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Understanding the Aggregate Effects of Credit Frictions and Uncertainty*

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Abstract

We examine the interaction of uncertainty and credit frictions in a New Keynesian framework. To do so, uncertainty is modeled as time-varying stochastic volatility – the product of monetary policy uncertainty, financial risk (micro-uncertainty), and macro-uncertainty. The model is solved using a pruned third-order approximation and estimated by the Simulated Method of Moments. We find that: 1) Micro-uncertainty aggravates the information asymmetry between lenders and borrowers, worsens credit conditions, and has first-order effects on real economic activity. 2) When credit conditions are poor, as indicated by elevated credit spreads, additional micro-uncertainty shocks produce even larger real effects. 3) Poor credit conditions notably affect the transmission mechanism of monetary policy amplifying the real effects of monetary shocks while mitigating the economic boost from TFP shocks. 4) While macro-uncertainty and policy uncertainty exert relatively little direct impact on aggregate economic activity, policy uncertainty accounts for around 40% of the business cycle volatility by affecting the size of monetary policy shocks in the presence of nominal rigidities.

JEL Classification: E32, E44, D8, C32

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1 Introduction

In the latter 2000s, the U.S. experienced its longest recession in the post-World War II period. Credit market disruptions, unseen in the U.S. since the Great Depression, occurred while uncertainty heightened. The unique character of the 2007−09 financial recession has sparked, therefore, a renewed interest in the role of credit market frictions and their interaction with increased uncertainty uncertainty in propagating and prolonging the recession.

One interpretation of credit frictions often posited in the literature stems from information asymmetry and costly loan contract enforcement. This gives rise to agency costs that are incorporated in credit spreads and borrowing costs. The strand of research that focuses on this credit channel highlights the credit frictions' role in: (a) amplifying cyclical movements of real economic activity (Bernanke and Gertler (1989), Bernanke et al. (1996), Carlstrom and Fuerst (1997), Kiyotaki and Moore (1997), Bernanke et al. (1999), Martínez-García (2014)); and (b) influencing the transmission mechanism of monetary policy (Carlstrom et al. (2009), Gilchrist et al. (2013), Christiano et al. (2014)).

The literature has also investigated the effects of time-varying uncertainty on real economic activity.[1] In partial equilibrium settings, increases in uncertainty can depress investment, real economic activity, and employment. Agents subject to fixed costs or partial irreversibility may delay purchases when facing an increase in uncertainty (*a real option value of waiting motive*; e.g., Bernanke (1983), Pindyck (1988)). Likewise, risk averse agents may cut back on consumption expenditure and generally work more today to build up their savings and self-insure against an uncertain future (*a precautionary savings motive*; e.g., Carroll and Kimball (2008)). In a general equilibrium setting, many of these mechanisms continue to imply a role for time-varying uncertainty, although some effects are attenuated.

In this paper, we build a Dynamic New Keynesian model where capital accumulation is financed through risky nominal debt subject to endogenous default under asymmetric information and costly-state verification (based on the work of Bernanke et al. (1999), Christiano et al. (2014), and Martínez-García (2014)). We introduce uncertainty in this framework to examine the relationship between credit frictions and different forms of uncertainty and the role of their interaction in generating fluctuations in output, credit spreads, policy rates, and other macroeconomic variables.[2] We consider three distinct types of uncertainty:

[1] At a general level, uncertainty is defined as the conditional volatility (second-moment) of a disturbance that is unforecastable by economic agents and arises independently of economic and policy shocks.

[2] Financial constraints can tighten in response to higher uncertainty, increasing the cost of borrowing and lowering expenditures (*a financial lever effect*). Dorofeenko et al. (2008), Gilchrist et al. (2013), Christiano et al. (2014), Cesa-Bianchi and Fernández-Corugedo (2018), among others, have noted that this *financial*

(i) *Macro-uncertainty* represents uncertainty about the evolution of the economy brought about by time-varying stochastic volatility of innovations in total factor productivity (TFP) (Alexopoulos and Cohen (2009), Bloom (2009), Bloom et al. (2018)).

(ii) *Monetary policy uncertainty* is the time-varying stochastic variance of innovations to the monetary policy shock (Fernández-Villaverde et al. (2010), Born and Pfeifer (2014)).[3]

(iii) Finally, *micro-uncertainty* captures time-varying stochastic dispersion in the distribution of the idiosyncratic technology shock to entrepreneurs and represents idiosyncratic uncertainty about the evolution of individual firms' productivity (Dorofeenko et al. (2008), Gilchrist et al. (2013), Christiano et al. (2014), Cesa-Bianchi and Fernández-Corugedo (2018)). This form of uncertainty plays a key role in the genesis of the financial frictions that are priced into the credit spreads between the borrowers and the lenders.

We examine how these three types of uncertainty propagate and interact with the key frictions of the model—credit frictions, but also nominal and real rigidities. In particular, we consider the degree to which aggregate and monetary policy uncertainty interact with credit frictions through their effect on entrepreneurs' aggregate net worth and leverage. Financial contracts are written in nominal rather than real terms, unlike in Bernanke et al. (1999). This raises the possibility that shocks that increase inflation uncertainty will heighten the riskiness of the real payoff of the nominal loan contract. In addition, we also recognize that macro-uncertainty and monetary policy uncertainty can affect the price of capital through their impact on the discounting of future payoffs from investment projects. Changes in the price of capital, in turn, affect the entrepreneurs' net worth and leverage, as well as the extent of credit frictions (as measured by the credit risk premium on borrowing).

Our model also addresses a question that, to our knowledge, has received only limited attention thus far: whether the effects of shocks are conditional on the degree of uncertainty and on the size of the credit frictions. That is, do shocks have different qualitative and quantitative effects depending on the current state of credit frictions or degree of uncertainty? We exploit the nonlinearity of the model by conducting generalized impulse response analysis conditioned on the initial state of the economy at the time of the shock. Specifically, we investigate the symmetry, scalability, and path-dependence of the responses to shocks conditional on the degree of uncertainty and size of credit frictions. That is to say, we ask whether uncertainty, aside from being a source of shocks, amplifies or modifies in some way the responses of key real and financial endogenous variables to possibly unrelated shocks.

lever effect can be significant in general equilibrium settings.

[3] We differ from some of the previous papers that have considered monetary policy uncertainty in that our model also features a prominent role for credit frictions and their interactions.

We model time-varying uncertainty using stochastic volatility models (as in Fernández-Villaverde (2010), Fernández-Villaverde et al. (2010), Fernández-Villaverde et al. (2011), Born and Pfeifer (2014), and Basu and Bundick (2017)).[4] We solve the model using a third-order approximation and, following in the footsteps of Born and Pfeifer (2014), we use a combination of calibration and estimation based on the Simulated Method of Moments (SMM) to discipline the values of the model's key structural parameters. Our limited information estimation approach permits us to use other moments on the same U.S. data for model cross-validation purposes and, most importantly, to obtain parameter estimates with which to pin down salient aspects, chiefly among them, credit frictions and micro-uncertainty. These limited information estimates are less sensitive to omitted variables or omitted features of the model than parameter estimates obtained under full-information estimation techniques.

From our analysis, we draw four principal insights. First, we find that shocks to micro-uncertainty have first-order effects of similar magnitude to level shocks to TFP or to monetary policy. The response of our model economy to the micro-uncertainty shock exacerbates credit frictions and results in a decline in investment and production along with a significant decline in labor use consistent with related results in Christiano et al. (2014). These shocks overwhelm the relatively small quantitative amplification that credit frictions induce on standard macro and policy shocks (Kocherlakota (2000), Córdoba and Ripoll (2004), and Martínez-García (2014)). Moreover, micro-uncertainty is a major source of exogenous business cycle fluctuations and the main driver of credit spreads in the model.

Second, we show that macro uncertainty shocks, on average, have effects that are orders of magnitude smaller than level TFP or micro-uncertainty shocks. Monetary policy uncertainty shocks also have effects substantially smaller than shocks to the level of monetary policy or TFP. However, monetary policy uncertainty has larger effects than TFP uncertainty on the dynamics of the economy. We find that the effect of monetary policy uncertainty depends on the extent of nominal rigidities in the model. While TFP uncertainty and to a lesser extent monetary policy uncertainty shocks have little direct effect on real economic variables, they do impact the size of TFP and monetary policy shocks. In that sense, uncertainty, particularly monetary policy uncertainty, becomes an important indirect source of business cycle fluctuations in the presence of nominal rigidities. Moreover, significant asymmetries and non-scalability of responses are present in the reaction to monetary policy shocks depending on the extent of policy uncertainty and nominal rigidities in the model.

Third, we find that TFP and monetary shocks, whether to the level (first-moment) or to

[4] We specify mean-preserving stochastic volatility shocks to isolate them from first-order moment shocks.

the uncertainty (second-moment), do not have large effects on credit risk spreads. Credit risk spread movements largely result from exogenous changes in micro-uncertainty. The feedback from economic conditions (as measured by the aggregate leverage of entrepreneurs) to credit conditions is relatively small, consistent with the results of Levin et al. (2004).

Finally, we find that the effects of shocks on economic activity depend on the initial credit conditions. Large initial credit spreads tend to slightly dampen TFP shocks' impact on output. If spreads are already wide, the effect of micro-uncertainty shocks on output is nearly 40% larger than when spreads are narrow. This suggests that when credit conditions are benign (narrow spreads), additional credit shocks disproportionately worsen the situation. Similarly, when spreads are already wide, the effect of contractionary monetary shocks is nearly 20% larger than when spreads are low.[5] In turn, conditioning on TFP uncertainty or monetary uncertainty has limited quantitative effect on the responses to shocks aside from the fact that their respective shock innovations are larger when uncertainty is high.

The remainder of the paper proceeds as follows: Section 2 describes our model with credit market imperfections and stochastic volatility. Section 3 discusses the perturbation approach we use to compute a third-order approximation of the model solution and the SMM strategy to estimate the key structural parameters of the model. Section 4 presents our nonlinear impulse response analysis and the business cycle implications of uncertainty. It also highlights the main quantitative findings from our model. Section 5 argues the significance of the interaction between credit frictions and uncertainty for our understanding of the propagation of shocks and the transmission mechanism of monetary policy, while Section 6 concludes. All listed tables and figures are provided in the Appendix.[6]

2 Credit Frictions and Uncertainty

In this paper, we explore the significance of uncertainty shocks and their interaction with financial frictions in general equilibrium. For that, we extend the benchmark Dynamic Stochastic New Keynesian business cycle model with nominal and real rigidities to incorporate: (a) a financial accelerator mechanism based on the costly-state verification framework of Townsend (1979) and Gale and Hellwig (1985) with risky debt in nominal terms,[7] and

[5] Our findings also suggest that nominal rigidities introduce a degree of asymmetry and non-scalability in the responses, more notable in the propagation of standard monetary policy shocks.

[6] Additional details on the model solution and the simulation and estimation methods together with a rich set of supplementary results can be found in Balke et al. (2017).

[7] We build on Bernanke and Gertler (1989), Bernanke et al. (1999), Cohen-Cole and Martínez-García (2010), Martínez-García (2014), and Christiano et al. (2014), among others, to incorporate risky debt and

(b) shocks to the cross-sectional dispersion of the idiosyncratic productivity shocks (micro-uncertainty) together with time-varying uncertainty in TFP (macro-uncertainty) and monetary policy (policy uncertainty). This section describes the building blocks of the model.

2.1 Households

The economy is populated by a continuum of mass one of identical and infinitely-lived households. Preferences are defined over household consumption, C_t, and household labor, H_t, based on an additively separable specification with internal habits in consumption:

$$U \equiv \mathbb{E}_0 \sum\nolimits_{t=0}^{\infty} \beta^t \left\{ \frac{\left(C_t - bC_{t-1}\right)^{1-\chi}}{1-\chi} - \kappa \frac{H_t^{1+\xi}}{1+\xi} \right\}, \tag{1}$$

where $\chi \geq 0$ is the inverse of the intertemporal elasticity of substitution and $0 \leq b \leq 1$ the internal habit persistence (which influence the *precautionary savings motive* of uncertainty), $\xi \geq 0$ the inverse of the Frisch elasticity of labor supply, $\kappa \geq 0$ the scaling of household labor disutility, and $0 < \beta < 1$ the intertemporal discount factor.

Households face the following nominal budget constraint:

$$P_t C_t + B_t \leq W_t H_t + I_{t-1} B_{t-1} + DIV_t. \tag{2}$$

At time t, households consume an amount C_t of the final good at a nominal price P_t and save an amount B_t through one-period nominal deposits offered by the financial intermediaries at time t and maturing at $t+1$. Households receive on their one-period nominal deposits maturing at time t a gross nominal risk-free interest rate I_{t-1} (known at $t-1$), and earn income from supplying household labor H_t at its competitive nominal wage rate W_t. Households own all financial and non-financial firms and receive nominal dividend payments DIV_t from the profits or losses retail firms generate (all others make zero profits in equilibrium).

