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Uncertainty shocks, banking frictions and economic activity

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A B S T R A C T

In this paper we investigate the effects of uncertainty shocks on economic activity in the euro area by using 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.

1. Introduction

The macroeconomic effects of uncertainty on economic activity is a prevalent topic in both economic policy and academic research. Policy makers 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 (Fig. 1).

The relationship between macroeconomic uncertainty shocks and economic activity 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

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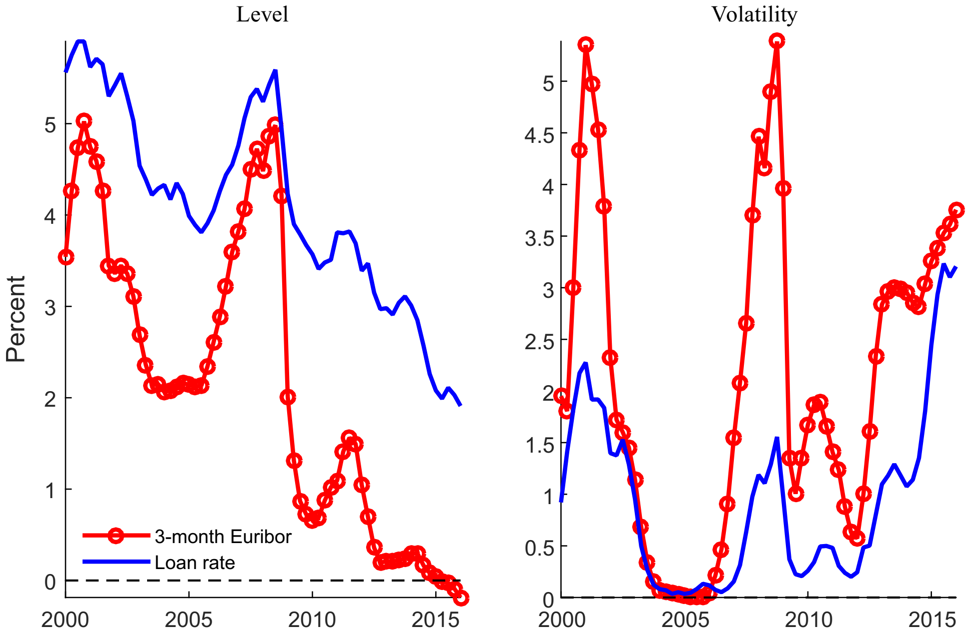

Fig. 1. Level and volatility of 5-year loan rate and 3-month Euribor. *Notes*: Interest rate volatilities are estimated using a GARCH(1,1) model.

disputed. While Bachmann and Bayer (2013) claim there are no significant effects of uncertainty shocks in general equilibrium, Basu and Bundick (2014) 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 (2015) 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 bond holders, 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 for 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 (2014) 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 (2014); Christiano et al. (2014), and Balke et al. (2013). While Basu and Bundick (2014) 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

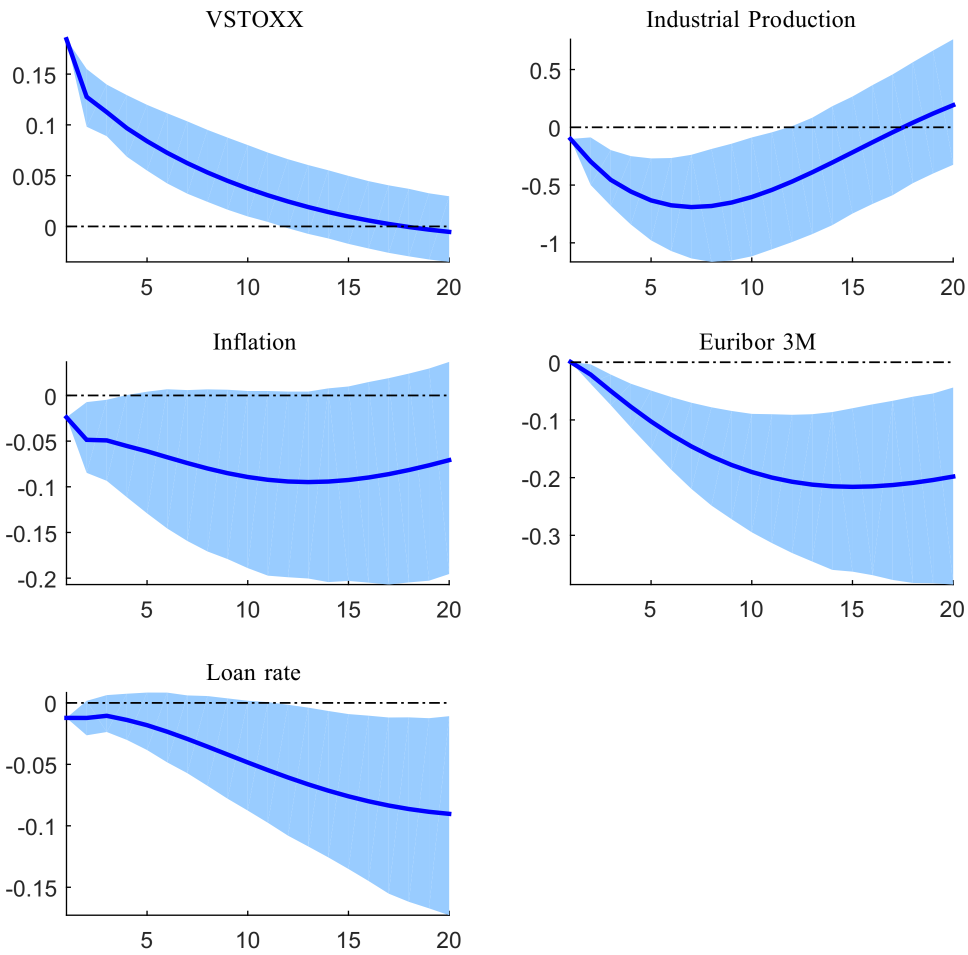

Fig. 2. Impulse responses to a VSTOXX shock. *Notes*: The VSTOXX is ordered first. The blue solid lines are responses of the endogenous variables to a standardized increase in the innovations to uncertainty. Shaded areas represent 95 error bands computed as in Sims and Zha (1999). (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

Rotemberg (1982). Moreover, the model is augmented by a stylized banking sector inspired by Gerali et al. (2010). The main results of our analysis is 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 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 3 we present the DSGE model with borrowing constrained entrepreneurs and a monopolistically competitive banking sector. In Section 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 5.

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 orthogonalized 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 EuroStoxx50 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

[1] Basu and Bundick (2014) use a similar implied volatility index for the United States (VIX) in order to identify the uncertainty shock.

