, \tag{1.5}$$

where α is the share of capital employed in the production process.

As previously mentioned, entrepreneurs are allowed to borrow an amount of resources that is commensurate with the value of physical capital the entrepreneurs own. Hence, they face a borrowing constraint à la Kiyotaki and Moore (1997) that is given by:

$$(1 + r_t^b)b_t(j) \leq m\mathbb{E}_t[q_{t+1}^k(1 + \pi_{t+1})(1 - \delta)k_t(j)], \tag{1.6}$$

where the left-hand side is the amount to be repaid by the entrepreneur and the right-hand side represents the value of the collateral. In particular m represents the loan-to-value (LTV) ratio.

Capital producers

Capital producing firms are introduced in order to obtain a price for capital that is necessary to determine the value the entrepreneur's collateral. These firms are owned by the entrepreneurs and act in a perfectly competitive market. They purchase last period's undepreciated capital $(1 - \delta)k_{t-1}$ from the entrepreneurs at a price Q_t^k and i_t units of final goods from retail firms, and transform these into new capital facing quadratic adjustment costs. The new capital is then sold back to the entrepreneurs at the same price Q_t^k. Let $q_t^k \equiv \frac{Q_t^k}{P_t}$ be the real price of capital. Capital producers maximize then their expected discounted profits:

$$\max_{\{k_t, i_t\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^e \left(q_t^k \Delta k_t - i_t \right), \tag{1.7}$$

subject to:

$$\Delta k_t = \left[1 - \frac{\kappa_i}{2} \left(\frac{i_t}{i_{t-1}} - 1 \right)^2 \right] i_t, \tag{1.8}$$

where Δk_t is the change in the stock of capital $k_t - (1 - \delta)k_{t-1}$. The capital producing firms take the entrepreneurs' stochastic discount factor (i.e. the intertemporal marginal rate of susbtitution) $\Lambda_{0,t}^e \equiv \frac{\beta_e c_{e,0}}{c_{e,t}}$ as given. The parameter κ_i governs the magnitude of the adjustment costs associated with the transformation of the final good into capital.

1.3.2 Retailers

The retailing firms are modeled similarly as in Bernanke (1983). These firms are owned by the households, they act in monopolistic competition and their prices are sticky. They purchase the intermediate-good from entrepreneurs in a competitive market, then slightly differentiate it, e.g. by adding a brand name, at no additional cost. Let $y_t(\nu)$ be the quantity of output sold by the retailer ν, and $P_t(\nu)$ the associated price.

The total amount of final good produced in the economy is:

$$y_t = \left[\int_0^1 y_t(\nu)^{(\varepsilon^y-1)/\varepsilon^y} \mathrm{d}\nu\right]^{\varepsilon^y/(\varepsilon^y-1)}, \tag{1.9}$$

with the associated price index:

$$P_t = \left[\int_0^1 P_t(\nu)^{(1-\varepsilon^y)} \mathrm{d}\nu\right]^{1/(1-\varepsilon^y)}. \tag{1.10}$$

In (1.9) and (1.10), ε^y represents the elasticity of substitution between differentiated final goods. Given (1.9), the demand that each retailer faces is equal to:

$$y_t(\nu) = \left(\frac{P_t(\nu)}{P_t}\right)^{-\varepsilon^y} Y_t. \tag{1.11}$$

Each firm ν chooses its price to maximize the expected discounted value of profits subject to the demand for consumption goods (1.11):

$$\max_{\{P_t(\nu)\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^h \left[\left(P_t(\nu) - P_t^W\right) y_t(\nu) - \frac{\kappa_p}{2}\left(\frac{P_t(\nu)}{P_{t-1}(\nu)} - (1+\pi)\right)^2 P_t Y_t\right], \tag{1.12}$$

It is assumed that firms take the households' (who own the firms) stochastic discount factor , $\Lambda_{0,t}^h \equiv \frac{\beta_h c_{h,t}}{c_{h,t}}$, as given. The last term of the objective function represents quadratic adjustment costs the retailer ν faces whenever she wants to adjust her prices beyond indexation (Rotemberg, 1982). As we have already mentioned P_t^W represents the price of intermediate goods that the retailers take as given.

1.3.3 Financial sector

The financial sector consists of commercial banks modeled similarly as in Gerali et al. (2010). Households are the shareholders of these banks that operate on a wholesale and on a retail level. The wholesale branch operates in a perfectly competitive market, collecting deposits from the households, paying interest at the policy rate r_t. It also issues wholesale loans to the retail branch. Finally, it manages the total capital of the bank. All bank assets consist of loans to firms b_t, whereas liabilities consist of bank capital (net worth) K_t^b, and wholesale deposits d_t. The bank's balance sheet identity is given by:

$$b_t = d_t + K_t^b, \tag{1.13}$$

which can be graphically represented by:

Banks Balance Sheet

Assets	***Liabilities***
b_t	K_t^b
	d_t

The retail branch of the bank operates in a monopolistically competitive market and is responsible for lending resources to the entrepreneurs. The market power in this market is modeled in a Dixit-Stiglitz fashion. Every loan retail branch marginally differentiates the loan contract. All these contracts are then assembled in a CES basket that is taken as given by entrepreneurs and households. The demand for loans at bank n can be derived by minimizing the total debt repayment of entrepreneur j:

$$\min_{b_t(j,n)} \int_0^1 r_t^b(n) b_t(j,n) \mathrm{d}n, \tag{1.14}$$

subject to

$$b_t(j) \leq \left[\int_0^1 b_t(j,n)^{(\varepsilon^b - 1)/\varepsilon^b} \mathrm{d}n \right]^{\varepsilon^b/(\varepsilon^b - 1)}, \tag{1.15}$$

where ε^b is the elasticity of substitution of loan contracts. The aggregate demand for loans at bank n is then given by:

$$b_t(n) = \left(\frac{r_t^b(n)}{r_t^b} \right)^{-\epsilon_t^b} b_t. \tag{1.16}$$

The demand function $b_t(n)$ depends negatively (as the elasticity of substitution of loan demand ϵ_t^b is assumed to be larger than 1) on the loan interest rate $r_t^b(n)$, and positively on the total amount of loans b_t.

Wholesale branch

As mentioned above, the wholesale banking market is perfectly competitive. The wholesale branch of each bank maximizes the discounted sum of cash flows by choosing wholesale loans and deposits, b_t and d_t, taking into account the stochastic discount factor of the households $\Lambda_{0,t}^h$:

$$\max_{\{b_t, d_t\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^h \left[(1+R_t^b) b_t - (1+\pi_{t+1}) b_{t+1} + d_{t+1} - (1+R_t^d) d_t + (K_{t+1}^b (1+\pi_{t+1}) - K_t^b) \right], \tag{1.17}$$

subject to the budget constraint:

$$b_t = d_t + K_t^b, \tag{1.18}$$

and given the following law of motion for bank capital:

$$(1+\pi_t)K_t^b = (1-\delta^b)K_{t-1}^b + \varphi J_{t-1}^b. \tag{1.19}$$

Given the first order conditions, it is moreover assumed that banks can obtain unlimited funding from the central bank at the policy rate r_t. The no-arbitrage condition hence implies that the wholesale deposit and loan rates coincide with r_t:

$$R_t^b = R_t^d = r_t. \tag{1.20}$$

Retail branch

In loan activities, retail banks operate in monopolistic competition and are therefore profit maximizers. They maximize their expected discounted profits by choosing the interest rate on loans and facing quadratic adjustment costs. These banks borrow liquidity from the wholesale branch at rate R_t^b (which as we previously showed is equal to the policy rate) and lend it to the entrepreneurs at rate $r_t^b(n)$. The optimization problem of the loan-retail division n is given by:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^h \left[r_t^b(n) b_t(n) - r_t b(n) - \frac{\kappa_b}{2} \left(\frac{r_t^b(n)}{r_{t-1}^b(n)} - 1 \right)^2 r_t^b b_t \right], \tag{1.21}$$

subject to the demand for loans (1.16).

1.3.4 Monetary Authority

The central bank sets the nominal interest rate through a conventional Taylor-type rule:

$$\frac{1+r_t}{1+r} = \left(\frac{1+r_{t-1}}{1+r} \right)^{\phi_r} \left[\left(\frac{1+\pi_t}{1+\pi} \right)^{\phi_\pi} \left(\frac{y_t}{y_{t-1}} \right)^{\phi_y} \right]^{(1-\phi_r)}, \tag{1.22}$$

where ϕ_r is a smoothing parameter that captures the gradual movements in the interest rate as in Clarida et al. (1999), r and π are respectively the steady-state values of the policy rate and of inflation. ϕ_π and ϕ_y represent the weights the central bank gives to deviations of inflation from its steady state level and to output growth.

1.3.5 Market clearing

Ultimately the model is closed by combining the first order conditions of all agents to the clearing condition of the goods market:

$$Y_t = C_t + [k_t - (1-\delta)k_{t-1}] + \delta^b \frac{K^b_{t-1}}{(1+\pi_t)} + ADJ_t, \tag{1.23}$$

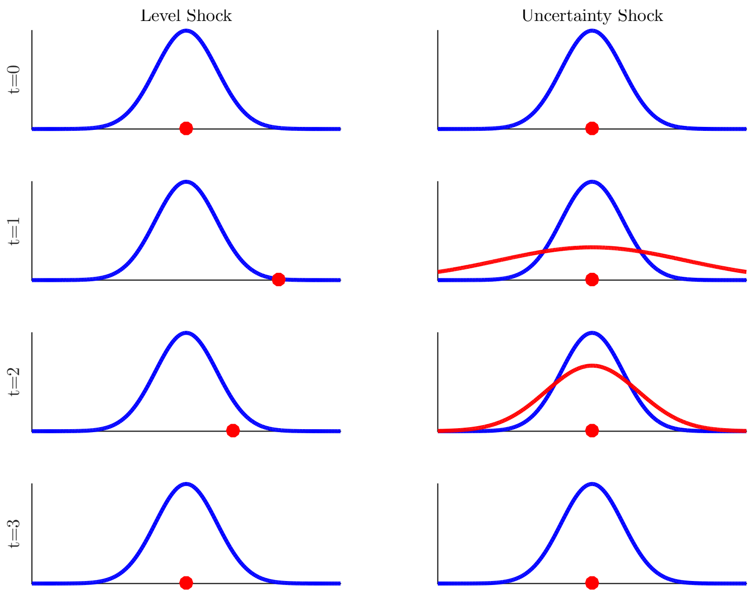
where $C_t \equiv c_{h,t} + c_{e,t}$ is aggregate consumption, k_t is aggregate physical capital and K^b_t, as mentioned before, represents aggregate bank capital. Ultimately ADJ_t includes all real adjustment costs for prices and interest rates:

$$ADJ_t \equiv \frac{\kappa_p}{2}\left(\frac{1+\pi_t}{1+\pi} - 1\right)^2 Y_t + \frac{\kappa_b}{2}\left(\frac{r^b_{t-1}}{r^b_{t-2}} - 1\right)^2 r^b_{t-1} b_{t-1}. \tag{1.24}$$

1.3.6 Shock processes

In order to model uncertainty shocks, we use the stochastic volatility approach as proposed by Fernandez-Villaverde et al. (2011), assuming time-varying volatility of the preference shock (z_t). An uncertainty shock is a second-moment shock that affects the shape of the distribution by widening the tails of the level shock and keeping its mean unchanged. A level shock is a first-moment shock that varies the level of z_t, keeping its distribution unchanged. A graphical comparison between the two types of shocks is shown in Figure 1.5.

Figure 1.5: *Level and uncertainty shock*



NOTES: The left column represents a preference level shock. The right column represents a second-moment shock. We assume the shock to die out in period $t = 3$.

The red dot represents the level of z_t that increases after a positive level shock and returns to its initial state after three periods. With a positive uncertainty shock, instead, the level of z_t remains constant, while its distribution becomes wider as the variance of the first-moment shock increases. As the effect of the shock dissipates, the distribution returns to its initial shape.

The stochastic volatility approach ensures that the dispersion of the level shocks varies over time, such that the probability of observing very large shocks varies over time. We consider an exogenous shock to the volatility of z_t, that can also be interpreted as demand-side uncertainty. The preference variable z_t follows an AR(1) process with time-varying volatility:

$$z_t = (1-\rho_z) + \rho_z z_{t-1} + \sigma_t^z e_t^z, \quad \text{where } e_t^z \sim \mathcal{N}(0,1) \tag{1.25}$$

where the coefficient $\rho_z \in (-1,1)$ determines the persistence of the level shock. The innovation to the preference shock, e_t^z, follows an *i.i.d.* standard normal process. Furthermore, the time-varying standard deviation of the innovations, σ_t^z, follows the stationary process:

$$\sigma_t^z = (1-\rho_{\sigma^z})\sigma^z + \rho_{\sigma^z}\sigma_{t-1}^z + \eta_z e_t^{\sigma_z}, \quad \text{where } e_t^{\sigma_z} \sim \mathcal{N}(0,1) \tag{1.26}$$

in which ρ_{σ^z} determines the persistence of the uncertainty shock, σ^z is the steady state value of σ_t^z and η_z is the (constant) standard deviation of the uncertainty shock, $e_t^{\sigma_z}$.

1.3.7 Solution and simulation method

The model is solved with the algorithm and software developed by Lan and Meyer-Gohde (2013b). Their solution method consists of a nonlinear moving average perturbation technique that maps our nonlinear DSGE model:

$$E_t f(x_{t+1}, x_t, x_{t-1}, e_t) = 0, \tag{1.27}$$

into a system of equations, known as policy function:

$$x_t = h(\sigma, e_t, e_{t-1}, e_{t-2}, \dots). \tag{1.28}$$

In (1.27) and (1.28), x_t and e_t represent the vectors of endogenous (control and state) variables and exogenous shocks. $\sigma \in [0,1]$ denotes a scaling parameter for the distribution of the stochastic shocks e_t, such that $\sigma = 1$ corresponds to the original stochastic model (1.27), and $\sigma = 0$ to the non-stochastic case. The basic idea behind this solution method is to approximate the policy function with Volterra series expansion around the deterministic steady state:

$$x_t = \sum_{j=0}^{J} \frac{1}{j!} \prod_{l=1}^{j} \sum_{i_l=0}^{\infty} \left(\sum_{n=0}^{J-j} \frac{1}{n!} x_{\sigma^n i_1 i_2 \dots i_j} \sigma^n \right) (e_{t-i_1} \otimes e_{t-i_2} \otimes e_{t-i_3} \dots). \tag{1.29}$$

As noted by Schmitt-Grohe and Uribe (2004), with a first order approximation, shocks only enter with their first moments. The first moments of future shocks in turn drop out when taking expectations of the linearized equations. This determines the property of certainty equivalence, i.e. agents completely disregard of the uncertainty associated with $\mathbb{E}_t[e_{t+1}]$. This property makes the first order approximation not suitable for the analysis of second moment shocks. In a second order approximation there are effects of volatility shocks that enter as cross-products with the other state variables (Fernandez-Villaverde et al., 2011). This order of approximation is therefore not sufficient to isolate the effects of uncertainty from those of the level shock. As we are interested in analyzing the effects of uncertainty shocks, keeping the first moment shocks shut off, it is necessary to approximate (1.28) up to a third order:

$$
\begin{aligned}
x_t =& \bar{x} + \frac{1}{2} y_{\sigma^2} + \frac{1}{2} \sum_{i=0}^{\infty} (x_i + x_{\sigma^2,i}) e_{t-i} + \frac{1}{2} \sum_{j=0}^{\infty} \sum_{i=0}^{\infty} x_{j,i} (e_{t-j} \otimes e_{t-i}) \\
&+ \frac{1}{6} \sum_{k=0}^{\infty} \sum_{j=0}^{\infty} \sum_{i=0}^{\infty} x_{k,j,i} (e_{t-k} \otimes e_{t-j} \otimes e_{t-i}). \qquad (1.30)
\end{aligned}
$$

A common problem when simulating time series with higher-order approximated solutions is that it often leads to explosive paths for x_t. A usual solution, suggested by Kim et al. (2008), is that of "pruning" out the unstable higher-order terms. Nevertheless, with the algorithm we have adopted (Lan and Meyer-Gohde, 2013a) the stability from the first order solution is passed on to all higher order recursions, and no pruning is hence required.

1.3.8 Calibration

We calibrate the benchmark model on a quarterly basis for the euro area and set the parameter values according to stylized facts and to previous findings in the literature. The calibrated structural parameters of the model are illustrated in Table 1.1. The discount factor for households is set to 0.9943 which results in a steady state policy interest rate of approximately 2 percent, while we set the entrepreneurs' discount factor to 0.975 as in Iacoviello and Neri (2010). The inverse of the Frisch labor supply elasticity is set to 1.0, in line with Christiano et al. (2014). We set the depreciation rate of capital δ to 0.025 and the share of capital in the production process α to 0.25. In the goods market we assume a markup of 20 percent and set ε^y to 6, a value frequently used in the literature. According to the posterior estimates of Gerali et al. (2010), we calibrate the parameter for the investment adjustment costs κ_i to 10.2 and the one for the price adjustment costs κ_p to 30.

Regarding the parameters for the banking sector, we base our calibration on Gerali et al. (2010). We set the loan-to-value ratio for entrepreneurs m to 0.35, reflecting the average ratio of long-term loans to the value of shares and other equities for the nonfinancial corporations' sector in the euro area. We set the elasticity of substitution of the loan rate to 3.12, which implies a steady-state markup of the loan rate on the policy rate of about 2 percentage points. In addition, bank management costs δ^b are set to 0.09 such that the ratio of bank capital to total loans is 9 percent in steady-state. Banks retain half of their profits in order to cover bank management costs. For this reason, we set φ equal to 0.5. Furthermore, we set the loan rate adjustment costs κ_b to 9.5 and the deposit rate adjustment costs κ_d to 3.5, consistent with the estimation results of Gerali et al. (2010). We assume the central bank to react aggressively to inflation by setting the parameter ϕ_π to 2.0, while it responds only marginally to changes in output growth ($\phi_y = 0.3$). Additionally, we include interest rate smoothing with a smoothing parameter ρ_r equal to 0.75.

The first-moment process z_t is calibrated according to the empirical evidence in the euro area. The persistence parameter of the first moment z_t shock, ρ_z, is equal to 0.9 in line with Gerali et al. (2010). The volatility of the second moment shock η_z is set to 0.0012, in order to match the standard deviation of the loan rate with its empirical counterpart. The persistence parameter of the second moment shock ρ_{σ^z} is equal to 0.7 as in Basu and Bundick (2017).

Table 1.1: *Deep parameters of the benchmark model*

Parameter	Value	Description
Non-financial sector		
β_e	0.9943	Discount factor private households (savers)
β_e	0.975	Discount factor entrepreneurs (borrowers)
ϕ	1	Inverse of Frisch labor supply elasticity
δ	0.025	Depreciation rate of physical capital
α	0.25	Weight of capital in aggregate production function
ε^y	6	Elasticity of substitution in the goods market
κ_i	10.2	Investment adjustment costs
κ_p	30	Price adjustment costs (Rotemberg)
m	0.35	Loan-to-value (LTV) ratio for the entrepreneurs
Financial sector		
ε^b	3.12	Elasticity of substitution for loans
φ	0.5	Share of banks' retained earnings
δ^b	0.09	Bank management costs
κ_b	9.5	Loan rate adjustment costs
Monetary Policy		
ϕ^y	0.30	Weight on output in Taylor rule
ϕ^π	2.0	Weight on inflation in Taylor rule
ρ^r	0.75	Interest rate smoothing parameter
Shocks		
σ^z	0.01	Steady-state volatility of the first moment shock
ρ_z	0.9	Persistence parameter of the first moment shock
ρ_{σ^z}	0.7	Persistence parameter of the second moment shock
η_z	0.0012	Volatility of the second moment shock

1.4 Macroeconomic effects of uncertainty

In the following section, we analyze the effects of an uncertainty shock to demand on main macroeconomic aggregates using impulse response functions. The aim is to assess the importance of financial frictions and financial intermediation in response to increases in uncertainty. Therefore, we illustrate alternative specifications of our model.

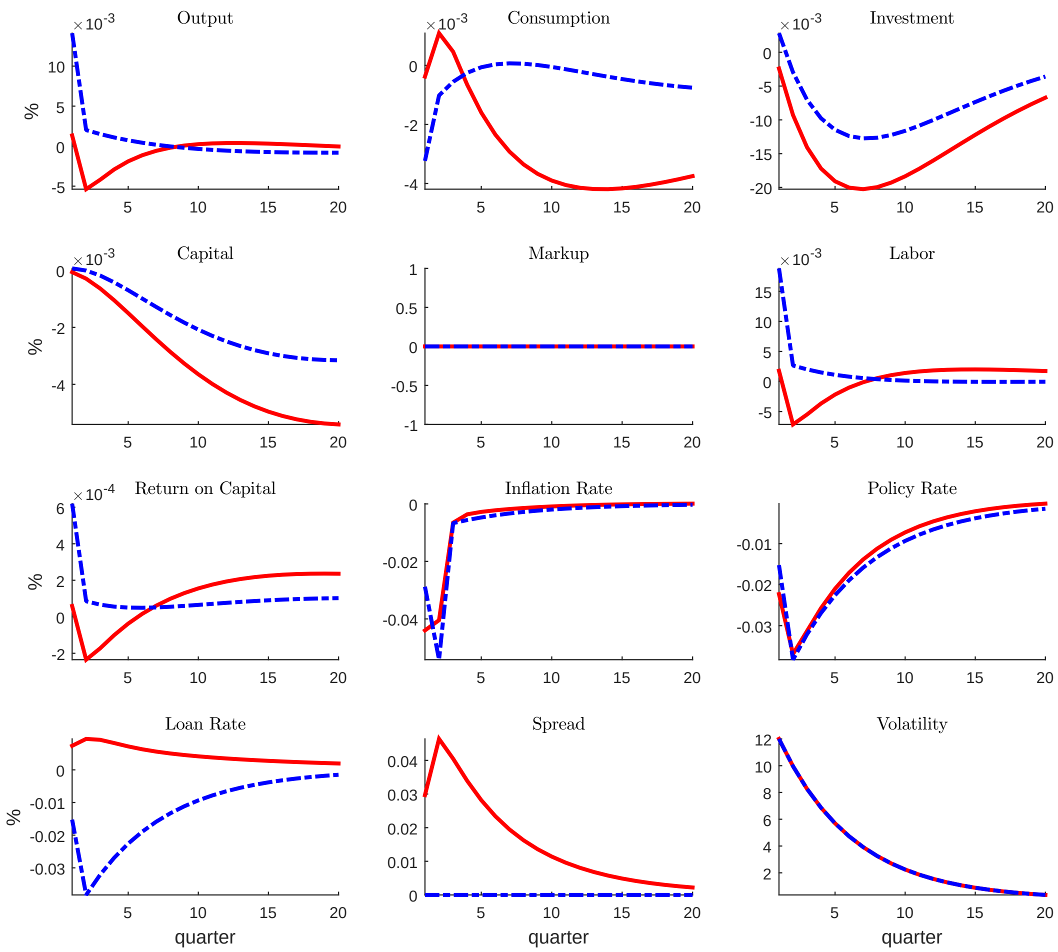
1.4.1 Effects of a demand uncertainty shock

Figure 1.7 shows the impulse response functions of a one-standard deviation shock to macroeconomic (preference) uncertainty for the scenarios with a sticky (SLR, red solid lines) and a flexible loan rate (FLR, blue dashed lines). Consistent with the literature, we find that a standard deviation increase in uncertainty dampens macroeconomic aggregates. As in Basu and Bundick (2017), we show that output, consumption and investment co-move negatively under sticky prices, while this is generally not the case under flexible prices. In a model without any nominal rigidities (see Figure 1.6, blue line), an exogenous rise in uncertainty leads households to reduce consumption and increase labour supply for precautionary reasons. Since capital is predetermined, the rise in hours increases output, which in a closed economy implies a rise in investment on impact. Instead, when prices do not adjust immediately to changing marginal costs (Figure 1.7), an uncertainty shock raises markups and firms reduce labour demand.

The rise in markups is due to two channels: 1) an aggregate demand channel and 2) an upward pricing bias channel (Fernandez-Villaverde et al., 2015). The first channel relates to the fact that, when facing a rise in uncertainty, households want to consume and invest less. As prices do not fully accommodate lower demand, markups increase and output declines. The second channel instead leads firms to increase their prices after an increase in uncertainty, because of the asymmetry of the profit function. More specifically, firms find it less costly to set a price that is too high relative to the competitors, rather than setting it too low. Similarly as in Born and Pfeifer (2014) and Fernandez-Villaverde et al. (2015), we find therefore that an increase in uncertainty leads to an initial rise in inflation due to the upward pricing bias channel. The rise in markups due to the aforementioned channels leads retail firms to reduce the demand for intermediate goods.

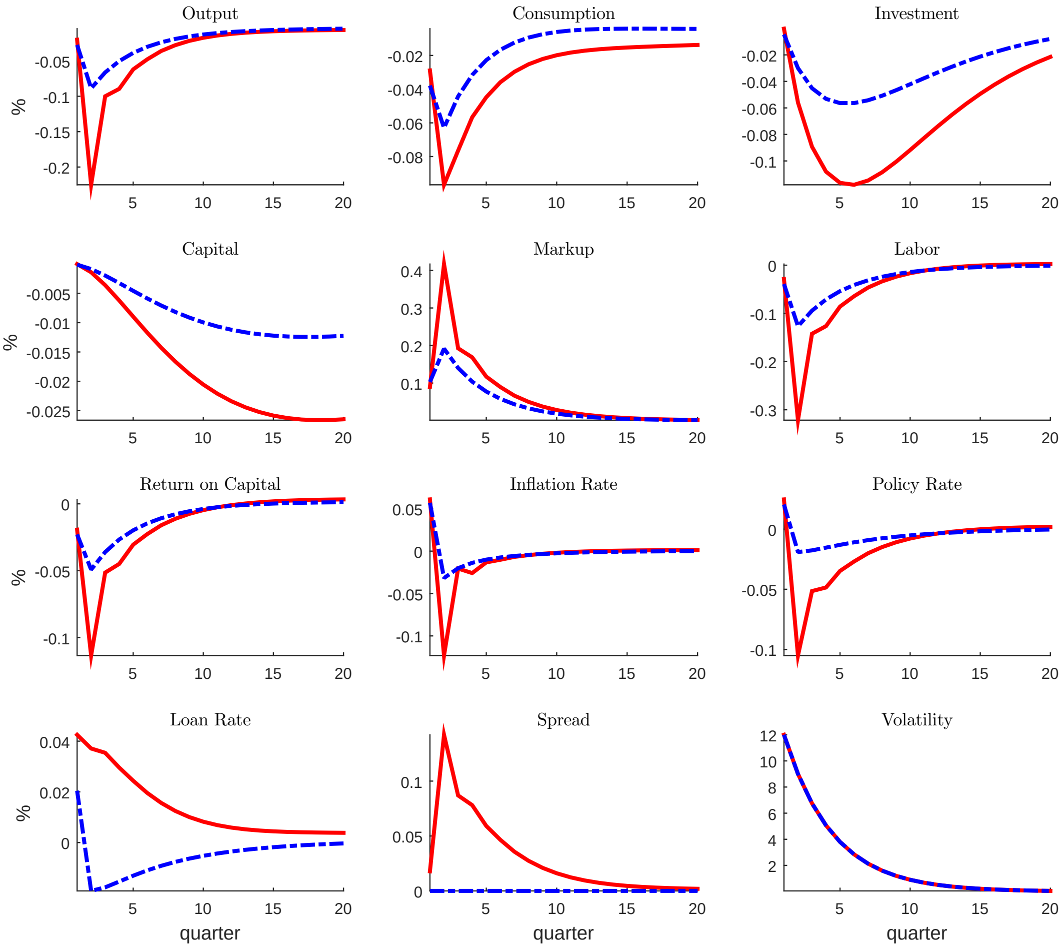
The negative effects of the uncertainty shock are partly offset by the reaction of the monetary authority. After the increase in the policy rate due to initial jump in inflation, the monetary authority reduces the interest rates to both counteract the fall in inflation relative to its steady-state value and to falling output growth. This policy is effective in reducing the impact of the uncertainty shock (Born and Pfeifer, 2014). When accounting for stickiness in the loan rate, the central bank's policy is

Figure 1.6: *Impulse response functions to a demand uncertainty shock under flexible prices*



NOTES: Red line: Flexible prices and sticky loan rate; Blue line: Flexible prices and flexible loan rate. All variables are expressed in percentage deviations from steady state, except interest rates and inflation which are expressed in annualized absolute deviations from steady-state.