Solving the households' optimization problem, we obtain that:

$$\frac{W_t}{P_t} = \frac{\kappa H_t^{\xi}}{\Lambda_t}, \tag{3}$$

$$1 = \beta \mathbb{E}_t \left[\left(\frac{\Lambda_{t+1}}{\Lambda_t} \right) \frac{P_t}{P_{t+1}} I_t \right], \tag{4}$$

which are the labor supply equation and consumption-savings Euler equation, respectively.

adopt the assumption that all financial contracts are agreed upon in nominal (rather than real) terms.

Here, $\Lambda_t \equiv (C_t - bC_{t-1})^{-\chi} - b\beta\mathbb{E}_t\left[(C_{t+1} - bC_t)^{-\chi}\right]$ is the Lagrange multiplier on the households' budget constraint expressed in units of the final good. The households' equilibrium conditions also include the appropriate initial and no-Ponzi transversality conditions.

2.2 Financial Business Sector

2.2.1 Entrepreneurs (Borrowers)

There is a continuum of entrepreneurs of unit mass with identical linear preferences defined over entrepreneurial consumption, C_t^e, as follows:

$$\mathbb{E}_0 \sum\nolimits_{t=0}^{\infty} (\gamma\beta)^t \, C_t^e, \tag{5}$$

where the parameter $0 < \gamma < 1$ scaling the intertemporal discount factor β in (5) captures the probability of each entrepreneur surviving until next period. We assume full replacement of the fraction of entrepreneurs $1-\gamma$ who *die* to keep the mass of entrepreneurs constant and equal to one in each period. Entrepreneurs that *die* do not purchase capital, work, or sign new loan contracts, but instead simply consume their accumulated resources and disappear. The new entrepreneurs that replace them come with no resources of their own, but earn income by inelastically supplying entrepreneurial labor.

At time $t-1$, entrepreneurs purchase the aggregate stock of physical capital available at time t, K_t, at a price of Q_{t-1} units of the final good per unit of physical capital from capital producers. The nominal expenditures on physical capital, $P_{t-1}Q_{t-1}K_t$, are financed with a combination of the entrepreneurs' accumulated nominal net worth (internal funds), N_{t-1}, and external funding from financial intermediaries (via one-period loans), $L_{t-1} = P_{t-1}Q_{t-1}K_t - N_{t-1}$. A linear technology transforms each unit of physical capital acquired at time $t-1$ into ω_{t-1} units of capital services at time t where ω_{t-1} is a purely idiosyncratic productivity shock (i.i.d. across entrepreneurs) known to entrepreneurs at $t-1$.[8]

At time t, each entrepreneur rents ω_{t-1} units of capital services to the wholesale producers and accrues a nominal capital income of $\omega_{t-1}\left[R_t^w + P_t\overline{Q}_t(1-\delta)\right]$ at time t per unit of physical capital acquired at time $t-1$. This nominal capital income accrues from the earned competitive nominal rental rate on capital services, R_t^w, and also from the resale value in units of the final good, $\overline{Q}_t$, on the entrepreneurs' depreciated physical capital purchased back

[8] While all entrepreneurs face the same physical capital purchasing decision problem *ex ante* and make identical choices to acquire and fund it at $t-1$, *ex post* differences emerge because each entrepreneur receives a different draw from ω_{t-1} which affects the nominal capital income it can accrue at time t.

by the capital producers. From here it follows that each entrepreneur's nominal return on physical capital is given by $\omega_{t-1} R_t^e$ where R_t^e is the aggregate nominal return given as:

$$\frac{R_t^e}{\Pi_t} \equiv \left[\frac{\frac{R_t^w}{P_t} + \overline{Q}_t (1-\delta)}{Q_{t-1}} \right], \tag{6}$$

with $\Pi_t \equiv \frac{P_t}{P_{t-1}}$ being the gross inflation rate on final goods and δ the depreciation rate.

The idiosyncratic technology shock ω_t is log-normally distributed, i.e., $\ln(\omega_t) \sim N(\mu_{\omega,t}, \sigma_{\omega,t}^2)$. We denote the probability distribution function (pdf) and the cumulative distribution function (cdf) for ω_t as $\phi(\omega_t \mid \sigma_{\omega,t})$ and $\Phi(\omega_t \mid \sigma_{\omega,t})$, respectively. The conditional variance, $\sigma_{\omega,t}^2$, reflects the time t dispersion of the cross-sectional distribution of ω_t. We set $\sigma_{\omega,t} \equiv \sigma_\omega e^{\widehat{\sigma}_{\omega,t}}$ and model the time-varying log-conditional variance $\widehat{\sigma}_{\omega,t} \equiv \ln \sigma_{\omega,t} - \ln \sigma_\omega$, which we refer to as an exogenous micro-uncertainty shock, in the following form:

$$\widehat{\sigma}_{\omega,t} = \upsilon_\omega \widehat{\sigma}_{\omega,t-1} + \eta_\omega u_{\omega,t}, \tag{7}$$

where $u_{\omega,t}$ is i.i.d. $N(0,1)$ and uncorrelated with all other shock innovations. The parameter $0 < \upsilon_\omega < 1$ determines the persistence of $\widehat{\sigma}_{\omega,t}$, $\sigma_\omega > 0$ the unconditional expected log-volatility, and $\eta_\omega \geq 0$ the standard deviation of the innovations. We set the time-varying conditional mean $\mu_{\omega,t}$ to be $\mu_{\omega,t} = -\frac{\sigma_{\omega,t}^2}{2}$ for the unconditional mean of ω_t to be $\mathbb{E}(\omega_t) = 1$ and mean-preserving.[9] Given this, by the law of large numbers, aggregating capital services across all entrepreneurs must equate their aggregate stock of physical capital each period.

Each individual entrepreneur's nominal capital income at time t equals $\omega_{t-1}\left[R_t^w + P_t \overline{Q}_t (1-\delta)\right] K_t = \omega_{t-1} R_t^e P_{t-1} Q_{t-1} K_t$. The idiosyncratic technology shock ω_{t-1} is realized after the $t-1$ financial contract is signed and is costlessly observed by the individual entrepreneur then. However, ω_{t-1} is not observed by the financial intermediaries and verification (through monitoring) of the terms of the loan is costly. A financial distortion arises here from the agency costs associated with this informational asymmetry between entrepreneurs (borrowers) and financial intermediaries (lenders). At time t, default on a nominal loan occurs whenever the capital income earned is insufficient to cover the repayment of the loan, i.e., whenever

$$\omega_{t-1} R_t^e P_{t-1} Q_{t-1} K_t \leq R_t^L L_{t-1}, \tag{8}$$

where, R_t^L, is the nominal return required by the financial intermediaries on the risky nominal

[9] Using mean-preserving volatility shocks allows us to cleanly disentangle the effect of first moment and second moment shocks. See Balke et al. (2017) for a detailed description of our approach.

one-period loan, L_{t-1}. The return R_t^L is defined implicitly in terms of a default threshold set on the idiosyncratic productivity shock, $\overline{\omega}_{t-1}$, which corresponds to the draw of ω_{t-1} that equates the nominal loan repayment owed to financial intermediaries with the nominal capital income accrued by the entrepreneur—i.e., $\overline{\omega}_{t-1}$ such that $R_t^L L_{t-1} = \overline{\omega}_{t-1} R_t^e P_{t-1} Q_{t-1} K_t$.

If $\omega_{t-1} < \overline{\omega}_{t-1}$, the entrepreneur does default at time t. Under limited liability, the financial intermediaries can only recover the nominal capital income of the defaulting entrepreneur's stock of capital in that period, i.e., $\omega_{t-1} \left[R_t^w + P_t \overline{Q}_t (1-\delta)\right] K_t = \omega_{t-1} R_t^e P_{t-1} Q_{t-1} K_t$. The financial intermediaries always monitor the defaulting entrepreneurs to prevent misrepresentations of the nominal capital income at a cost proportional to the amount recovered (i.e., a cost $\mu \omega_{t-1} R_t^e P_{t-1} Q_{t-1} K_t$ where $0 \leq \mu < 1$). The defaulting entrepreneur gets nothing, while the financial intermediaries recover $(1-\mu) \omega_{t-1} R_t^e P_{t-1} Q_{t-1} K_t$ after paying off the verification costs. If $\omega_{t-1} \geq \overline{\omega}_{t-1}$, the entrepreneur does not default at time t and simply pays $\overline{\omega}_{t-1} R_t^e P_{t-1} Q_{t-1} K_t$ to the financial intermediaries and retains $(\omega_{t-1} - \overline{\omega}_{t-1}) R_t^e P_{t-1} Q_{t-1} K_t$.

The entrepreneurs' budget constraint can be expressed as follows:

$$P_t C_t^e + P_t Q_t K_{t+1} \leq W_t^e H_t^e + \int_{\overline{\omega}_{t-1}}^{\infty} \left[\omega_{t-1} R_t^e P_{t-1} Q_{t-1} K_t - R_t^L L_{t-1}\right] \phi\left(\omega_{t-1} \mid \sigma_{\omega,t-1}\right) d\omega_{t-1} + L_t. \tag{9}$$

Apart from nominal capital income net of borrowing costs, entrepreneurs get revenue from inelastically supplying one unit of entrepreneurial labor ($H_t^e = 1$) to wholesale producers at the competitive nominal wage, W_t^e, and from new loans (L_t) secured with the financial intermediaries. These nominal resources are allocated to today's entrepreneurial consumption, C_t^e, and for the acquisition of tomorrow's stock of physical capital, K_{t+1}. Entrepreneurs maximize their lifetime utility in (5) subject to the sequence of nominal budget constraints in (9) and the entrepreneurs' balance sheet identity given by $P_t Q_t K_{t+1} = L_t + N_t$.

2.2.2 Financial Intermediaries (Lenders)

There is a continuum of mass one of identical, competitive financial intermediaries. At each time t, financial intermediaries offer one-period, fully-insured nominal deposits to households, B_t, which pay a gross nominal risk-free rate, I_t. These nominal deposits channel households' saving into one-period nominal loans for the entrepreneurs, L_t.[10] The loan contracting problem reduces to optimally choosing the physical capital, K_{t+1}, and the default threshold,

[10] The financial intermediaries' balance sheet identity is given by $B_t = L_t$ (i.e., deposits equal total loans).

$\overline{\omega}_t$, that maximize the entrepreneurs' nominal capital return net of borrowing costs, i.e.,

$$P_t Q_t K_{t+1} \mathbb{E}_t \left[R^e_{t+1} f\left(\overline{\omega}_t, \sigma_{\omega,t}\right) \right], \tag{10}$$

subject to the following participation constraint for the financial intermediaries:

$$P_t Q_t K_{t+1} \mathbb{E}_t \left[R^e_{t+1} g\left(\overline{\omega}_t, \sigma_{\omega,t}\right) \right] \geq I_t \left[P_t Q_t K_{t+1} - N_t \right], \tag{11}$$

where $f\left(\overline{\omega}_t, \sigma_{\omega,t}\right) > 0$ and $g\left(\overline{\omega}_t, \sigma_{\omega,t}\right) > 0$ denote the share of nominal capital income going to the entrepreneurs and the financial intermediaries, respectively. The participation constraint in (11) means that financial intermediaries can pool defaulting and non-defaulting loans and must be compensated to at least repay the depositors (households) in full. In equilibrium, financial intermediaries break even in each period and make zero profits.

Three equilibrium conditions characterize the solution of the loan contract problem in (10)−(11). First, an income sharing rule between entrepreneurs and financial intermediaries:

$$f\left(\overline{\omega}_t, \sigma_{\omega,t}\right) + g\left(\overline{\omega}_t, \sigma_{\omega,t}\right) = 1 - \mu G\left(\overline{\omega}_t, \sigma_{\omega,t}\right), \tag{12}$$

where $\mu G\left(\overline{\omega}_t, \sigma_{\omega,t}\right) \geq 0$ determines the fraction of nominal capital income lost due to monitoring costs (which would be zero only if monitoring costs are zero, i.e., if $\mu = 0$).[11]

Second, an optimal leverage condition:

$$\frac{P_t Q_t K_{t+1}}{N_t} = 1 + \lambda\left(\overline{\omega}_t, \sigma_{\omega,t}\right) \frac{g\left(\overline{\omega}_t, \sigma_{\omega,t}\right)}{f\left(\overline{\omega}_t, \sigma_{\omega,t}\right)}, \tag{13}$$

where $\lambda\left(\overline{\omega}_t, \sigma_{\omega,t}\right)$ is the Lagrange multiplier on the participation constraint in (11), i.e., $\lambda\left(\overline{\omega}_t, \sigma_{\omega,t}\right)$ is the shadow cost of enticing the financial intermediaries' participation. Equation (13) implies that the default threshold $\overline{\omega}_t$ depends on the micro-uncertainty shock, $\sigma_{\omega,t}$, and on the entrepreneurs' asset-to-net-worth ratio, $\frac{P_t Q_t K_{t+1}}{N_t}$.