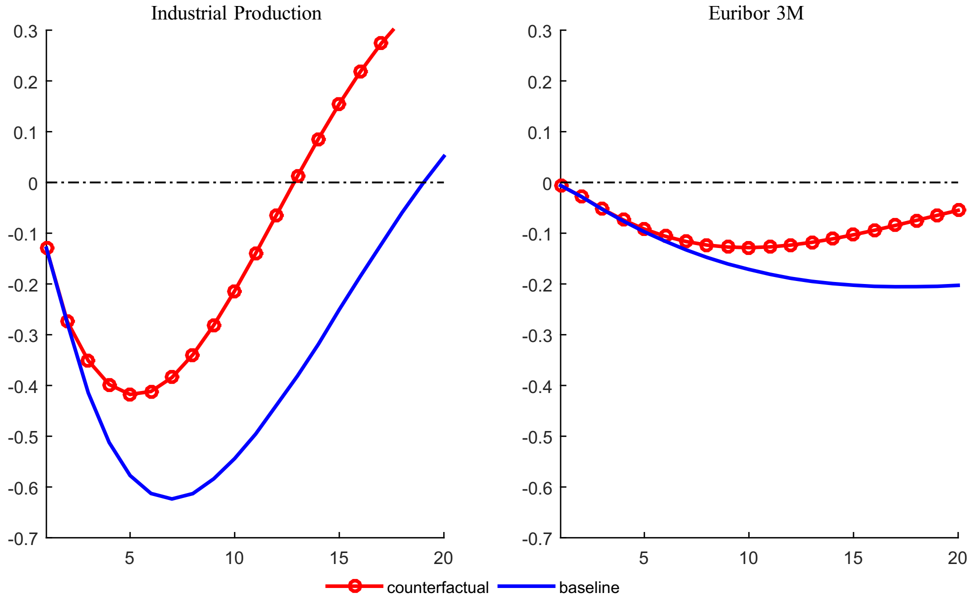

Fig. 3. Isolating the role of the loan rate. *Notes*: The blue solid lines represent impulse responses of industrial production and the Euribor in the baseline model. The red line represents the impulse responses of industrial production and the Euribor in the counterfactual exercise. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

the following form:

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

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 Choleski 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., 2015)).[2]

The impulse responses to a VSTOXX shock are depicted in Fig. 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 (2015) and Basu and Bundick (2014), 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. Fig. 3 displays the impulse in 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 hypotetical 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

[2] For robustness, we test for alternative ordering of the variables, partiulalry when the uncertainty index is ordered last. In addition, we estimate Bayesian VARs with alternative prior distributions. Results can be found in the appendix. The results do not substantially differ from the ones reported here.

[3] Bloom (2009) and Baker et al. (2015) 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.

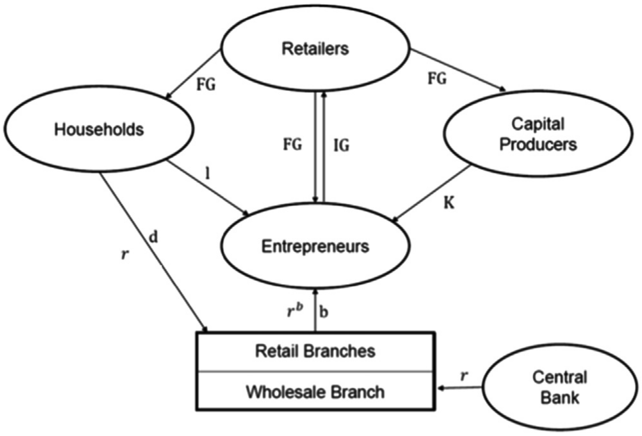

Fig. 4. The model economy. *Notes*: FG denotes the final good and IG the intermediate good.

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 limitiations 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 EUROSTOXX 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 meaures of uncertainty used in the literature, is highly endogenous and may respond contemporaneously to other variables in the VAR. Nevertheless, the 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.

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, $r \le r^b$. Furthermore we assume that banks pay adjustment costs when changing the retail interest rates. In Fig. 4 we depict the model economy.

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.

3.1.1. 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:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta_h^t z_t \left[log\left(c_{h,t}(i)\right) - \frac{l_t(i)^{1+\phi}}{1+\phi} \right], \tag{2}$$

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

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:

$$c_{h,t}(i)+d_t(i)=w_t l_t(i)+\frac{1+r_{t-1}}{(1+\pi_t)}d_{t-1}(i)+J_t^R(i)+(1-\varphi)J_t^B(i). \tag{3}$$

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.

3.1.2. Entrepreneurs

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

$$\mathbb{E}_0\sum_{t=0}^{\infty}\beta_e^t\left[\log(c_{e,t}(j))\right], \tag{4}$$

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:

$$y_t^e(j)=[k_{t-1}(j)]^{\alpha}l_t(j)^{1-\alpha}, \tag{5}$$

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:

$$(1+r_t^b)b_t(j)\le m\mathbb{E}_t\left[q_{t+1}^k(1+\pi_{t+1})(1-\delta)k_t(j)\right], \tag{6}$$

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.

3.1.3. 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:

$$\max_{\{k_t,i_t\}}\mathbb{E}_0\sum_{t=0}^{\infty}\Lambda_{0,t}^e\left(q_t^k\Delta k_t-i_t\right), \tag{7}$$

subject to:

$$\Delta k_t=\left[1-\frac{\kappa_i}{2}\left(\frac{i_t}{i_{t-1}}-1\right)^2\right]i_t, \tag{8}$$

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.

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:

$$y_t=\left[\int_0^1 y_t(\nu)^{(\epsilon^y-1)/\epsilon^y}\mathrm{d}\nu\right]^{\epsilon^y/(\epsilon^y-1)}, \tag{9}$$

with the associated price index:

$$P_t = \left[\int_0^1 P_t(\nu)^{(1-\varepsilon^y)} \mathrm{d}\nu \right]^{1/(1-\varepsilon^y)}. \tag{10}$$

In (9) and (10), ε^y represents the elasticity of substitution between differentiated final goods. Given (9), the demand that each retailer faces is equal to:

$$y_t(\nu) = \left(\frac{P_t(\nu)}{P_t} \right)^{-\varepsilon^y} Y_t. \tag{11}$$

Each firm ν chooses its price to maximize the expected discounted value of profits subject to the demand for consumption goods (11):

$$\max_{\{P_t(\nu)\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_{0,t}^h \left[\left(P_t(\nu) - P_t^W \right) y_t(\nu) - \frac{\kappa_p}{2} \left(\frac{P_t(\nu)}{P_{t-1}(\nu)} - (1+\pi) \right)^2 P_t Y_t \right], \tag{12}$$

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.