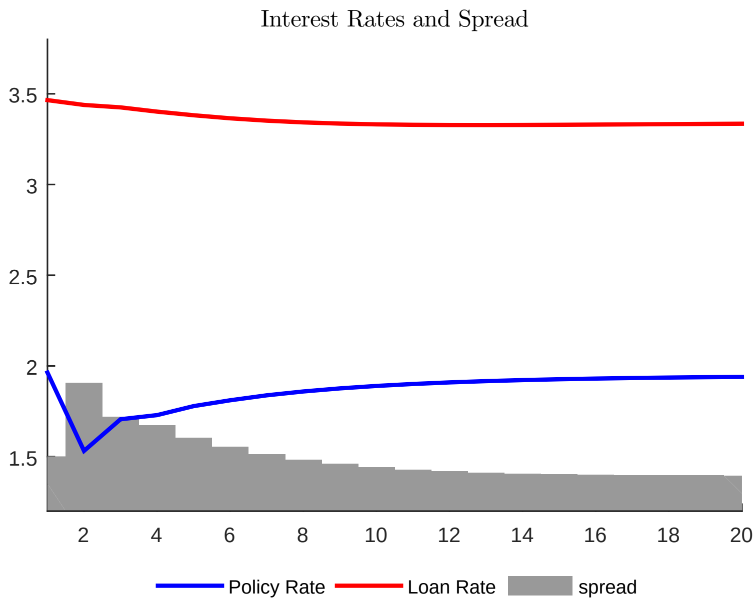
Figure 1.7: *Impulse response functions to a demand uncertainty shock under sticky prices*



NOTES: Red solid line: Model with sticky loan rate (SLR); Blue dashed line: Model with flexible loan rate (FLR). All variables are expressed in percentage deviations from steady state, except interest rates and inflation which are expressed in annualized absolute deviations from steady-state.

not perfectly passed through to the private sector and the offsetting power of the monetary authority is notably undermined. The dynamics of the loan rate (red line), policy rate (blue line) as well as the spread between the two (grey bars) is displayed in Figure 1.8. Both the policy rate and the loan rate rise on impact. However, the policy rate subsequently falls because of declining inflation, while the loan rate exhibits a more persistent behaviour. This leads to an increase in the spread between the two rates.

Figure 1.8: *Response of policy and retail interest rates to an uncertainty shock*



NOTES: The blue line represents the policy rate; the red line represents the loan rate. The two lines represent responses to a 3-standard deviation shock in uncertainty. Grey bars represent the spread between the two interest rates.

The role of stickiness in the lending rate in amplifying the effects of uncertainty shocks is evident when comparing the SLR and the FLR models in Figure 1.7. In particular, in the SLR model, the lending rate does not closely follow the policy rate for two main reasons. First of all, as inflation and therefore the policy rate rise on impact, the lending rate also increases initially, nevertheless it does not subsequently fall due to the assumed stickiness. Secondly, the lending rate stems from the profit maximization problem of the retail banks. The profit function of the banks features the same asymmetry as that of the firms, and by the same principle as described above leads the retails banks to prefer to raise the loan rate when faced with higher uncertainty (upward rate-setting bias channel). The latter effect is evident when we look at the model with flexible prices and sticky loan rate (see Figure 1.6, red line). In this case, an uncertainty shock makes inflation and the policy rate go down (since prices are flexible), but the banks still raise the loan rate. The higher borrowing costs put downward pressure on investment, which falls more than in absence of this rigidity. In the fully fledged model (SLR), investment falls roughly three times as much in the FLR scenario and similarly for hours and output.

The role of lending rate stickiness can be related to the case of a binding zero lower bound (ZLB), as analysed in Basu and Bundick (2017) and Fernandez-Villaverde et al. (2015). When the monetary authority is constrained by the ZLB, the effects of uncertainty become much more significant, as the central bank cannot perfectly respond to the shock. Similarly, accounting for frictions in the banking sector affects the transmission mechanism of monetary policy. When changes in the central bank's policy rate are not perfectly passed through to the private sector, the offsetting power of the monetary authority is notably hindered. The ZLB is a more extreme constraint on monetary policy than in the case of imperfect pass-through. Nevertheless, it is important to point out that the ZLB is constraining only under the circumstance in which the policy interest rate actually is close to zero. The amplification channel considered in this paper occurs in "normal" times as well, when the interest rate is far from the zero lower bound.

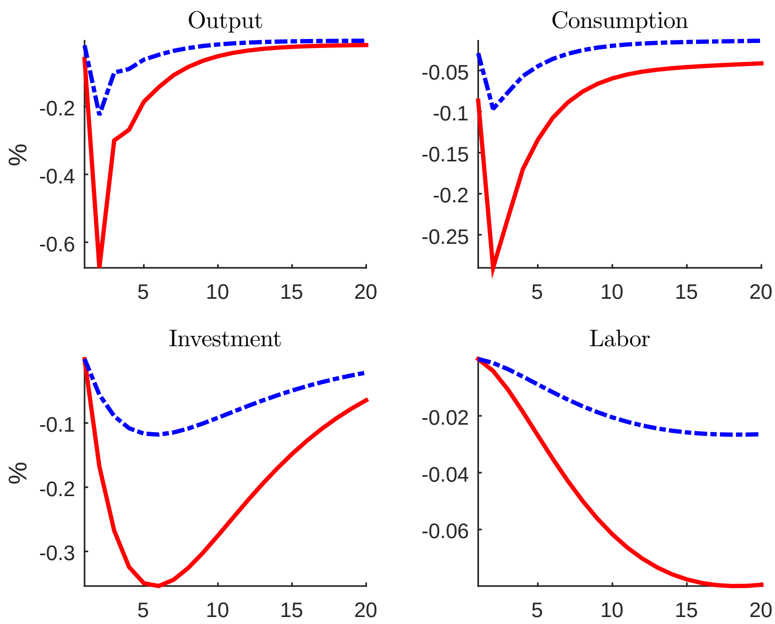
The overall effects of uncertainty shocks in our model are qualitatively in line with other papers in the literature. Some caution is required when interpreting the results of this paper. The model is admittedly kept relatively simple to focus on the financial friction that is at the core of the paper. The results of the model are therefore relatively small compared to our empirical findings in Section 1.2. The friction introduced in this paper represents one source of amplification that helps to bring the results in the theoretical model closer to the response in the data. There are other potential sources of amplification that have not been considered in this paper, such as search and matching frictions as in Leduc and Liu (2016). More quantitative models such as Born and Pfeifer (2014) that do not include any financial frictions, find the effects of uncertainty to be even smaller.

1.4.2 The role of non-linearities

One important aspect that is often overlooked in the literature, is the role of non-linearities, which may help to get the model closer to the data. More specifically, the stronger effects in the empirical section may be due to strong nonlinear effects during the financial crisis. The empirical literature (van Roye, 2013; Caggiano et al., 2014; Bonciani, 2015) has found that in times of high financial stress or of recessions, the effects of uncertainty on economic activity are stronger and potentially qualitatively different. To highlight why nonlinearities should not be neglected when analysing uncertainty shocks, Figure 1.9 displays two scenarios. The blue and red lines represent the effects of the same uncertainty shock respectively in a scenario of "normal" steady-state macroeconomic volatility ($\bar{\sigma} = 0.01$) and in a scenario of relatively high steady-state macroeconomic volatility ($\bar{\sigma} = 0.03$). Given that we hit the economy with the same uncertainty shock, i.e. keeping the same value of the standard deviation of the uncertainty shock, the percentage increase in volatility is smaller in the high steady-state volatility scenario. Nevertheless, as it is clear from Figure 1.9, the effects of uncertainty shocks on the main macroeconomic aggregates is much larger in the high volatility scenario.

Figure 1.10 displays the stochastic steady state of output $\bar{Y}$ as a function of the steady-state value of uncertainty $\bar{\sigma}$[5]. The strong non-linearity in the average value of output is the cause of the amplification in Figure 1.9. Explaining the source of these nonlinearities, the implications for uncertainty shocks and potentially other shocks goes beyond the scope of this paper and is left for further research.

Figure 1.9



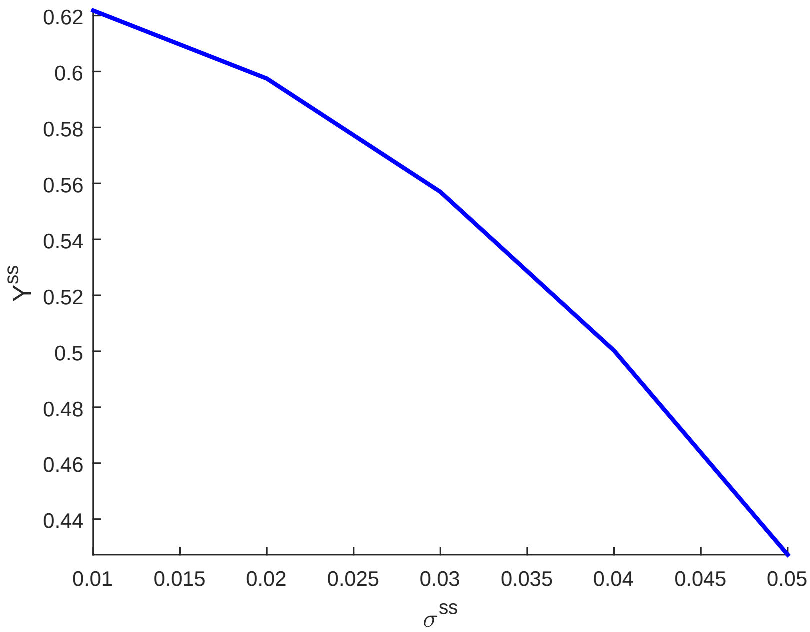
Notes: The blue line represents the IRF to an uncertainty shock in the baseline case; the red line represents the IRF to an uncertainty shock in a state of of high volatility.

1.5 Conclusion

In this paper, we present a framework to analyze the impact of uncertainty shocks on macroeconomic aggregates under financial frictions. In particular, we include a

[5]These nonlinearities do not depend on the specific features of our models and can also be obtained in a more standard DSGE model.

Figure 1.10: *Relationship between the Stochastic Steady-State of Output and Uncertainty*



banking sector that operates in a monopolistically competitive environment and sticky retail rates in a DSGE model with heterogeneous agents. We depart from the strand of literature that analyzes uncertainty shocks under financial frictions on the credit demand side by focusing on frictions on the credit supply side. This seems to be a very important channel through which uncertainty shocks transmit to the real economy. In fact, we show that these features amplify significantly the effects of uncertainty shocks. This finding is mainly due to a reduction in the effectiveness of the transmission mechanism of monetary policy. A possible extension of our analysis could be to include uncertainty in the financial sector. We leave this to future research.

Chapter 2

Estimating the Effects of Uncertainty over the Business Cycle

Keywords: Uncertainty Shocks, Local Projection Methods, Real Options, Growth Options, wait-and-see.
JEL classification: E21, E32.

2.1 Introduction

> *"It (Uncertainty) affects consumption and investment decisions and is largely behind the dramatic collapse in demand we have observed over the last three months. Sure, consumers have lost a good part of their wealth, and this is reason enough for them to retrench. But there is more at work. If you think that another depression might be around the corner, better to be careful and save more. Better to wait and see how things turn out. Buying a new house, a new car or a new laptop can surely be delayed a few months. The same goes for firms: given the uncertainty, why build a new plant or introduce a new product now? Better to pause until the smoke clears. "*
>
> Olivier Blanchard, January 2009

During the last financial crisis, we witnessed a surge in uncertainty that was often advocated by economists and the press as an important factor that held back the economy from recovering. As the quotation by Olivier Blanchard shows heightened uncertainty is considered one of the causes of the fall in demand following the collapse of Lehman Brothers, as it leads firms to postpone investment decisions, reduce hiring and consumers to increase their savings for precautionary reasons. Explaining how uncertainty affects business cycle fluctuations is hence a relevant question from both theoretical and policy perspectives. Therefore, a growing body of literature, initiated by the seminal contribution of Bloom (2009), has been studying the effects of uncertainty shocks on economic activity (e.g. Bloom, 2009; Leduc and Liu, 2016; Born and Pfeifer, 2014) and has shown that uncertainty shocks act like negative demand shocks.

In this paper, I show that the effects of uncertainty shocks strongly depend on the phase of the business cycle. I find that in times of recession uncertainty shocks do act like negative demand shocks, reducing industrial production, increasing unemployment and pushing down prices. Nevertheless, in times of expansion, uncertainty shocks are quite beneficial to macroeconomic activity and act like positive demand shocks. One possible interpretation of the results is that during economic upturns uncertainty acts through the "growth options" channel. Empirical evidence of growth-option effects is for example provided by Segal et al. (2014) and Rossi and Sekhposyan (2015), who decompose uncertainty into "good" and "bad" type of uncertainty. They find that the former increases in expansions and fosters investment and demand, while instead bad uncertainty is predominant in recessions and dampens economic activity.

In order to estimate the response of economic activity to uncertainty shocks during recessions and expansions, I employ the local projection method developed by Jorda (2005). The econometric framework is similar to Auerbach and Gorodnichenko (2012) and Tenreyro and Thwaites (2013) that adapt the local projection method to the Smooth Transition regression used and discussed in Terasvirta et al. (2010). This methodology easily accommodates state dependence and does not impose the dynamic restrictions involved in vector autoregressive models (VARs). Related work is that by Caggiano et al. (2014), who estimate a Smooth Transition Vector Autoregressive (STVAR) model as in Auerbach and Gorodnichenko (2013). Given the econometric framework adopted in their work, they only concentrate their attention on recessions, while in the present paper I am able to analyze both recessions and expansions. The use of the local projection method compared to the standard VARs allows to more robustly estimate the effects of uncertainty shocks during the two states of the business cycle, as it naturally allows for possible transitions from one state to the other and it is more robust to model misspecifications.

More generally, this paper is related to the literature on uncertainty shocks, initiated by the seminal contribution of Bloom (2009). Analysing the macroeconomic effects of uncertainty shocks is a challenging task both from an empirical and a theoretical point of view. The latent nature of uncertainty has led the empirical literature to investigate its effects on the economy using various proxies, such as survey data (e.g., Leduc and Liu, 2016; Bachmann et al., 2013) and stock market's implied and realized volatility (Bloom, 2009; Caggiano et al., 2014). This literature has found that shocks increasing uncertainty have significant contractionary effects on the economy and act like negative demand shocks, by increasing unemployment and reducing inflation (Leduc and Liu, 2016).

From a theoretical perspective, the micro- and macroeconomic literature has identified several transmission channels through which uncertainty can potentially affect economic activity: (*i*) the real options channel, that can lead firms to increase ("growth options") or decrease ("wait-and-see") their investment (Bernanke, 1983); (*ii*) the Hartman-Abel effect that leads firms to expand in response to increases in demand or cost uncertainty and contract after decreases in uncertainty, under the assumption that profits are convex in demand or costs (Hartman, 1976; Abel, 1983); (*iii*) the precautionary savings channel that makes risk-averse agents reduce their consumption when uncertainty increases (Leland, 1968) and (*iv*) the risk-premium effect that increases the cost of financing when uncertainty rises (Christiano et al., 2014; Gilchrist et al., 2014). These four channels have potentially contrasting effects and in a general equilibrium (GE) context they may offset each other. For this reason, the macroeconomic literature has provided mixed evidence on the importance of uncertainty shocks in determining business cycle fluctuations in a GE framework[1]. Basu and Bundick (2017) show that uncertainty shocks are able to generate business cycle fluctuations only in sticky-prices (New-Keynesian) frameworks. Furthermore, they show that the effects of uncertainty shocks strongly depend on how effective the response of monetary policy is. If the nominal rates have approached the zero lower bound and the monetary authority cannot further reduce its policy rate, then the effects of uncertainty shocks on economic activity are strongly amplified. Gilchrist et al. (2014) and Bonciani and van Roye (2016) highlight the importance of financial and banking frictions as a mechanism through which idiosyncratic and aggregate uncertainty affect macroeconomic activity.

The remainder of this paper is organized as follows: section 2.2 presents the econometric framework and the local projection method; section 2.3 presents the empirical evidence on the asymmetric macroeconomic effects of uncertainty shocks and a possible interpretation of the results; section 1.5 concludes the paper with some final remarks.

2.2 Empirical Evidence: a LPM Analysis

2.2.1 Econometric Framework

In this section, I present empirical evidence on the asymmetric effects of uncertainty shocks on economic activity. The empirical strategy adopted to analyse the state-dependent effects of uncertainty shocks follows Auerbach and Gorodnichenko (2012) and Owyang et al. (2013), who apply the local projection technique developed by Jorda

[1] Relevant contributions have been provided by Bachmann and Bayer (2013), Born and Pfeifer (2014), Fernandez-Villaverde et al. (2015).

(2005) to a Smooth Transition regression and to a Threshold regression respectively. The calculation of the IRFs involves the estimation of a set of regressions for each horizon $h = 0, 1, \ldots, H$:

$$\begin{aligned} Y_{t+h} = &\left(1 - F\left(v_{t-1}\right)\right)\left[A_h^{EXP}\left(L\right)Y_{t-1} + B_h^{EXP}\left(L\right)X_t + \gamma_h^{EXP}Z_t + C_h^{EXP}\left(L\right)Z_{t-1}\right] \\ &+ F\left(v_{t-1}\right)\left[A_h^{REC}\left(L\right)Y_{t-1} + B_h^{REC}\left(L\right)X_t + \gamma_h^{REC}Z_t + C_h^{REC}\left(L\right)Z_{t-1}\right] + \varepsilon_{t+h} \end{aligned} \tag{2.1}$$

$$F(v_t) = \frac{\exp(-\alpha v_t)}{1 + \exp(-\alpha v_t)} = \frac{1}{1 + \exp(\alpha v_t)}, \quad \alpha > 0 \tag{2.2}$$

$$\mathbb{E}\left[v_t\right] = 0 \text{ and } \operatorname{var}\left(v_t\right) = 1 \tag{2.3}$$

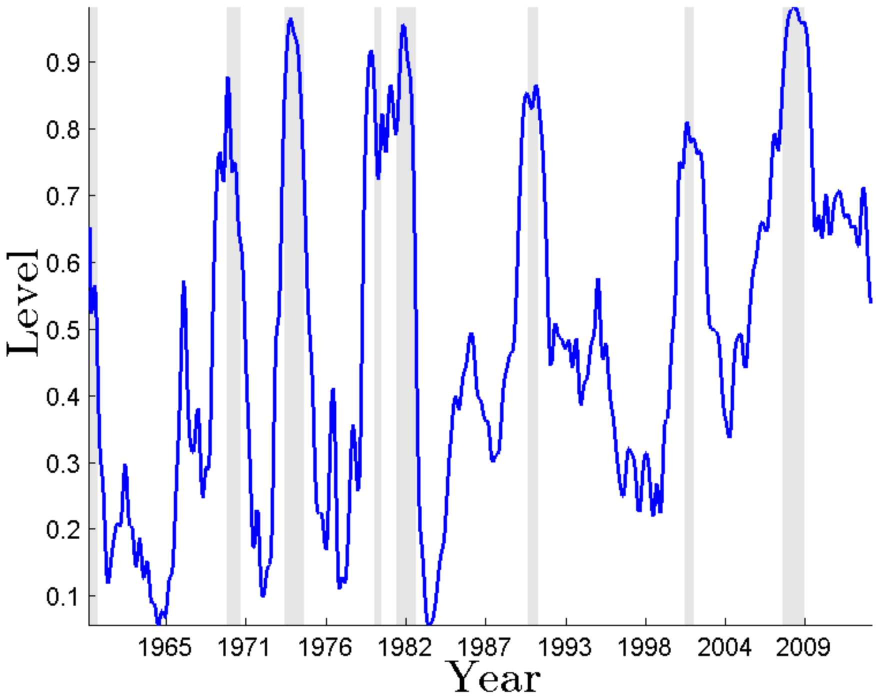
where Y is the response variable of interest, X are controls and Z is the variable we are shocking. $F\left(\cdot\right)$ is a logistic function and v_t is the variable that defines the transition from one state to the other. The matrices $A_h^{EXP}\left(L\right)$, $A_h^{REC}\left(L\right)$, $B_h^{EXP}\left(L\right)$, $B_h^{REC}\left(L\right)$, $C_h^{EXP}\left(L\right)$ and $C_h^{REC}\left(L\right)$ are lag polynomials, whose coefficients depend on the state of the business cycle (EXP stands for expansion and REC stands for recession). The coefficients γ_h^{EXP} and γ_h^{REC} are the state-dependent impulse response of Z_t upon Y in h steps ahead. The vector ε_{t+h} is the error term at time $t + h$. These errors are assumed to be normally distributed.

Similarly as in Auerbach and Gorodnichenko (2013) and Bachmann and Sims (2012), the transition variable v is defined as a standardized centered seven-quarter moving average of the growth rate of real gross domestic output (GDP)[2]. The logistic function $F\left(v_t\right)$ is bounded between 0 and 1 and can be interpreted as the probability of being in a recession, given observations on v_t. If $F\left(v_t\right) \approx 1$, v_t must be very negative , while if $F\left(v_t\right) \approx 0$, v_t is very positive. As in Auerbach and Gorodnichenko (2013), a recession is defined as a period in which $F\left(v_t\right) > 0.8$. The parameter α is calibrated to match the observed frequency of recessions in the United States since 1960 according to the NBER business cycles dates (approximately 14%). Thus $\Pr\left(F\left(v_t\right) > 0.8\right) \approx 0.14$ yields $\alpha = 1.32$. When α is equal to 0 the logistic function becomes constant and the model (2.1) collapses into a linear (state-independent) model. When $\alpha \rightarrow \infty$, the function $F(\cdot)$ becomes a Dirac function and the model (2.1) becomes a two regime Threshold model as in Tong (1983). Figure 2.1 compares the cyclical indicator $F\left(v_t\right)$ with the recessions as dated by the NBER (gray shaded areas). Given that the GDP is measured at a quarterly frequency, while the rest of our data are monthly, I

[2] I consider also a backward looking moving average of real GDP growth, but there are no significant changes in the results.

perform a spline interpolation of the transition variable, in order to obtain the missing observations.

Figure 2.1: *Probability of being in a recessionary state*



NOTES: The blue line is the probability of being in a recession, $F(v_t)$; the grey shaded areas are the recessionary phases as dated by the NBER; black line is threshold value I used to define a recession.

2.2.2 Local Projection Method (LPM)

In the standard VAR literature, impulse responses are estimated from the Wold representation of the VAR process. This involves a two steps procedure. First the model needs to be estimated and secondly, the estimates need to be inverted. As Jorda (2005) points out, this is only justified if the model is not misspecified, i.e. the VAR under consideration is actually the true data generating process (DGP). The projection technique combines the two steps mentioned above into one and is more robust to model misspecifications. More specifically, consider the definition of the impulse response by Koop et al. (1996), that abstracts from any reference to the DGP:

$$IRF(t,h,d_i) \equiv \mathbb{E}\left[Y_{t+h}|v_t = d_i; S_t\right] - \mathbb{E}\left[Y_{t+h}|v_t = 0; S_t\right] \tag{2.4}$$

where: $E[\cdot|\cdot]$ is conditional expectation function; y_t is a vector of dimension $n \times 1$; S_t is the vector of lags of Y_t and other controls; v_t is the vector of reduced form errors;

d_i is the identified structural shock. The IRF as defined in equation (2.4) is the best multi-step prediction of Y_{t+h} given S_t. Best, in the sense that it minimizes the mean squared error. Unless the VAR is the DGP, recursively iterating on the estimated VAR model is not an optimal way of computing the IRFs. Direct forecasting models, re-estimated for each h, produce better multi-step predictions.

As an illustration of the LPM, consider to estimate the following linear regression (2.5):

$$Y_{t+h} = A_h\left(L\right)Y_{t-1} + B_h\left(L\right)X_t + \gamma_h Z_t + C_h\left(L\right)Z_{t-1} + \varepsilon_{t+h}. \tag{2.5}$$

For example, projecting Y_{t+2} onto the variables on the right-hand side, we obtain the estimate $\hat{\gamma}_2$. This is the effect of an increase in Z_t on Y two-months ahead, that is orthogonal to the other variables on the right-hand-side of the equation. Estimating H regressions for each response variable Y of interest gives us the sequence of "*local projections*". The estimated IRFs are given by the sequence $(\hat{\gamma}_h)_{h=0}^{H}$. The main complication associated with the local projection method is the serial correlation in the error terms due to the successive leading of the dependent variable. It is therefore important to use HAC (heteroskedasticity and autocorrelation) robust standard errors. Error bands can then be computed for various confidence levels simply as:

$$\begin{aligned}
&68\%\text{ confidence:} && 0.9945 \pm \left(d_i'\hat{\Sigma}_{HAC}d_i\right)\\
&90\%\text{ confidence:} && 1.6449 \pm \left(d_i'\hat{\Sigma}_{HAC}d_i\right)\\
&95\%\text{ confidence:} && 1.96 \pm \left(d_i'\hat{\Sigma}_{HAC}d_i\right)\\
&99\%\text{ confidence:} && 2.5758 \pm \left(d_i'\hat{\Sigma}_{HAC}d_i\right)
\end{aligned} \tag{2.6}$$

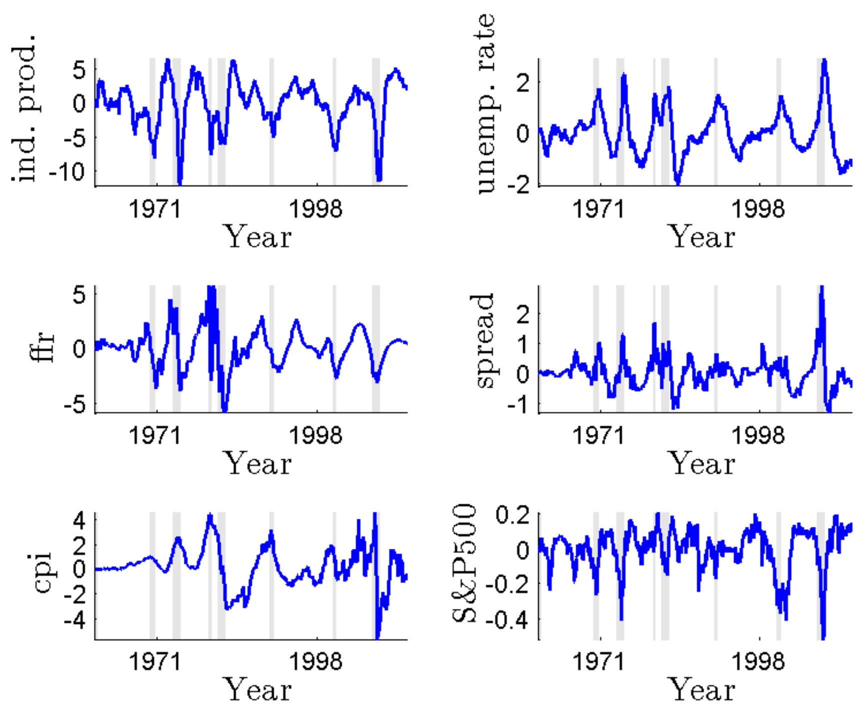
where $\hat{\Sigma}_{HAC}$ is the estimate matrix of HAC robust standard errors. An example of such estimator is that suggested by Newey and West (1987).