Finally, expected gross returns to entrepreneurs must satisfy that:

$$\mathbb{E}_t \left[R^e_{t+1} \right] = s\left(\frac{P_t Q_t K_{t+1}}{N_t}, \sigma_{\omega,t} \right) I_t, \tag{14}$$

where $s\left(\frac{P_t Q_t K_{t+1}}{N_t}, \sigma_{\omega,t} \right) \equiv 1$ if $\mu = 0$ while, otherwise, the endogenous credit risk spread

[11] Balke et al. (2017) provides a detailed derivation of the optimal one-period nominal loan contract in (10) − (11) and a formal characterization of the functions $f\left(\overline{\omega}_t, \sigma_{\omega,t}\right)$, $g\left(\overline{\omega}_t, \sigma_{\omega,t}\right)$, and $G\left(\overline{\omega}_t, \sigma_{\omega,t}\right) \equiv \int_0^{\overline{\omega}_t} \omega_t \phi\left(\omega_t \mid \sigma_{\omega,t}\right) d\omega_t$ under the log-normal distribution assumption on ω_t.

$s\left(\frac{P_t Q_t K_{t+1}}{N_t}, \sigma_{\omega,t}\right) \equiv \frac{\lambda(\overline{\omega}_t, \sigma_{\omega,t})}{f(\overline{\omega}_t,\sigma_{\omega,t})+\lambda(\overline{\omega}_t,\sigma_{\omega,t})g(\overline{\omega}_t,\sigma_{\omega,t})} > 1$ is a function of micro-uncertainty, $\sigma_{\omega,t}$, and of the entrepreneurs' asset-to-net-worth ratio, $\frac{P_t Q_t K_{t+1}}{N_t}$. External funding via nominal loans at a nominal cost of $s\left(\frac{P_t Q_t K_{t+1}}{N_t}, \sigma_{\omega,t}\right) I_t$ is therefore more expensive than internal funds (net worth) whose opportunity cost is the nominal risk-free rate paid on deposits, I_t. Hence, equation (14) shows expected nominal capital returns, $\mathbb{E}_t\left[R^e_{t+1}\right]$, are above the nominal risk-free rate, I_t, when entrepreneurs are leveraged and loans are costly to monitor.[12]

Entrepreneurial Net Worth Dynamics. The entrepreneurs' budget constraint in (9), which in equilibrium holds with equality, and the nominal loan contract's optimality condition in (13) pin down entrepreneurial nominal net worth, N_t, as:

$$\begin{aligned} N_t = P_t Q_t K_{t+1} - L_t &= W^e_t H^e_t + f\left(\overline{\omega}_{t-1}, \sigma_{\omega,t-1}\right) R^e_t P_{t-1} Q_{t-1} K_t - P_t C^e_t \\ &= W^e_t H^e_t + \left(f\left(\overline{\omega}_{t-1}, \sigma_{\omega,t-1}\right) + \lambda\left(\overline{\omega}_{t-1}, \sigma_{\omega,t-1}\right) g\left(\overline{\omega}_{t-1}, \sigma_{\omega,t-1}\right)\right) R^e_t N_{t-1} - P_t C^e_t. \end{aligned} \tag{15}$$

As noted in regards to their preferences in (5), entrepreneurs are risk-neutral and *die* with probability $1-\gamma$ each period. Entrepreneurs postpone their consumption until death when they eat their accumulated net worth, so their aggregate consumption, C^e_t, is given by:

$$C^e_t = (1-\gamma)\left(f\left(\overline{\omega}_{t-1}, \sigma_{\omega,t-1}\right) + \lambda\left(\overline{\omega}_{t-1}, \sigma_{\omega,t-1}\right) g\left(\overline{\omega}_{t-1}, \sigma_{\omega,t-1}\right)\right) \frac{R^e_t}{\Pi_t}\left(\frac{N_{t-1}}{P_{t-1}}\right), \tag{16}$$

but neither work nor save more at that point. Dying entrepreneurs get replaced by the same fraction $1-\gamma$ of new entrepreneurs with no net worth of their own who, nonetheless, start earning income immediately by supplying entrepreneurial labor. Accordingly, it follows from equation (15) that the law of motion for N_t can be expressed as:

$$\frac{N_t}{P_t} = \frac{W^e_t}{P_t} H^e_t + \left(\gamma\left(f\left(\overline{\omega}_{t-1}, \sigma_{\omega,t-1}\right) + \lambda\left(\overline{\omega}_{t-1}, \sigma_{\omega,t-1}\right) g\left(\overline{\omega}_{t-1}, \sigma_{\omega,t-1}\right)\right) \frac{R^e_t}{\Pi_t}\right) \frac{N_{t-1}}{P_{t-1}}, \tag{17}$$

where H^e_t is inelastically supplied and set to one (as indicated before). That is, the entrepreneurs' aggregate net worth includes the per-period capital income that surviving entrepreneurs earn net of borrowing costs and the entrepreneurial labor income of new and surviving entrepreneurs minus the aggregate consumption of the dying entrepreneurs in (16).

[12] The asset-to-net-worth ratio equals $\frac{P_{t-1} Q_{t-1} K_t}{N_{t-1}} = \frac{N_{t-1}+L_{t-1}}{N_{t-1}} = 1 + \frac{L_{t-1}}{N_{t-1}}$ where $\frac{L_t}{N_t}$ is a conventional measure of debt-to-net-worth (or leverage). We report subsequently our findings using the inverse of this leverage measure, i.e., using the net-worth-to-asset ratio (or equity ratio) $\frac{N_{t-1}}{P_{t-1} Q_{t-1} K_t} = \frac{1}{1+\frac{L_{t-1}}{N_{t-1}}}$ instead.

2.3 Non-Financial Business Sector

2.3.1 Capital Producers

There is a continuum of mass one of identical capital producers. As in Hayashi (1982), the aggregate physical capital, K_{t+1}, evolves according to a law of motion with adjustment costs:

$$K_{t+1} = (1-\delta)K_t + s_k\left(\frac{X_t}{K_t}\right)K_t, \tag{18}$$

where X_t denotes units of the final good used for aggregate investment, $\frac{X_t}{K_t}$ is the investment-to-capital ratio, and $s_k\left(\frac{X_t}{K_t}\right)$ is the capital adjustment cost function. The production of physical capital is subject to technological constraints implicit in the adjustment cost specification proposed by Jermann (1998) and Boldrin et al. (2001), among others, i.e., in

$$s_k\left(\frac{X_t}{K_t}\right) = \left(\frac{\delta}{1-\frac{1}{\varphi_k}}\right)\left[\left(\frac{\frac{X_t}{K_t}}{\delta}\right)^{1-\frac{1}{\varphi_k}} - \frac{1}{\varphi_k}\right], \tag{19}$$

where $\varphi_k > 0$ is the concavity of $s_k\left(\frac{X_t}{K_t}\right)$ (affects the *real options value motive* of uncertainty).

At time t, entrepreneurs purchase their physical capital for next period, K_{t+1}, at a price in units of the final good (or Tobin's q), Q_t, and sell today's depreciated stock of physical capital, $(1-\delta)K_t$, at a resale price of $\overline{Q}_t$ units of the final good. Capital producers purchase the depreciated physical capital back as well as X_t units of the final good for the production of $\left[s_k\left(\frac{X_t}{K_t}\right)\frac{K_t}{X_t}\right]X_t$ units of new physical capital. Given this, the nominal per-period (static) profits of the capital producers are $P_t\left(Q_tK_{t+1} - X_t - (1-\delta)\overline{Q}_tK_t\right)$. Solving the capital producers' static profit maximization problem to choose investment, X_t, subject to the constraints in (18) – (19), it follows that Tobin's q, Q_t, is given by:

$$Q_t = \left[s'_k\left(\frac{X_t}{K_t}\right)\right]^{-1} = \left(\frac{\frac{X_t}{K_t}}{\delta}\right)^{\frac{1}{\varphi_k}}. \tag{20}$$

Imposing that, in equilibrium, capital producers make zero profits in every period, i.e.,

$$Q_t s_k\left(\frac{X_t}{K_t}\right) - \frac{X_t}{K_t} - (1-\delta)\left(\overline{Q}_t - Q_t\right) = 0, \tag{21}$$

pins down $\overline{Q}_t$ as a function of Tobin's q, Q_t, and the investment-to-capital ratio, $\frac{X_t}{K_t}$.

2.3.2 Wholesale Firms

There is a continuum of mass one of identical wholesale producers. Wholesale goods, Y_t^w, are produced with the following Cobb-Douglas technology:

$$Y_t^w \leq e^{a_t - a} (K_t)^{\alpha} (H_t^e)^{\vartheta} (H_t)^{1-\alpha-\vartheta}, \tag{22}$$

combining labor from households, H_t, and labor and rented capital services from entrepreneurs, H_t^e and K_t respectively. The capital share satisfies that $0 \leq \alpha < 1$, the entrepreneurial labor share is $0 < \vartheta < 1$, and the household labor share is $0 < (1 - \alpha - \vartheta) < 1$.

The stochastic process for aggregate productivity (TFP) in logs, a_t, in (22) is:

$$a_t = \mu_{a,t} + \rho_a \left(a_{t-1} - \mu_{a,t-1}\right) + \sigma_{a,t}\varepsilon_{a,t}. \tag{23}$$

where $0 < \rho_a < 1$ denotes its persistence. The macro-uncertainty shock is defined as a shock to the stochastic volatility in TFP, $\sigma_{a,t} \equiv \sigma_a e^{\widehat{\sigma}_{a,t}}$, where $\sigma_a > 0$, and

$$\widehat{\sigma}_{a,t} = \upsilon_a \widehat{\sigma}_{a,t-1} + \eta_a u_{a,t}, \tag{24}$$

with $0 < \upsilon_a < 1$ and $\eta_a \geq 0$. The shock innovations $\varepsilon_{a,t}$ and $u_{a,t}$ are i.i.d. $N(0,1)$ and uncorrelated with each other and with all other shock innovations. The time-varying conditional mean, $\mu_{a,t}$, satisfies the following recursion: $\mu_{a,t} = -\frac{\sigma_{a,t}^2}{2} + \rho_a^2 \mu_{a,t-1}$ ensuring the process is mean-preserving. The unconditional mean can then be expressed as $a \equiv -\frac{1}{2}\frac{\sigma_a^2}{1-\rho_a^2}$.

All wholesale producers operate in competitive markets and produce a homogeneous wholesale good sold at a nominal price P_t^w. Households and entrepreneurs' labor is paid their nominal wages, W_t and W_t^e respectively, and entrepreneurs' capital services its nominal rental rate, R_t^w, generating per-period profits of $P_t^w Y_t^w - R_t^w K_t - W_t H_t - W_t^e H_t^e$. Solving the (static) profit-maximization of the wholesale firms subject to (22) results in zero profits in equilibrium and the factors of production being remunerated at their marginal product,

$$\frac{W_t}{P_t} = (1 - \alpha - \vartheta) \frac{P_t^{wr} Y_t^w}{H_t}, \tag{25}$$

$$\frac{W_t^e}{P_t} = \vartheta \frac{P_t^{wr} Y_t^w}{H_t^e}, \tag{26}$$

$$\frac{R_t^w}{P_t} = \alpha \frac{P_t^{wr} Y_t^w}{K_t}, \tag{27}$$

where $P_t^{wr} \equiv \frac{P_t^w}{P_t}$ is the relative price of wholesale goods in units of the final good.

2.3.3 Final Goods and Retail Firms

There is a continuum of differentiated retail varieties of mass one indexed $j \in [0,1]$. Final output is Y_t is bundled with a constant elasticity of substitution (CES) aggregator, $Y_t \equiv \left[\int_0^1 Y_t(j)^{\frac{\epsilon-1}{\epsilon}} dj\right]^{\frac{\epsilon}{\epsilon-1}}$, where $\epsilon > 1$ is the elasticity of substitution across varieties and $Y_t(j)$ denotes the amount of each variety j. The corresponding final goods price, P_t, is given by $P_t = \left[\int_0^1 P_t(j)^{1-\epsilon} dj\right]^{\frac{1}{1-\epsilon}}$, which is a function of the prices of each variety j, $P_t(j)$. The optimal allocation of expenditure is:

$$Y_t(j) = \left(\frac{P_t(j)}{P_t}\right)^{-\epsilon} Y_t,\ \forall j \in [0,1], \tag{28}$$

which implies that retailers face a downward-sloping demand function.