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:

$$b_t = d_t + K_t^b, \tag{13}$$

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:

$$\min_{b_t(j,n)} \int_0^1 r_t^b(n) b_t(j,n) \mathrm{d}n, \tag{14}$$

subject to

$$b_t(j) \le \left[\int_0^1 b_t(j,n)^{(\varepsilon^b - 1)/\varepsilon^b} \mathrm{d}n \right]^{\varepsilon^b/(\varepsilon^b - 1)}, \tag{15}$$

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

$$b_t(n) = \left(\frac{r_t^b(n)}{r_t^b} \right)^{-\epsilon_t^b} b_t. \tag{16}$$

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.

3.3.1. 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

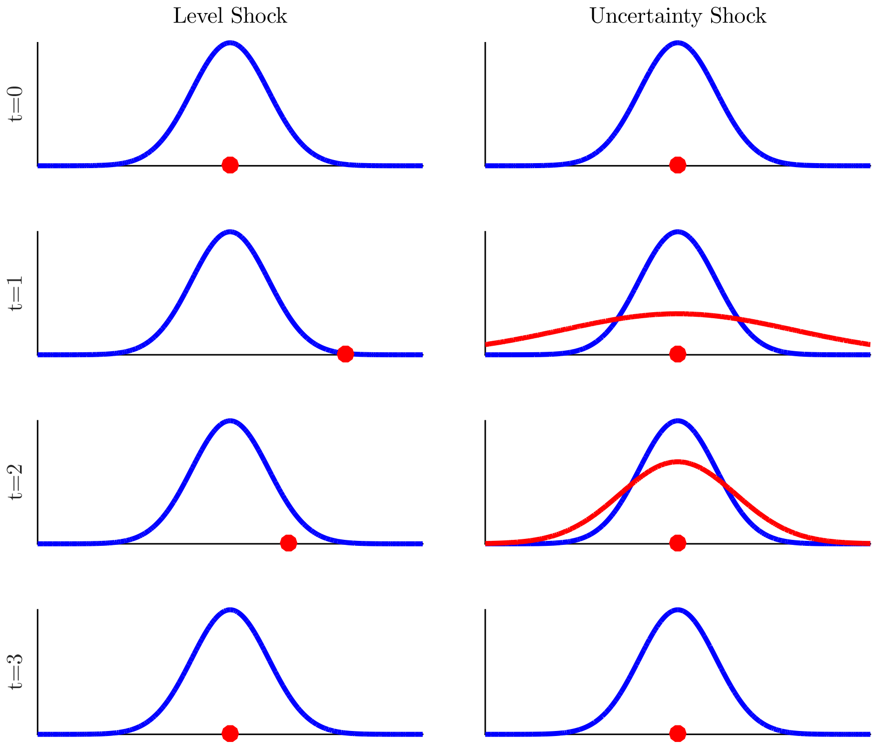

Fig. 5. Level and uncertainty shock. *Notes*: The left column represents a preference level shock. The right column represents a second moment shock. We assume the shock to die out in period $t=3$.

stochastic discount factor of the households $\Lambda^h_{0,t}$:

$$\max_{\{b_t,d_t\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda^h_{0,t}\left[\left(1+R^b_t\right)b_t-(1+\pi_{t+1})b_{t+1}+d_{t+1}-\left(1+R^d_t\right)d_t+\left(K^b_{t+1}(1+\pi_{t+1})-K^b_t\right)\right], \tag{17}$$

subject to the budget constraint:

$$b_t = d_t + K^b_t, \tag{18}$$

and given the following law of motion for bank capital:

$$(1+\pi_t)K^b_t = (1-\delta^b)K^b_{t-1}+\varphi J^b_{t-1}. \tag{19}$$

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:

$$R^b_t = R^d_t = r_t. \tag{20}$$

3.3.2. 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^b_t (which as we previously showed is equal to the policy rate) and lend it to the entrepreneurs at rate $r^b_t(n)$. The optimization problem of the loan-retail division n is given by:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda^h_{0,t}\left[r^b_t(n)b_t(n)-r_t b(n)-\frac{\kappa_b}{2}\left(\frac{r^b_t(n)}{r^b_{t-1}(n)}-1\right)^2 r^b_t b_t\right], \tag{21}$$

subject to the demand for loans (16).

3.4. Monetary authority

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

$$\frac{1+r_t}{1+r}=\left(\frac{1+r_{t-1}}{1+r}\right)^{\phi_r}\left[\left(\frac{1+\pi_t}{1+\pi}\right)^{\phi_\pi}\left(\frac{y_t}{y_{t-1}}\right)^{\phi_y}\right]^{(1-\phi_r)}, \tag{22}$$

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.

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:

$$Y_t=C_t+\left[k_t-(1-\delta)k_{t-1}\right]+\delta^b\frac{K^b_{t-1}}{(1+\pi_t)}+ADJ_t, \tag{23}$$

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:

$$ADJ_t\equiv\frac{\kappa_p}{2}\left(\frac{1+\pi_t}{1+\pi}-1\right)^2Y_t+\frac{\kappa_b}{2}\left(\frac{r^b_{t-1}}{r^b_{t-2}}-1\right)^2r^b_{t-1}b_{t-1}. \tag{24}$$

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 Fig. 5.

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.

Table 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

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:

$$z_t = (1-\rho_z) + \rho_z z_{t-1} + \sigma_t^z e_t^z \quad \text{where } e_t^z \sim \mathcal{N}(0,1) \tag{25}$$

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:

$$\sigma_t^z = (1-\rho_{\sigma^z})\sigma^z + \rho_{\sigma^z}\sigma_{t-1}^z + \eta_z e_t^{\sigma_z} \quad \text{where } e_t^{\sigma_z} \sim \mathcal{N}(0,1) \tag{26}$$

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, $e_t^{\sigma_z}$.