The LPM as defined by equation (2.1) has several advantages over the STVAR considered by Caggiano et al. (2014). First, it involves only linear estimations and is therefore computationally less cumbersome. Second, it does not impose dynamic restrictions on the IRFs. As a result, the impulse responses computed with the local projection method are less sensitive to model misspecifications. Third, the methodology conveniently accommodates for nonlinearities in the response function. Last but not least, the impulse responses computed with this methodology incorporate the average transitions of the economy from one state to another since the set of regressors in (2.1) does not vary with h. In the STVAR used by Caggiano et al. (2014) instead, the impulse responses were computed under the assumption that the regime was fixed.

2.2.3 Data

The model is estimated with monthly data for the United States. The time span considered is July 1960 to December 2014. I collect the data on real gross domestic product (quarterly), industrial production, unemployment rate, consumer price index, real gross domestic product, federal funds rate, spread between the yield on BAA corporate bonds and the 10-year treasury bonds yield from the FRED database of the Federal Reserve of St.Louis. The series of the $S\&P500$ index is taken from Yahoo-Finance. I take the logarithm of the series for production,$S\&P500$ index and uncertainty (described below). Similarly as Bloom (2009) I remove trends with the Hodrick-Prescott (HP) filter[3] with smoothing parameter $129,600$. Given the dynamic procedure used to estimate the impulse responses, I opt for the one-sided HP filter. Figure 2.2 displays the series of the variables used in the baseline estimation.

Figure 2.2: *Variables used for the estimation*



NOTES: The variables displayed are the variables used for the estimation of the Smooth Transition LPM model. The series of industrial production, cpi, and S& P500 index are in logs percent and filtered with a one-sided HP filter with smoothing parameter equal to $129,600$.

The measurement of uncertainty has been widely discussed in the literature (see e.g., Bloom, 2009; Baker et al., 2016; Jurado et al., 2015). Economic uncertainty refers

[3] As will be discussed in section 2.3.1, I also run the regression leaving all variables unfiltered and including a deterministic quadratic trend. The main results are unchanged.

to an environment in which little or nothing is known about the future state of the economy. Economic uncertainty can stem from various sources such as economic and financial policies, dispersion in future growth prospects, productivity movements, wars, terrorist attacks, and natural disasters (Bloom, 2009). The latent nature of uncertainty makes this variable difficult to quantify. Macroeconomic uncertainty has been often proxied by the VIX and VXO indexes. These indexes are measures of the implied volatility respectively of the S&P 500 and S&P 100 option prices. In other words, they represent measures of the market's expectation of stock market volatility over the next 30 days. As it has been pointed out by Jurado et al. (2015) and Bekaert et al. (2013), stock market volatility may be a poor proxy for macroeconomic uncertainty, as it is driven also by other factors such as risk aversion, leverage, and sentiments. For this reason in this paper I will use the uncertainty measure estimated by Jurado et al. (2015) that is available at a monthly frequency from July 1960 to December 2014. This measure of macroeconomic uncertainty is defined as the common dispersion in the unforecastable component of a large number of economic indicators. Figure 2.3 displays the aforementioned uncertainty measure and compares it to the stock market volatility index used in Bloom (2009), which is based on the VXO[4]. Since the VXO is available only from 1986 onward, the observations prior to 1986 are calculated as the monthly standard deviation of the daily S&P500 index normalized to the same mean and variance as the VXO index. As it is clear from the figure, uncertainty tends to be relatively high during economic downturns. The measure by Jurado et al. (2015) reveals three periods of high uncertainty in the considered sample, namely the recessions in 1973-74, 1981-1982 and the Great Recession in 2007-2009. The VXO instead reveals 17 periods of high uncertainty, which may not all be related to macroeconomic fundamentals. For example, the index reaches a larger value during the Black Monday (19th October 1987) than during the Great Recession in 2007, although the changes in macroeconomic activity that occurred during the last crisis are incomparably larger than those in the late 1980's.

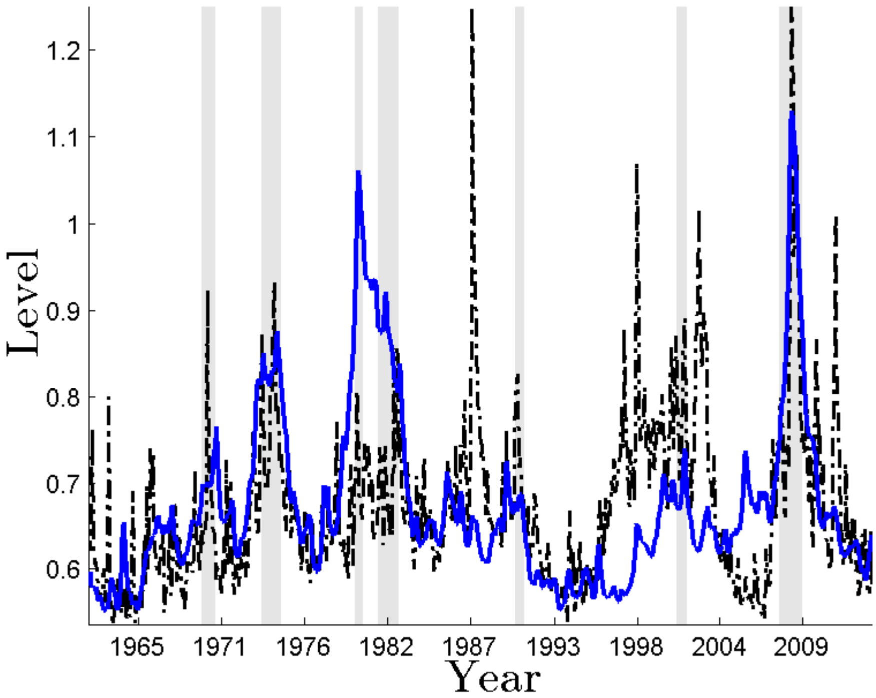
2.3 Results

In this section, I discuss the impulse responses (IRFs) obtained from the linear (state-independent) model as in equation (2.5) and compare them to those obtained with the Smooth Transition model given by equation (2.1) for the two different states, i.e. Recession and Expansion.

Figures 2.4 and 2.5 display the state-independent and state-dependent IRFs to a 1 percent increase in uncertainty to two real macroeconomic variables, namely industrial

[4]For comparison purposes, in figure 2.3 the stock market volatility index has been rescaled to have same mean and variance as the uncertainty measure by Jurado et al. (2015)

Figure 2.3: *Macroeconomic Uncertainty*



NOTES: The blue line is the macroeconomic uncertainty measure estimated by Jurado et al. (2015), $\bar{\mathcal{U}}_t^y(1)$. The black dash-dotted line is the VXO series used by Bloom (2009). Grey shaded areas are the NBER recession dates.

production and unemployment. Using the same notation as in equation (2.5), we have that Y is given by industrial production (unemployment), X_t is a vector consisting of the lagged federal funds rate r_{t-1}, the lagged spread s_{t-1}, lagged value of the log $S\&P500$ index, $sp500_{t-1}$[5], lagged unemployment u_{t-1} (industrial production, y_{t-1}). The Z_t is given by the lagged value of the log of the uncertainty variable σ_{t-1}. The IRFs of the nominal variables, i.e. the federal funds rate and the spread between the yield on BAA corporate bonds relative to yield on 10-year treasury bonds, are displayed in figures B.1 and 2.6. In this case Y is given by r (or s), and X_t is the vector $[y_t, u_t, s_t, sp500_t]'$ (or $[y_t, u_t, r_t, sp500_t]'$). The Z_t is now the uncertainty variable at time t, σ_t. Implicitly I am assuming that the real variables respond with a lag to uncertainty and the nominal variables, while the response of the nominal variables, i.e. the federal funds rate, and the spread, is immediate to both uncertainty and the real variables[6]. I believe this identification strategy is plausible given the monthly frequency of the data. Nevertheless, the results are very similar if we assume that also industrial production and unemployment respond immediately to uncertainty shocks. The order of the lag-polynomials is 6, as suggested by the AIC.[7]

The IRFs of the linear model displayed in figure 2.4 show that a 1 percent increase in uncertainty worsens macroeconomic activity, reducing industrial production and increasing unemployment in a fairly persistent way. These effects are significant at a 68% significance level[8]. This result confirms what has been found previously in the literature (see e.g., Bloom, 2009; Jurado et al., 2015; Caggiano et al., 2014). An important difference is that the quick rebound and "overshoot" that has been found in Bloom (2009) is not present in this case. As I will discuss in subsection 2.3.1, this result is not driven by the choice of the uncertainty variable as the overshoot is not present even when I use stock market volatility as a proxy for macroeconomic uncertainty.

The IRFs of the Smooth-Transition model, displayed in figure 2.5, show that a 1 percent increase in uncertainty significantly worsens macroeconomic activity during recessions (black line). This confirms the results in Caggiano et al. (2014), that find that uncertainty shocks lead to a larger increase in unemployment during recessions than a linear model would predict. Perhaps more surprisingly, (red circled line) an increase in uncertainty during expansions appears to raise industrial production and sluggishly reduce unemployment. Moreover, in recessions, an increase in uncertainty

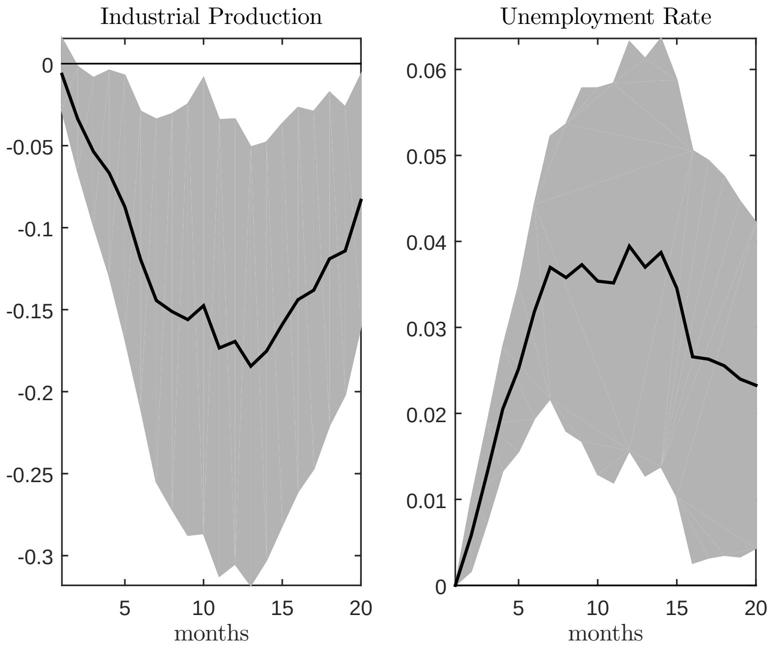
[5] This follows Bloom (2009), who includes the $S\&P500$ index to control for movements in the stock market.

[6] I also consider the possibility that the real variables also respond immediately to changes in uncertainty and results remain unchanged.

[7] The local projection method guarantees more robust results in case of lag-order misspecification than the VARs.

[8] The fall in industrial production is not significant at a 90% significance level

Figure 2.4: *State-independent IRFs after an uncertainty shock*



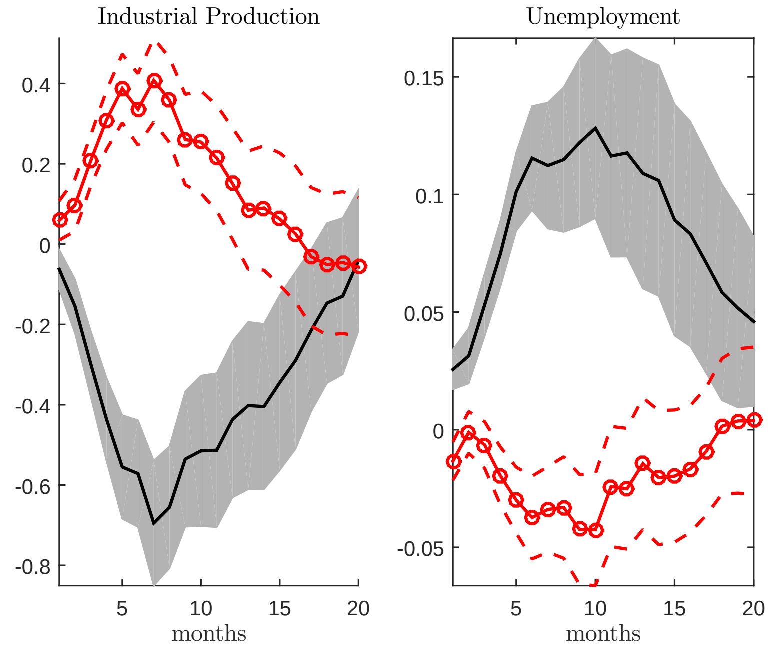
NOTES: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The gray shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

tends to reduce federal funds rate and increase the spread between the BAA corporate bond yield relative to the yield on the 10-year Treasury bond. The fall in macroeconomic activity and in the federal funds rate (see figure 2.6) confirms (partially) the result in Basu and Bundick (2017) and Leduc and Liu (2016) that uncertainty shocks act as negative demand shocks. On the contrary, uncertainty shocks in expansions appear to act as positive demand shocks, increasing macroeconomic activity and raising prices. In subsections 2.3.1 and 2.3.2 I discuss how sensitive the results are to various changes to the baseline specifications and a possible interpretation. Furthermore, I explain how my results relate to existing theoretical and empirical findings in the literature.

2.3.1 Robustness Checks

In this subsection, I discuss the robustness of the results described above. First, I replace the uncertainty measure with the stock market volatility. Figure B.2 displays the result. The main difference is in the response of the federal funds rate, while for the real variables, the results seem to be confirmed, i.e. uncertainty seems to have positive effects on macroeconomic activity in expansions and negative effects in recessions.

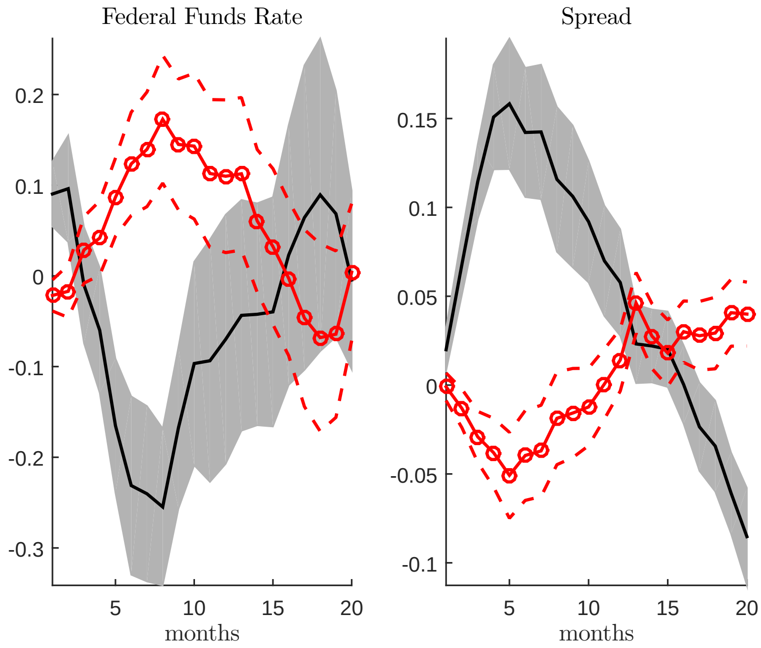
Figure 2.5: *State-dependent IRFs after an uncertainty shock*



NOTES: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The red circled line is the IRF of the response variable in an expansionary regime. The red dashed line and the gray shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

Second, I check whether my results are sensitive to the inclusion in the sample of the period where the federal funds rate has approached the zero lower bound (ZLB). Figure B.3 in the appendix displays the IRFs when the sample considered is July 1960 to November 2008. As the figure shows, the main result does not change. Uncertainty affects negatively economic activity during recessions, and positively during expansions. Two points need be mentioned: (i) the exclusion of the period with the ZLB notably mitigates the effects of uncertainty shocks. In particular, in recessions, the fall in industrial production is only 1/3 as strong than in the baseline case. Also, unemployment rises more mildly than the in the baseline case. (ii) The fall (rise) in economic activity in recession (expansion) is less persistent when the ZLB is omitted. In particular, after an increase in uncertainty, the fall (rise) in industrial production last only 10 months approximately and displays an overshoot. Both results are in line with Basu and Bundick (2017) and Bonciani and van Roye (2016), who explained with New-Keynesian Dynamic Stochastic General Equilibrium models that the monetary authority plays a crucial role in mitigating the effects of uncertainty shocks. Moreover, they show that the effects of these shocks are strongly amplified if the central bank is constrained by the ZLB or if its policy is not perfectly passed-through by the banking sector. However, what should be noted is that by removing the sample from

Figure 2.6: *State-dependent IRFs after an uncertainty shock*



NOTES: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The red circled line is the IRF of the response variable in an expansionary regime. The red dashed line and the gray shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

November 2008 onwards, we are also removing some observations from the relatively short sample of recession dates, which might affect the estimation of the IRFs.

Third, I check for the sensitivity of the results with respect to the α parameter in equation (2.1) (see figure B.4). For any variable that I considered, results do not seem to change much if I increase α from 1.32 to 2. Fourth, I control for consumer confidence by adding the OECD confidence indicator to X_t in equation (2.1). As figure B.5 shows, results are robust to this type of variation. Fifth, I check whether varying the order of the lag polynomials in equation (2.1) may significantly affect the results. Both for a lag order of 3 (figure B.6) and lag order of 10 (figure B.7), results remain stable. This is not very surprising since, with the local projection method, the parameters in the lag polynomials should not affect the dynamics of the IRF. Sixth, I check whether the results may be driven by the assumptions imposed to identify the uncertainty shocks. Consistently with Bloom (2009) and Jurado et al. (2015), I consider the case that the real variables (industrial production and unemployment) may respond immediately to an uncertainty shock. As figure (B.8) shows, results remain substantially unchanged. Seventh, I check whether the results still hold if I consider a backward-looking moving average of real GDP growth as a transition variable v instead of the centered moving average used in the baseline analysis. The reason for this check is that the error term in the regression could be correlated with the transition variable if we consider the centred moving average. Figure(figure B.9) shows that the results still hold under this change. Last, I test whether my results could be biased from the filtering of the data. To this end, I re-estimate the baseline model using only the raw data with their trend and the results are displayed in figure B.10. It is clear that even in this case, the results are unchanged and only become slightly more persistent.

Overall, the results are stable to various changes to the baseline analysis. The main difference is due to the change in the uncertainty variable. Nevertheless, as discussed above, the choice of the Jurado et al. (2015)'s uncertainty measure seems to be more appropriate to analyze the effects of macroeconomic uncertainty.

2.3.2 Explaining the Asymmetric Effects

The results of the linear model and of the recessionary regime are in line with what had been found previously in most of the empirical literature. Increases in uncertainty strongly dampen economic activity through various channels such as the *"wait-and-see"* channel and precautionary savings. Moreover, uncertainty shocks can be strongly amplified by financial frictions (see e.g., Gilchrist et al., 2014; Bonciani and van Roye, 2016) that may be especially stringent in recessionary times and lead the stabilizing effects of monetary policy to be less effective than in expansion. With the methodology adopted in this paper, the fall in economic activity after an increase in uncertainty can be very persistent. The rebound and overshoot in industrial production that is usually found in the literature is not present in the baseline case but only once I omit the period in which the nominal rates approached the ZLB. The rebound and overshoot effects have been explained in Bloom (2009) through the wait-and-see channel in a partial equilibrium framework. More specifically, under uncertainty, firms have an option of delay when investment is partially or completely irreversible. Uncertainty shocks lead in the short-run to a drop in investment and hiring, while in the medium run they generate a rebound and an overshoot. As discussed in subsection 2.3.1, the results in my paper suggest that a prompt response by the monetary authority may be necessary to obtain the effects mentioned above.

Why do uncertainty shocks have positive effects on economic activity during expansions? The theoretical literature does not usually distinguish between the two regimes. According to the channels mentioned above (i.e. the wait-and-see and the precautionary savings channels), we would expect uncertainty shocks to have similar (at least qualitatively) effects on the macroeconomy regardless of the state of the business cycle. One possible explanation is related to the fact that during expansions uncertainty spurs investment and therefore economic activity via the *"growth options"* channel.

More specifically, according to the "growth options" channel, the initial investment can often be seen as the purchase of a call option to expand in the future. If the value of such option is large enough to compensate for the initial investment, then the firm may be willing to undertake it. The value of such options is positively related to uncertainty if this (uncertainty) increases the potential return. Therefore, if uncertainty in expansions is mostly associated with increases in the potential returns on investments, while in recessions uncertainty is mainly associated with a reduction in returns, then real options effects ("growth-options" and "wait-and-see") can explain the opposite effects of uncertainty during the different states of the business cycle. Two recent works by Segal et al. (2014) and Rossi and Sekhposyan (2015) provide empirical support that uncertainty affects economic activity via the growth options channel by decomposing total uncertainty into two components: *"Good"* (or *"Upside"*) and *"Bad"* (*or "Downside"*) uncertainty. Good or Upside uncertainty consists in uncertainty associated with news or outcomes that are unexpectedly positive (e.g. higher GDP than expected). An example of an upside uncertainty shock is the high-tech revolution of the 1990's, that with the introduction of the *world wide web* led to the common view that the new technology would give rise to persistent growth, yet it was uncertain by how much and for how long. Bad or downside uncertainty instead consists of uncertainty that stems from news or outcomes that are unexpectedly negative (e.g. lower GDP than expected). An example of a downside uncertainty shock is the large surge in uncertainty after the collapse of Lehman Brothers in 2008. After this event people expected the economy to be hit negatively, but they did not know how much and for how long. Segal et al. (2014) estimate good and bad uncertainty following Barndorff-Neilsen et al. (2010) and Patton and Sheppard (2013), decomposing the realized variance into two components that separately capture positive (good) and negative (bad) movements in the underlying variable[9]. Rossi and Sekhposyan (2015) instead propose new uncertainty indexes for upside and downside uncertainty based on the percentile in the historical distribution of forecast errors associated with the realized error[10]. Both papers find good uncertainty to have positive effects on economic activity, while bad uncertainty affects it negatively, acting as a negative demand shock. Moreover, uncertainty has a predominant downside component during recessions, while upside uncertainty is more frequent in expansions.

2.4 Concluding Remarks

Uncertainty is considered to have particularly severe effects when the economy is in a recessionary phase. The present paper provides empirical evidence on the asymmetric

[9]Good and bad uncertainty are estimated by projecting the logarithm of the positive realized semi-variance, RV^P, and negative realized semi-variance, RV^N of the underlying macroeconomic variable (such as industrial production) onto a set of predictors X_t.

[10]Let e_{t+h} be the $h-$ step ahead forecast error of y_{t+h} defined as $y_{t+h} - E_t[y_{t+h}]$ and let $f(e)$ be its forecast error distribution. Uncertainty is then defined as the cumulative distribution $U_{t+h} = \int_{-\infty}^{e_{t+h}} f(e)de$. Upside and downside uncertainty are defined respectively as $U^+_{t+h} = \frac{1}{2} + max\left\{U_{t+h} - \frac{1}{2}, 0\right\}$ and $U^-_{t+h} = \frac{1}{2} + max\left\{\frac{1}{2} - U_{t+h}, 0\right\}$

macroeconomic effects of uncertainty shocks depending on the state of the business cycle. To this end, I estimate state-dependent impulse responses for the US economy with the local projection method developed by Jorda (2005). I find that during recessions positive uncertainty shocks have significant dampening effects on economic activity and act as negative demand shocks. In expansions instead, uncertainty shocks have a positive effect on economic activity. In line with the theoretical literature (Basu and Bundick, 2017), I find that by excluding from the sample the period in which the federal funds rate approached the Zero Lower Bound, the effects of uncertainty on the macro-economy are strongly mitigated in both phases of the business cycle. One potential interpretation of the asymmetric effects of uncertainty during expansions and recessions is that in upturns uncertainty is mostly driven by "good" uncertainty and positively affects economic activity through the "growth options" channel. During downturns instead, uncertainty is mostly "bad" and tends to affect negatively the economy via other channels such as the "wait-and-see" effect.

Chapter 3

The Long-Run Effects of Uncertainty Shocks

Keywords: Uncertainty Shocks, R&D, Endogenous Growth.
JEL classification: E21, E32.

3.1 Introduction

Since the Great Recession, there has been a growing interest by economists and policymakers in understanding how uncertainty affects economic activity. Heightened uncertainty is in fact considered one of the main factors behind the depth of the recession and the subdued recovery (e.g. see Stock and Watson, 2012). In this paper I study how shocks to uncertainty affect economic activity both in the short-run and in the long-run through the lenses of a dynamic stochastic general equilibrium (DSGE) model augmented with an endogenous growth mechanism. I find that rises in uncertainty act as negative demand shocks, causing a fall in output, consumption and investment in physical capital and R&D. The reduction in R&D leads to a permanent decline in economic activity due to the knowledge spillovers mechanism. Furthermore, I show that when agents have recursive preferences à la Epstein and Zin (1989), taking future risk into account, the long-run effects of uncertainty strongly amplify the precautionary savings motive of households and the markup channel.

This work is related to the growing literature on uncertainty shocks, which started with the seminal contribution by Bloom (2009). Numerous papers (e.g. Backus et al., 2015; Born and Pfeifer, 2014; Bachmann et al., 2013; Fernandez-Villaverde et al., 2015; Basu and Bundick, 2017) have investigated how uncertainty shocks could generate business cycle fluctuations both with empirical and theoretical frameworks.

From an empirical perspective, the literature has found that rises in uncertainty can cause a significant fall in economic activity. This result has been found using various measures of uncertainty such as financial volatility indexes (Bloom, 2009), macroeconomic uncertainty measures (Jurado et al., 2015; Rossi and Sekhposyan, 2015) or political uncertainty news-based indexes (Baker et al., 2016; Caldara and Iacoviello, 2016).