Each variety j is produced by a monopolistically competitive retail firm that chooses price $P_t(j)$ to maximize its expected discounted stream of nominal profits, i.e.,

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \lambda_t \left[\left(P_t(j) - P_t^w\right) Y_t(j) - s_p\left(P_t(j), P_{t-1}(j)\right) P_t Y_t\right], \tag{29}$$

subject to the demand function in (28) and the household's intertemporal marginal rate of substitution $\lambda_t \equiv \beta^t \frac{\Lambda_t}{\Lambda_0}\frac{P_0}{P_t}$ where $\Lambda_t \equiv (C_t - bC_{t-1})^{-\chi} - b\beta\mathbb{E}_t\left[(C_{t+1} - bC_t)^{-\chi}\right]$. For each unit of its own variety sold, the retail firm needs to acquire a unit of the wholesale good at the nominal price P_t^w. Nominal retail prices can change every period subject to Rotemberg (1982) adjustment costs, $s_p\left(P_t(j), P_{t-1}(j)\right)$, given by:

$$s_p\left(P_t(j), P_{t-1}(j)\right) = \frac{\varphi_p}{2}\left(\frac{P_t(j)}{P_{t-1}(j)} - 1\right)^2,\ \forall j \in [0,1], \tag{30}$$

where $\varphi_p \geq 0$ scales the quadratic cost term. All retailers face the same optimization problem, choose the same optimal price $P_t(j)$, and have their profits or losses rebated lump-sum to the households. Thus, a symmetric equilibrium emerges where $P_t(j) = P_t$ and $Y_t(j) = Y_t$. It also follows in this symmetric equilibrium that $Y_t = Y_t^w$. The optimal price-setting equation from the retailers' optimization problem for the symmetric equilibrium is:

$$\left[1 - \varphi_p\left(\Pi_t - 1\right)\Pi_t\right] + \varphi_p\beta\mathbb{E}_t\left[\left(\frac{\Lambda_{t+1}}{\Lambda_t}\right)\left(\left(\Pi_{t+1} - 1\right)\Pi_{t+1}\frac{Y_{t+1}}{Y_t}\right)\right] = \left(1 - P_t^{wr}\right)\epsilon, \tag{31}$$

where $\Pi_t \equiv \frac{P_t}{P_{t-1}}$ is the gross inflation rate and P_t^{wr} is the retailers' real marginal cost.

Finally, the aggregate per-period resource constraint for final output is:

$$Y_t = C_t + X_t + \frac{\varphi_p}{2}\left(\Pi_t - 1\right)^2 Y_t + \mu G\left(\overline{\omega}_{t-1}, \sigma_{\omega,t-1}\right)\frac{R^e_t}{\Pi_t} Q_{t-1} K_t. \tag{32}$$

Equilibrium in the final goods market means the production of the final good Y_t in each period t is allocated either to households' consumption, C_t, and capital producers' investment, X_t, or gets lost due to price adjustment costs in the retail sector, $\frac{\varphi_p}{2}\left(\Pi_t - 1\right)^2 Y_t$, and to agency costs in the financial intermediation sector, $\mu G\left(\overline{\omega}_{t-1}, \sigma_{\omega,t-1}\right)\frac{R^e_t}{\Pi_t} Q_{t-1} K_t$.

2.4 Monetary Policy

The monetary authority sets the nominal interest rate, I_t, following a modified Taylor (1993)-type monetary policy rule with inertia which we express in index form as,

$$\frac{I_t}{I} = \left(\frac{I_{t-1}}{I}\right)^{\rho_i}\left(\left(\frac{\Pi_t}{\Pi^*_t}\right)^{\psi_\pi}\left(\frac{Y_t}{Y_{t-1}}\right)^{\psi_x}\right)^{1-\rho_i} e^{m_t - m}, \tag{33}$$

where I is the steady-state nominal interest rate, $\Pi_t \equiv \frac{P_t}{P_{t-1}}$ is the gross inflation rate on final goods prices, $\Pi^*_t = 1$ is the target gross inflation rate (zero net inflation), and $\frac{Y_t}{Y_{t-1}}$ is the gross final output growth.[13] The parameters $\psi_\pi > 1$ and $\psi_x > 0$ determine the sensitivity of the policy instrument's response to inflation deviations from target and to output growth fluctuations, respectively. The parameter $0 \leq \rho_i < 1$ is the monetary policy inertia.

The stochastic process for the monetary policy shock, m_t, can be written as:

$$m_t = \mu_{m,t} + \rho_m\left(m_{t-1} - \mu_{m,t-1}\right) + \sigma_{m,t}\varepsilon_{m,t}, \tag{34}$$

where the persistence is given by $0 < \rho_m < 1$. The stochastic volatility of monetary policy shocks (monetary policy uncertainty), $\sigma_{m,t} \equiv \sigma_m e^{\widehat{\sigma}_{m,t}}$, where $\sigma_m > 0$, follows this process:

$$\widehat{\sigma}_{m,t} = \upsilon_m \widehat{\sigma}_{m,t-1} + \eta_m u_{m,t}, \tag{35}$$

with $0 < \upsilon_m < 1$ and $\eta_m \geq 0$. The shock innovations $\varepsilon_{m,t}$ and $u_{m,t}$ are i.i.d. $N(0,1)$ and uncorrelated with each other and with all other innovations. The time-varying conditional mean, $\mu_{m,t}$, satisfies the following recursion: $\mu_{m,t} = -\frac{\sigma^2_{m,t}}{2} + \rho^2_m \mu_{m,t-1}$ ensuring the process is mean-preserving. The unconditional mean of the process m is $m \equiv -\frac{1}{2}\frac{\sigma^2_m}{1-\rho^2_m}$.

[13] Expressed in logs, equation (33) incorporates inertia and responds to inflation and output growth (akin to the "growth gap" in the policy reaction function used by Fernández-Villaverde et al. (2010)).

3 Estimating the Model

As in Fernández-Villaverde et al. (2010), Fernández-Villaverde et al. (2011), and Born and Pfeifer (2014), we use a third-order perturbation with the control and state variables expressed in logs to locally approximate the rational expectations model solution.[14] Following Andreasen et al. (2013), we prune the third-order approximation to avoid dynamic instability problems.

3.1 Solution Strategy

The equilibrium conditions that characterize the model solution can be compactly stated as:

$$\mathbb{E}_t f\left(\mathbf{y}_{t+1}, \boldsymbol{y}_t, \mathbf{x}_{t+1}, \mathbf{x}_t, \mathbf{v}_{t+1}, \mathbf{v}_t\right) = 0, \tag{36}$$

where $\mathbb{E}_t$ denotes the mathematical expectations operator conditional on information available at time t, $\mathbf{y}_t$ is a vector of n_y control variables expressed in logs, $\mathbf{x}_t$ is a vector of n_x state variables in logs, and the vector v_t contains all n_v structural shock innovations. The nonlinear equilibrium relationships of the model are represented with the functional operator $f(\cdot)$. The solution to (36) can be cast in the following measurement and state equations:

$$\mathbf{y}_t = g\left(\mathbf{x}_t, \tau\right), \tag{37}$$

$$\mathbf{x}_{t+1} = h\left(\mathbf{x}_t, \tau\right) + \tau\boldsymbol{\Sigma}\mathbf{v}_{t+1}, \tag{38}$$

where $\boldsymbol{\Sigma}$ is an $n_x \times n_v$ variance-covariance matrix of the shock innovations and τ is the perturbation parameter scaling it. We use a third-order approximation to functions $g(\cdot)$ and $h(\cdot)$ around the deterministic steady state where $\mathbf{x}_t = \mathbf{x}$ and $\tau = 0$.

The first, second, and third partial derivatives of $g(\cdot)$ and $h(\cdot)$ with respect to the components of $\mathbf{x}_t$ and the perturbation parameter τ are used to compute the third-order approximation. We examine a pruned third-order approximation that eliminates terms of higher order than three from the impulse responses and other dynamic analysis as these higher order terms can lead to dynamic instability, as proposed by Andreasen et al. (2013). If the first-order approximation is stationary, then so are the pruned second- and third-order

[14] The log-linearizing approach discussed in Martínez-García (2018) and used in related environments by Bernanke et al. (1999) and Martínez-García (2014), among others, does not suffice here. This is because, even with a second-order approximation of the solution, stochastic volatility shocks—except micro-uncertainty—would not enter into the decision rules in an interesting way.

approximations. Here, the pruned third-order approximation has the following form:

$$\begin{aligned}\mathbf{y}_t^{rd} &= g_x\left(\mathbf{x}_t^f + \mathbf{x}_t^s + \mathbf{x}_t^{rd}\right) + \tfrac{1}{2}G_{xx}\left(\left(\mathbf{x}_t^f \otimes \mathbf{x}_t^f\right) + 2\left(\mathbf{x}_t^f \otimes \mathbf{x}_t^s\right)\right)\ldots \\ &\quad + \tfrac{1}{6}G_{xxx}\left(\mathbf{x}_t^f \otimes \mathbf{x}_t^f \otimes \mathbf{x}_t^f\right) + \tfrac{1}{2}g_{\tau\tau}\tau^2 + \tfrac{3}{6}g_{\tau\tau x}\tau^2\mathbf{x}_t^f + \tfrac{1}{6}g_{\tau\tau\tau}\tau^3,\end{aligned} \tag{39}$$

$$\mathbf{x}_{t+1}^f = h_x\mathbf{x}_t^f + \tau\Sigma\mathbf{v}_{t+1}, \tag{40}$$

$$\mathbf{x}_{t+1}^s = h_x\mathbf{x}_t^s + \frac{1}{2}H_{xx}\left(\mathbf{x}_t^f \otimes \mathbf{x}_t^f\right) + \frac{1}{2}h_{\tau\tau}\tau^2, \tag{41}$$

$$\mathbf{x}_{t+1}^{rd} = h_x\mathbf{x}_t^{rd} + H_{xx}\left(\mathbf{x}_t^f \otimes \mathbf{x}_t^s\right) + \frac{1}{6}H_{xxx}\left(\mathbf{x}_t^f \otimes \mathbf{x}_t^f \otimes \mathbf{x}_t^f\right) + \frac{3}{6}h_{\tau\tau x}\tau^2\mathbf{x}_t^f + \frac{1}{6}h_{\tau\tau\tau}\tau^3, \tag{42}$$

where $\mathbf{y}_t^{rd}$ are the pruned third-order approximations of the control variables, $\mathbf{x}_t^f$ are state variables based on the first-order approximation, $\mathbf{x}_t^s$ are the state variables second-order approximation terms, and $\mathbf{x}_t^{rd}$ are the state variables third-order terms. The first-order derivatives are: g_x ($n_y \times n_x$ matrix) and h_x ($n_x \times n_x$ matrix). The second-order derivatives are: G_{xx} ($n_y \times n_x^2$ matrix), H_{xx} ($n_x \times n_x^2$ matrix), $g_{\tau\tau}$ ($n_y \times 1$ vector), and $h_{\tau\tau}$ ($n_x \times 1$ vector). The third-order derivatives are: G_{xxx} ($n_y \times n_x^3$ matrix), H_{xxx} ($n_x \times n_x^3$ matrix), $g_{\tau\tau x}$ ($n_y \times n_x$ matrix), $h_{\tau\tau x}$ ($n_y \times n_x$ matrix), $g_{\tau\tau\tau}$ ($n_y \times 1$ vector), and $h_{\tau\tau\tau}$ ($n_x \times 1$ vector). We use Dynare to find the first-, second-, and third-order perturbation solutions and extract the matrices relevant for the pruned third-order approximation.

3.2 Estimation Strategy

Table 1 summarizes the parameterization and estimation of the model parameters. The parameterized preference and technological parameters (β, χ, ξ, α, ϑ, and δ) follow closely the values used for the financial accelerator model of Bernanke et al. (1999). We set the elasticity of substitution across varieties ϵ as in Basu (1996). The values for the parameters of the exogenous TFP shock process, the monetary policy shock process, and their corresponding stochastic volatilities (ρ_a, σ_a, υ_a, η_a, ρ_m, σ_m, υ_m, and η_m) as well as the policy parameters (ρ_i, ψ_π, and ψ_x) are based on the estimates from Born and Pfeifer (2014). Born and Pfeifer (2014) obtain their estimates directly from observed U.S. TFP and by fitting an inertial Taylor (1993) rule on U.S. short-term interest rates.