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:

$$E_t f(x_{t+1}, x_t, x_{t-1}, e_t) = 0, \tag{27}$$

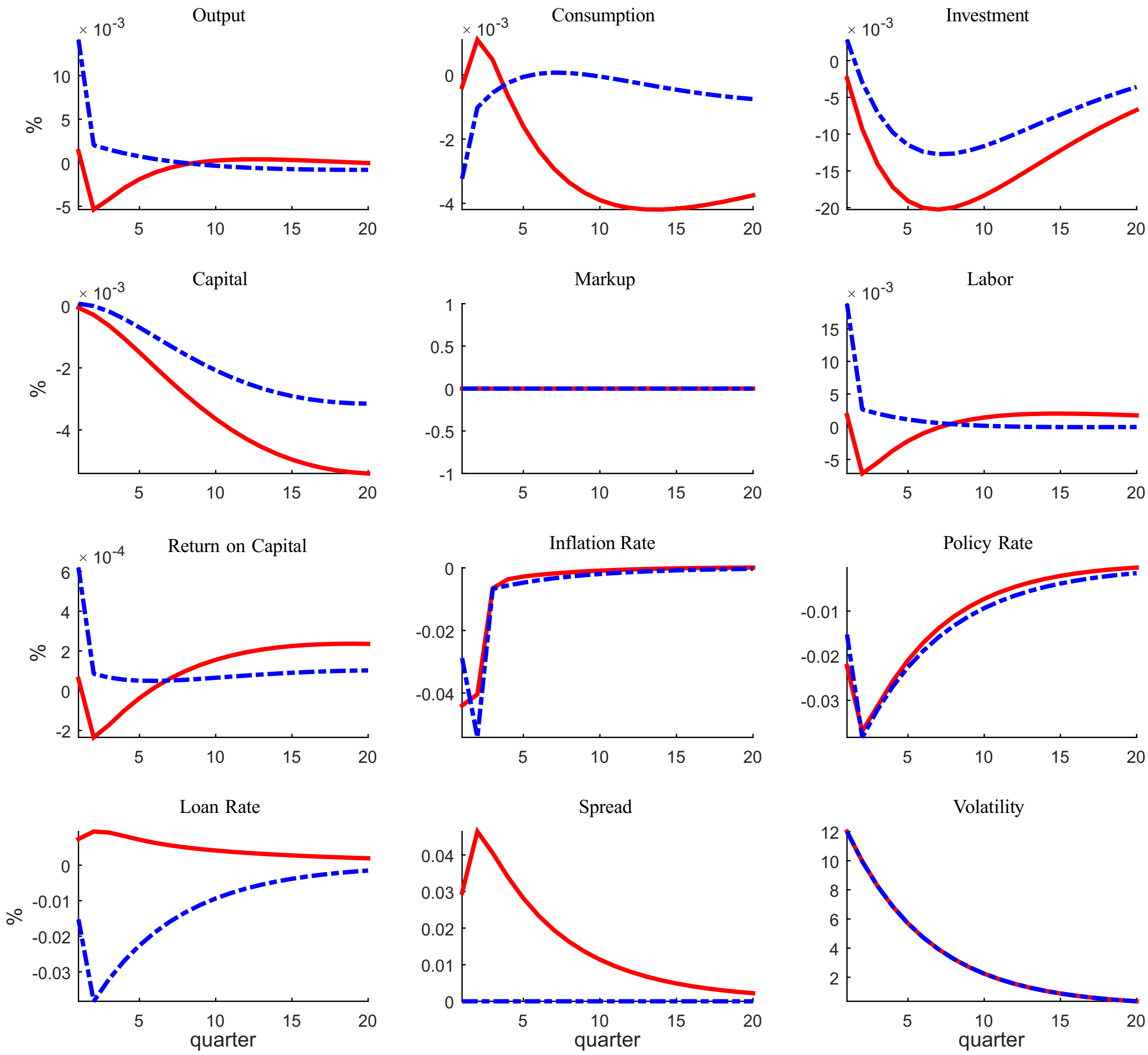

Fig. 6. Impulse response functions to a demand uncertainty shock under flexible prices. *Notes*: Red line: Flexible prices and sticky loan rate; Blue line: Flexible prices and flexible loan rate. All variables are expressed in percentage deviations from steady state, except interest rates and inflation which are expressed in annualized absolute deviations from steady-state. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

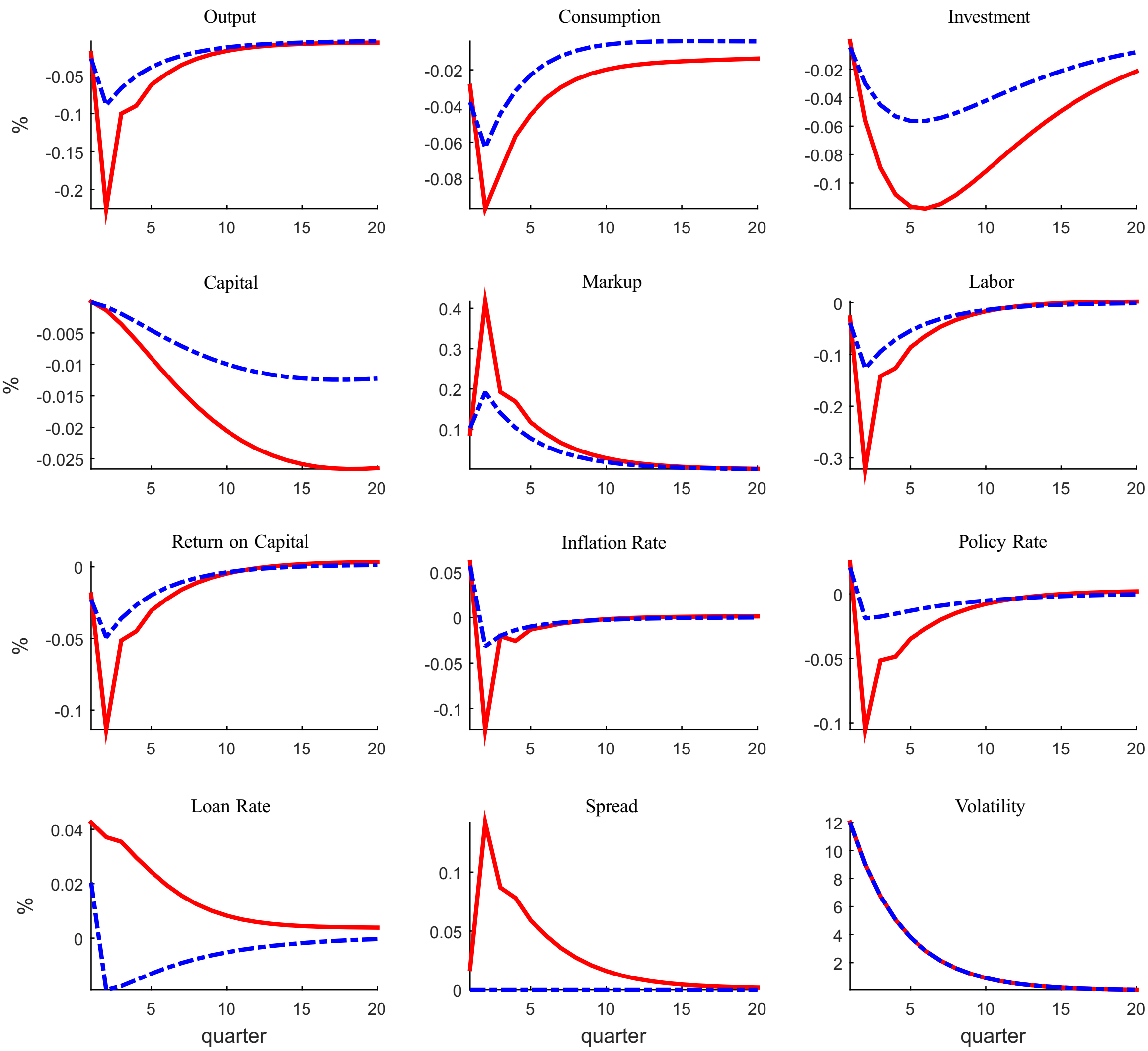

Fig. 7. Impulse response functions to a demand uncertainty shock under sticky prices. *Notes*: Red solid line: Model with sticky loan rate (SLR); Blue dashed line: Model with flexible loan rate (FLR). All variables are expressed in percentage deviations from steady state, except interest rates and inflation which are expressed in annualized absolute deviations from steady-state. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