From a theoretical point of view, the literature has concentrated on disentangling the potential transmission channels through which uncertainty can affect macroeconomic variables and on quantifying the effects within Dynamic Stochastic General Equilibrium Models (DSGE). The main transmission channels that have been discussed in the literature are: (i) the precautionary savings channel, that leads risk-averse agents to reduce consumption and increase labour supply (Leland, 1968; Kimball, 1990); (ii) the real options channel, which causes firms to postpone irreversible investments (Bernanke, 1983; Bertola and Caballero, 1994; Pindyck, 1991); (iii) the convex marginal cost revenues channel, for which a higher uncertainty in productivity raises investment, hours and output if the optimal choices of capital and labour are convex in productivity (Oi, 1961; Abel, 1983; Hartman, 1976); (iv) the cost of financing channel, for which rises in uncertainty lead to increases in risk premia that in turn make borrowing more costly and therefore reduce investment (Christiano et al., 2014; Gilchrist et al., 2014; Arellano et al., 2016).

While in partial equilibrium these transmission channels have clear-cut effects, they may offset each other in a general equilibrium framework. Basu and Bundick (2017) show that in a model with sticky prices and time-varying markups uncertainty shocks can generate business cycle fluctuations, i.e. co-movement between output, consumption, and investment.

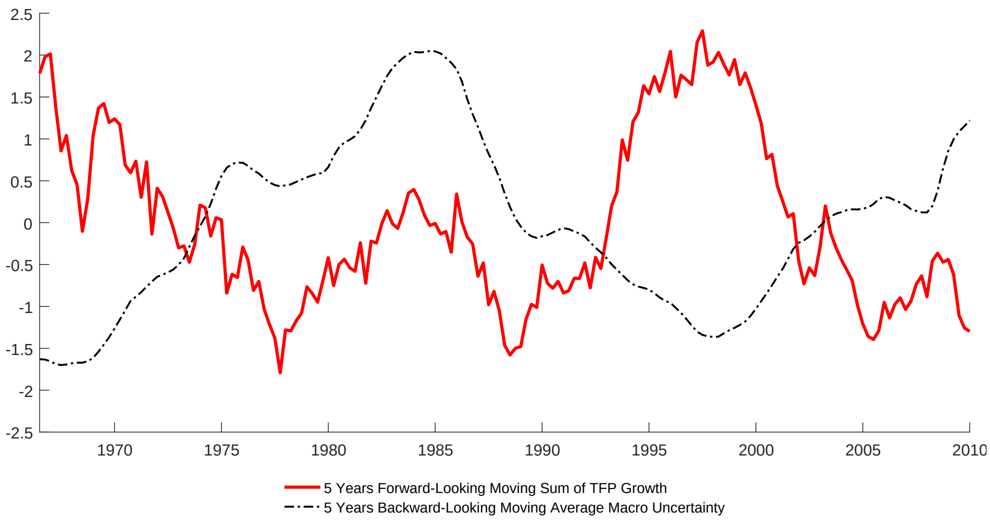
The literature has provided mixed evidence on the quantitative relevance of uncertainty shocks. With standard business cycle models, the effects of uncertainty shocks tend to be economically insignificant (e.g. Born and Pfeifer, 2014; de Groot et al., 2017; Bachmann and Bayer, 2013). The reason for the small effects found in the literature is that the shocks are small and not sufficiently amplified. One particular problem is that the standard business cycle models are very close to linear. Accounting for non-linearities such as the zero lower bound has been found to be an important source of amplification Basu and Bundick (2017); Fernandez-Villaverde et al. (2015). Another strand of literature has also shown that uncertainty could be amplified in the presence of frictions in the financial sector (Christiano et al., 2014; Bonciani and van Roye, 2016), in the labour market (Leduc and Liu, 2016; Guglielminetti, 2016). In this paper, I consider an additional source of nonlinearity deriving from the aversion of agents for the long-term effects of uncertainty on consumption, in the spirit of the long-run risk literature (Bansal and Yaron, 2004).

By analysing how uncertainty affects economic activity in the long-run, I depart from the previous literature which only focused on the business cycle effects of uncertainty.

Therefore, this work bridges the literature on uncertainty shocks with another relatively recent strand of the literature that analyses the long-run growth impact of business cycle shocks (e.g. Anzoategui et al., 2016; Bianchi et al., 2014). This paper also relates to the more general discussion on "Secular stagnation" (e.g. Summers, 2013; Benigno and Fornaro, 2015; Fernald and Jones, 2014).

To motivate that uncertainty may negatively affect economic activity in the long-run, in Figure 3.1 I show how past uncertainty is a strong predictor of future movements in TFP. In particular, I compare the backward-looking moving average of macroeconomic uncertainty over the previous 20 quarters and the forward-looking moving average of the Total Factor Productivity (TFP) growth rate over the next 20 quarters. The uncertainty measure is the one estimated by Jurado et al. (2015). The measure of TFP growth is taken from Fernald (2012), which is adjusted for capacity utilisation. For comparative purposes, I have rescaled the two series to have mean 0 and unit standard deviation. Evidently, the two series negatively co-move, with a correlation of -60.3%. The correlation remains very strong after partialling out the effects of past GDP growth (results are displayed in Table C.1).

Figure 3.1: *Negative Correlation between past Macroeconomic Uncertainty and future TFP growth*



This result is in line with the analysis conducted in the seminal study by Ramey and Ramey (1995), who found that countries with higher volatility have a lower mean growth. The evidence provided in figure 3.1, while suggestive, does not imply any causality in one direction or the other, nor it excludes the possibility that a third factor is driving both measures. In the remainder of the paper, I will provide empirical evidence (section 3.2) that higher uncertainty causes a reduction in economic activity in the long-run and a theoretical explanation (Section 3.3) through the lenses of a DSGE model with an endogenous growth mechanism. Section 3.4 presents some concluding remarks.

3.2 Empirical Evidence

In this section, I examine the effects of shocks to macroeconomic uncertainty in the data. As a measure of uncertainty, I consider that estimated by Jurado et al. (2015), defined as the average conditional volatility of the unforecastable component of the future value of many macroeconomic variables. To further check the robustness of my VAR, I then conduct several exercises, which are reported in subsection 3.2.2.

3.2.1 VAR Evidence

In order to provide empirical evidence that uncertainty shocks cause long-run declines in economic activity, I estimate a Vector Autoregressive (VAR) Model and analyse the impulse responses to orthogonalised shocks to macroeconomic uncertainty. I adopt a recursive identification scheme (i.e. Cholesky identification), assuming that uncertainty is contemporaneously affected by shocks to the S&P500, but not by the other macroeconomic variables. In subsequent periods, however, uncertainty responds to all shocks through its relation with the lags of the variables included in the VAR model. A similar identification strategy has been adopted in previous works (Fernandez-Villaverde et al., 2015; Leduc and Liu, 2016; Bloom, 2009) and are standard in the literature. In the appendix, I am going to show that placing uncertainty last (as in Jurado et al., 2015), would not affect the results.

The baseline VAR contains 8 variables, entering in the following order: the log of the Standard and Poors 500 index, $S\&P500$, which is commonly included in the literature to control for movements in the stock market; the measure of uncertainty estimated by Jurado et al. (2015), *uncertainty*; the log of private consumption in nondurables and services, C; the log of private investment in $R\&D$; the log of Private Fixed Investment I; the log of US gross domestic product Y; the log of CPI, P; the effective federal funds rates R. This ordering is in line with that by Bloom (2009) and the subsequent literature. Consumption, Investment, R&D Investment and GDP are expressed in real per capita terms. All variables are collected from the FRED database of the Federal Reserve Bank of St. Louis, except for the uncertainty measure[1]. Data are at a quarterly frequency, spanning the period 1960Q3-2016Q2, and all variables that come at a higher frequency, have been averaged over the quarter. I estimate the reduced-form VAR in equation (3.1) by ordinary least squares:

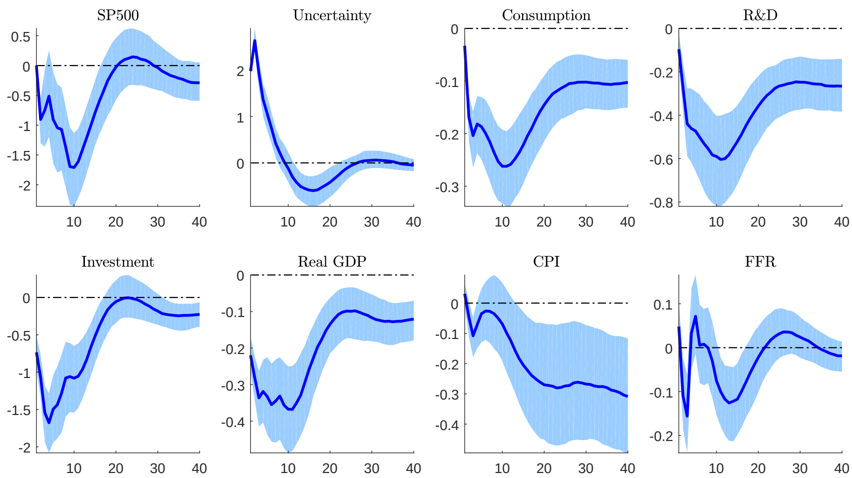
$$\begin{gathered} X_t = A(L)X_{t-1} + u_t, \;\; u_t \sim (0, \Sigma)\,. \\ \text{where} \\ X_t = [S\&P500, Uncertainty, C, R\&D, I, Y, P, R]'\,. \end{gathered} \tag{3.1}$$

[1]The uncertainty measure is take from Sydney Ludvigson's website

$A(L)$ is a lag polynomial of order 3 as suggested by the Akaike Information Criterion and the vector u_t represents the reduced form innovations, which have zero mean and variance Σ. All variables in the VAR enter in levels, as differencing or filtering the data throws away information about the long run properties of the data (Canova, 2007; Lütkepohl, 2013). The previous literature neglected potential long-run effects by filtering/differencing the data (Bloom, 2009; Basu and Bundick, 2017; Leduc and Liu, 2016), or including deterministic trends (Fernandez-Villaverde et al., 2015).

Figure 3.2 displays the Impulse Responses obtained from the VAR. The blue solid lines are median responses of the endogenous variables to one-standard-deviation uncertainty shock, while the shaded areas represent 68 percent confidence intervals. In line with Leduc and Liu (2016), unexpected increases in uncertainty act like negative demand shocks, which lead to a substantial decline in real economic activity as well as in the nominal variables. Real GDP declines by about 0.45 percent, while consumption and investment decline by 0.3 and 1.5 percent after 10 quarters. Rises in uncertainty also lead to a significant fall in prices and a milder fall in the federal funds rate, though both measures do not decline on impact but only subsequently. Furthermore, the impulse responses show that uncertainty shocks significantly dampen R&D expenditure, which falls by 0.6 percent. All real variables fall in a very persistent manner, especially GDP, R&D and consumption which do not revert back to their mean after 10 years.

Figure 3.2: *VAR Impulse Responses to an Uncertainty Shock*



Notes: The blue solid line and shaded areas are the median responses and 90% bootstrapped confidence bands.

3.2.2 Robustness Checks

The main results from the baseline VAR are robust to a variety of changes[2]. First, I estimate a VAR with the Macroeconomic Uncertainty Index by Rossi and Sekhposyan (2015) and the Financial Uncertainty measure by Ludvigson et al. (2015). Second, I consider a different ordering of the variables, in which Uncertainty is placed last. Third, I show that the aggregate demand effects of uncertainty are not confounded with the macroeconomic effects of shocks to consumer confidence. Fourth, I estimate a monthly FAVAR to check that my results are not affected by the quarterly frequency of the data and the insufficient information content in the VAR. Last, I estimate a mixed-frequency VAR, to exploit the higher information content of some variables that have been averaged over the quarter for the baseline analysis.

Alternative Measure of Macroeconomic Uncertainty

Rossi and Sekhposyan (2015) start from a similar definition of uncertainty as Jurado et al. (2015), i.e. uncertainty is defined as how predictable the economy is. Differently, from Jurado et al. (2015), they measure uncertainty from the distance between the realized value of a variable (Real GDP) and its unconditional forecast error distribution, obtained from the survey of professional forecasters. The IRFs reported in figure C.2.1 to a one standard deviation shock display a similar pattern both qualitatively and quantitatively. Consumption, GDP, and R&D Investment fall significantly by 0.3, 0.4 and 0.6 percent and the decline is very prolonged. The median response to Investment is also very persistent, though not significant after 15 quarters. Differently from the baseline evidence, the price level significantly increases on impact and the effect of uncertainty becomes negative only in the long-run. As a further robustness, I consider the measure of financial uncertainty by Ludvigson et al. (2015), estimated along the lines of Jurado et al. (2015), using only financial variables. Also in this case uncertainty has very persistent negative effects on macroeconomic variables, though the responses of GDP and R&D are significant only for about 20 quarters. Consumption persistently falls and the response becomes insignificant only after 30 quarters.

Alternative Identification Strategy

Throughout the literature on uncertainty shocks, the Cholesky identification strategy has been so far the most commonly adopted one. In the baseline SVAR, I assumed that uncertainty was not contemporaneously affected by the other shocks (except S&P500 shocks). As a robustness check, I consider an alternative ordering, placing uncertainty last, similarly as in Jurado et al. (2015). The IRFs reported in figure C.3 display a similar decline in the macroeconomic variables as in the baseline scenario, though the response to R&D investment becomes now insignificant after 25 quarters.

[2]Results are reported in the appendix C.2

Controlling for Consumer Confidence

To avoid that the effects of uncertainty reflect the agents' perception of bad economic times, I include a consumer confidence indicator as an additional variable in the VAR, similarly as Baker et al. (2016) and Leduc and Liu (2016). Figure C.4 displays the results of this alternative VAR specification. The inclusion of the consumer confidence index does not substantially affect the baseline results, neither qualitatively nor quantitatively. This finding suggests that the uncertainty shocks are not confounded with changes in consumer confidence.

Monthly FAVAR

Two potential issues with my baseline specification relate to the quarterly frequency of the data and the potential insufficient information contained in the model to capture the true effects of macroeconomic uncertainty shocks. In order to overcome these issues, I estimate a Factor-Augmented Vector Autoregressive (FAVAR) model in the spirit of Bernanke et al. (2004). The factors are extracted as principal components from a large dataset for the US economy, FRED-MD (McCracken and Ng, 2015), which includes 128 macroeconomic series. As suggested by the Forni-Gambetti test (Forni and Gambetti, 2014), I include the first two factors in the VAR, which account for about 96% of the total variation in the dataset. The FAVAR contains the following variables $X_t = [f1, f2, S\&P500, \text{Uncertainty}, IP, C, \text{Confidence}, CPI, FFR]$, where f1,f2 and IP are respectively the first two factors and industrial production. Figure C.5 displays the results of this alternative VAR specification for the main variables. The inclusion of the factors and the higher frequency of the data does not affect the baseline results, as all the real variables (IP and Consumption) fall persistently and do not revert back to their initial trend.

Mixed-Frequency VAR

As an additional robustness check to my baseline results, I estimate a Mixed-Frequency VAR, which allows me to include several variables at a monthly frequency, without having to average them out over the quarter. This exercise should be seen as complementary to the previous robustness exercise (Monthly FAVAR) and is aimed at showing that the quarterly frequency of the baseline specification does not drive the main results. Foroni and Marcellino (2016) discuss in depth the issues related to the identification and inference using time-aggregated data and highlight the advantage of mixed-frequency methodologies in overcoming these problems. In the construction of my model, I follow Ghysels (2016) and Ferrara and Guérin (2016), who employ a Mixed-frequency VAR, in which the variables are stacked depending on the timing of the data releases. One of the advantages of this methodology is that the estimation is rather straightforward, as it is carried out by ordinary least squares. More specifically, this type of mixed-frequency VAR is estimated at the low-frequency (quarterly) unit and the higher frequency (monthly) variables are reorganized at the quarterly frequency depending on the month of the quarter they refer to. Denote $Y_t^{(j)}$ the uncertainty measure in month j of quarter t, and Ψ_t a vector of quarterly variables. The mixed-frequency VAR is then written as a standard VAR:

$$X_t = A(L)X_{t-1} + u_t, \;\; u_t \sim (0, \Sigma)\,. \tag{3.2}$$

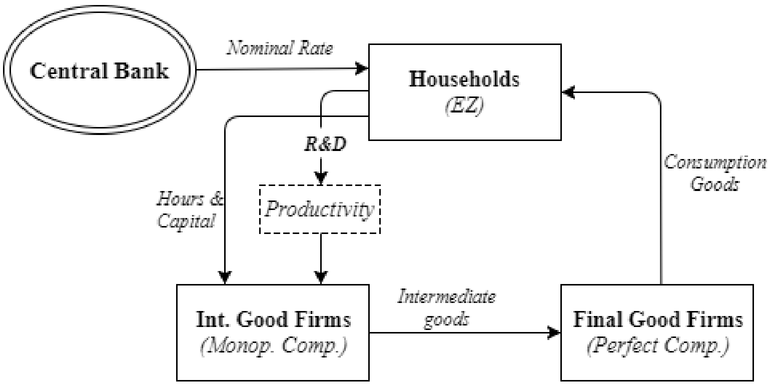
where $X_t = \left(Y_t^{(1)}, Y_t^{(2)}, Y_t^{(3)}, \Psi_t\right)$. In this case, I include three monthly-frequency data: the log stock market index (S&P500), the uncertainty measure and the log of consumption, i.e. Y_t^j=[s&p500, uncertainty, consumption]. The other variables, log of R&D (r&d), log of Investment (*inv*), log of Real GDP (*gdp*), FFR and log of CPI (*cpi*) enter at a quarterly frequency, i.e. Ψ_t=[r&d500,*inv*,*gdp*, FFR, *cpi*]. To calculate impulse responses, I again use the standard Cholesky identification strategy, with the ordering of the variables corresponding to the timing of the data releases, i.e. monthly variables are placed above the quarterly ones, and consistently with the baseline VAR, uncertainty comes second in the ordering. The IRFs obtained from this mixed-frequency model are presented in the appendix C.2.5. Uncertainty shocks identified within this model cause very persistent declines R&D, consumption, and GDP, confirming the main results obtained with the baseline VAR.

3.3 DSGE Model

This section studies the transmission channels of uncertainty shocks in New-Keynesian DSGE model with endogenous growth through R&D investment. I show that uncertainty shocks in such a model act like negative demand shocks, dampening real variables, as well as prices and interest rates. The decline in economic activity is permanent due to the fall in R&D, and these long-run fluctuations are an important source of amplification of the uncertainty shocks.

Households have recursive preferences à la Epstein and Zin (1989) (EZ) to separately calibrate the parameters governing relative risk aversion and the elasticity of intertemporal substitution. Moreover, these preferences allow households to care about long-run risk. R&D investment and endogenous growth are introduced as in Kung (2015), Bianchi et al. (2014) and Kung and Schmid (2015). Uncertainty shocks are modelled assuming that the exogenous component of TFP follows an AR(1) process with Stochastic Volatility as in Bloom (2009), Born and Pfeifer (2014) and Fernandez-Villaverde et al. (2015). Figure 3.3 displays a graphical summary of the model.

Figure 3.3: *New Keynesian Model with Endogenous Growth*



3.3.1 Households

The representative household maximises its lifetime utility choosing consumption C_t, hours worked L_t, next period bond holdings B_t, physical capital K_t and R&D N_t, and investment in physical capital I_t and in R&D S_t. The parameters ψ and γ govern the household's elasticity of intertemporal substitution and risk aversion. If $\psi = \frac{1}{\gamma}$ the utility function reduces to the standard power utility. In our case instead, under the assumption $\gamma \geq \frac{1}{\psi}$, this type of utility function implies a preference for the early resolution of uncertainty, i.e. agents dislike uncertainty over future utility. The problem of the household is then formalised as follows:

$$V_t = \max \left[(1-\beta)\, \Upsilon_t^{1-\frac{1}{\psi}} + \beta \left(E_t \left[U_{t+1}^{1-\gamma} \right]^{\frac{1-1/\psi}{1-\gamma}} \right) \right]^{\frac{1}{1-1/\psi}} \tag{3.3}$$

where E_t is the conditional expectation operator, and β is the subjective discount factor of the households. The variable Υ_t aggregates consumption and leisure, $\bar{L} - L_t$, in a Cobb-Douglas fashion:

$$\Upsilon_t = C_t^{\tau} \left(\bar{L} - L_t\right)^{1-\tau}. \tag{3.4}$$

The maximisation problem is subject to the following budget constraint:

$$C_t + b_t + I_t + S_t = D_t + w_t L_t + r_t^K K_{t-1} + r_t^N N_{t-1} + \frac{R_{t-1}}{\Pi_t} b_{t-1} \tag{3.5}$$

Where b_t are real bond holdings at time t, R_{t-1} is the nominal return on last period bonds, and Π_t is today inflation. Physical capital and the stock of R&D evolve according to the following laws of motions:

$$K_t = (1-\delta) K_{t-1} + \Lambda_K \left(\frac{I_t}{K_{t-1}}\right) K_{t-1}, \tag{3.6}$$

$$N_t = (1-\delta) N_{t-1} + \Lambda_N \left(\frac{S_t}{N_{t-1}}\right) N_{t-1}, \tag{3.7}$$

where δ_i are the depreciation rates and $\Lambda_i(\cdot)$ $(i = \{K, N\})$ are positive, concave adjustment cost functions, defined as in Jermann (1998):

$$\Lambda_{K,t} = \frac{\alpha_{K,1}}{1 - \frac{1}{\zeta_K}} \left(\frac{I_t}{K_{t-1}}\right)^{1-\frac{1}{\zeta_K}} + \alpha_{K,2} \tag{3.8}$$

$$\Lambda_{N,t} = \frac{\alpha_{N,1}}{1 - \frac{1}{\zeta_N}} \left(\frac{S_t}{N_{t-1}}\right)^{1-\frac{1}{\zeta_N}} + \alpha_{N,2} \tag{3.9}$$

Adjustment costs capture the idea that changing the capital and R&D stock rapidly is more costly than changing it slowly. The presence of these adjustment costs also implies that the shadow prices of K_t and N_t will not be constant and equal to 1. I will show that the presence of adjustment costs is crucial to obtain a fall in investment in physical capital and R&D after an uncertainty shock. The household's stochastic discount factor derived under the EZ preferences is given by the following condition:

$$\mathcal{M}_{t,t+1} = \beta \left(\frac{\Upsilon_{t+1}}{\Upsilon_t}\right)^{1-\frac{1}{\psi}} \left(\frac{C_t}{C_{t+1}}\right) \left(\frac{U_{t+1}}{E_t\left[U_{t+1}^{1-\gamma}\right]^{\frac{1}{1-\gamma}}}\right)^{\frac{1}{\psi}-\gamma} \tag{3.10}$$

3.3.2 Intermediate Goods Firms

There exists a continuum of intermediate-goods producing firms indexed by $j \in (0,1)$ that rent labour $L_{j,t}$, physical capital $K_{j,t}$ and R&D $N_{j,t}$ from the households at the respective prices w_t (real wage), r_t^k (rental rate of physical capital) and r_t^n (rental rate of R&D). These firms act in a monopolistically competitive environment, they set their price $P_{j,t}$ facing quadratic adjustment costs à la Rotemberg (1982)[3]. As firms are owned by the households, they discount future profits by the stochastic discount factor $\mathcal{M}_{0,t}$ defined in equation (3.10) and solve the following optimisation problem:

$$\max_{P_{j,t}, L_{j,t} K_{j,t}, N_{j,t}} \quad E_0 \sum_{t=0}^{\infty} \mathcal{M}_{0,t} \left\{ \frac{P_{j,t}}{P_t} X_{j,t} - w_t L_{j,t} - r_t^k K_{j,t} - r_t^n N_{j,t} \right. \\ \left. - \frac{\phi_p}{2} \left(\frac{P_{j,t}}{P_{j,t-1} \Pi_{SS}} - 1 \right)^2 Y_t \right. \tag{3.11}$$

subject to

$$X_{j,t} = \bar{K}_{j,t}^{\alpha} \left(A_t N_{j,t}^{\eta} N_{t-1}^{1-\eta} L_{j,t} \right)^{1-\alpha} \tag{3.12}$$

$$X_{i,t} = Y_t \left(\frac{P_{i,t}}{P_t} \right)^{-\nu} \tag{3.13}$$

where P_t is the equilibrium price of the final goods, $X_{j,t}$ is the product of firm j, $\bar{\Pi}$ is the (non-stochastic) steady-state level of inflation and Y_t is the final (equilibrium) output. The parameter $\eta \in (0,1)$ governs the degree of technological spillovers. In the spirit of Romer (1990), technological spillovers capture the idea that accumulated knowledge facilitates the creation of new knowledge.

3.3.3 Monetary Policy

The central bank sets the nominal rate R_t following a policy rule à la Taylor (1993). More specifically, I assume that the nominal policy rate depends on its past value and on deviations of inflation and detrended output from their respective non-stochastic steady state values:

$$\frac{R_t}{R_{SS}} = \left(\frac{R_{t-1}}{R_{SS}} \right)^{\rho_r} \left[\left(\frac{\Pi_t}{\Pi_{SS}} \right)^{\phi_\pi} \left(\frac{\hat{Y}_t}{\hat{Y}_{SS}} \right)^{\phi_y} \right]^{1-\rho_r} \tag{3.14}$$

The variable $\hat{Y}_t$ is aggregate output detrended by the endogenous component of productivity N_{t-1}.

[3]The assumption of Rotemberg adjustment costs over the Calvo (1983) framework is to keep the model more parsimonious in terms of state variables.

3.3.4 Closing the Model

Aggregate output Y_t is used for expenditure in consumption C_t, investment in R&D S_t, investment in physical capital I_t and price adjustment costs. The model is hence closed by the usual resource constraint:

$$Y_t = C_t + S_t + I_t + \frac{\phi_p}{2}\left(\frac{\Pi_t}{\Pi_{SS}} - 1\right)^2 Y_t \tag{3.15}$$

3.3.5 Exogenous Stochastic Processes

The exogenous component of productivity follows a stationary $AR(1)$ with stochastic volatility, similarly as Bloom (2009), Fernandez-Villaverde et al. (2015) and Basu and Bundick (2017):

$$log\left(A_t\right) = \left(1 - \rho^A\right) log\left(A_{SS}\right) + \rho^A log\left(A_{t-1}\right) + \sigma_t^A \varepsilon_t^A, \tag{3.16}$$

where $\rho^A \in (-1, 1)$ is the parameter governing the persistence of the technology shock ε_t^A, which is assumed to follow an iid standard normal stochastic process. Similarly, the time-varying standard deviation of the first-moment shock, σ_t^A, follows itself a stationary AR(1) process:

$$log\left(\sigma_t^A\right) = \left(1 - \rho^{\sigma^A}\right) log\left(\sigma_{SS}^A\right) + \rho^{\sigma^A} log\left(\sigma_{t-1}^A\right) + \sigma^{\sigma^A} \varepsilon_t^{\sigma^A}. \tag{3.17}$$

The term σ_t^A is what I define as uncertainty in the DSGE model and $\varepsilon_t^{\sigma^A}$ is the uncertainty shock, which follows an iid standard normal process. The parameter $\rho^{\sigma^A} \in (-1, 1)$ measures the persistence of the uncertainty shock.

3.3.6 Solving the Model and Calibration

In order to induce stationarity, I detrend consumption, R&D investment, physical capital investment, capital and output by the trend component in TFP, N_{t-1}. I then solve the model with perturbation methods, approximating the policy function to a third-order around its non-stochastic balanced growth path. As emphasized in Fernández-Villaverde et al. (2010), the third-order approximation of the policy function is necessary to analyse the effects of uncertainty shocks independently of the first moment shocks. With lower orders of approximation, in fact, uncertainty shocks either do not matter at all (certainty equivalence of the first order approximation) or they enter as cross-products with the other state variables. Furthermore, as discussed in Caldara et al. (2012), perturbation methods for DSGE models with stochastic volatility and recursive preferences are comparable, in terms of accuracy, to global solution methods such as Chebyshev polynomials and value function iteration, while being computationally more efficient.