We estimate the values of the remaining nine structural parameters of the model (κ, b, φ_k, φ_p, γ, μ, σ_ω, υ_ω, and η_ω) with the Simulated Method of Moments (SMM) approach—matching simulated moments from the model to values that are consistent with key empirical regularities found in the U.S. data and a couple of model parameter normalizations. Table 2 lists these moments, their data sources, and their empirical values. Prior to computing any of the empirical moments reported in the paper, we extract the cyclical component of each series with a one-sided Hodrick-Prescott filter using a lambda of 1600 and a power of 2, except for the net-worth-to-asset ratio that is demeaned instead. We apply the same filtering to the corresponding endogenous data simulated by the model to ensure the comparability between simulated and empirical moments.

Our SMM estimation strategy is a limited information technique that relies solely on a subset of key moments—not the full information in the data—in order to discipline the estimation of the estimated structural parameters. The advantage of using a limited information estimation method here is two-fold: first, we can investigate other moments of the model on the same U.S. data for cross-validation purposes and, second, we can obtain parameter estimates that are less sensitive to omitted variables or unmodeled features of the economy than estimates obtained with full-information techniques.

The estimated parameter values for κ, b, φ_k, φ_p, γ, μ, σ_ω, υ_ω, and η_ω are chosen to minimize the weighted squared distance between nine key moments implied by the model and their counterparts in the data. The moments we choose to match are:[15]

1. the mean of the credit risk spread $\left(400 \times \mathbb{E}_t\left(\ln\left(\frac{R^e_{t+1}}{I_t}\right)\right)\right)$,
2. the mean of the net-worth-to-asset ratio in levels $\left(100 \times \frac{N_t}{P_t Q_t K_{t+1}}\right)$,
3. the mean default probability $\left(100 \times \Phi^{default}_t \text{ where } \Phi^{default}_t \equiv \Phi\left(\overline{\omega}_t \mid \sigma_{\omega,t}\right)\right)$,
4. the mean household hours $(400 \times \ln(H_t))$,
5. the variance of the credit risk spread $\left(400 \times \mathbb{E}_t\left(\ln\left(\frac{R^e_{t+1}}{I_t}\right)\right)\right)$,
6. the ratio of investment variance $(400 \times \ln(X_t))$ to output variance $(400 \times \ln(Y_t))$,
7. the first-order autocorrelation of the credit risk spread $\left(400 \times \mathbb{E}_t\left(\ln\left(\frac{R^e_{t+1}}{I_t}\right)\right)\right)$,
8. the first-order autocorrelation of nondurable consumption $(400 \times \ln(C_t))$,
9. the first-order autocorrelation of inflation $(400 \times \ln(\Pi_t))$.

Specifically, we minimize the following quadratic form:

$$\min_{\kappa, b, \varphi_k, \varphi_p, \gamma, \mu, \sigma_\omega, \upsilon_\omega, \eta_\omega} \mathbf{M}'\mathbf{W}\mathbf{M}$$

[15] For the default probability $(100 \times \Phi^{default}_t)$ and the mean hours $(400 \times \ln(H_t))$ there is no actual sampling variation. In practice, we add a tiny bit of sampling noise to their corresponding moment conditions for computational convenience so we can use them along with the others in the same computer subroutine.

where $\mathbf{W}$ is a weighting matrix and $\mathbf{M}$ is given by

$$\mathbf{M} \equiv \begin{pmatrix} \sum_{t=1}^{T} \frac{\widehat{spread}_t}{T} - 0 \\ \sum_{t=1}^{T} \frac{\widehat{equity\_ratio}_t}{T} - 0 \\ \mathbb{E}_{\text{model}}\left(100 \times \Phi^{default}\right) - 0.75 \\ \mathbb{E}_{\text{model}}\left(400 \times \ln\left(H\right)\right) - 0 \\ \sum_{t=1}^{T} \left[\frac{\widehat{spread}_t{}^2 - \mathbb{VAR}_{\text{model}}\left(400 \times \mathbb{E}_{\text{model}}\left(\ln\left(\frac{R^e}{I}\right)\right)\right)}{T} \right] \\ \sum_{t=1}^{T} \left[\frac{\widehat{400 \times \ln(X_t)}^2 - \frac{\mathbb{VAR}_{\text{model}}(400 \times \ln(X))}{\mathbb{VAR}_{\text{model}}(400 \times \ln(Y))} \times \widehat{400 \times \ln(Y_t)}^2}{T} \right] \\ \sum_{t=1}^{T} \left[\frac{\widehat{spread}_t \times \widehat{spread}_{t-1} - \rho_{\text{model}}\left(400 \times \mathbb{E}_{\text{model}}\left(\ln\left(\frac{R^e}{I}\right)\right)\right) \times \widehat{spread}_t{}^2}{T} \right] \\ \sum_{t=1}^{T} \left[\frac{\widehat{400 \times \ln(C_t)} \times \widehat{400 \times \ln(C_{t-1})} - \rho_{\text{model}}(400 \times \ln(C)) \times \widehat{400 \times \ln(C_t)}^2}{T} \right] \\ \sum_{t=1}^{T} \left[\frac{\widehat{400 \times \ln(\Pi_t)} \times \widehat{400 \times \ln(\Pi_{t-1})} - \rho_{\text{model}}(400 \times \ln(\Pi)) \times \widehat{400 \times \ln(\Pi_t)}^2}{T} \right] \end{pmatrix}.$$

Here, we define $\widehat{spread}_t = 400 \times \left[\mathbb{E}_t\left(\ln\left(\frac{R^e_{t+1}}{I_t}\right)\right) - \mathbb{E}_{\text{model}}\left(\ln\left(\frac{R^e}{I}\right)\right)\right]$, $\widehat{equity\_ratio}_t = 100 \times \left[\frac{N_t}{P_t Q_t K_{t+1}} - \mathbb{E}_{\text{model}}\left(\frac{N}{PQK}\right)\right]$, $\widehat{400 \times \ln\left(X_t\right)} = 400 \times \left(\ln\left(X_t\right) - \mu_{\ln X}\right)$, $\widehat{400 \times \ln\left(Y_t\right)} = 400 \times \left(\ln\left(Y_t\right) - \mu_{\ln Y}\right)$, $\widehat{400 \times \ln\left(C_t\right)} = 400 \times \left(\ln\left(C_t\right) - \mu_{\ln C}\right)$, and $\widehat{400 \times \ln\left(\Pi_t\right)} = 400 \times \left(\ln\left(\Pi_t\right) - \mu_{\ln \Pi}\right)$ with $\mu_{\ln Z}$ being the sample mean of the corresponding variable Z_t. $\mathbb{E}_{\text{model}}(\cdot)$, $\mathbb{VAR}_{\text{model}}(\cdot)$, and $\rho_{\text{model}}(\cdot)$ are the simulated unconditional mean, the simulated unconditional variance, and the simulated first-order autocorrelation, all of them implied by the pruned third-order approximation of the model. For the mean default probability $(100 \times \Phi^{default}_t)$ and mean hours $(400 \times \ln\left(H_t\right))$ no sample data was used; the *target* moments were normalized to 0.75 (as in Carlstrom and Fuerst (1997) and Bernanke et al. (1999)) and zero, respectively.

We selected the means implied by the model for the credit spread $\left(400 \times \mathbb{E}_t\left(\ln\left(\frac{R^e_{t+1}}{I_t}\right)\right)\right)$, for the net-worth-to-asset ratio in levels $(100 \times \frac{N_t}{P_t Q_t K_{t+1}})$, and for the default probability $(100 \times \Phi^{default}_t)$ as well as for the variance and first-order autocorrelation of the risk spread $(\widehat{spread}_t)$ primarily to determine the values of γ, μ, σ_ω, υ_ω, and η_ω.[16] We use the variance of investment $(400 \times \ln\left(X_t\right))$ relative to the variance of output $(400 \times \ln\left(Y_t\right))$ as well as the autocorrelations for inflation $(400 \times \ln\left(\Pi_t\right))$ and nondurable consumption $(400 \times \ln\left(C_t\right))$ to help determine the values of b, φ_k, and φ_p. We aim to select a price adjustment cost parameter φ_p consistent

[16] In the model, the dispersion of the idiosyncratic shock (micro-uncertainty) is time-varying unlike in the Bernanke et al. (1999) framework, making it all the more relevant that we pin down the financial accelerator and micro-uncertainty parameters jointly to be consistent with the features observed in the data.

with the observed inflation persistence and, similarly, a habit persistence parameter b that gets at the observed consumption persistence and a capital adjustment cost parameter φ_k that aligns the volatility of investment relative to the volatility of output with that found in the data. Finally, the scaling disutility of household labor κ is largely determined by setting the average hours $(400 \times \ln(H_t))$ in logs to zero.

Simulated variances and autocorrelations are based on $20,000$ simulated values of the model. The weighting matrix $\mathbf{W}$ is set to be the identity matrix. For each parameter value evaluated, the same random number seed was used to generate the simulated samples. The estimated values for the vector (κ, b, φ_k, φ_p, γ, μ, σ_ω, υ_ω, and η_ω) are reported in Table 1. It turns out that our estimates of γ, μ, and σ_ω are quite similar to those in Bernanke et al. (1999) while the parameters for υ_ω and η_ω are not very far from those used by Christiano et al. (2014) to describe their risk shocks. Similarly, the parameters for b, φ_k, and φ_p are all well within the ranges typically seen in the literature.[17]

4 Quantitative Findings

4.1 Business Cycle Moments

Table 3, Table 4, and Table 5 display business cycle statistics implied by the estimated benchmark model as well as by various modeling alternatives where we shut down different modeling features each time. In particular, we examine the estimated benchmark ($M1$) against alternative specifications where all stochastic volatilities are shut down ($\upsilon_\omega = \eta_\omega = \upsilon_a = \eta_a = \upsilon_m = \eta_m = 0$, $M2$), where each stochastic volatility is shut down singly ($\upsilon_\omega = \eta_\omega = 0$, $M3$; $\upsilon_a = \eta_a = 0$, $M4$; $\upsilon_m = \eta_m = 0$, $M5$), where financial frictions are shut down ($\mu = 0$, $M6$), where nominal price rigidities are shut down ($\varphi_p = 0$, $M7$), and where risk aversion (intertemporal elasticity of substitution) is set to be high (low) ($\chi = 7$, $M8$).

Table 3 reports the standard deviation of output and the standard deviation of the key macro variables of interest relative to that of output in the data as well as for the different model specifications under consideration ($M1 - M8$). Table 4 shows the first-order autocorrelation (persistence) of the key macro variables and Table 5 displays the correlations of the key macro variables with output (cyclicality) and with the endogenous credit spread, in the data and across all model specifications ($M1 - M8$). Most of these business cycle

[17] References for b include Christiano et al. (2005), Smets and Wouters (2007), and Christiano et al. (2014); for φ_k references include Bernanke et al. (1999), and Justiniano et al. (2011); and for φ_p references include Carlstrom et al. (2009) and Ascari and Sbordone (2014).

moments were not used to estimate the structural parameters under the SMM estimation strategy discussed in Section 3. Comparing the empirical against the simulated (not-used-for-estimation) moments provides some form of cross-validation for the benchmark model ($M1$). Moreover, by isolating the individual contributions of the most salient features of the model ($M1$ vs. $M2 - M8$), we establish the relative importance of each for the observed macro volatility, persistence, and cyclicality over the business cycle.

Business cycle volatility. Comparing the benchmark model ($M1$) with the model without stochastic volatilities ($M2$) in Table 3, we observe that the stochastic volatilities are an important contributor to the overall volatility of output implied by the model—output volatility is 40% lower in the model without stochastic volatility. Of the various sources of time-varying uncertainty that are incorporated in our estimated benchmark model, monetary policy uncertainty contributes most to output volatility (compare $M2$ vs. $M5$). In terms of relative variability, we observe that shutting down some or all the stochastic volatilities (as in $M2 - M5$) does not have a dramatic impact on the standard deviations of other macro variables relative to the standard deviation of output. We interpret this as suggesting that monetary policy uncertainty has a major role on overall macroeconomic volatility, but only a modest effect on the relative volatilities across the key macro variables of interest.

We observe that the relative volatility of the net-worth-to-asset ratio or equity ratio ($100 \times \frac{N_t}{P_t Q_t K_{t+1}}$) and that of the endogenous credit spread ($400 \times \mathbb{E}_t \left(\ln \left(\frac{R^e_{t+1}}{I_t} \right) \right)$) is fairly consistent with the data and largely unchanged with or without aggregate (TFP) uncertainty (compare $M1$ vs. $M4$). The relative volatilities of these two financial variables decline to near zero if micro-uncertainty is excluded ($M1$ vs. $M3$) while, at the same time, the relative volatility of investment falls by as much as 6%. In turn, the relative volatilities of the equity ratio and credit spread are higher than the estimated benchmark in $M1$ (and the data) by as much as 50% when we exclude monetary policy uncertainty ($M1$ vs. $M5$). We infer from all of this that: (a) macro-uncertainty is of second-order importance to explain volatility over the business cycles, and (b) monetary policy uncertainty is an important contributor to macroeconomic volatility while micro-uncertainty is important for financial volatility (with regard to the equity ratio, credit spread, and investment volatility).