into a system of equations, known as policy function:

$$x_t = h(\sigma, e_t, e_{t-1}, e_{t-2}, \ldots). \tag{28}$$

In (27) and (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 (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:

$$x_t = \sum_{j=0}^{J} \frac{1}{j!} \prod_{l=1}^{j} \sum_{i_l=0}^{\infty} \left(\sum_{n=0}^{J-j} \frac{1}{n!} x_{\sigma^n i_1 i_2 \ldots i_j} \sigma^n \right) (e_{t-i_1} \otimes e_{t-i_2} \otimes e_{t-i_3} \ldots). \tag{29}$$

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

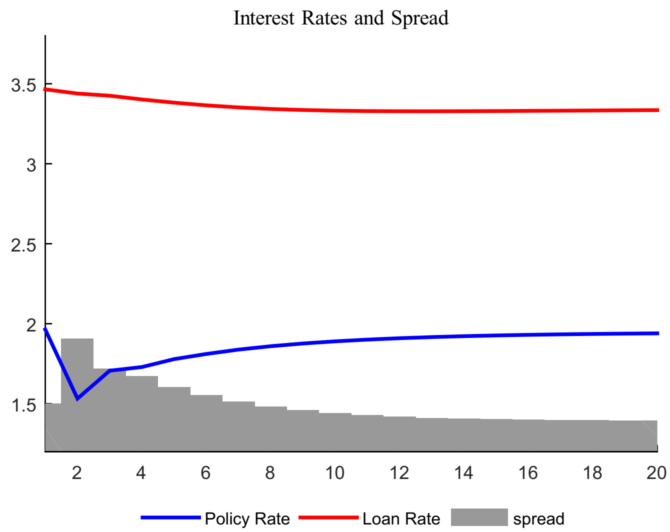

Fig. 8. Response of policy and retail interest rates to an uncertainty shock. *Notes*: The blue line represents the policy rate; the red line represents the loan rate. The two lines represent responses to a 3-standard deviation shock in uncertainty. Grey bars represent the spread between the two interest rates. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

shocks shut off, it is necessary to approximate (28) up to a third order:

$$x_t = \overline{x} + \frac{1}{2}y_{\sigma^2} + \frac{1}{2}\sum_{i=0}^{\infty}(x_i + x_{\sigma^2,i})e_{t-i} + \frac{1}{2}\sum_{j=0}^{\infty}\sum_{i=0}^{\infty}x_{j,i}(e_{t-j}\otimes e_{t-i})$$
$$+\frac{1}{6}\sum_{k=0}^{\infty}\sum_{j=0}^{\infty}\sum_{i=0}^{\infty}x_{k,j,i}(e_{t-k}\otimes e_{t-j}\otimes e_{t-i}). \tag{30}$$

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.

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. The discount factor for households is set to 0.9943 which results into 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 paramater 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 (2014).

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.

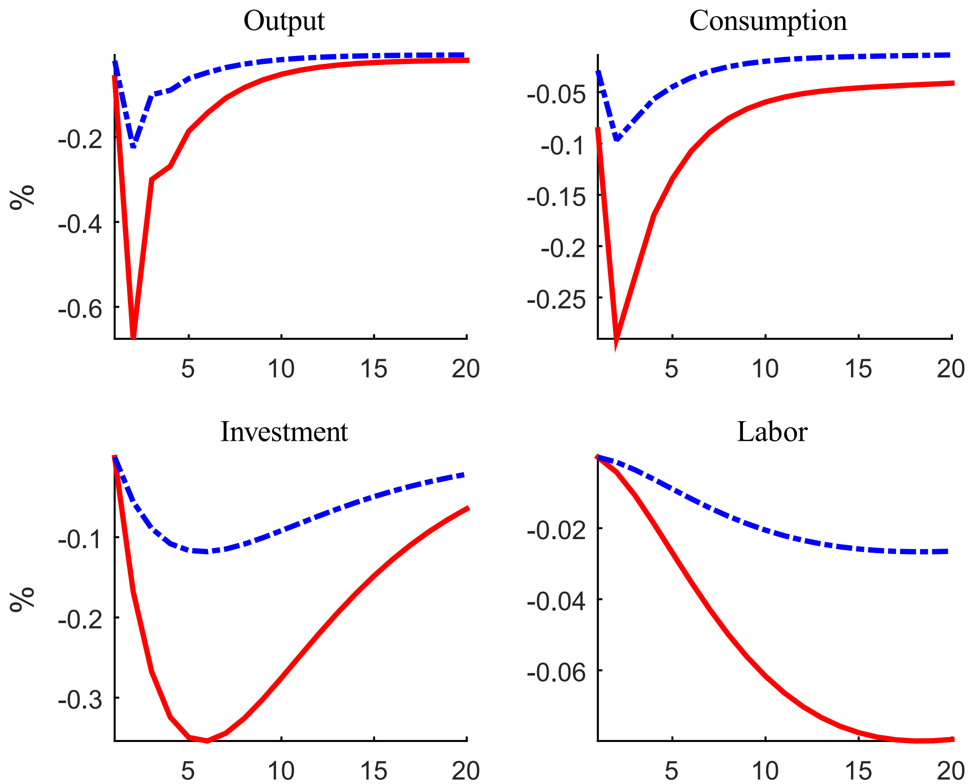

Fig. 9. *Notes*: The blue line represents the IRF to an uncertainty shock in the baseline case; the red line represents the IRF to an uncertainty shock in a state of high volatility. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

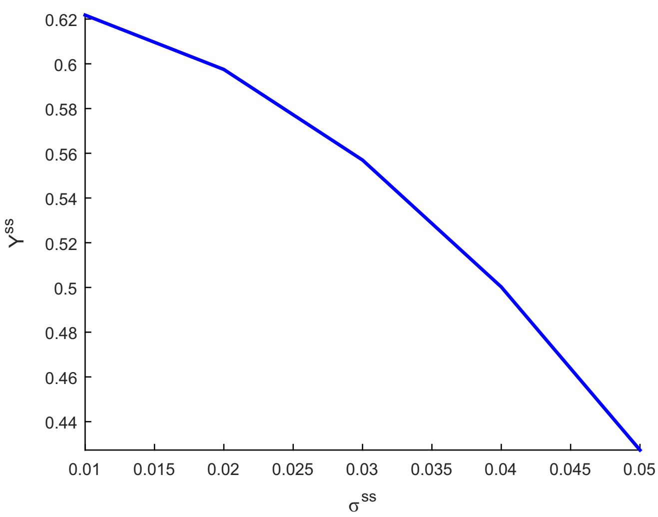

Fig. 10. Relationship between the Stochastic Steady-State of Output and Uncertainty.