Table 3.1 reports the values of the parameters used for the simulations of the model. The parameters relative to the preferences of the representative household are in line with the long-run risk literature. The discount factor β is set equal to 0.997 while the coefficient of relative risk aversion γ equal to 66 and the intertemporal elasticity of substitution ψ equal to 1.75, in line with the estimates by van Binsbergen et al. (2012). An intertemporal elasticity larger than 1 is also in line with Bansal and Yaron (2004) and its role is discussed in greater detail in subsection 3.3.7. The parameters relative to the investment adjustment costs, ζ_K and ζ_N are set to 1.5 and 9, in order to match the responses to the VAR evidence. The depreciation rate of physical capital is standard in the business cycle literature (0.02), used to match the average capital-investment ratio. The depreciation rate of R&D is set in line with Kung and Schmid (2015) to 0.0375, which corresponds to an annualised depreciation rate of 15%, a standard value assumed by the Bureau of Labour Statistics in the R&D stock calculations. The parameters relative to the firms' technology are standard in the business cycle literature. The share of capital in the production function α is equal to 1/3 and the demand elasticity (ϵ^y) is equal to 6, implying a steady-state markup of 20%. The Rotemberg price adjustment parameter κ_p is set to 60, which to a first order approximation implies a Calvo parameter of 0.75. The parameter of technological spillovers η is set to 0.1, in order to match the R&D investment rate in the steady state. The Taylor rule coefficients are standard in the New Keynesian literature. The steady state value of TFP $\bar{A}$ is calibrated to 0.22 to match the mean growth rate of output (2.75 percent annualised). The persistence and the standard deviation of TFP are set to 0.95 and 0.01, which are usual values for the TFP process in the RBC literature.

From the VAR evidence we see that the uncertainty measure gradually declines over time reaching about 30 percent of its peak after four quarters, which suggests a persistence parameter ρ_{σ^z} of 0.73, if uncertainty were to be approximated by an AR(1) process like in this model, which is in line with previous literature (e.g. Leduc and Liu, 2016). There is no consensus on how to calibrate the size of the uncertainty shock. I set the standard deviation of the uncertainty shock is calibrated to obtain the same response of consumption as in the VAR and allow for comparability of the impulse responses. The value of 0.4 is in line with the DSGE literature (Born and Pfeifer, 2014; Guglielminetti, 2016; Leduc and Liu, 2016). It should be noted that the model presented in this paper is kept very stylised in order to highlight the main transmission mechanisms, and abstracts from a variety of additional real (e.g. labour search and matching) and financial frictions (e.g. sticky lending rates or zero lower bound) which have been found to amplify the role of uncertainty. Born and Pfeifer (2014) discuss in great detail why the effects of uncertainty shocks in standard general equilibrium framework are small. The larger effects reported in Basu and Bundick (2017), in a similarly stylized model (but without long-run effects) is due to the erroneous modeling of the preference uncertainty shocks and the choice of the IES parameter below and very close to 1 (de Groot et al., 2017).

Table 3.1: *Parameter values used in the quantitative analysis*

Parameter	**Value**	**Description**
Households		
Preferences		
β	0.997	Discount Factor
ψ	1.75	Intertemporal Elasticity of Substitution
γ	66	Risk Aversion
Investment Adjustment Costs		
ζ_N	9	R&D Adj. Cost Parameter
ζ_K	1.5	Capital Adj. Cost Parameter
δ_N	0.0375	R&D Depreciation Rate
δ_K	0.02	Capital Depreciation Rate
Firms		
α	1/3	Output Elasticity of Capital
ϵ^y	6	Goods Elasticity of Substitution
κ_p	60	Price Adjustment Cost Parameter
η	0.1	Technological Spillovers
Monetary Policy		
ϕ^y	0.1	Weight on Output in Policy Rule
ϕ^π	1.5	Weight on Inflation in Policy rule
ρ^r	0.25	Interest Rate Smoothing Parameter
Exogenous Processes		
A_{SS}	0.22	Steady State TFP
σ^A_{SS}	0.01	Steady state St.Dev. of TFP Shock
ρ_A	0.95	Persistence of TFP Shock
ρ_{σ^z}	0.75	Persistence of Prod. Uncertainty Shock
σ_{σ_z}	0.4	St.Dev. of Prod. Uncertainty Shock

3.3.7 Results

In this subsection, I analyse the effects of the TFP Volatility shocks under the baseline calibration. Figure 3.4 displays the IRFs to a TFP uncertainty shock, which I interpret as supply-side uncertainty shock, i.e. an exogenous increase in the probability of large (either positive or negative) TFP shocks. As in the empirical section, an uncertainty shock causes a long-run decline in economic activity. Consumption falls by 0.3 percent on impact and remains permanently 0.1 percent below its trend. Output and Investment in physical capital fall by 0.5 and 0.1 percent on impact and remain 0.1 percent below their respective trends. R&D Investment, S_t, falls by 0.6 percent on impact and remains roughly 0.2 percent below trend. The permanent effects of uncertainty shocks in this theoretical model are due to the technological spillovers. More specifically, the fall in R&D investment implies a decline in the stock of R&D, which reduces the accumulation of new ideas and has, therefore, a negative impact on long-run growth. The negative effects of the uncertainty shock are partly offset by the reaction of the monetary authority, which reduces the interest rates to both counteract the fall in inflation and to the fall in output. Frictions in the labour market (see e.g. Leduc and Liu, 2016 and Guglielminetti, 2016) and in the financial markets (see e.g. Christiano et al., 2014 and Bonciani and van Roye, 2016) would exacerbate the effects of uncertainty shocks and make them economically more significant.

When analysing how uncertainty shocks affect economic activity in a general equilibrium framework, it is important to bear in mind that many channels play a role in determining the response from a qualitative and a quantitative point of view. Two crucial assumptions are usually made in the literature (Basu and Bundick, 2017; Fernandez-Villaverde et al., 2015; Born and Pfeifer, 2014) to induce a negative response of the main macroeconomic variables to an uncertainty shock: sticky prices and capital adjustment costs.

Price stickiness is a crucial assumption in order to obtain co-movement between Consumption, Output and Investment (Basu and Bundick, 2017). More specifically, the uncertainty shock generates a fall in consumption for precautionary reasons and induces agents to supply more labour, which lowers real marginal costs and hence firms' markups rise by the same amount. As markups rise, firms demand less labour and hours in equilibrium fall. Given that physical capital and R&D are predetermined, we see a fall in Output. The fall in output induces a fall in investment in physical capital and in R&D. Figure C.7 in the appendix displays the impulse responses for various degrees of price stickiness, to highlight that indeed time-varying markups are a crucial feature in order to obtain the aforementioned co-movement of the main macroeconomic aggregates. Moreover, as highlighted in Fernandez-Villaverde et al. (2015) and Born and Pfeifer (2014), sticky prices represent also an important amplification mechanism. Figure C.7 shows how under flexible prices, consumption falls for precautionary reasons and output, investment and R&D rise. Under sticky prices, we obtain the negative co-movement and the larger the price stickiness parameter, the more significant become the effects of uncertainty, both on impact and in the long run.

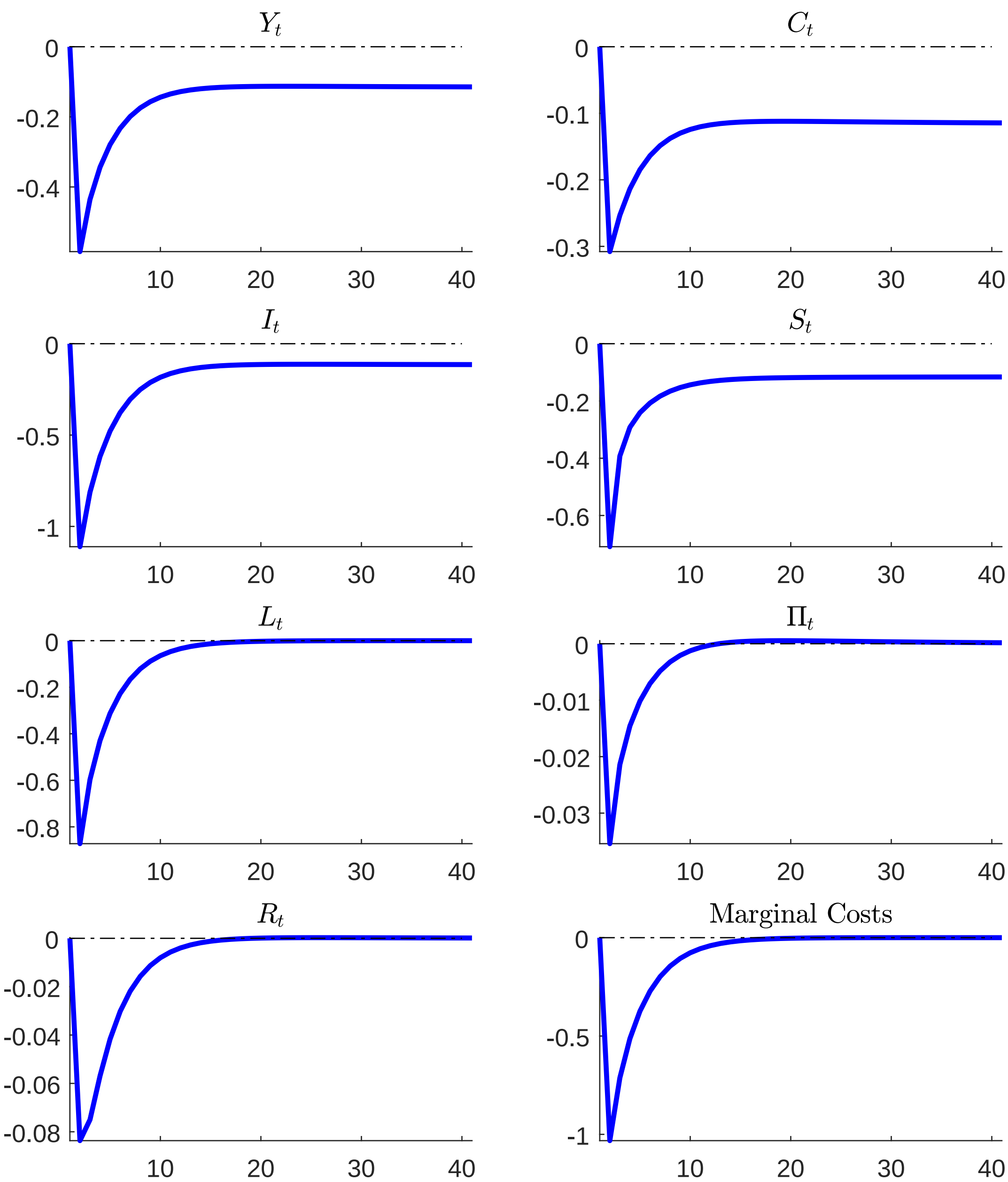
The second important assumption is the presence of adjustment costs to investment in Physical Capital and R&D. These adjustment costs are crucial for the results in Basu and Bundick (2017), Fernandez-Villaverde et al. (2015) and Born and Pfeifer (2014), though this mechanism is hardly mentioned in these papers. In particular, in order for the Markup Channel to work, we need capital not to be too flexible. In this case, firms, that are price-setting with some degree of monopoly power, will find it optimal to reduce output by reducing the labour input on impact. Nevertheless, when there are no investment adjustment costs, rises in uncertainty lead to an increase in investment because of the Abel-Hartman-Oi effect (Abel, 1983; Hartman, 1976; Oi, 1961). More specifically, constant returns to scale imply that the marginal revenue product of capital is convex in TFP and therefore larger TFP uncertainty may increase the expected return on capital. The presence of capital adjustment costs mitigates. Figures C.8 and C.9 display the effects of TFP uncertainty shocks for different degrees of capital adjustments costs. Without adjustment costs, this effect is able to offset the markup channel and while reducing consumption, uncertainty shocks have expansionary effects on output and investment. Nevertheless, given the lack of co-movement, uncertainty shocks could not be considered suitable drivers of business cycle fluctuations.

In the following subsections I will show that the short-run and long-run effects of uncertainty crucially depend also on the degree of Relative Risk Aversion, Intertemporal Elasticity of Substitution and their interplay. Moreover, the presence of long-run fluctuations due to the R&D spillovers gives rise to a very strong amplification of the effects of uncertainty shocks through a long-run risk channel.

The Role of the IES and RRA Parameters

An advantage of the use of EZ preferences compared to more standard non-recursive preferences is that the latter constrain the relative risk aversion (RRA) parameter to be the inverse of the intertemporal elasticity of substitution (IES). With EZ preferences instead, these two parameters can be set independently from one another. In the baseline calibration, the RRA and IES parameters are set to 66 and 1.75 respectively. The response of investment to an exogenous rise in uncertainty is very sensitive to these parameters, in line with Epaulard and Pommeret (2003) and Saltari and Ticchi (2007). These two parameters, in fact, affect the concavity of the stochastic discount, which in turn affects the Euler Equations with respect to the riskless bonds, physical capital, and R&D. More specifically, the RRA affects the precautionary savings motive and how agents value the return on risky investments (in physical capital and R&D). A larger RRA reduces the risk-adjusted expected return of the expected return on investment. In other words, the larger the RRA, the more agents reduce consumption for precautionary reasons and the less they want to invest in physical capital and R&D compared to the risk-less bond (*safe haven*). This effect is a *flight to quality effect* and can be clearly seen in figure 3.5, in which we compare the impulse responses to a TFP uncertainty shock for different values of RRA. For very low values of RRA, investment in physical capital and R&D increases because of the Abel-Hartman-Oi effect, which leads to positive long-run effects. For higher values of RRA, both types of investment significantly fall and lead to a decline in economic activity both in the short- and in the long-run. Concerning the IES, this parameter governs how substitutable today's and tomorrow's consumption are. In other words, it affects the propensity of agents to smooth their lifetime consumption.

Figure 3.4: *Productivity Uncertainty Shock*



The larger this parameter, the more consumption is intertemporally substitutable, i.e. agents will care less about smoothing consumption across time. For low values of the IES, an increase in uncertainty actually leads to a rise in investment in R&D (for IES$\in \{0.1, 0.5, 0.9, 1.5\}$). This is because the uncertainty shock causes a decline in the risk-adjusted expected return of the expected return to R&D investment, which makes agents feel poorer and will strengthen their propensity to save and smooth out consumption by investing more. This will lead uncertainty to have negative output effects in the short-run, but positive long-run effects thanks to the rise in R&D investment. For higher values of the IES (as in the baseline case), this income effect is less strong, and agents will see the fall in the expected return as a deterrent for investment.

The two parameters play an important role in determining the size and the sign of the responses of investment and output to a rise in uncertainty. In the exercises described above, each parameter is changed whilst keeping the other fixed at its baseline value. This exercise, while explaining the underlying mechanisms, does not focus on the interplay between the two effects. It is therefore important to highlight that for different values of the RRA parameter, there exists a different threshold of the IES for which investment falls after a rise in uncertainty. Figure C.11 in the appendix displays the impact responses of investment in Physical Capital and R&D for different combinations of the RRA and IES. In particular, each line represents a different value of the RRA parameter, while the x-axis is the IES parameter. For example, for unrealistically low levels of the RRA (0.9 or 0.1), it is possible to obtain a decline in investment for lower values of the IES. When both RRA and IES are low, in fact, uncertainty shocks increase the expected return to investment due to the Hartman-Abel-Oi effect, which makes agents reduce less consumption, as they feel richer, and investment in physical capital and R&D falls. For higher RRA (e.g. RRA equal to 4) the IES needs to be relatively high (above 1.5) in order to obtain a fall in both types of investment.

The Long-Run Risk Channel

The long-run implications described above strongly amplify the effects of uncertainty shocks on economic activity. More specifically, when agents have recursive preferences, they care about both short-term as well as long-term risks of consumption growth (Bansal and Yaron, 2004; Kung and Schmid, 2015). When long-run risk is included in the model, it is as if agents became much more risk-averse. Hence, after an uncertainty shock hits the economy, there will be a permanent decline in economic activity, which will amplify the precautionary savings and the flight-to-quality channels. More precautionary savings and labour supply by the households, in turn, amplifies the markup channel, discussed above, and the overall decline becomes much more sizable.

To highlight the long-run risk channel, I perform two exercises. First, I compare

Figure 3.5: *Productivity Uncertainty Shock with Different Values of the RRA*

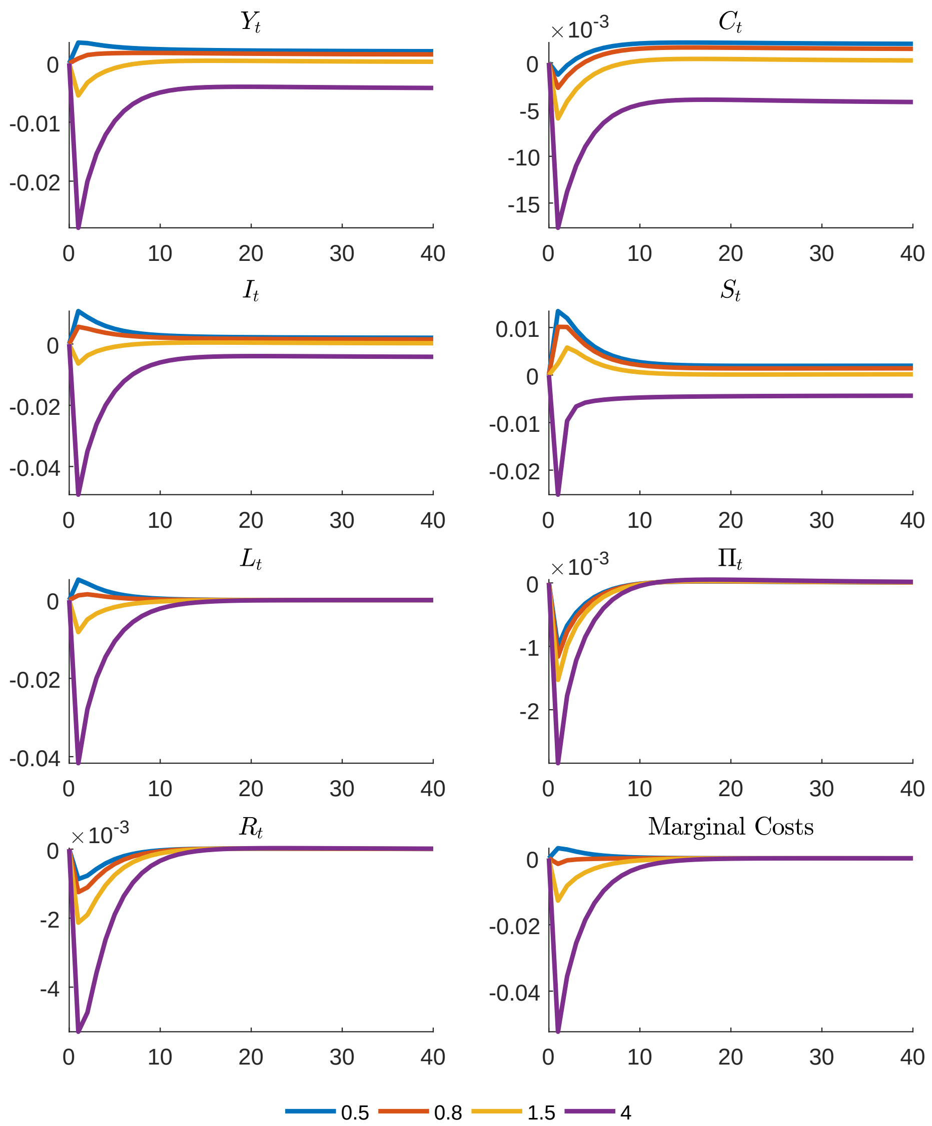
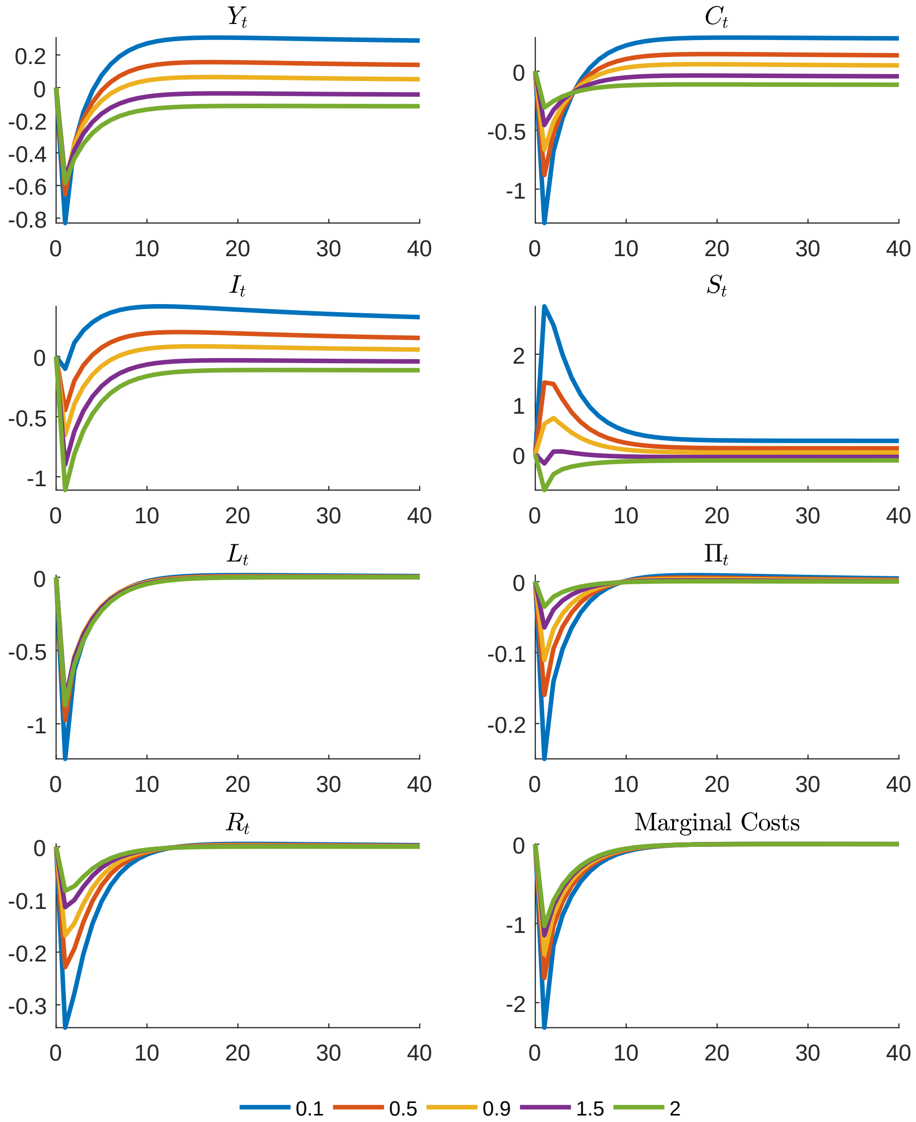


Figure 3.6: *Productivity Uncertainty Shock with Different Values of the IES*



the results from our baseline model and those from the same model without R&D. Figure 3.7 displays the results and highlights how strong the amplification mechanism is. In the standard New Keynesian model without R&D the effects of the uncertainty shock are only temporary and therefore agents will react only to the increase in the short-run uncertainty. Moreover, the responses of investment and output to an uncertainty shock are positive, just like when RRA is set to a low value. In order to induce a fall in investment or output, RRA needs to be much larger than in the baseline case (RRA= 10). In the baseline model, agents react to the rise in both short-run and long-run uncertainty, which delivers a strong persistent decline in economic activity.

As a second exercise, I compare the models with and without R&D, when agents do not fear long-run risk. In particular, I modify the stochastic discount factor, so that it does not depend on the continuation value anymore:

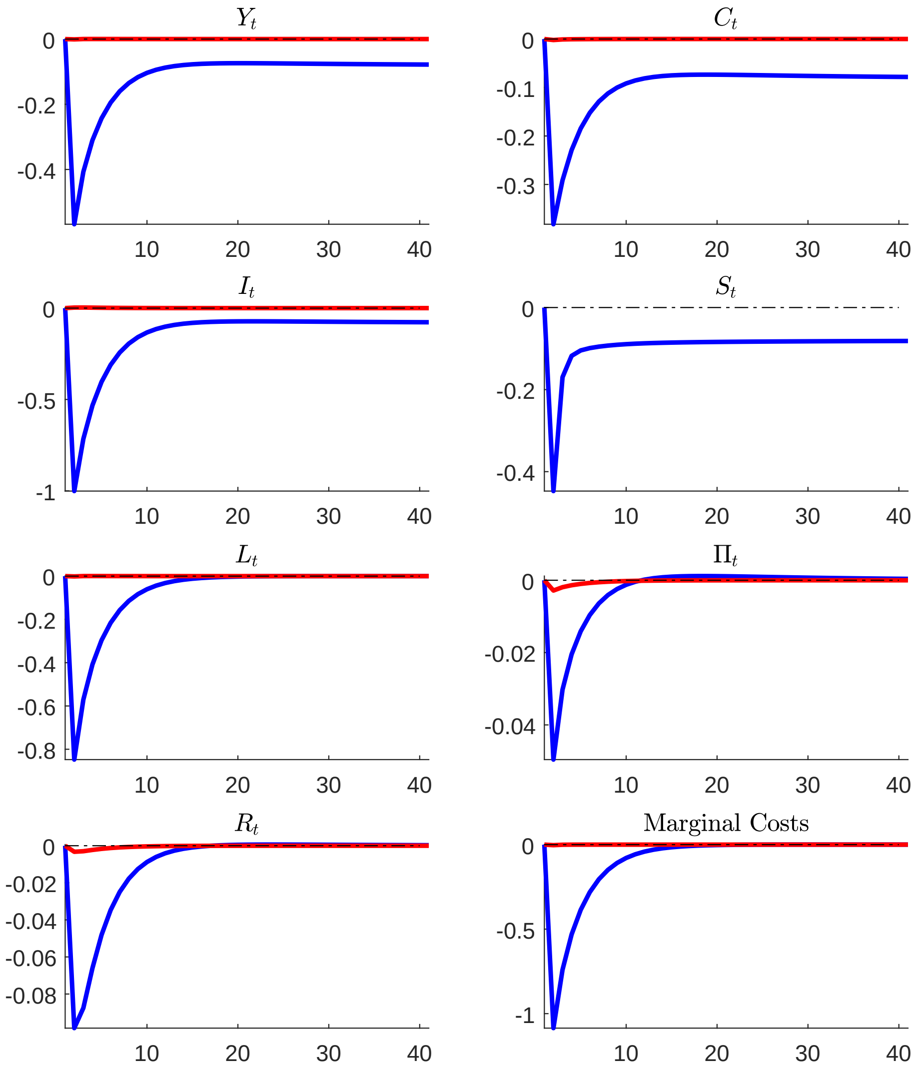
$$\mathcal{M}_{t,t+1} = \beta \left(\frac{\Upsilon_{t+1}}{\Upsilon_t} \right)^{1-\frac{1}{\psi}} \left(\frac{C_t}{C_{t+1}} \right) \tag{3.18}$$

This is equivalent to considering non-recursive preferences, as in this case the RRA parameter γ does not enter the stochastic discount factor and the IES parameter ψ is the only parameter appearing in 3.18. Figure 3.8 shows that the difference between the two models is not as pronounced as before. Furthermore, in this case, both models do not feature co-movement between consumption, investment, and output. The uncertainty shock now leads to a rise in investment, as agents do not take into account future risk and are not risk-averse enough.