While shutting down financial frictions ($M6$) does not have a large impact on the variability of output implied by the benchmark model ($M1$) or on most of the relative volatilities for the other key macro variables, Table 3 shows that it lowers the relative volatility of investment with respect to that of output by as much as 15%. Moreover, counterfactually, the relative volatility of the equity ratio falls near zero and that of the credit spread becomes exactly zero. The effects of micro-uncertainty depend on the degree of financial frictions in the model and, notably, that tends to generate higher investment volatility—output volatility is more than 7% lower and the relative volatility of investment is almost 11% without micro-uncertainty ($M3$) than without financial frictions ($M6$). We interpret this as evidence that the financial accelerator amplification mechanism, with or without micro-uncertainty, adds modestly to the overall macro volatility and tends to show itself in connection with micro-uncertainty most noticeably on higher investment and financial volatility.[18]

The specification where nominal price rigidities are removed ($M7$) further highlights the significance of monetary policy uncertainty. With costless price adjustments ($M7$) as well as without monetary policy uncertainty ($M5$), the volatility of output falls by about 40%. The relative volatility of the credit spread and the equity ratio nearly doubles relative to those same moments under the benchmark model ($M1$), but changes in the volatility of investment are otherwise very minor. While relative (non-financial) variables appear largely similar with or without monetary policy uncertainty ($M1$ vs. $M5$), removing nominal rigidities induces very substantial volatility shifts ($M5$ vs. $M7$) which are largely counterfactual with the data. Under the Taylor rule in (33), the relative volatility of the nominal interest rate shoots up more than twofold and the relative volatility of inflation more than fourfold. Monetary policy uncertainty leads to heightened nominal volatility (inflation risk) under flexible prices and this carries over along the consumption-labor margin—increasing the volatility of consumption relative to output by about 20% while concurrently decreasing the relative volatility of hours worked by about 65%.[19]

A model with a high risk aversion (a low intertemporal elasticity of substitution) parameter of $\chi = 7$ ($M8$) raises the risk prudence in steady state and generally strengthens the *precautionary savings motive*. This lowers the volatility of consumption relative to output well below what we observe in the data while increasing the relative volatility of investment somewhat. It also notably decreases the overall macro volatility relative to that of the estimated benchmark ($M1$) by about 15%. This suggests that, given the preferences in (5), households beef up their precautionary savings to self-insure against future risks contributing to mitigate the effects of uncertainty on macro volatility as risk aversion increases.

[18] Including capital adjustment costs in the benchmark model ($\varphi_k > 0$ as seen in Table 1), not surprisingly, introduces a *real options motive* for uncertainty but also tends to mitigate the impact of the financial accelerator mechanism on the relative volatility of investment.

[19] The large impact on hours worked reflects the strength of the wealth effects of the preferences in (5) which heighten the volatility response of hours to monetary policy shocks in the presence of nominal rigidities.

Business cycle persistence and cyclicality. From Table 4, we find that introducing stochastic volatility or financial frictions has little effect on the autocorrelations of the model. The only exception is that the persistence on inflation and on the nominal interest rate are substantially lower while real persistence on output and investment is somewhat higher when there are no nominal rigidities ($M7$) than in the benchmark ($M1$). This indicates that price adjustment costs affect nominal persistence and have some spillovers into real persistence. In turn, the persistence of the macro variables is largely unaffected by the other major features of the model. Interestingly, this is the case even though financial frictions with short-maturity loan contracts open up an important conduit for the propagation of shocks (notably micro-uncertainty shocks) through the funding of capital channel.

On the one hand, the benchmark model ($M1$) closely matches the persistence of consumption and that of the credit spread, moments that are targeted under our SMM estimation strategy. The inflation volatility implied by the model is a bit higher than its targeted empirical counterpart, though. On the other hand, the persistence on output, hours worked, and investment appears somewhat lower than in the data. We argue that this is related to the well-known consumption puzzles in the literature (Caballero (1990)): That is, while in the data output tends to be as persistent as consumption, precautionary savings generally lead to excess-consumption-smoothness, which tends to be reflected in excess-consumption-persistence. The findings in Table 4 suggest that lowering price adjustment costs can partly mitigate this issue by increasing the output persistence and lowering the inflation persistence, while adding credit frictions or stochastic volatilities does not do much.

From Table 5, one observes that the model gets many of the cross-correlations of output with other real macro variables largely right. The most notable exception being the correlation between output and the real wage. In the data real wages are largely acyclical, while they appear robust and procyclical in the model. In turn, the estimated benchmark model ($M1$) appears less precise when it comes to pin down the cyclicality of the nominal and financial variables (inflation, nominal interest rate, equity ratio, and credit spread). We also note that monetary policy uncertainty ($M5$) as well as nominal rigidities ($M7$) play a substantive role in the simulated cyclicality of inflation and the nominal interest rate.[20]

Comparing columns $M1$ through $M5$ in Table 5 suggests that including stochastic volatility does not change the correlations of output with other real macro variables all that much, but it does change the cross-correlation of output and the credit spread in an economically meaningful way. We observe that the model without stochastic volatility ($M2$) (which comes

[20] We argue that the sensitivity of the policy rule to inflation in particular is another important factor.

closest to the original financial accelerator model of Bernanke et al. (1999)) results in procyclical movements in the credit spread. That is, endogenous movements in credit spreads implied by this financial accelerator mechanism are not as strongly countercyclical as they appear in the data.[21] Including time-varying micro-uncertainty is, therefore, key to generate a more plausible countercyclical credit spread (compare $M1$ vs. $M3$). Even so, the model correlations between output and the credit spread are smaller (in absolute value) than those found in the data. This suggests that a general equilibrium model, even one with credit frictions and time-varying micro-uncertainty like ours, still misses part of the interaction between the credit risk spread and real economic activity observed in the data.

4.2 Generalized Impulse Response Analysis

We conduct an impulse response analysis similar to what is typically done with linear models to investigate the propagation of exogenous shocks. Given the nonlinear nature of the model solution that we pursue here, we use the generalized impulse response approach of Koop et al. (1996) and calculate how the conditional expectation of the endogenous variables ($\mathbf{y}_t^{rd}$) changes as a result of a shock innovation ($\mathbf{v}_t$). Specifically, we examine:

$$GIRF\left(k, \mathbf{v}_t, \mathbf{x}_{t-1}\right) = \mathbb{E}\left[y_{t+k}^{rd} | \mathbf{v}_t, \mathbf{x}_{t-1}\right] - \mathbb{E}\left[y_{t+k}^{rd} | \mathbf{x}_{t-1}\right], \tag{43}$$

where the state vector of the pruned third-order approximation is $\mathbf{x}_t = (\mathbf{x}_t^f, \mathbf{x}_t^s, \mathbf{x}_t^{rd})'$. We denote an endogenous variable of interest k-periods-ahead generically as y_{t+k}^{rd} (shorthand k).

Standard impulse responses for a linear (or first-order approximation) model satisfy three well-known properties: symmetry, scalability, and path-independence (past and future). Given the pruned third-order approximation of the non-linear model here, the impulse responses in (43) do not, in principle, have to be symmetric with the direction and scale up with the size of the shock innovation, $\mathbf{v}_t$. Furthermore, the impulse responses may be path-dependent too—conditional on the initial conditions of the state variables.

In general, there are many possible initial conditions to evaluate and typically researchers would simply take the initial condition to be a particular realization, say the deterministic steady state or the unconditional mean of the state variables. Unfortunately, while responses conditional on a particular realization are relatively easy to compute, one is not sure how to evaluate how likely it is that the economy would be at that particular initial state. Our

[21] Gomes et al. (2003) favor the Bernanke et al. (1999) framework because, unlike in Carlstrom and Fuerst (1997)'s related model, asset price movements can interact with the financial imperfections. Faia and Monacelli (2007) provide additional results on the model's countercyclicality of the credit spread.

approach is to use the information not only from a particular realization, but from the unconditional distribution implied by the model to help choose initial conditions for our impulse response analysis that are economically relevant for our analysis. Hence, we concentrate our impulse response analysis on the differences in the propagation of shocks (to both the mean and variance) arising from different initial conditions on: (a) the types of uncertainty under consideration, and, (b) endogenous variables related to the state (tight or loose) of financial conditions such as the credit spread, the equity ratio, and the nominal interest rate.

4.2.1 Unconditional Impulse Responses

As part of our impulse response analysis, we first get a sense of the *average* effect of shocks over all possible initial conditions. In other words, we look at the expected (or *average*) generalized impulse response given the unconditional distribution implied by the model, i.e.,

$$GIRF_{average}\left(k, \mathbf{v}_t\right) = \int GIRF\left(k, \mathbf{v}_t, \mathbf{x}_{t-1} = \mathbf{x}\right) p\left(\mathbf{x}\right) d\mathbf{x}, \tag{44}$$

where $p(\mathbf{x})$ is the unconditional density of the state vector $\mathbf{x}$ implied by the model, k is again shorthand for the horizon of interest, while $\mathbf{v}_t$ refers to the shock innovations. To obtain an estimate of the unconditional distribution of the endogenous variables implied by the model, we simulate the pruned third-order approximation starting at the unconditional mean for 300 time periods. We repeat this $20,000$ times to obtain an estimate of the unconditional distribution. We then draw a sample of initial conditions (500 draws), calculate the change in conditional expectations for each initial condition, and average the responses.

Figure 1 displays the *average* impulse responses for the various shocks in the model.[22] In general, shocks that affect the conditional means of TFP and monetary policy directly have substantially larger effects than shocks that affect their volatilities. In the estimated benchmark model, on *average*, shocks to macro-uncertainty and shocks to monetary policy uncertainty are of second-order importance. Furthermore, the effects of macro- and policy uncertainty shocks on the credit spread as well as on the price of capital (Tobin's q) and the equity ratio are negligible. This indicates that the contribution of the financial accelerator mechanism to amplify uncertainty shocks (except for micro-uncertainty) is quite modest. Macro-uncertainty shocks display some precautionary saving effects (causing consumption

[22] Balke et al. (2017) (Figure 11) compares the *average* impulse responses over the unconditional distribution of initial conditions with the impulse response with an initial condition equal to the unconditional mean. The two sets of responses are qualitatively similar, but the *average* response to interest rate shocks is larger in magnitude than the corresponding response starting at the unconditional mean.

to fall, and hours, investment, and output to rise), but these effects are fairly small relative to a standard TFP shock. Monetary policy uncertainty shocks also lead to declines in consumption and increases in hours, investment, and output. While still modest by comparison with the micro-uncertainty shocks, the responses to policy uncertainty are of an order of magnitude larger than those of macro-uncertainty.

Overall, these results are broadly consistent with the existing literature on TFP and monetary policy uncertainty. In both Born and Pfeifer (2014) and Fernández-Villaverde et al. (2010), which also consider TFP and policy uncertainty shocks, most of the individual stochastic volatility shocks had small direct effects. In fact, when examining the importance of stochastic volatility shocks, the existing literature often focuses on the response to a simultaneous two standard deviation shock to all sources of uncertainty showcasing episodes of heightened overall uncertainty (albeit episodes that occur very infrequently). In our subsequent analysis, we also explore tail events over the distribution of the uncertainty shocks and, not surprisingly, reach similar conclusions—economically macro- and policy uncertainty shocks are most relevant at those infrequent times when their size is fairly large.

In contrast, Figure 1 shows that micro-uncertainty shocks have sizeable first-order effects on their own. A mean-preserving spread shock to the distribution of the entrepreneur's idiosyncratic productivity has strong negative effects on output, investment, hours, and the price of capital (or Tobin's q) while strongly positive effects on the credit spread. The effects of a micro-uncertainty shock, on *average*, appear to be of the same order of magnitude as those of a TFP shock and about half the impact of a monetary policy shock on output. The credit friction that underpins our benchmark model is key for that. Credit markets are incomplete and idiosyncratic technology shocks cannot be fully insured due to existing information asymmetries between entrepreneurs (borrowers) and lenders. As a result, greater micro-uncertainty makes lending to entrepreneurs riskier and leads to a higher default probability and a higher required credit risk spread. The higher cost of borrowing discourages investment, pushes down the price of capital, and encourages entrepreneurs to free up more internal funds (increasing the equity ratio). In response to the falling investment, households increase consumption initially and cut down labor input. As a result, output shrinks.