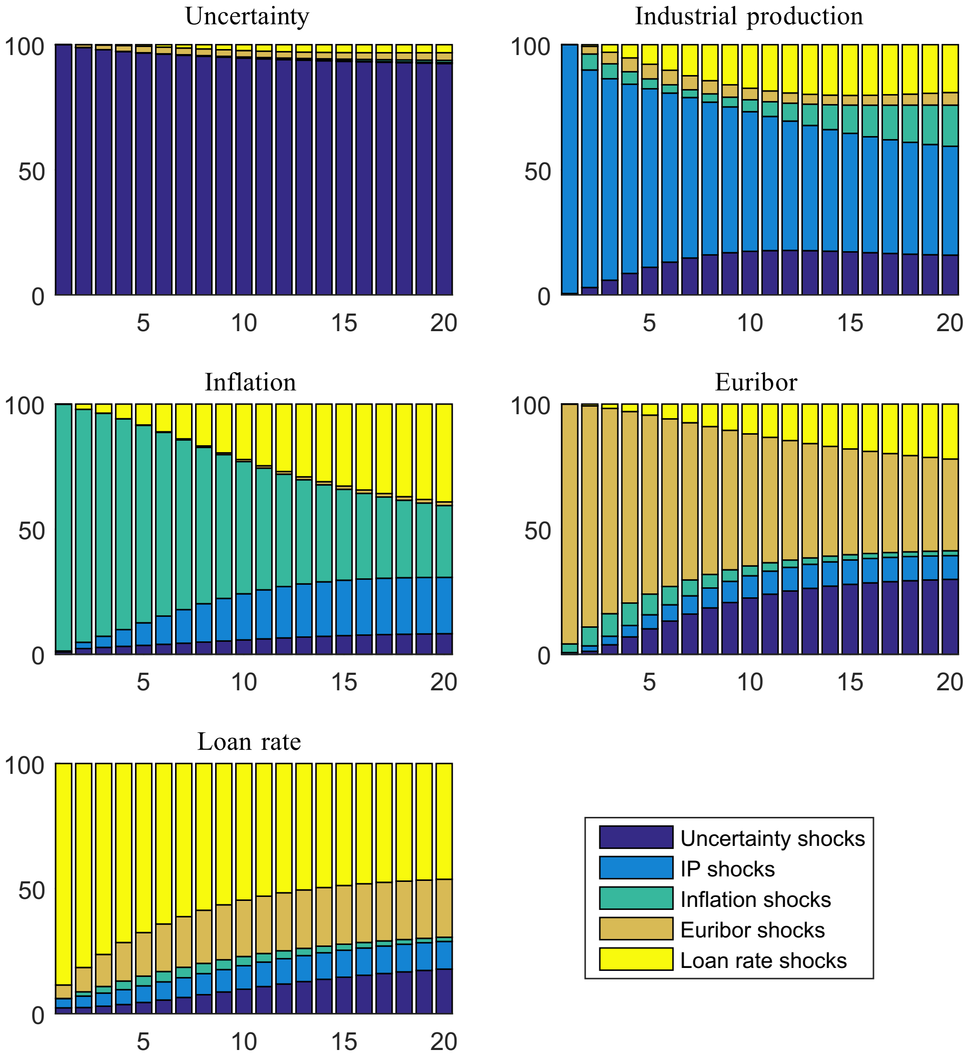

Fig. 11. Forecast error variance decomposition. *Notes*: Monthly horizon.

4.1. *Effects of a demand uncertainty shock*

Fig. 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 (2014) 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 Fig. 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 (Fig. 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 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 Fig. 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.

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 Fig. 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 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 Fig. 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 (2014) 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 2. The friction introduced in this paper represents one source of amplification that helps bringing 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 (2015). 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.

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, 2014; 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, Fig. 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 ($\overline{\sigma} = 0.01$) and in a scenario of relatively high steady state macroeconomic volatility ($\overline{\sigma} = 0.03$). 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 Fig. 9, the effects of uncertainty shocks on the main macroeconomic aggregates is much larger in the high volatility scenario.

Fig. 10 displays the stochastic steady state of output $\overline{Y}$ as a function of the steady state value of uncertainty $\overline{\sigma}$[5]. The strong non-linearity in the average value of output is the cause of the amplification in Fig. 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.

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 banking sector that operates in a monopolistically competitive environment and sticky retail rates in a DSGE model with heterogenous agents. We depart from the strand of literature that analyzes

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

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 in 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 (Fig. 11).

Acknowledgments

We would like to thank Brent Bundick, Stefano Neri and Eric Swanson for coding assistance. In addition, we would also like to thank Maik Wolters, Sanjay Chugh, Daria Finocchiaro, Michele Lenza and participants of the Macro, Banking and Finance Workshop University of Milan Bicocca for very helpful comments and discussions.