3.4 Concluding Remarks

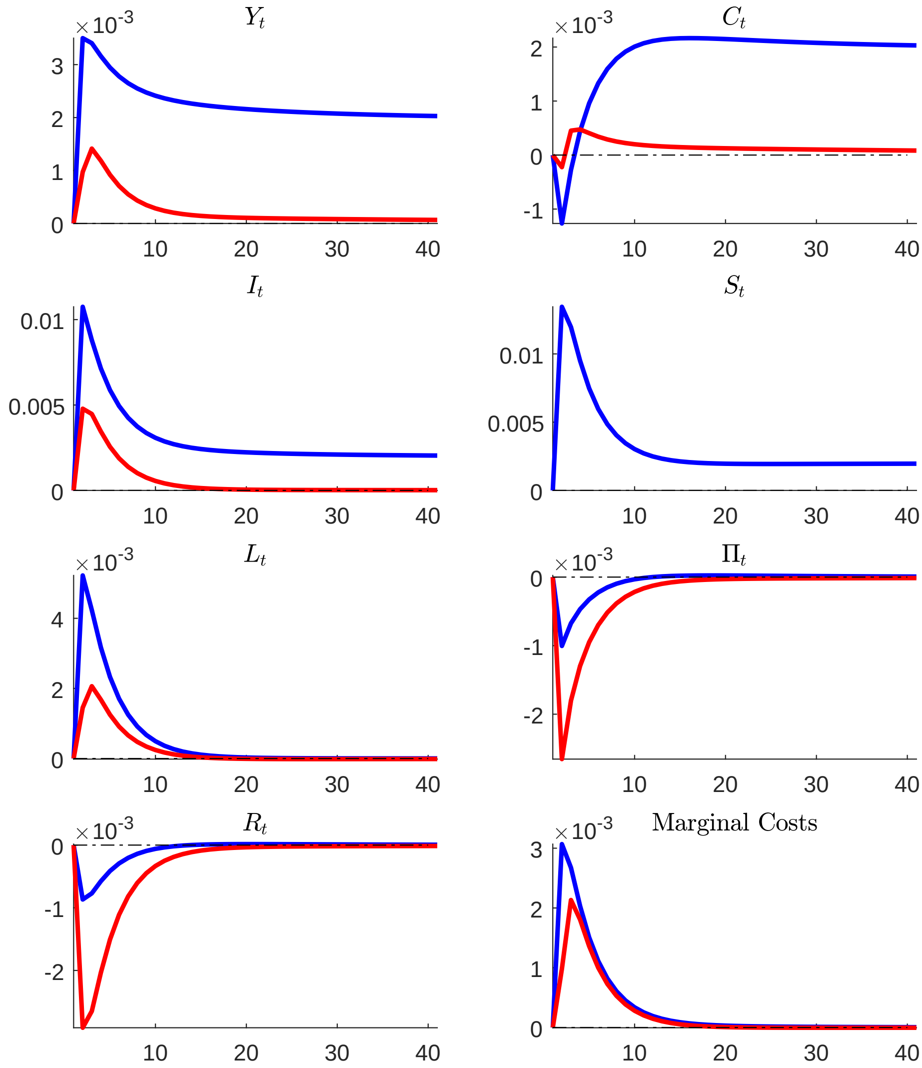
The present paper documents how shocks to macroeconomic uncertainty have negative long-run effects on economic activity. These empirical results can be rationalized through the lenses of a DSGE model with an endogenous growth mechanism and sticky prices. Because of the Epstein-Zin preferences, households take the long-run effects of uncertainty into account, which makes them more risk-averse. This in turn strongly amplifies the precautionary savings motive of households, as well as the markup channel. This leads to a much more pronounced decline in economic activity than in a model that does not feature this "long-run risk channel".

Figure 3.7: *Productivity Uncertainty Shock With and Without Long-Run Effects*



Notes: The blue line represents the model with long-run risk through R&D. The red line is the model without R&D.

Figure 3.8: *Productivity Uncertainty Shock with non-Recursive Preferences*



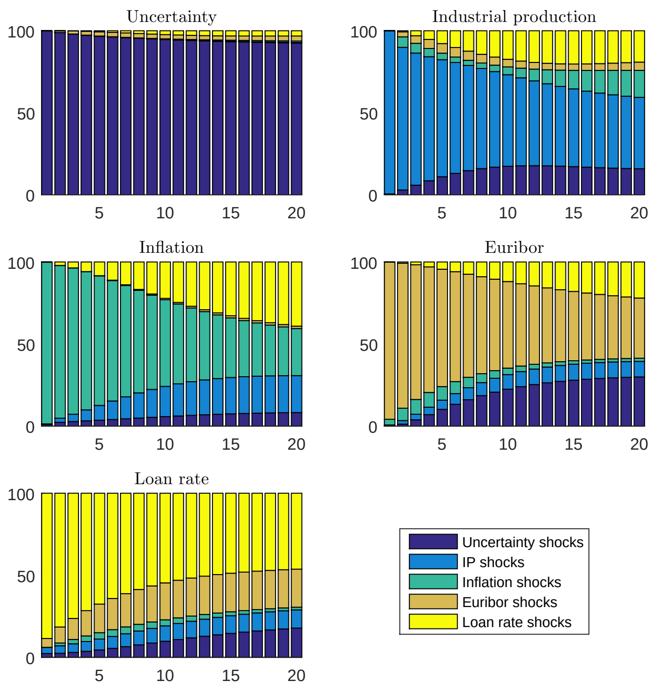
Notes: The blue line is the model with R&D. The red line is the model without R&D.

Appendix A

Appendix to Chapter 1

A.1 Forecast error variance decomposition

Figure A.1: *Forecast error variance decomposition*



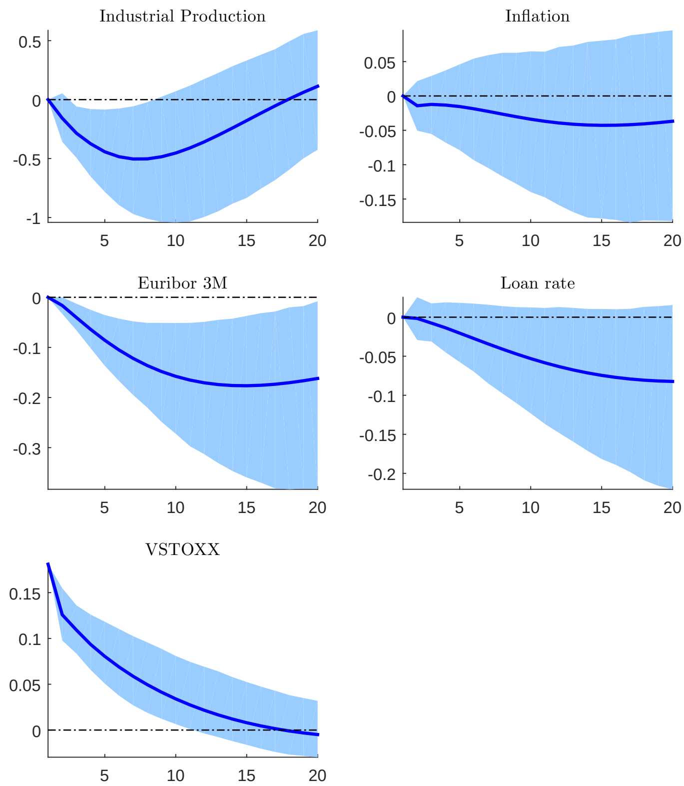
NOTES: Monthly horizon.

A.2 Robustness of the Empirical Results

A.2.1 Alternative ordering in the VAR

One standard robustness check in structural VAR models is to change the ordering of the variables. In Figure A.2, we order the uncertainty variable last, in contrast to the baseline case where uncertainty is ordered first. In this case, industrial production falls by 0.5 percent after 7 quarters. The downward adjustment of the loan rate is still much more persistent and smaller compared to the money-market rate such that the main empirical result is not altered by the oredering of the variables.

Figure A.2: *Impulse responses to an VSTOXX shock with alternative ordering*



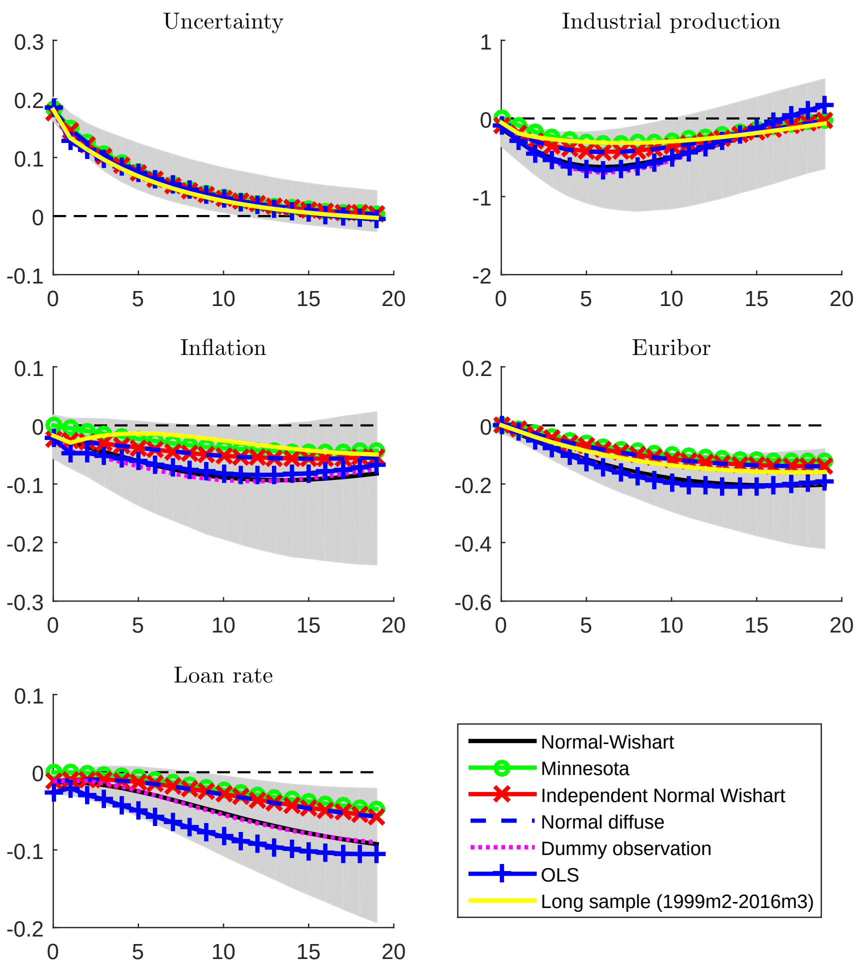
NOTES: The VAR includes a lag of 2 months, chosen according to the AIC. Different lag orders do not alter the basic results.

A.2.2 Alternative estimation techniques - A Bayesian VAR

As a robustness exercise we estimate the VAR model with Bayesian techniques. After having optimized the hyperparameters as in (Giannone et al., 2015), we test the model using different prior distributions. In particular, we use a classical Minnesota prior, a Normal-Wishart prior, an Independent Normal-Wishart prior, a Normal Diffuse prior and a Dummy Observation prior as in (Banbura et al., 2010). The grid search procedure finds hyperparameters that maximise the marginal likelihhod at 0.9 for the autoregressive parameter, with overall tightness $\lambda_1 = 0.08$, and lag decay $\lambda_3 = 1$.

The impact of uncertainty on selected variables is robust across different prior distributions. An increase in uncertainty leads to persistently lower industrial production and inflation. The policy rate reacts stronger than the loan rate. The results confirm loan rate stickiness empirically and show that this result is very robust for the euro area.

Figure A.3: *Impulse responses to an VSTOXX shock using alternative estimation techniques*



NOTES: The VAR includes a lag of 2 months, chosen according to the AIC. Different lag orders do not alter the basic results.

A.3 Details on data used in estimation

Below we describe the data we use in the empirical exercise in section 1.2.

Uncertainty index We use the implied volatility index VSTOXX provided by Thomson Financial Datastream. Source: Thomson Financial Datastream.

Industrial production Industrial production for 19 euro area countries excluding construction: Y-o-Y percentage change. Source: Haver Analytics.

Inflation Harmonized HICP: Y-o-Y percentage change. Source: Haver Analytics.

Money-market rate We use the 3-month average of the unsecured Euro interbank offered rate (Euribor). Source: Thomson Financial Datastream (Code: EMINTER3)

Loan rate Interest rate charged by monetary financial institutions (excluding Eurosystem) for loans to non-financial corporations (outstanding amounts, all maturities), in percent (ECB). Source: ECB and Thomson Financial Datastream (Code: EMBANKLPB).

A.4 Complete model equations

A.4.1 Households

Shadow Price of Consumption

$$\lambda_{h,t} = \frac{1}{c_{h,t}} \tag{A.1}$$

Households' Euler equation

$$1 = \beta_h \mathbb{E}_t \left[\frac{\lambda_{h,t+1}}{\lambda_{h,t}} \frac{(1+r_t)}{(1+\pi_{t+1})} \right], \tag{A.2}$$

Labor supply equation

$$l_t^{\phi} = w_t \lambda_{h,t}, \tag{A.3}$$

Households' budget constraint

$$c_{h,t} + d_t = w_t l_t + (1+r_{t-1}) \frac{d_{t-1}}{(1+\pi_t)} + J_t^R, \tag{A.4}$$

A.4.2 Entrepreneurs

Shadow Price of Consumption

$$\lambda_{e,t} = \frac{1}{c_{e,t}} \tag{A.5}$$

$$q_t^k = s_t m E_t \left[q_{t+1}^k \left(1+\pi_{t+1}\right)\left(1-\delta\right) \right] + \tag{A.6}$$

$$\beta_e E_t \left\{ \frac{\lambda_{e,t+1}}{\lambda_{e,t}} \left[q_{t+1}^k \left(1-\delta\right) + r_{t+1}^k \right] \right\}, \tag{A.7}$$

Wage Equation

$$w_t = (1-\alpha) \frac{y_t^e}{l_t x_t}, \tag{A.8}$$

Euler Equation Entrepreneurs

$$1 - \left(1 + r_t^b\right) s_t = \left(1 + r_t^b\right) \beta_e E_t \left[\frac{\lambda_{e,t+1}}{\lambda_{e,t}} \frac{1}{1+\pi_{t+1}} \right], \tag{A.9}$$

Budget Constraint Entrepreneurs

$$c_{e,t} + \left(\frac{(1+r_{t-1}^b) b_{t-1}}{1+\pi_t} \right) + w_t l_t + q_t^k k_t \tag{A.10}$$

$$= \frac{y_t^e}{x_t} + b_t + q_t^k (1-\delta) k_{t-1},$$

Production Function

$$y_t^e = \left(k_{t-1}\right)^\alpha l_t^{1-\alpha}, \tag{A.11}$$

Borrowing Constraint

$$(1+r_t^b) b_t = m \mathbb{E}_t \left[q_{t+1}^k (1+\pi_{t+1}) k_t (1-\delta) \right], \tag{A.12}$$

Return on Capital

$$r_t^k = \alpha \frac{y_t^e}{k_{t-1} x_t}, \tag{A.13}$$

A.4.3 Capital producers

Capital Asset Equation

$$q_t^k \left[1 - \phi_i \left(\frac{i_t}{i_{t-1}} - 1 \right) \frac{i_t}{i_{t-1}} - \frac{\phi_i}{2} \left(\frac{i_t}{i_{t-1}} - 1 \right)^2 \right] + \tag{A.14}$$

$$\phi_i E_t \left[\beta_e \frac{\lambda_{e,t+1}}{\lambda_{e,t}} q_{t+1}^k \left(\frac{i_{t+1}}{i_t} - 1 \right) \left(\frac{i_{t+1}}{i_t} \right)^2 \right] = 1 \tag{A.15}$$

Law of Motion of Capital

$$k_t = (1-\delta) k_{t-1} + \left[1 - \frac{\kappa_i}{2} \left(\frac{i_t}{i_{t-1}} - 1 \right)^2 \right] i_t, \tag{A.16}$$

A.4.4 Wholesale Branch

$$K_t^b(1+\pi_t) = (1-\delta^b)K_{t-1}^b + \varphi J_{t-1}^b, \tag{A.17}$$

$$b_t = d_t + K_t^b, \tag{A.18}$$

A.4.5 Loan Retail Branch

Markup on loans

$$1 - \frac{\epsilon_t^b}{(\epsilon_t^b - 1)} + \frac{\epsilon_t^b}{(\epsilon_t^b - 1)}\frac{r_t}{r_t^b} - \kappa_b\left(\frac{r_t^b}{r_{t-1}^b} - 1\right)\frac{r_t^b}{r_{t-1}^b} \tag{A.19}$$
$$+ \beta_h\mathbb{E}_t\left[\frac{\lambda_{h,t+1}}{\lambda_{h,t}}\kappa_b\left(\frac{r_{t+1}^b}{r_t^b} - 1\right)\left(\frac{r_{t+1}^b}{r_t^b}\right)^2\frac{b_{t+1}^E}{b_t}\right] = 0,$$

Bank profits

$$J_t^b = r_t^b b_t - r_t d_t - \frac{\kappa_b}{2}\left(\frac{r_t^b}{r_{t-1}^b} - 1\right)^2 r_t^b b_t, \tag{A.20}$$

A.4.6 Retailers

$$J^R = \left[1 - \frac{1}{x_t} - \frac{\kappa_p}{2}\left(\frac{1+\pi_t}{1+\pi} - 1\right)^2\right]Y_t, \tag{A.21}$$

Nonlinear Phillips curve

$$(1-\varepsilon^y) + \frac{\varepsilon^y}{x_t} - \kappa_p\left(\frac{1+\pi_t}{1+\pi} - 1\right)\left(\frac{1+\pi_t}{1+\pi}\right) + \tag{A.22}$$

$$\beta_h E_t\left[\frac{\lambda_{h,t+1}}{\lambda_{h,t}}\kappa_p\left(\frac{1+\pi_{t+1}}{1+\pi} - 1\right)\left(\frac{1+\pi_{t+1}}{1+\pi}\right)\frac{Y_{t+1}}{Y_t}\right] = 0 \tag{A.23}$$

A.4.7 Aggregation and Equilibrium

$$C_t = c_{h,t} + c_{e,t}, \tag{A.24}$$

$$Y_t = C_t + [k_t - (1-\delta)k_{t-1}] + \delta^b\frac{k_{t-1}^b}{\pi_t} + ADJ_t, \tag{A.25}$$

A.4.8 Taylor Rule and Profits CB

$$\frac{1+r_t}{1+r} = \left(\frac{1+r_{t-1}}{1+r}\right)^{\phi_r}\left[\left(\frac{1+\pi_t}{1+\pi}\right)^{\phi_\pi}\left(\frac{y_t}{y_{t-1}}\right)^{\phi_y}\right]^{(1-\phi_r)}, \tag{A.26}$$

A.4.9 Exogenous Processes

TFP level shock

$$z_t = (1-\rho_z)z + \rho_z z_{t-1} + \sigma_t^z e_t^z, \tag{A.27}$$

TFP uncertainty shock

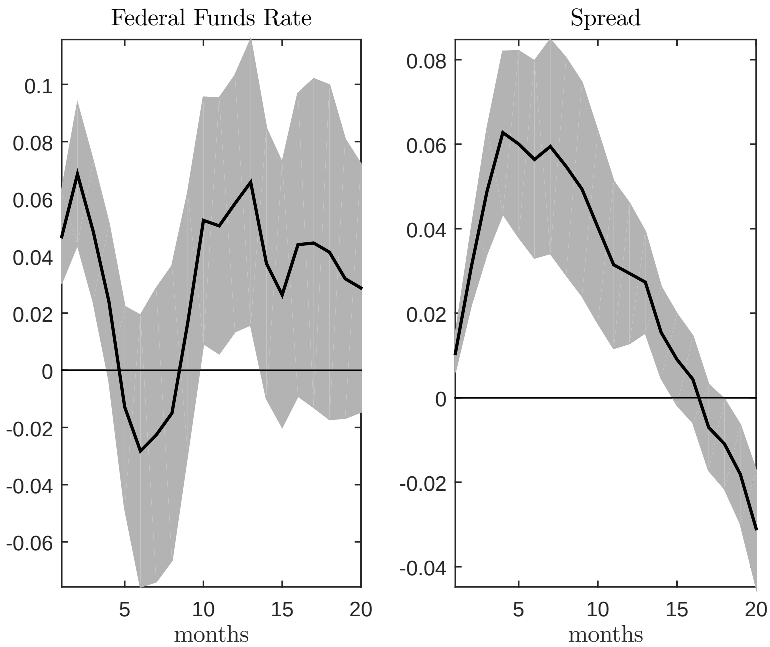
$$\sigma_t^z = (1-\rho_{\sigma^z})\sigma^z + \rho_{\sigma^z}\sigma_{t-1}^z + \eta_z e_t^{\sigma_z}, \quad \text{where } e_t^{\sigma_z} \sim \mathcal{N}(0,1) \tag{A.28}$$

Appendix B

Appendix to Chapter 2

B.1 Additional Figure

Figure B.1: *State-dependent IRFs after an Uncertainty Shock*

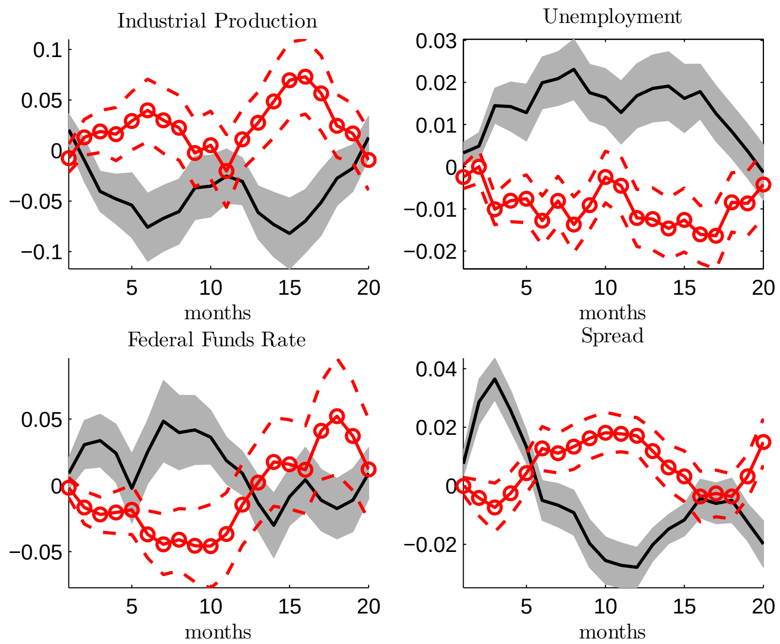


NOTES: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

B.2 Robustness Checks

B.2.1 VXO as measure of uncertainty

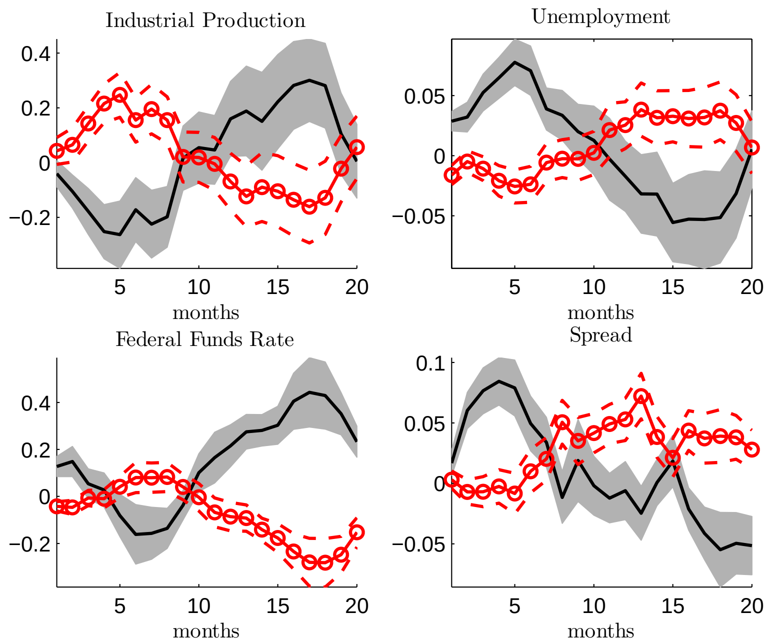
Figure B.2: *State-dependent IRFs after an Uncertainty Shock*



NOTES: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

B.2.2 Excluding the Zero Lower Bound Period

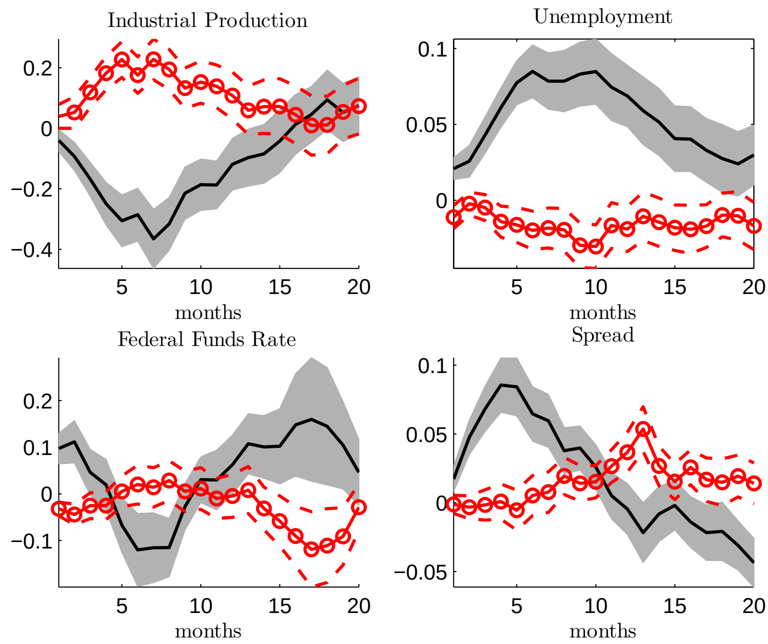
Figure B.3: *State-dependent IRFs after an uncertainty shock*



Notes: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

B.2.3 Sensitivity of α: $\alpha = 2$

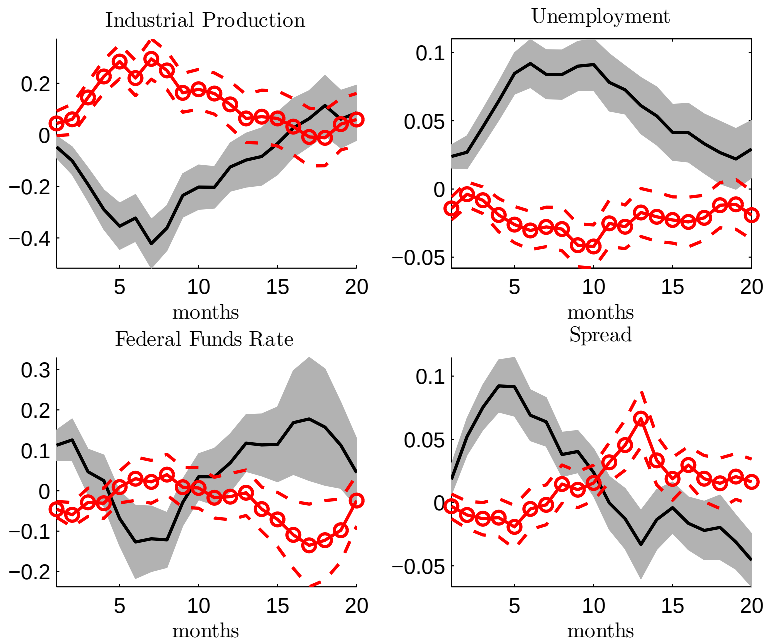
Figure B.4: *State-dependent IRFs after an uncertainty shock*