The effect of key features of the model on unconditional impulse responses. Figure 2 plots the *average* impulse responses of output, the credit spread, and the nominal interest rate for alternative models (the benchmark $M1$ vs. $M6 - M8$). We observe from Figure 2 that if we increase the risk aversion parameter (decrease the intertemporal elasticity of substitution) χ from one ($M1$) to seven ($M7$) the responses of the variables of interest to macro-uncertainty and monetary policy uncertainty shocks increase (although their effects are still rather modest). For the first moment shocks and for micro-uncertainty, higher values of χ strengthen the *precautionary savings motive* and typically dampen the effects.[23]

If prices are perfectly flexible ($M7$), the effect of the macro-uncertainty and of the monetary policy uncertainty shocks, already small in the benchmark model, declines notably—virtually disappearing. Removing nominal rigidities also implies monetary policy shocks have no real effects, lessens the impact of micro-uncertainty shocks, and increases the effect of TFP shocks on economic activity (albeit the output response to a TFP shock is no longer hump-shaped). The output response of the micro-uncertainty shock is almost two times larger on impact in the baseline ($M1$) than in the flexible prices case ($M7$). This shows that credit frictions alone can explain only part of the *punch* we get from micro-uncertainty shocks in the model. The lesson from this is that, although micro-uncertainty is tied to financial frictions arising in the credit market, inefficiencies in the goods markets (nominal rigidities) greatly amplify the impact of exogenous micro-uncertainty shocks.

Comparing the benchmark ($M1$) with a costless monitoring model ($M6$), we see that financial frictions do not qualitatively change the *average* response of the variables of interest to TFP or to monetary policy shocks but do lower the magnitude of the *average* responses. The removal of the monitoring costs does neither appear to alter the response to macro-uncertainty nor to policy uncertainty shocks (which were already small in the benchmark model) but it implies micro-uncertainty shocks have no effect. In other words, micro-uncertainty shocks matter only in the presence of credit frictions.

In summary, the evidence illustrated in Figure 2 conditional on the *average* over all possible initial conditions suggests that the interaction between financial frictions and nominal rigidities tempers the response of economic activity to standard TFP shocks. In turn, the combination of both frictions makes the economy more responsive to micro-uncertainty and to monetary policy shocks. Macro-uncertainty and monetary policy uncertainty shocks are of second-order importance, yet nominal rigidities appear to be an important amplifier of uncertainty shocks overall as well as of monetary policy shocks in the benchmark model.

Non-scalability and asymmetry of the unconditional impulse responses. The pruned third-order approximation of the nonlinear benchmark model allows for non-scalable and asymmetric responses to positive and negative shocks. To explore those properties, Figure 3 displays the response of output to $\pm$ one and two standard deviation shocks. For the

[23] Setting $\varphi_k = 0$ removes the capital adjustment cost and weakens the *real options value motive* for uncertainty relative to the baseline model with a estimated $\varphi_k > 0$.

benchmark, on *average*, the responses to negative and positive uncertainty shocks—micro-uncertainty, policy uncertainty, and macro-uncertainty—are virtually mirror images of one another and are close to being symmetric and to scaling up. In turn, the responses to negative and positive TFP and monetary policy shocks display non-scalability and asymmetry.

For TFP shocks, two standard deviation shocks lead to a more pronounced hump-shaped response of output than one standard deviation shocks. The magnitude of the response falls short of doubling on impact when doubling the size of the shock, and also appears to rise by less on impact in absolute value when doubling the size of a negative shock than when doubling it for a positive one. For monetary policy shocks, the evidence of non-scalability and asymmetry is larger than that for TFP shocks. A negative (expansionary) two-standard deviation policy shock is, on *average*, almost 20% larger on impact in absolute value than a positive (contractionary) two-standard deviation shock.

This suggests that, on *average*, the response of output to shocks does not always scale up or behave symmetrically, unlike what we would observe in a linear model. Most notably, these nonlinear features appear to be more quantitatively relevant for the propagation of monetary policy shocks. We interpret this as evidence that the nonlinearities in the model partly emerge from the nominal rigidities.[24]

4.2.2 Conditional Impulse Responses

Thus far, we have examined the *average* effect of shocks on key variables in our model. However, in general, shocks in nonlinear models are not path-independent. That is, the effect of the shocks could depend on the initial state of the economy. To get at this notion of conditional responses, we consider generalized impulse responses defined as:

$$GIRF_{y=y_0}\left(k, \mathbf{v}_t\right) = \int GIRF\left(k, \mathbf{v}_t, \mathbf{x}_{t-1} = \mathbf{x}\right) p\left(\mathbf{x} | y = y_0\right) d\mathbf{x}, \tag{45}$$

where k is again shorthand for the horizon of interest, $\mathbf{v}_t$ refers to the shock innovations, and $p\left(\mathbf{x}|y = y_0\right)$ is the conditional density of the vector of states $\mathbf{x}$ implied by the model when the endogenous variable y is initially at y_0. That is, given that a variable y is initially at y_0, we average over the possible states consistent with this initial condition.

In our benchmark, the expected costs of monitoring defaulting entrepreneurs are priced into the credit spreads that lenders charge on their loans. Hence, credit spreads reflect the extent to which credit is distorted and entrepreneur risk is present and, thus, instances where

[24] On this point, see e.g. Balke et al. (2017) (Figure 7) which considers output responses in the model abstracting from financial frictions ($M6$) compared with responses under flexible prices ($M7$).

the credit spread is high are thought to coincide with episodes when financial conditions are poor (large credit frictions). As we are interested in the interaction of financial conditions and shocks, we consider a generalized impulse response analysis in which the initial conditions correspond to states where the credit spread level is either high or low.[25]

We also explore the initial conditions on two other endogenous variables related to financial conditions. First, the endogenous equity ratio which together with exogenous micro-uncertainty are the two components that determine the credit spread in (14). When the equity ratio is high, the strength of the entrepreneurs' balance sheet acts as a financial buffer since then entrepreneurs are less leveraged on external borrowed funds. Second, the policy rate together with the credit spread determines the cost of borrowing for entrepreneurs. When the nominal interest rate is elevated, the rate on deposits is high and that, in turn, means current borrowing costs would be high too *ceteris paribus*.

The amplifying effect of 'poor' financial conditions. Figure 4.A displays the response of output to the five structural shocks in the model conditional on the credit spread being either high or low. Specifically, we define *high spread* initial states as states where the credit spread is roughly at the 95^{th} percentile of its unconditional distribution and *low spread* initial states as states where the spread is at its 5^{th} percentile.[26] We observe that the effect of both macro-uncertainty and policy uncertainty shocks does not depend on current credit conditions. The responses are virtually identical and tiny regardless of whether the spread was initially high or low. However, when initial spreads are high, the expansionary effect of a positive TFP shock is mitigated while the contractionary effects of a positive micro-uncertainty shock and a positive monetary policy shock are amplified.

Indeed, in Figure 4.A, the output response to a TFP shock retains its hump-shaped form regardless of whether credit spreads are high or low, but, at its peak four quarters into the future, the impact is almost 10% higher when financial conditions are benign (*low spread*) than when they are poor (*high spreads*). That is, if credit frictions are already large, the expansionary effect of a TFP shock is somewhat muted. The contractionary effect of an increase in micro-uncertainty when the spread is initially high is about 35% larger than when

[25]Balke (2000) examines, in the context of a threshold VAR, whether the effects of shocks depend on current credit conditions. Balke et al. (2017) (Figures 2 to 5) show—looking at the tails of the distribution of the credit spread and of micro-uncertainty—that the non-scalability and asymmetry of the responses to micro-uncertainty as well as to TFP and monetary policy shocks indeed depends on initial credit conditions.

[26]For impulse responses conditional on variable y being at its ι-th percentile, $y(\iota^{th})$, we average the responses for initial conditions corresponding to realizations from the unconditional distribution where variable $y \in [y(\iota - .3)^{th}, y(\iota + .3)^{th}]$. Given our 20,000 draws of the unconditional distribution, we get 121 initial conditions. Balke et al. (2017) (Figure 5) looks at the 1^{th} and 99^{th} percentile as well as the 5^{th} and 95^{th}.

the spread is initially low. Similarly, if the spread is initially high, the effect of a positive (contractionary) monetary policy shock is larger. On impact, the contractionary effect on output is about 20% more severe when financial conditions are poor (*high spreads*).

Figure 4.B displays the response of the credit spread to various shocks conditional on whether the spread was initially high or low. The increase in the spread in response to TFP, monetary policy, and micro-uncertainty shocks is larger when the spread is already high. This is particularly striking for micro-uncertainty shocks—the effect on the credit spread of a positive micro-uncertainty shock is about 80% larger on impact when the credit spread is initially high as opposed to when the spread is initially small. In turn, the effect of a positive monetary policy shock on the credit spread is smaller than that of a TFP shock and at least one order of magnitude lower than that from a micro-uncertainty shock. The response of the spread to macro-uncertainty and to monetary policy uncertainty is negligible.

This suggests that, if current credit conditions are poor (*high spread*), then the effect of supply-side shocks (TFP) tends to be dampened while the effect of contractionary financial shocks (a positive monetary policy shock or a positive micro-uncertainty shock) is substantially magnified. Micro-uncertainty works primarily through its impact on the credit spread. In turn, the amplification of monetary policy shocks has only small effects on the credit spread and works because it raises the financial intermediaries' cost of attracting household deposits. Simply put, it works because the same increase in the nominal interest rate increases the overall entrepreneurs' external borrowing cost by more when the credit spread is initially high than if financial conditions were good (*low spread*).

Figure 5 displays the response of output, the credit spread, and the nominal interest rate to the three structural shocks in the model that have first-order effects (i.e., TFP, micro-uncertainty, and monetary policy shocks). The generalized impulse responses are computed conditional on the credit spread (same as Figure 4.A and Figure 4.B), the nominal interest, and the equity ratio being high. Specifically, we take *high* initial states to be where each of the variables is roughly at the 95^{th} percentile of its unconditional distribution.

We find that low leverage (high equity ratio) acts as a financial buffer that mitigates the impact of the first moment shocks on the endogenous credit spread and, ultimately, on real economic activity. This is more noticeable in the output response to monetary policy shocks—a stronger balance sheet position means the economy is in a better position to limit the output drag from a positive (contractionary) monetary policy shock. Even more striking, we find that contractionary monetary policy shocks have much larger effects when interest rates are already high. In turn, the effect of TFP and micro-uncertainty shocks on the credit spread is smaller when interest rates are already high.

The financial and macro effects of uncertainty. The unconditional impulse responses in Figure 1 suggest that high or low credit spreads are largely the result of cumulative shocks to micro-uncertainty. To further explore the contribution of each shock to the spread, Figure 6 displays scatter plots implied by the unconditional distribution of the model of the credit spread against each of the five shocks separately (TFP, monetary policy, macro-uncertainty, policy uncertainty, and micro-uncertainty). As is clear from Figure 6, there is a strong relationship between exogenous micro-uncertainty and the endogenous credit spread. The correlation coefficient between $\widehat{\sigma}_{\omega,t}$ and the spread is 0.84. Interestingly, this relationship also appears to be nonlinear to some extent. In turn, none of the other shocks appears to have a strong relationship with the spread. This tends to confirm that credit spread fluctuations largely arise from the micro-uncertainty shock and to a much lesser extent from the endogenous response to other shocks.[27]

Similarly, we also show with the scatter plots in Figure 7 that there is a significant negative relationship between the credit spread and the nominal interest rate.[28] When nominal interest rates are high, the credit spreads tend to be more compressed as borrowers (entrepreneurs) deleverage their balance sheet and demand less capital. Moreover, periods when credit spreads are high are typically periods of economic distress when the policy rule implies that policymakers respond to output growth declines by lowering interest rates.

While the response of shocks is conditional on current credit conditions, our model also illustrates the extent to which output responses to shocks are conditional on uncertainty directly. Figure 8.A displays the responses of output, the credit spread, and the nominal interest rate to TFP, micro-uncertainty, and monetary policy shocks conditional on their own uncertainty being high (95^{th} percentile). For comparison, we also include the responses when credit spreads are high. For micro-uncertainty, the responses of output to shocks conditional on the level of micro-uncertainty ($\widehat{\sigma}_{\omega,t}$) are very similar to the output responses conditional on the credit spread being high. Given the relatively strong relationship between realizations of $\widehat{\sigma}_{\omega,t}$ and the credit spread discussed previously (see Figure 6), this is not too surprising.

We also find in Figure 8.A that the output response to TFP shocks and monetary policy shocks is larger when their own uncertainty is high, primarily because a high level of their own uncertainty increases the size of the shocks. In particular, the contraction resulting from

[27] The correlations between the spread and $\{a_t, m_t, \widehat{\sigma}_{a,t}, \widehat{\sigma}_{m,t}\}$ are $\{0.07, 0.00, 0.00, 0.00\}$, respectively. Macro shocks affect the numerator and denominator of the equity ratio roughly in a similar proportion. As a result, this elicits only a modest endogenous response of the credit spread. Consequently, exogenous changes in micro-uncertainty end up being the dominant force on the spread.