Appendix A. Appendix

A.1. Forecast error variance decomposition

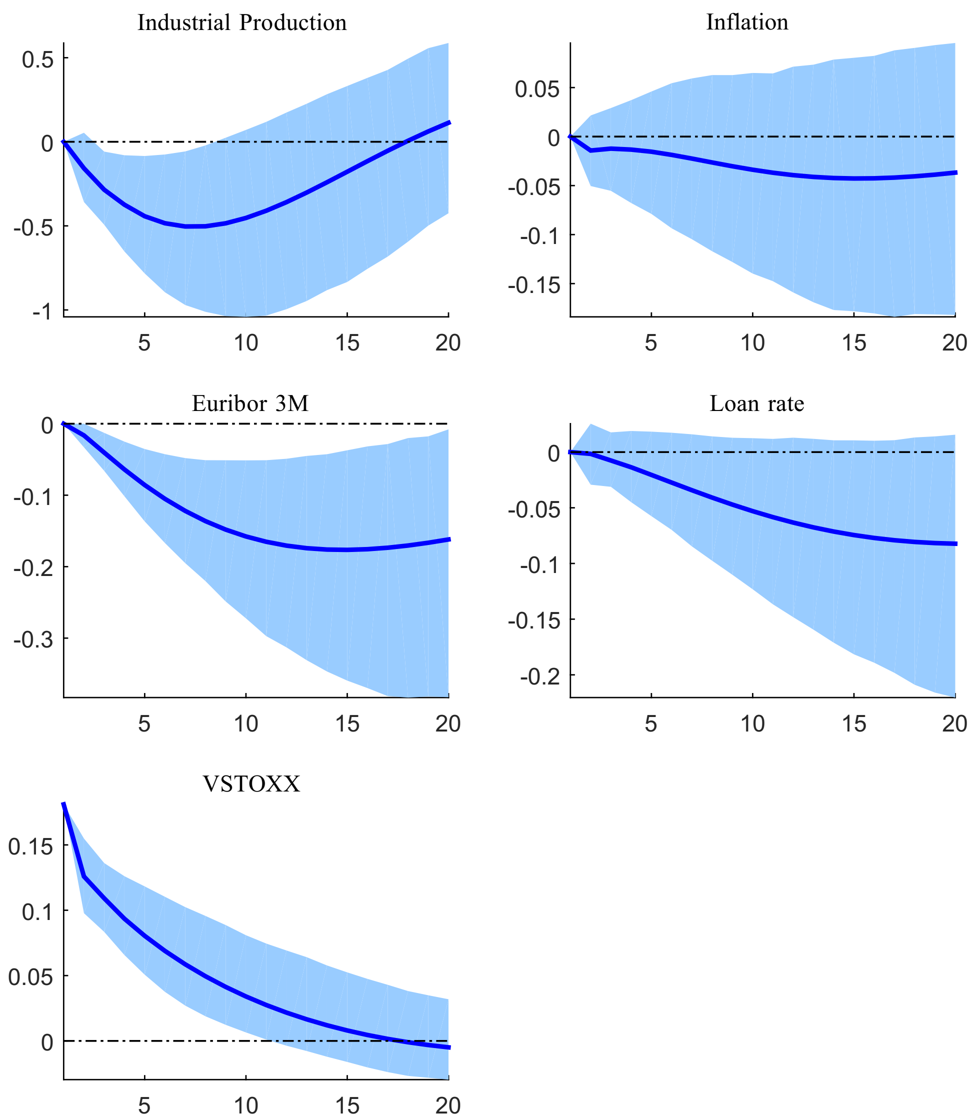

Fig. 12. Impulse responses to an VSTOXX shock with alternative ordering. *Notes*: The VAR includes a lag of 2 months, chosen according to the AIC. Different lag orders do not alter the basic results.

A.2. *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 Fig. 12, 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 (Fig. 13).

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.

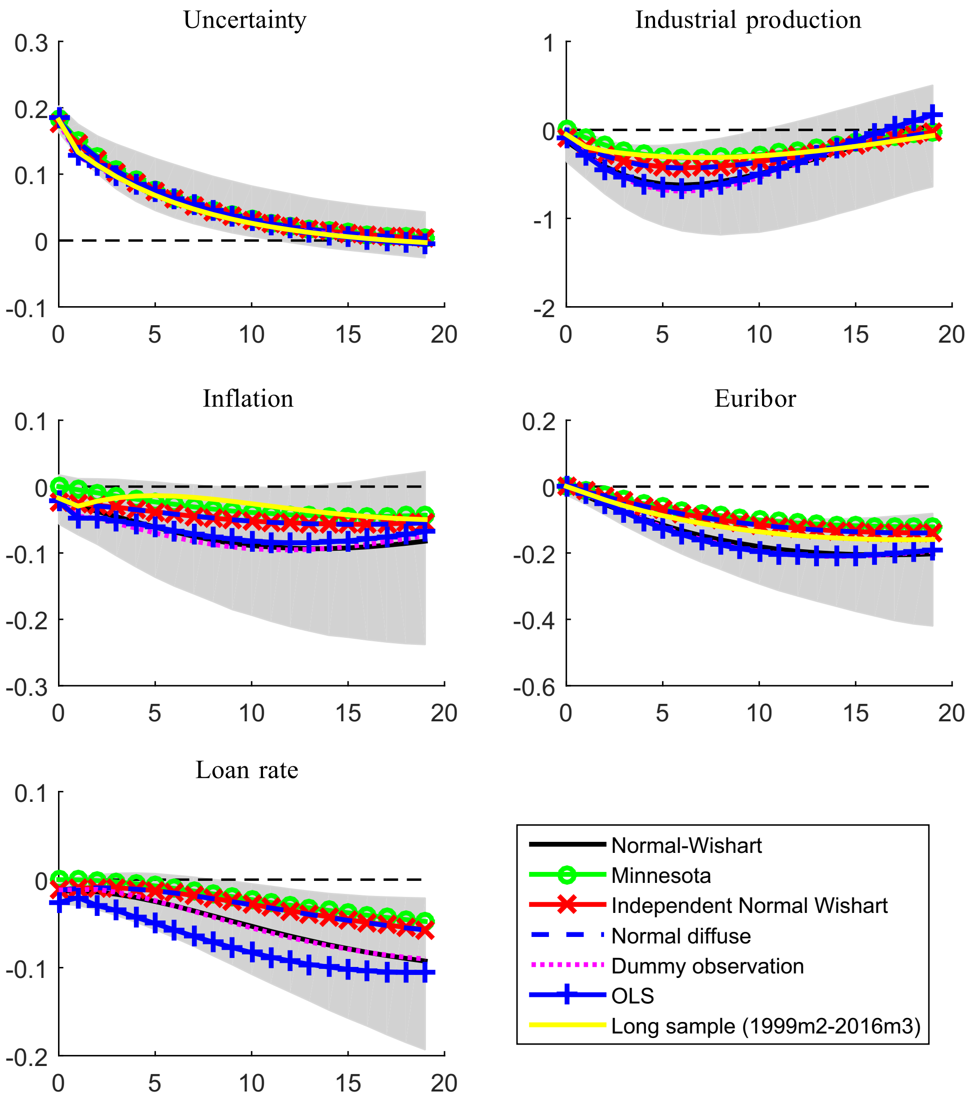

Fig. 13. Impulse responses to an VSTOXX shock using alternative estimation techniques. *Notes*: The VAR includes a lag of 2 months, chosen according to the AIC. Different lag orders do not alter the basic results.