Notes: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

B.2.4 Controlling for Consumer Confidence

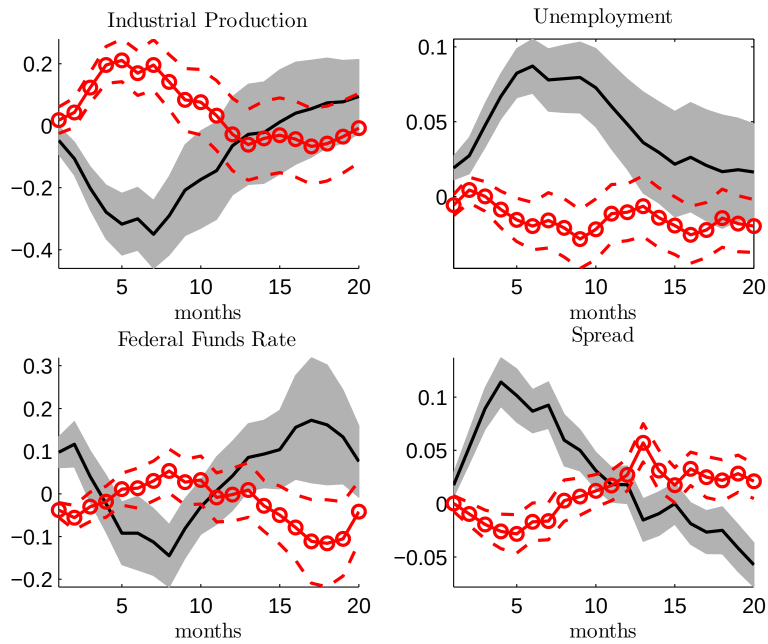
Figure B.5: *State-dependent IRFs after an uncertainty shock*



Notes: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

B.2.5 Reducing Order of Lag Polynomials to 3

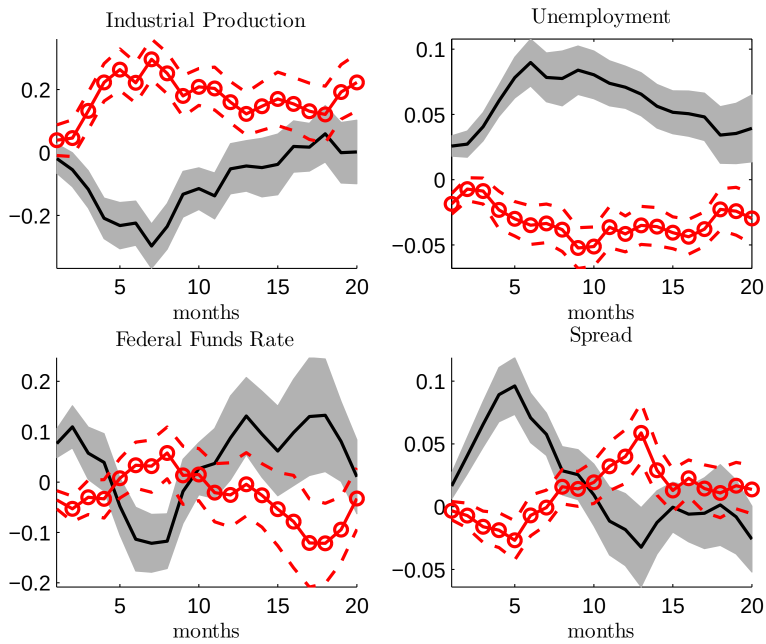
Figure B.6: *State-dependent IRFs after an uncertainty shock*



NOTES: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

B.2.6 Increasing Order of Lag Polynomials to 10

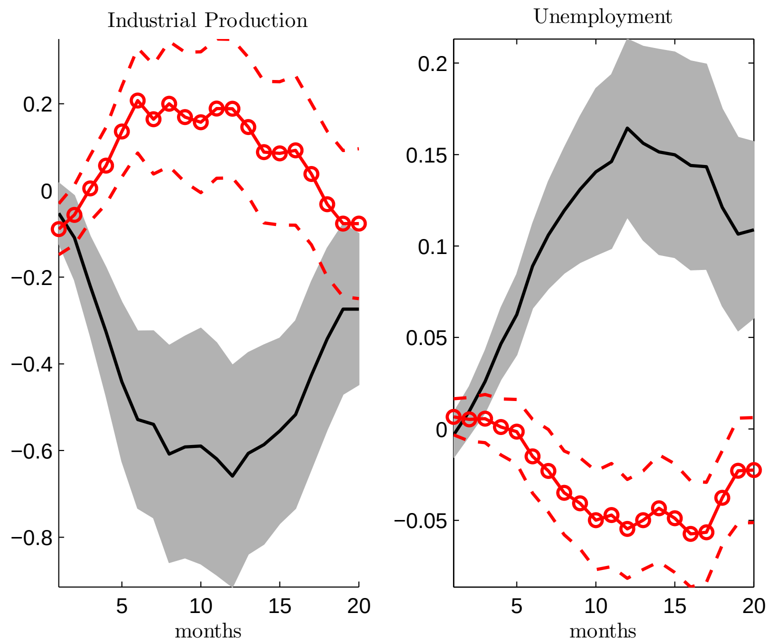
Figure B.7: *State-dependent IRFs after an uncertainty shock*



Notes: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

B.2.7 Different Identification Assumptions

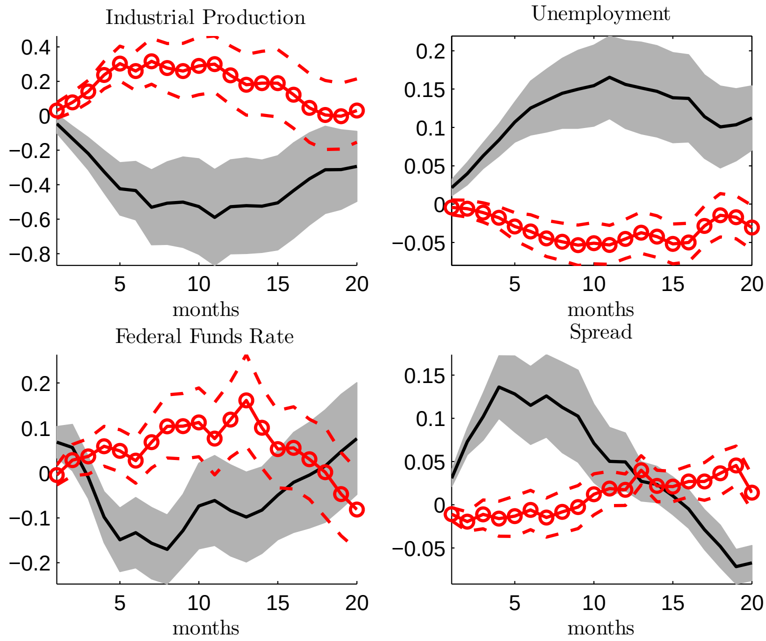
Figure B.8: *State-dependent IRFs after an uncertainty shock*



Notes: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

B.2.8 Backward-looking Transition Variable

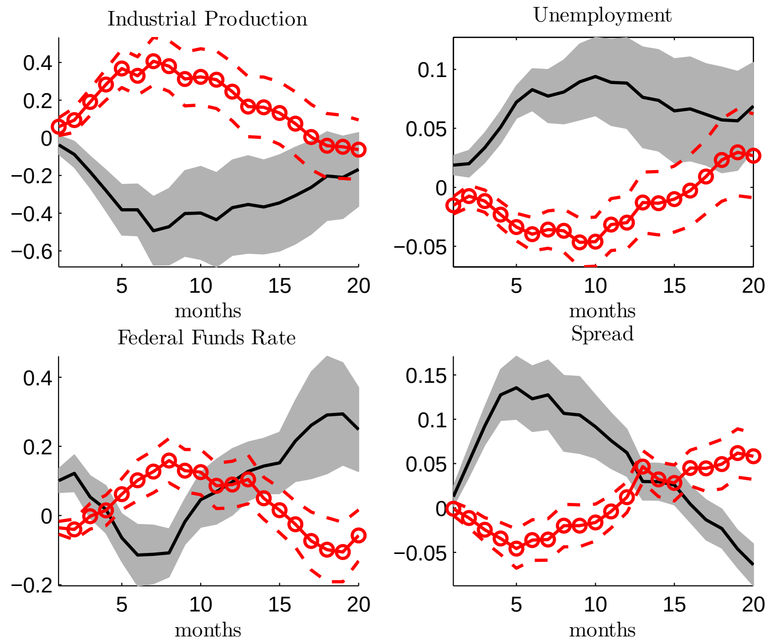
Figure B.9: *State-dependent IRFs after an uncertainty shock*



Notes: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

B.2.9 Unfiltered Data

Figure B.10: *State-dependent IRFs after an Uncertainty Shock*



Notes: The black solid line is the IRF of the response variable to an exogenous one-percentage increase in uncertainty in a recessionary regime. The grey shaded areas represent 68 percent error bands. Error bands are computed using Newey-West standard errors.

Appendix C

Appendix to Chapter 3

C.1 Long-Run Correlations Between Uncertainty and TFP

In this section of the appendix, I display the long-run correlations between p quarters backward-looking moving-average of uncertainty and the q quarters forward-looking moving-average of TFP growth. The correlations are calculated controlling for past GDP growth. In practice, I run the following regression:

$$tfp_{t,t+q} = \beta_1 uncertainty_{t-p,t} + \beta_2 gdp_{t-p,t} + \varepsilon_t \tag{C.1}$$

where tfp, *uncertainty* and *gdp* are standardised moving averages, so that β_1 can be interpreted as a correlation.

Table C.1: *Correlation Matrix*

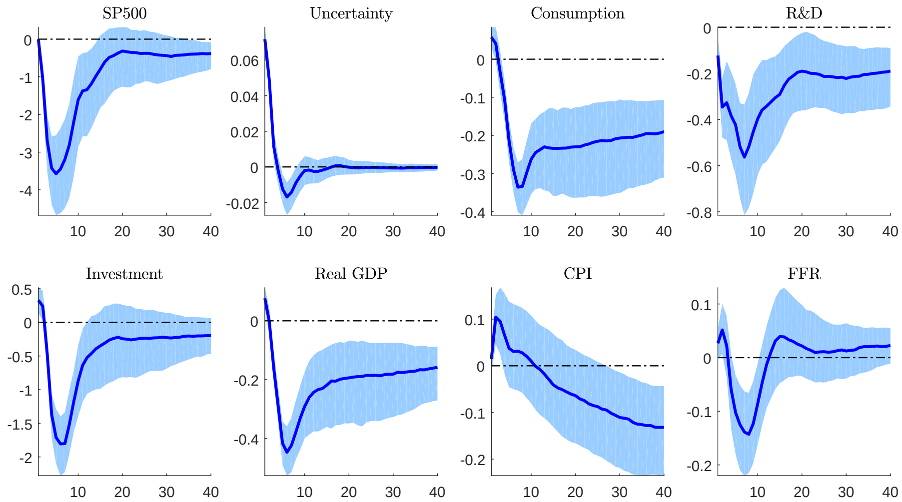
$p \backslash q$	**1**	**10**	**20**	**30**	**40**
1	−0.065	−0.269	−0.396	−0.483	−0.592
	0.082	0.105	0.097	0.114	0.136
10	−0.058	−0.249	−0.390	−0.615	−0.829
	0.105	0.163	0.18	0.207	0.195
20	−0.047	−0.245	−0.470	−0.677	−0.831
	0.097	0.19	0.222	0.237	0.184
30	−0.089	−0.405	−0.603	−0.748	−0.792
	0.114	0.171	0.216	0.199	0.161
40	−0.129	−0.454	−0.610	−0.680	−0.667
	0.136	0.181	0.216	0.204	0.166

Notes: For each correlation (p,q) we show the correlation β_1 (upper value) and Newey-West standard errors (lower value).

C.2 Robustness Checks

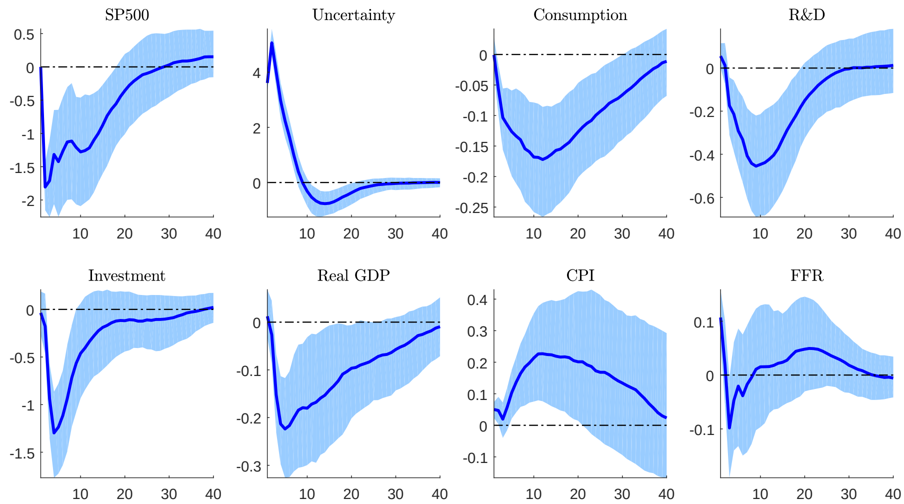
C.2.1 Alternative Uncertainty Measure

Figure C.1: *VAR Impulse Responses to an Uncertainty Shock*



Notes: The blue solid line and shaded areas are the median responses and 68% bootstrapped confidence bands.

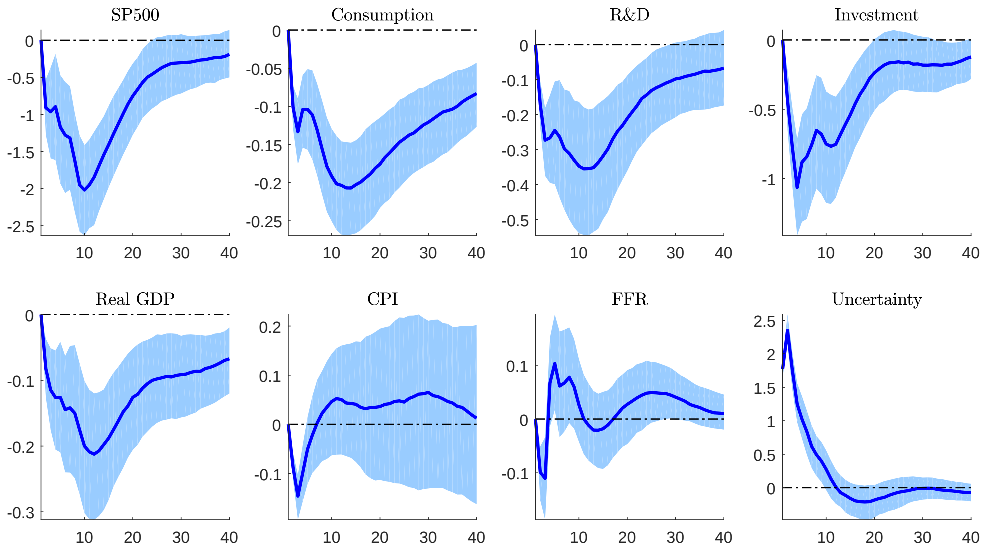
Figure C.2: *VAR Impulse Responses to an Uncertainty Shock*



Notes: The blue solid line and shaded areas are the median responses and 68% bootstrapped confidence bands.

C.2.2 Alternative Ordering of the Variables

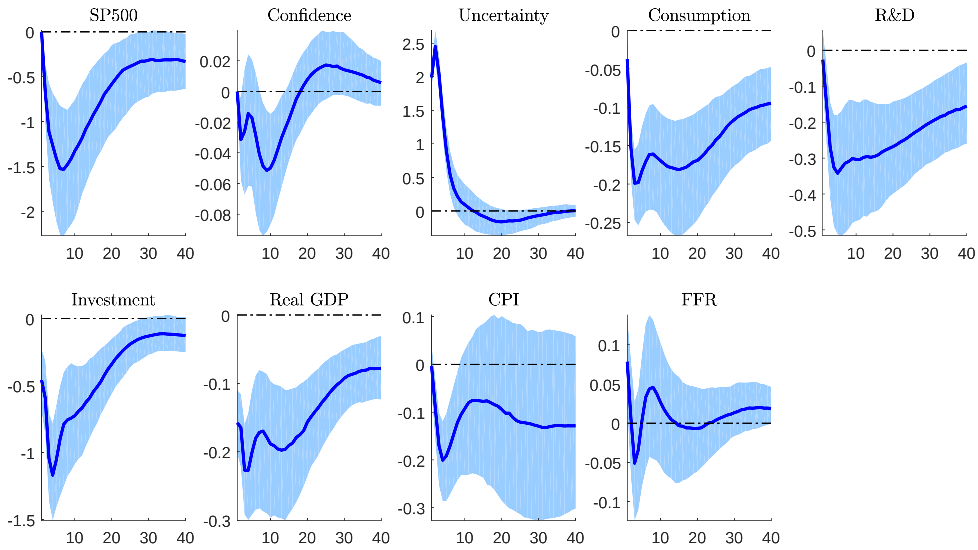
Figure C.3: *VAR Impulse Responses to an Uncertainty Shock*



Notes: The blue solid line and shaded areas are the median responses and 68% bootstrapped confidence bands.

C.2.3 Controlling for Consumer Confidence

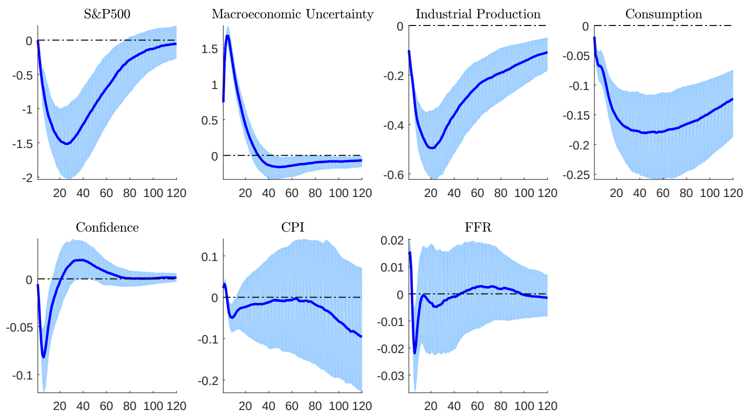
Figure C.4: *VAR Impulse Responses to an Uncertainty Shock*



Notes: The blue solid line and shaded areas are the median responses and 68% bootstrapped confidence bands.

C.2.4 FAVAR

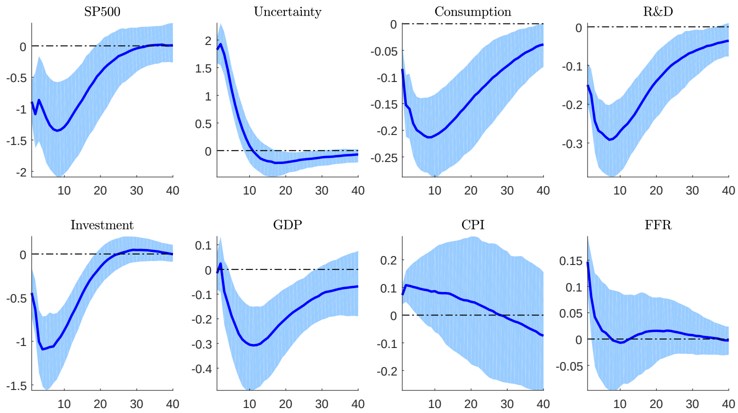
Figure C.5: *VAR Impulse Responses to an Uncertainty Shock*



Notes: The blue solid line and shaded areas are the median responses and 68% bootstrapped confidence bands.

C.2.5 Mixed Frequency VAR

Figure C.6: *VAR Impulse Responses to an Uncertainty Shock*



Notes: The blue solid line and shaded areas are the median responses and 68% bootstrapped confidence bands.

C.3 Equilibrium Conditions

$$U_t = \left[(1-\beta)\,\Upsilon_t^{1-\frac{1}{\psi}} + \beta \left(E_t \left[U_{t+1}^{1-\gamma} \right]^{\frac{1-1/\psi}{1-\gamma}} \right) \right]^{\frac{1}{1-1/\psi}} \tag{C.2}$$

$$\Upsilon_t = C_t^{\tau} \left(1 - L_t\right)^{1-\tau} \tag{C.3}$$

$$K_t = (1-\delta)\,K_{t-1} + \Lambda_K \left(\frac{I_t}{K_{t-1}} \right) K_{t-1} \tag{C.4}$$

$$N_t = (1-\delta)\,N_{t-1} + \Lambda_N \left(\frac{S_t}{N_{t-1}} \right) N_{t-1} \tag{C.5}$$

$$w_t = \tau \frac{C_t}{1 - L_t} \tag{C.6}$$

$$1 = R_t E_t \left[\frac{\mathcal{M}_{t,t+1}}{\Pi_{t+1}} \right] \tag{C.7}$$

$$1 = q_{K,t} \Lambda'_{K,t} \tag{C.8}$$

$$1 = q_{N,t} \Lambda'_{N,t} \tag{C.9}$$

$$q_{K,t} = E_t \mathcal{M}_{t,t+1} \left\{ r_{t+1}^{K} + q_{K,t+1} \left[1 - \delta_K - \Lambda'_K \cdot \frac{I_{t+1}}{K_t} + \Lambda_{K,t+1} \right] \right\} \tag{C.10}$$

$$q_{N,t} = E_t \mathcal{M}_{t,t+1} \left\{ r_{t+1}^{N} + q_{N,t+1} \left[1 - \delta_N - \Lambda'_N \cdot \frac{S_{t+1}}{N_t} + \Lambda_{N,t+1} \right] \right\} \tag{C.11}$$

$$(1-\nu) + \nu \mathrm{mc}_t = \phi_p \left(\frac{\Pi_t}{\Pi} - 1 \right) \frac{\Pi_t}{\Pi} - \phi_p E_t \mathcal{M}_{t,t+1} \left(\frac{\Pi_{t+1}}{\Pi} - 1 \right) \frac{\Pi_{t+1}}{\Pi} \frac{Y_{t+1}}{Y_t} \tag{C.12}$$

$$w_t = (1-\alpha)\,\mathrm{mc}_t \frac{Y_t}{L_t} \tag{C.13}$$

$$r_t^k = \alpha \mathrm{mc}_t \frac{Y_t}{K_{t-1}} \tag{C.14}$$

$$r_t^N = \eta\,(1-\alpha)\,\mathrm{mc}_t \frac{Y_t}{N_{t-1}} \tag{C.15}$$

$$\frac{R_t}{R} = \left(\frac{R_{t-1}}{R}\right)^{\rho_r} \left[\left(\frac{\Pi_t}{\Pi}\right)^{\phi_\pi} \left(\frac{\hat{Y}_t}{\hat{Y}_{SS}}\right)^{\phi_y}\right]^{1-\rho_r} \varepsilon_t^R \tag{C.16}$$

$$Y_t = C_t + S_t + I_t + \frac{\phi_p}{2}\left(\frac{\Pi_t}{\Pi} - 1\right)^2 Y_t \tag{C.17}$$

$$Y_t = K_{t-1}^{\alpha} \left(A_t N_{t-1} L_t\right)^{1-\alpha} \tag{C.18}$$

$$\Lambda_{K,t} = \frac{\alpha_{K,1}}{1 - \frac{1}{\zeta_K}} \left(\frac{I_t}{K_{t-1}}\right)^{1-\frac{1}{\zeta_K}} + \alpha_{K,2} \tag{C.19}$$

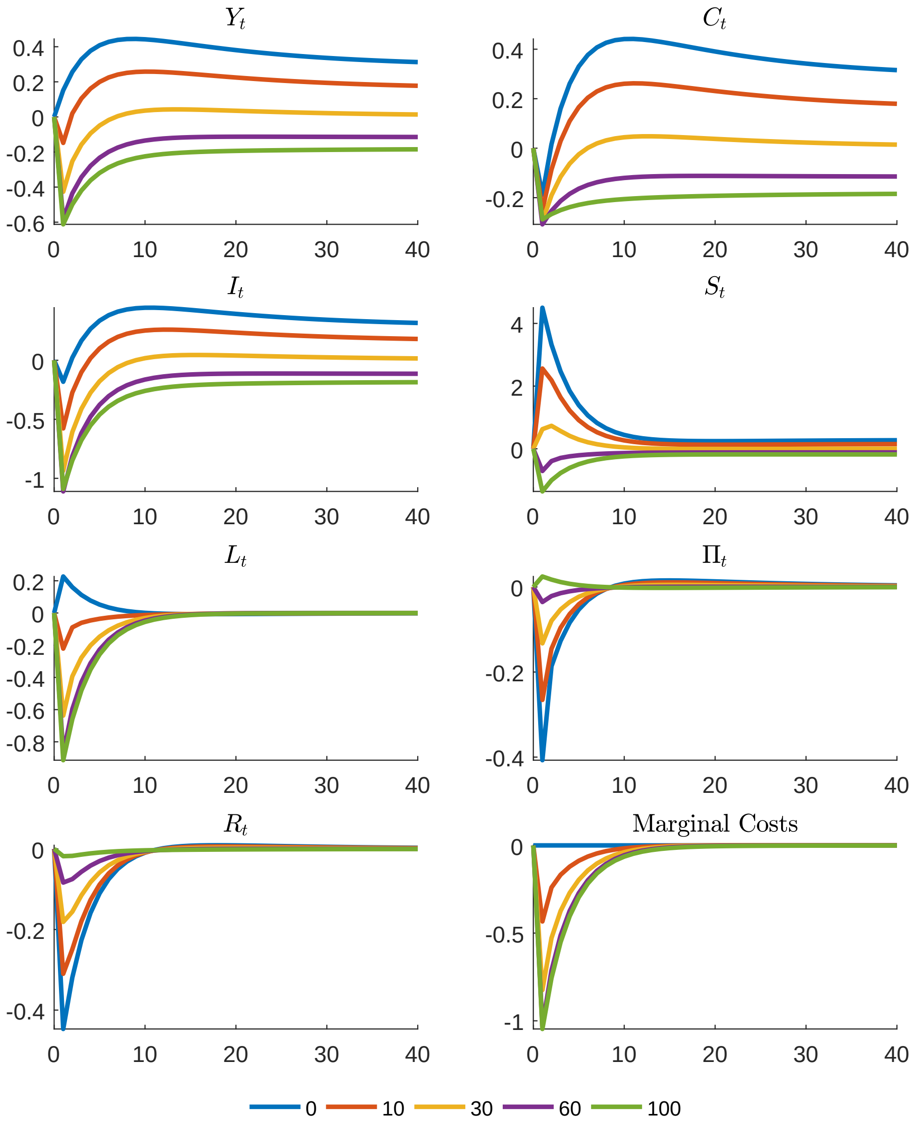
$$\Lambda'_{K,t} = \alpha_{K,1} \left(\frac{I_t}{K_{t-1}}\right)^{-\frac{1}{\zeta_K}} \tag{C.20}$$

$$\Lambda_{N,t} = \frac{\alpha_{N,1}}{1 - \frac{1}{\zeta_N}} \left(\frac{S_t}{N_{t-1}}\right)^{1-\frac{1}{\zeta_N}} + \alpha_{N,2} \tag{C.21}$$

$$\Lambda'_{N,t} = \alpha_1 \left(\frac{S_t}{N_{t-1}}\right)^{-\frac{1}{\zeta}} \tag{C.22}$$