A.3. Details on data used in estimation

Below we describe the data we use in the empirical exercise in Section 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

$$\lambda_{h,t} = \frac{1}{c_{h,t}} \tag{31}$$

Households' Euler equation

$$1 = \beta_h \mathbb{E}_t \left[\frac{\lambda_{h,t+1}}{\lambda_{h,t}} \frac{(1+r_t)}{(1+\pi_{t+1})} \right], \tag{32}$$

Labor supply equation

$$l_t^{\phi} = w_t \lambda_{h,t}, \tag{33}$$

Households' budget constraint

$$c_{h,t} + d_t = w_t l_t + (1+r_{t-1}) \frac{d_{t-1}}{(1+\pi_t)} + J_t^R, \tag{34}$$

A.4.2. Entrepreneurs

Shadow Price of Consumption

$$\lambda_{e,t} = \frac{1}{c_{e,t}} \tag{35}$$

$$q_t^k = s_t m E_t \left[q_{t+1}^k (1+\pi_{t+1})(1-\delta) \right] \tag{36}$$

$$\beta_e E_t \left\{ \frac{\lambda_{e,t+1}}{\lambda_{e,t}} \left[q_{t+1}^k (1-\delta) + r_{t+1}^k \right] \right\}, \tag{37}$$

Wage Equation

$$w_t = (1-\alpha) \frac{y_t^e}{l_t x_t}, \tag{38}$$

Euler Equation Entrepreneurs

$$1 - \left(1+r_t^b\right) s_t = \left(1+r_t^b\right) \beta_e E_t \left[\frac{\lambda_{e,t+1}}{\lambda_{e,t}} \frac{1}{1+\pi_{t+1}} \right], \tag{39}$$

Budget Constraint Entrepreneurs

$$\begin{aligned} c_{e,t} + \left(\frac{(1+r_{t-1}^b) b_{t-1}}{1+\pi_t} \right) + w_t l_t + q_t^k k_t \\ = \frac{y_t^e}{x_t} + b_t + q_t^k (1-\delta) k_{t-1}, \end{aligned} \tag{40}$$

Production Function

$$y_t^e = (k_{t-1})^{\alpha} l_t^{1-\alpha}, \tag{41}$$

Borrowing Constraint

$$(1+r_t^b)b_t = m\mathbb{E}_t\left[q_{t+1}^k(1+\pi_{t+1})k_t(1-\delta)\right], \tag{42}$$

Return on Capital

$$r_t^k = \alpha\frac{y_t^e}{k_{t-1}x_t}, \tag{43}$$

A.4.3. Capital producers

Capital Asset Equation

$$q_t^k\left[1-\phi_i\left(\frac{i_t}{i_{t-1}}-1\right)\frac{i_t}{i_{t-1}}-\frac{\phi_i}{2}\left(\frac{i_t}{i_{t-1}}-1\right)^2\right] \tag{44}$$

$$\phi_i E_t\left[\beta_e\frac{\lambda_{e,t+1}}{\lambda_{e,t}}q_{t+1}^k\left(\frac{i_{t+1}}{i_t}-1\right)\left(\frac{i_{t+1}}{i_t}\right)^2\right]=1 \tag{45}$$

Law of Motion of Capital

$$k_t=(1-\delta)k_{t-1}+\left[1-\frac{\kappa_i}{2}\left(\frac{i_t}{i_{t-1}}-1\right)^2\right]i_t, \tag{46}$$

A.4.4. Wholesale branch

$$K_t^b(1+\pi_t)=(1-\delta^b)K_{t-1}^b+\varphi J_{t-1}^b, \tag{47}$$

$$b_t=d_t+K_t^b, \tag{48}$$

A.4.5. Loan retail branch

Markup on loans

$$\begin{aligned}1-\frac{\epsilon_t^b}{(\epsilon_t^b-1)}+\frac{\epsilon_t^b}{(\epsilon_t^b-1)}\frac{r_t}{r_t^b}-\kappa_b\left(\frac{r_t^b}{r_{t-1}^b}-1\right)\frac{r_t^b}{r_{t-1}^b}\\ +\beta_h\mathbb{E}_t\left[\frac{\lambda_{h,t+1}}{\lambda_{h,t}}\kappa_b\left(\frac{r_{t+1}^b}{r_t^b}-1\right)\left(\frac{r_{t+1}^b}{r_t^b}\right)^2\frac{b_{t+1}^E}{b_t}\right]=0,\end{aligned} \tag{49}$$

Bank profits

$$J_t^b=r_t^bb_t-r_td_t-\frac{\kappa_b}{2}\left(\frac{r_t^b}{r_{t-1}^b}-1\right)^2r_t^bb_t, \tag{50}$$

A.4.6. Retailers

$$J^R=\left[1-\frac{1}{x_t}-\frac{\kappa_p}{2}\left(\frac{1+\pi_t}{1+\pi}-1\right)^2\right]Y_t, \tag{51}$$

Nonlinear Phillips curve

$$\left(1-\varepsilon^y\right)+\frac{\varepsilon^y}{x_t}-\kappa_p\left(\frac{1+\pi_t}{1+\pi}-1\right)\left(\frac{1+\pi_t}{1+\pi}\right) \tag{52}$$

$$\beta_hE_t\left[\frac{\lambda_{h,t+1}}{\lambda_{h,t}}\kappa_p\left(\frac{1+\pi_{t+1}}{1+\pi}-1\right)\left(\frac{1+\pi_{t+1}}{1+\pi}\right)\frac{Y_{t+1}}{Y_t}\right]=0 \tag{53}$$

A.4.7. Aggregation and equilibrium

$$C_t=c_{h,t}+c_{e,t}, \tag{54}$$

$$Y_t=C_t+\left[k_t-(1-\delta)k_{t-1}\right]+\delta^b\frac{k_{t-1}^b}{\pi_t}+ADJ_t, \tag{55}$$

A.4.8. Taylor rule and profits CB

$$\frac{1+r_t}{1+r}=\left(\frac{1+r_{t-1}}{1+r}\right)^{\phi_r}\left[\left(\frac{1+\pi_t}{1+\pi}\right)^{\phi_\pi}\left(\frac{y_t}{y_{t-1}}\right)^{\phi_y}\right]^{(1-\phi_r)}, \tag{56}$$

A.4.9. Exogenous processes

TFP level shock

$$z_t=(1-\rho_z)z+\rho_z z_{t-1}+\sigma_t^z e_t^z, \tag{57}$$

TFP uncertainty shock

$$\sigma_t^z=(1-\rho_{\sigma^z})\sigma^z+\rho_{\sigma^z}\sigma_{t-1}^z+\eta_z e_t^{\sigma_z} \quad \text{where } e_t^{\sigma_z}\sim\mathcal{N}(0,1) \tag{58}$$

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