C.4 The Role of Price Stickiness

Figure C.7: *Productivity Uncertainty Shock with Different Degrees of Price Stickiness*



C.5 Varying the Capital Adjustment Costs

Figure C.8: *Productivity Uncertainty Shock varying ζ_K*

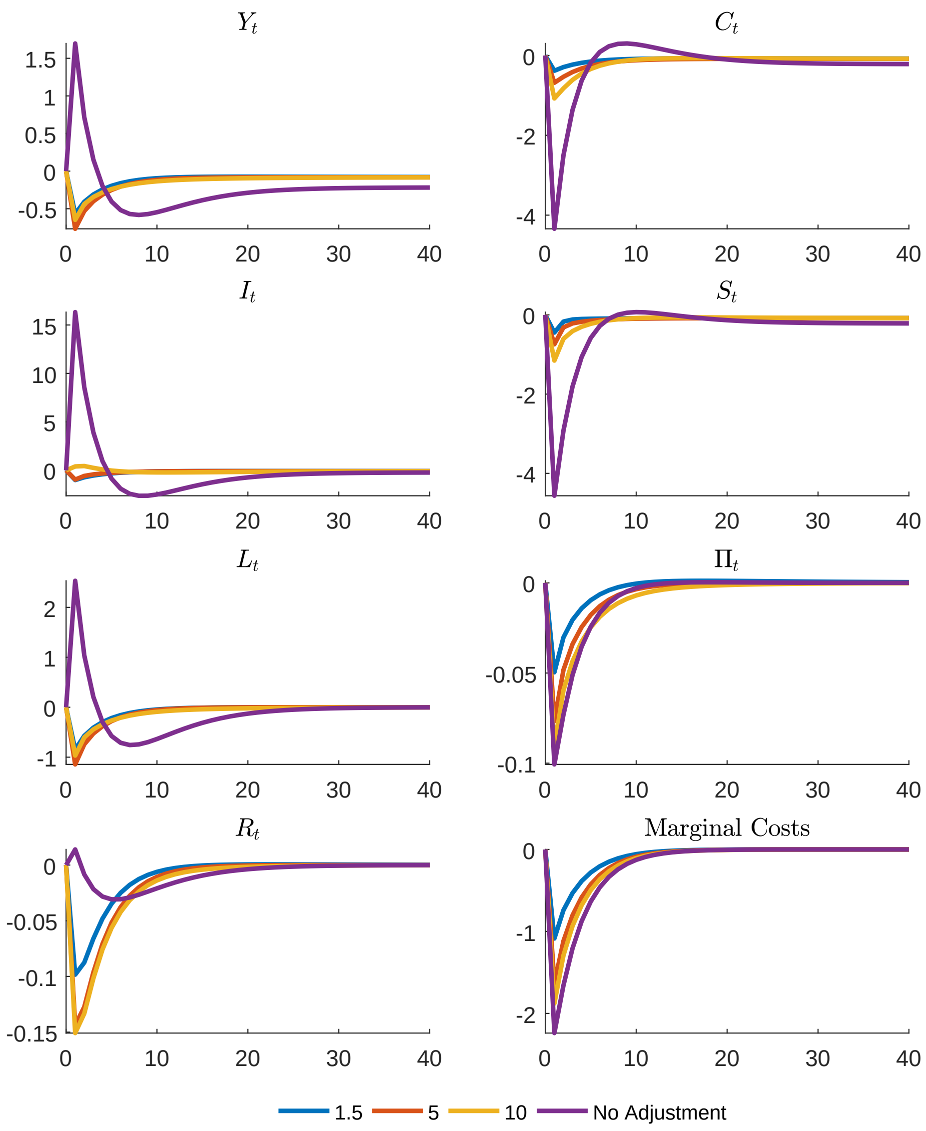
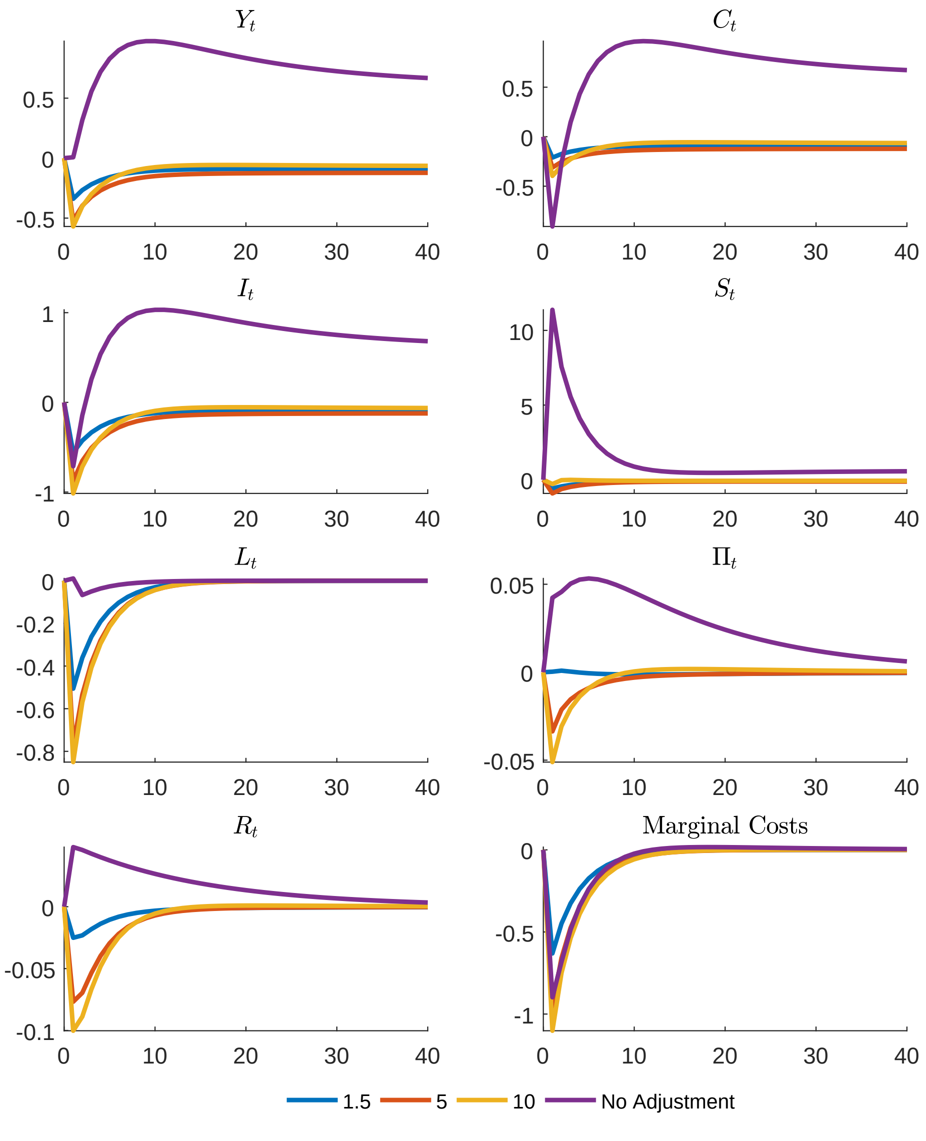
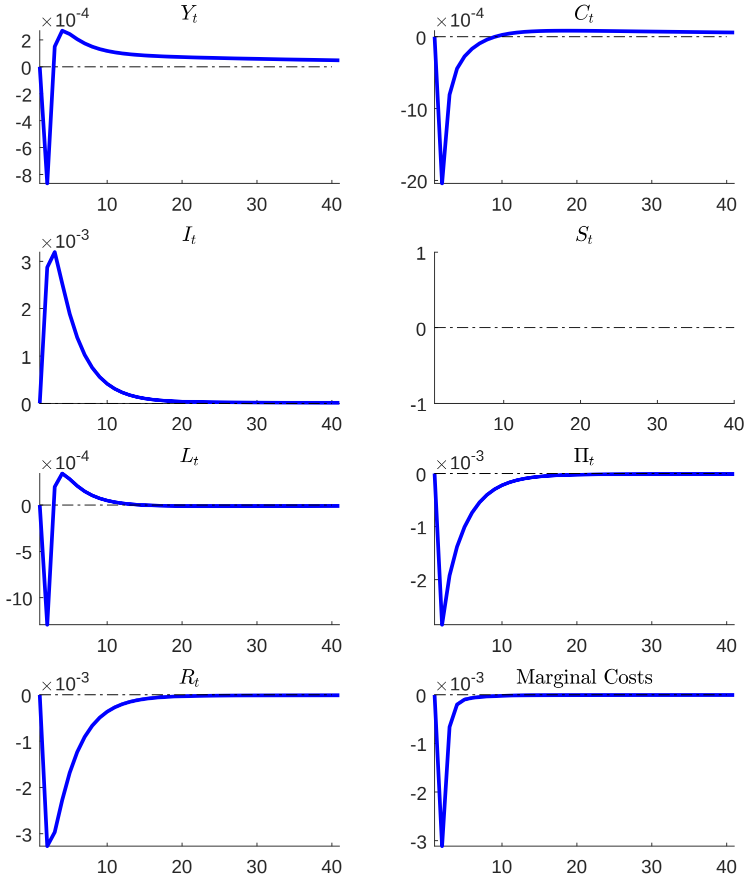


Figure C.9: *Productivity Uncertainty Shock varying* ζ_N



C.6 Model with no R&D

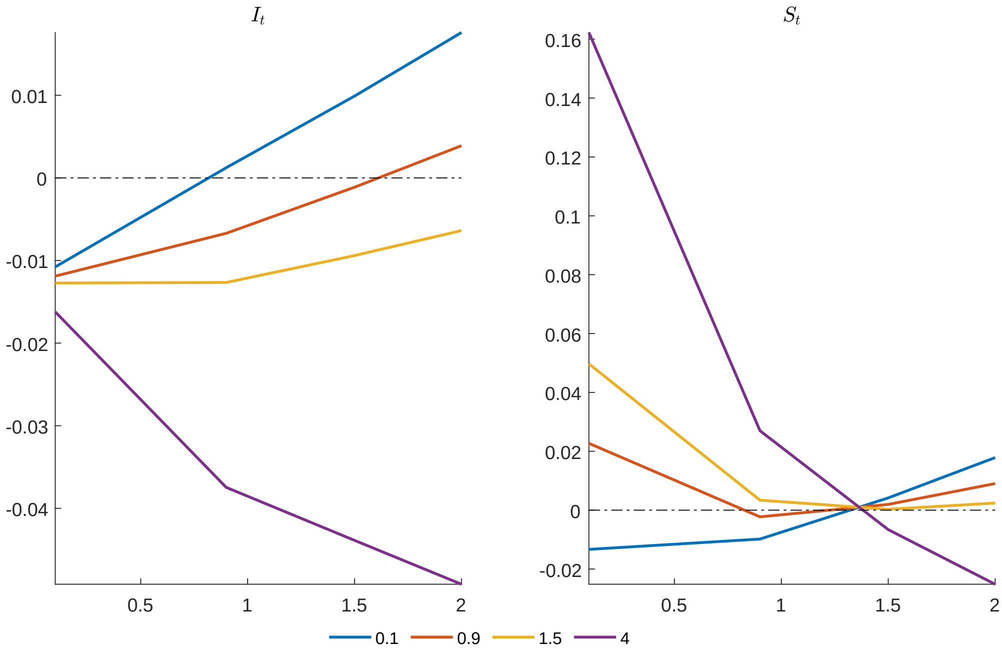
Figure C.10: *Productivity Uncertainty Shock in a model without R&D*



Notes: Each line is the impact response, varying the IES parameter (x-axis), given a certain value of the RRA.

C.7 IES and RRA Combinations

Figure C.11: *Productivity Uncertainty Shock Impact Responses for Different IES and RRA*



Notes: Each line is the impact response, varying the IES parameter (x-axis), given a certain value of the RRA.

Bibliography

Abel, A. B. (1983). Optimal investment under uncertainty. *American Economic Review*, 73(1):228–33.

Anzoategui, D., Comin, D., Gertler, M., and Martinez, J. (2016). Endogenous Technology Adoption and R&D as Sources of Business Cycle Persistence. NBER Working Papers 22005, National Bureau of Economic Research, Inc.

Arellano, C., Bai, Y., and Kehoe, P. J. (2016). Financial Frictions and Fluctuations in Volatility. NBER Working Papers 22990, National Bureau of Economic Research, Inc.

Auerbach, A. J. and Gorodnichenko, Y. (2012). Fiscal Multipliers in Recession and Expansion. In *Fiscal Policy after the Financial Crisis*, NBER Chapters, pages 63–98. National Bureau of Economic Research, Inc.

Auerbach, A. J. and Gorodnichenko, Y. (2013). Output Spillovers from Fiscal Policy. *American Economic Review*, 103(3):141–46.

Bachmann, R. and Bayer, C. (2013). Wait-and-See business cycles? *Journal of Monetary Economics*, 60(6):704–719.

Bachmann, R., Elstner, S., and Sims, E. R. (2013). Uncertainty and Economic Activity: Evidence from Business Survey Data. *American Economic Journal: Macroeconomics*, 5(2):217–49.

Bachmann, R. and Sims, E. R. (2012). Confidence and the transmission of government spending shocks. *Journal of Monetary Economics*, 59(3):235–249.

Backus, D., Ferriere, A., and Zin, S. (2015). Risk and ambiguity in models of business cycles. *Journal of Monetary Economics*, 69(C):42–63.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4):1593.

Balke, N., Martinez-Garcia, E., and Zeng, Z. (2013). Credit uncertainty cycle. Working Paper Forthcoming, Unpublished manuscript.

Banbura, M., Giannone, D., and Reichlin, L. (2010). Large Bayesian Vector Auto Regressions. *Journal of Applied Econometrics*, 25(1):71–92.

Bansal, R. and Yaron, A. (2004). Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles. *Journal of Finance*, 59(4):1481–1509.

Barndorff-Neilsen, O. E., Kinnebrouk, S., and Shephard, N. (2010). *Measuring downside risk: realised semivariance*, pages 117–136. Oxford University Press, (edited by t. bollerslev, j. russell and m. watson) edition.

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

Bekaert, G., Hoerova, M., and Lo Duca, M. (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics*, 60(7):771–788.

Benigno, G. and Fornaro, L. (2015). Stagnation Traps. Working Papers 832, Barcelona Graduate School of Economics.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *The Quarterly Journal of Economics*, 98(1):85–106.

Bernanke, B. S., Boivin, J., and Eliasz, P. (2004). Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach. NBER Working Papers 10220, National Bureau of Economic Research, Inc.

Bernanke, B. S., Gertler, M., and Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. In Taylor, J. B. and Woodford, M., editors, *Handbook of Macroeconomics*, volume 1 of *Handbook of Macroeconomics*, chapter 21, pages 1341–1393. Elsevier.

Bertola, G. and Caballero, R. J. (1994). Irreversibility and Aggregate Investment. *Review of Economic Studies*, 61(2):223–46.

Bianchi, F., Kung, H., and Morales, G. (2014). Growth, Slowdowns, and Recoveries. NBER Working Papers 20725, National Bureau of Economic Research, Inc.

Bloom, N. (2009). The impact of uncertainty shocks. *Econometrica*, 77(3):623–685.

Bonciani, D. (2015). Estimating the effects of uncertainty over the business cycle. MPRA Paper 65921, University Library of Munich, Germany.

Bonciani, D. and van Roye, B. (2016). Uncertainty shocks, banking frictions and economic activity. *Journal of Economic Dynamics and Control*, 73(C):200–219.

Born, B. and Pfeifer, J. (2014). Policy risk and the business cycle. *Journal of Monetary Economics*, 68(0):68 – 85.

Caggiano, G., Castelnuovo, E., and Groshenny, N. (2014). Uncertainty shocks and unemployment dynamics in u.s. recessions. *Journal of Monetary Economics*, 67(0):78 – 92.

Caldara, D., Fernandez-Villaverde, J., Rubio-Ramirez, J., and Yao, W. (2012). Computing DSGE Models with Recursive Preferences and Stochastic Volatility. *Review of Economic Dynamics*, 15(2):188–206.

Caldara, D. and Iacoviello, M. (2016). Measuring geopolitical risk. Working paper, Board of Governors of the Federal Reserve Board.

Calvo, G. A. (1983). Staggered prices in a utility-maximizing framework. *Journal of Monetary Economics*, 12(3):383–398.

Canova, F. (2007). *Methods for Applied Macroeconomic Research*, volume 13. Princeton University Press.

Cesa-Bianchi, A. and Fernandez-Corugedo, E. (2013). Uncertainty in a model with credit frictions. Working Paper Forthcoming, Bank of England.

Christiano, L. J., Motto, R., and Rostagno, M. (2014). Risk shocks. *American Economic Review*, 104(1):27–65.

Clarida, R., Gali, J., and Gertler, M. (1999). The science of monetary policy: A new keynesian perspective. *Journal of Economic Literature*, 37(4):1661–1707.

de Groot, O., Richter, A. W., and Throckmorton, N. A. (2017). Uncertainty Shocks in a Model of Effective Demand: Comment. CDMA Working Paper Series 201703, Centre for Dynamic Macroeconomic Analysis.

Degryse, H. and Ongena, S. (2007). The impact of competition on bank orientation. *Journal of Financial Intermediation*, 16(3):399–424.

Denis, S. and Kannan, P. (2013). The Impact of Uncertainty Shocks on the UK Economy. *IMF Working Paper*, 66.

Epaulard, A. and Pommeret, A. (2003). Recursive Utility, Endogenous Growth, and the Welfare Cost of Volatility. *Review of Economic Dynamics*, 6(3):672–684.

Epstein, L. G. and Zin, S. E. (1989). Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework. *Econometrica*, 57(4):937–969.

Fernald, J. G. (2012). A quarterly, utilization-adjusted series on total factor productivity. Working Paper Series 2012-19, Federal Reserve Bank of San Francisco.

Fernald, J. G. and Jones, C. I. (2014). The future of us economic growth. *American Economic Review*, 104(5):44–49.

Fernandez-Villaverde, J., Guerron-Quintana, P., Kuester, K., and Rubio-Ramírez, J. (2015). Fiscal Volatility Shocks and Economic Activity. *American Economic Review*, 105(11):3352–84.

Fernández-Villaverde, J., Guerrón-Quintana, P., and Rubio-Ramírez, J. F. (2010). Fortune or Virtue: Time-Variant Volatilities Versus Parameter Drifting in U.S. Data. PIER Working Paper Archive 10-015, Penn Institute for Economic Research, Department of Economics, University of Pennsylvania.

Fernandez-Villaverde, J., Guerron-Quintana, P., Rubio-Ramirez, J. F., and Uribe, M. (2011). Risk matters: The real effects of volatility shocks. *American Economic Review*, 101(6):2530–61.

Ferrara, L. and Guérin, P. (2016). What Are the Macroeconomic Effects of High-Frequency Uncertainty Shocks. Staff Working Papers 16-25, Bank of Canada.

Forni, M. and Gambetti, L. (2014). Sufficient information in structural VARs. *Journal of Monetary Economics*, 66(C):124–136.

Foroni, C. and Marcellino, M. (2016). Mixed frequency structural vector autoregressive models. *Journal of the Royal Statistical Society Series A*, 179(2):403–425.

Gambacorta, L. and Signoretti, F. M. (2014). Should monetary policy lean against the wind?: An analysis based on a {DSGE} model with banking. *Journal of Economic Dynamics and Control*, 43:146 – 174. The Role of Financial Intermediaries in Monetary Policy Transmission.

Gerali, A., Neri, S., Sessa, L., and Signoretti, F. M. (2010). Credit and Banking in a DSGE Model of the Euro Area. *Journal of Money, Credit and Banking*, 42(s1):107–141.

Ghysels, E. (2016). Macroeconomics and the reality of mixed frequency data. *Journal of Econometrics*, 193(2):294–314.

Giannone, D., Lenza, M., and Primiceri, G. E. (2015). Prior Selection for Vector Autoregressions. *The Review of Economics and Statistics*, 97(2):436–451.

Gilchrist, S., Sim, J. W., and Zakrajsek, E. (2014). Uncertainty, Financial Frictions, and Investment Dynamics. NBER Working Papers 20038, National Bureau of Economic Research, Inc.

Guglielminetti, E. (2016). The labor market channel of macroeconomic uncertainty. Temi di discussione (Economic working papers) 1068, Bank of Italy, Economic Research and International Relations Area.

Hartman, R. (1976). Factor demand with output price uncertainty. *American Economic Review*, 66(4):675–81.

Iacoviello, M. (2005). House prices, borrowing constraints, and monetary policy in the business cycle. *American Economic Review*, 95(3):739–764.

Iacoviello, M. and Neri, S. (2010). Housing market spillovers: Evidence from an estimated dsge model. *American Economic Journal: Macroeconomics*, 2(2):125–64.

Jermann, U. J. (1998). Asset pricing in production economies. *Journal of Monetary Economics*, 41(2):257–275.

Jorda, O. (2005). Estimation and Inference of Impulse Responses by Local Projections. *American Economic Review*, 95(1):161–182.

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring Uncertainty. *American Economic Review*, 105(3):1177–1216.

Kim, J., Kim, S., Schaumburg, E., and Sims, C. A. (2008). Calculating and using second-order accurate solutions of discrete time dynamic equilibrium models. *Journal of Economic Dynamics and Control*, 32(11):3397–3414.

Kimball, M. S. (1990). Precautionary saving in the small and in the large. *Econometrica*, 58(1):53–73.

Kiyotaki, N. and Moore, J. (1997). Credit cycles. *Journal of Political Economy*, 105(2):211–48.

Kobayashi, T. (2008). Incomplete Interest Rate Pass-Through and Optimal Monetary Policy. *International Journal of Central Banking*, 4(3):77–118.

Koop, G., Pesaran, M. H., and Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74(1):119–147.

Kung, H. (2015). Macroeconomic linkages between monetary policy and the term structure of interest rates. *Journal of Financial Economics*, 115(1):42 – 57.

Kung, H. and Schmid, L. (2015). Innovation, Growth, and Asset Prices. *Journal of Finance*, 70(3):1001–1037.

Lan, H. and Meyer-Gohde, A. (2013a). Decomposing risk in dynamic stochastic general equilibrium. SFB 649 Discussion Papers SFB649DP2013-022, Sonderforschungsbereich 649, Humboldt University, Berlin, Germany.

Lan, H. and Meyer-Gohde, A. (2013b). Solving DSGE models with a nonlinear moving average. *Journal of Economic Dynamics and Control*, 37(12):2643–2667.

Leduc, S. and Liu, Z. (2016). Uncertainty shocks are aggregate demand shocks. *Journal of Monetary Economics*, 82(C):20–35.

Leland, H. (1968). Saving and uncertainty: The precautionary demand for saving. *Quarterly Journal of Economics*, 82:465–473.

Ludvigson, S. C., Ma, S., and Ng, S. (2015). Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response? NBER Working Papers 21803, National Bureau of Economic Research, Inc.

Lütkepohl, H. (2013). Vector autoregressive models. In *Handbook of Research Methods and Applications in Empirical Macroeconomics*, Chapters, chapter 6, pages 139–164. Edward Elgar Publishing.

McCracken, M. W. and Ng, S. (2015). FRED-MD: A Monthly Database for Macroeconomic Research. Working Papers 2015-12, Federal Reserve Bank of St. Louis.

Newey, W. K. and West, K. D. (1987). A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, 55(3):703–08.

Oi, W. Y. (1961). The desirability of price instability under perfect competition. *Econometrica*, 29(1):58–64.

Owyang, M. T., Ramey, V. A., and Zubairy, S. (2013). Are government spending multipliers greater during periods of slack? evidence from twentieth-century historical data. *American Economic Review*, 103(3):129–34.

Paries, M. D., Sorensen, C. K., and Rodriguez-Palenzuela, D. (2011). Macroeconomic propagation under different regulatory regimes: Evidence from an Estimated DSGE Model for the Euro Area. *International Journal of Central Banking*, 7(4):49–113.

Patton, A. J. and Sheppard, K. (2013). Good volatility, bad volatility: Signed jumps and the persistence of volatility. *Economic Research Initiatives at Duke (ERID)*, Working Paper No. 168.

Pindyck, R. S. (1991). Irreversibility, Uncertainty, and Investment. *Journal of Economic Literature*, 29(3):1110–1148.

Ramey, G. and Ramey, V. A. (1995). Cross-Country Evidence on the Link between Volatility and Growth. *American Economic Review*, 85(5):1138–1151.

Romer, P. M. (1990). Endogenous Technological Change. *Journal of Political Economy*, 98(5):S71–102.

Rossi, B. and Sekhposyan, T. (2015). Macroeconomic uncertainty indices based on nowcast and forecast error distributions. *American Economic Review*, 105(5).

Rotemberg, J. J. (1982). Monopolistic price adjustment and aggregate output. *Review of Economic Studies*, 49(4):517–31.

Saltari, E. and Ticchi, D. (2007). Risk aversion, intertemporal substitution, and the aggregate-investment uncertainty relationship. *Journal of Monetary Economics*, 54(3):622 – 648.

Schmitt-Grohe, S. and Uribe, M. (2004). Solving dynamic general equilibrium models using a second-order approximation to the policy function. *Journal of Economic Dynamics and Control*, 28(4):755–775.

Segal, G., Shaliastovich, I., and Yaron, A. (2014). Good and Bad Uncertainty: Macroeconomic and Financial Market Implications. 2014 Meeting Papers 488, Society for Economic Dynamics.

Sims, C. A. and Zha, T. (1999). Error Bands for Impulse Responses. *Econometrica*, 67(5):1113–1156.

Stock, J. H. and Watson, M. W. (2012). Disentangling the Channels of the 2007-2009 Recession. NBER Working Papers 18094, National Bureau of Economic Research, Inc.

Summers, L. (2013). Why stagnation might prove to be the new normal. Financial times, Newspaper article.

Taylor, J. B. (1993). Discretion versus policy rules in practice. *Carnegie-Rochester Conference Series on Public Policy*, 39(1):195–214.

Tenreyro, S. and Thwaites, G. (2013). Pushing On a String: US Monetary Policy is Less Powerful in Recessions. CEP Discussion Papers dp1218, Centre for Economic Performance, LSE.

Terasvirta, T., Tjostheim, D., and Granger, C. W. J. (2010). *Modelling Nonlinear Economic Time Series*. Number 9780199587155 in OUP Catalogue. Oxford University Press.

Tong, H. (1983). *Threshold models in non-linear time series analysis*. Lecture notes in statistics. Springer-Verlag.

van Binsbergen, J. H., Fernández-Villaverde, J., Koijen, R. S., and Rubio-Ramírez, J. (2012). The term structure of interest rates in a DSGE model with recursive preferences. *Journal of Monetary Economics*, 59(7):634–648.

van Roye, B. (2013). Financial stress and economic activity in Germany. *Empirica*, pages 1–26.