[28] Balke et al. (2017) (Figures 12 to 13) provide the joint distribution of the credit spread against other economically-relevant variables of the model as well.

a positive monetary policy shock when monetary policy uncertainty is initially high almost triples that which we observe when financial conditions are poor (*high spreads*). This large sensitivity to monetary policy shocks when their own uncertainty is time-varying is what ultimately accounts for the large fall in business cycle volatility when we remove monetary policy uncertainty from the benchmark model (see Table 3).

Figure 8.B displays the responses of output, credit spread, and interest rate to TFP, micro-uncertainty, and monetary policy shocks conditional on other uncertainty types being high (95^{th} percentile). The output response to TFP shocks does not depend much on the state of policy uncertainty or micro-uncertainty, although spreads rise significantly less when initial policy uncertainty is high than when financial conditions are poor (*high spreads*). Output and spread responses to a micro-uncertainty shock are more muted if TFP uncertainty or policy uncertainty are higher than if financial conditions are poor (*high spreads*). The resulting output contraction is about 15% less severe on impact then. The output response to a contractionary policy shock is also less severe when micro-uncertainty or macro-uncertainty are high than when credit conditions are poor (*high spreads*).

While the response of the spread to monetary policy shocks does not depend very much on the state of macro-uncertainty or micro-uncertainty (Figure 8.B), the output response is rather substantial. Poor financial conditions (*high spreads*) lead to an almost 18% larger contraction on impact in response to a positive monetary policy shock than if macro-uncertainty or micro-uncertainty were initially high. Credit spreads are determined by exogenous micro-uncertainty as well as by the endogenous leverage position of the entrepreneurs. Hence, we interpret this last result as evidence that what affects the propagation of monetary policy shocks is that financial conditions are already poor (whatever the reason might be) rather than elevated financial risks (micro-uncertainty) *per se*.

5 Discussion

Our findings show that some forms of uncertainty (micro-uncertainty) can have first-order effects on economic activity through their interaction with credit frictions. Within the class of mainstream New Keynesian models that we consider here, the *financial lever effect* of micro-uncertainty clearly dwarfs the *real option value of waiting motive* and the *precautionary savings motive* of uncertainty. Furthermore, the credit friction introduces a crucial non-linearity which implies that the dynamic propagation of first moment shocks depends on financial conditions (credit spreads) and, because of that, on micro-uncertainty too.

The direct effects from macro-uncertainty and monetary policy uncertainty are relatively small overall. They remain relatively small compared to those from micro-uncertainty shocks even when amplified by increasing risk aversion. First-moment TFP and monetary policy shocks are on *average* larger when their own form of uncertainty is high, and their responses can display asymmetric and non-scalability features tied to the presence of nominal rigidities. Most notably, contractionary monetary policy shocks have a significantly lower (in absolute value) unconditional response than expansionary shocks of equal size and those differences widen with larger shock realizations at the tails of the distribution (Figure 3). Hence, monetary shocks appear more effective at providing accommodation than at removing it.

We find that the interaction between credit frictions and nominal rigidities, on the one hand, tempers the economic boost from a positive TFP shock while, on the other hand, exacerbates the drag on economic activity from either a positive micro-uncertainty or a positive monetary policy shock (Figure 2). Micro-uncertainty is a type of uncertainty that adds financial risk to the credit spread and, through that, has sizeable first-order direct effects. We show not just that micro-uncertainty in and of itself matters, but also that this form of uncertainty exacerbates the credit frictions arising from asymmetric information and costly monitoring (that is, it indirectly influences the propagation of first moment shocks).[29]

We argue that the propagation of first moment shocks and even micro-uncertainty is path-dependent, varying with current financial conditions. As seen in Figure 4.A and Figure 4.B, the effect of a positive micro-uncertainty shock on the credit spread and output is much larger when financial conditions are initially poor (*high spreads*) and, indeed, micro-uncertainty appears as a prominent driver of the credit spread in Figure 6. However, the nonlinearities that relate to financial conditions are particularly significant for the propagation of shocks whose real effects work partly through the *financial lever channel*—notably, the transmission of monetary policy shocks is heavily dependent on broad financial conditions.

We see that a contractionary monetary policy shock is more severe on impact when spreads are already high and, interestingly, more so than if micro-uncertainty were high (Figure 8.B). Also, we find that low leverage (a high equity ratio) can act as a financial buffer mitigating to some degree the output drag from a contractionary monetary shock (Figure 5). However, while a strong balance sheet means entrepreneurs are better positioned to withstand such a shock, we observe that the contractionary effects are amplified when nominal interest rates (and overall borrowing costs) are initially high (Figure 7).

Put together, these findings suggest that our understanding of financial risks tied to

[29] If there are other frictions that interact with micro-uncertainty (e.g., firm hiring decisions or firm-specific adjustment costs), then micro-uncertainty can also have an additional impact independent of credit frictions.

uncertainty and the monetary policy transmission mechanism misses important nonlinearities that we only begin to recognize when explicitly modeling and estimating the non-linear interaction between credit frictions and micro-uncertainty shocks (as we do in this paper).

6 Concluding Remarks

We have examined the interaction between aggregate uncertainty and credit frictions through the lens of a New Keynesian model with stochastic volatility and credit frictions arising from asymmetric information and costly monitoring. We use a pruned third order approximation to solve the model, calculate various business cycle moments, and conduct impulse response analysis. We find that the interaction between aggregate uncertainty (macro-uncertainty or monetary policy uncertainty) and the credit frictions is relatively small. However, we find that when policy uncertainty is time-varying the output sensitivity to monetary shocks accounts for a sizeable fraction of the business cycle volatility implied by the model.

The responses of first-moment TFP and monetary policy shocks can display asymmetric and non-scalability features arising from the presence of nominal rigidities. Interestingly, monetary policy shocks tend to be more effective at providing accommodation than at removing it in the model. We show that micro-uncertainty (or, equivalently, exogenous credit friction shocks) also has first-order effects of comparable magnitude to shocks to TFP or monetary policy. Moreover, our nonlinear impulse response analysis suggests that the effect of an increase in micro-uncertainty tends to be larger when the existing credit spread is wider (indicating a deteriorating credit environment). Most importantly, we also find that conditioning on the amount of micro-uncertainty has a significant qualitative and quantitative impact on the endogenous responses to other first moment shocks in the model. In particular, we find that the propagation of monetary policy shocks depends on the level of micro-uncertainty and more broadly on the prevailing financial conditions (impaired balance sheets and high nominal interest rates worsen the contractionary effects of such a shock).

Incorporating longer-term contracts perhaps might increase the effect of aggregate macro- and policy-uncertainty, particularly if contracts are set in nominal terms. Furthermore, in the model, net worth is largely affected by the price of capital; the size of fluctuations in the price of capital depends, in turn, largely on the adjustment costs of changing capital. Adding a stronger asset price channel might generate greater fluctuations in net worth and larger endogenous movements in the credit spread. We leave those and other avenues of research on the functioning of credit markets in general equilibrium for future research.

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8 Tables and Figures

Table 1. Parameters Used in the Model Simulations

Preference and Technological Parameters	Parameter	Value	Parameterization Source
Households' Intertemporal Discount Factor	$0 < \beta < 1$	0.990	Bernanke et al. (1999)
Households' Inverse of the Intertemporal Elasticity of Substitution	$\chi \geq 0$	1	Bernanke et al. (1999)
Households' Inverse of the Frisch Elasticity of Labor Supply	$\xi \geq 0$	$\frac{1}{3}$	Bernanke et al. (1999)
Households' Scaling Parameter on Labor Disutility	$\kappa \geq 0$	0.738	SMM estimate
Households' Habit Parameter	$0 \leq b \leq 1$	0.738	SMM estimate
Elasticity of Substitution Across Varieties	$\epsilon > 1$	10	Basu (1996)
Capital Share	$0 \leq \alpha \leq 1$	0.350	Bernanke et al. (1999)
Entrepreneurial Labor Share	$0 \leq \vartheta \leq 1$	0.010	Bernanke et al. (1999)
Depreciation Rate	$0 < \delta \leq 1$	0.025	Bernanke et al. (1999)
Adjustment Cost & Agency Cost Parameters			
Capital Adjustment Cost	$\varphi_k > 0$	3.369	SMM estimate
Rotemberg (1982) Price Adjustment Cost	$\varphi_p \geq 0$	121.730	SMM estimate
Monitoring Cost	$0 \leq \mu < 1$	0.145	SMM estimate
Survival Rate of Entrepreneurs	$0 < \gamma < 1$	0.978	SMM estimate
Taylor Rule Policy Parameters			
Interest Rate Smoothing	$0 \leq \rho_i < 1$	0.836	Born and Pfeifer (2014)
Sensitivity to Inflation Deviations from Target	$\psi_\pi > 1$	1.777	Born and Pfeifer (2014)
Sensitivity to Output Growth	$\psi_x > 0$	0.319	Born and Pfeifer (2014)
Exogenous Shock Parameters			
Unconditional Std. Dev. of Idiosyncratic Risk Shock	$\sigma_\omega > 0$	0.300	SMM estimate
Persistence of the Stochastic Volatility of Idiosyncratic Risk Shock	$0 < \upsilon_\omega < 1$	0.966	SMM estimate
Std. Dev. of the Stochastic Volatility of Idiosyncratic Risk Shock	$\eta_\omega \geq 0$	0.0254	SMM estimate
TFP Shock Persistence	$0 < \rho_a < 1$	0.814	Born and Pfeifer (2014)
TFP Shock Unconditional Standard Deviation	$\sigma_a > 0$	0.0054	Born and Pfeifer (2014)
Persistence of the Stochastic Volatility on TFP	$0 < \upsilon_a < 1$	0.632	Born and Pfeifer (2014)
Std. Dev. of the Stochastic Volatility on TFP	$\eta_a \geq 0$	0.312	Born and Pfeifer (2014)
Monetary Shock Persistence	$0 < \rho_m < 1$	0.367	Born and Pfeifer (2014)
Monetary Shock Unconditional Standard Deviation	$\sigma_m > 0$	0.0014	Born and Pfeifer (2014)
Persistence of the Stochastic Volatility of Monetary Shock	$0 < \upsilon_m < 1$	0.921	Born and Pfeifer (2014)
Std. Dev. of the Stochastic Volatility of Monetary Shock	$\eta_m \geq 0$	0.363	Born and Pfeifer (2014)

Note: SMM refers to the Simulated Method of Moments estimation method described in Section 3.

Table 2. Moments Used to Set Values of κ, b, φ_k, φ_p, γ, μ, σ_ω, υ_ω, and η_ω

Variable	Moment	Value	Data Source
1. Mean credit risk spread	$400 \times \mathbb{E}\left(\mathbb{E}_t\left(\ln\left(\frac{R^e_{t+1}}{I_t}\right)\right)\right)$	2.29	Spread between Moody's seasoned Baa corporate bond and 10-year Treasury rate (constant maturity)
2. Mean equity ratio	$100 \times \mathbb{E}\left(\frac{N_t}{P_t Q_t K_{t+1}}\right)$	52.14	(Net worth/Total assets)x100 (Non-financial corporate business)
3. Mean quarterly default probability	$100 \times \mathbb{E}\left(\Phi_t^{default}\right)$	0.75	Bernanke et al. (1999)
4. Mean log hours	$400 \times \mathbb{E}\left(\ln\left(H_t\right)\right)$	0	Normalization
5. Variance of credit risk spread	$\mathbb{VAR}\left(400 \times \mathbb{E}_t\left(\ln\left(\frac{R^e_{t+1}}{I_t}\right)\right)\right)$	0.52	Spread between Moody's seasoned Baa corporate bond and 10-year Treasury rate (constant maturity)
6. Var(investment)/Var(output)	$\frac{\mathbb{VAR}(400 \times \ln(X_t))}{\mathbb{VAR}(400 \times \ln(Y_t))}$	17.85	NIPA fixed investment plus consumer durables
7. Autocorrelation of the credit spread	$\rho\left(400 \times \mathbb{E}_t\left(\ln\left(\frac{R^e_{t+1}}{I_t}\right)\right)\right)$	0.90	Spread between Moody's seasoned Baa corporate bond and 10-year Treasury rate (constant maturity)
8. Autocorrelation of consumption	$\rho\left(400 \times \ln\left(C_t\right)\right)$	0.90	NIPA non-durable consumption
9. Autocorrelation of inflation	$\rho\left(400 \times \ln\left(\Pi_t\right)\right)$	0.39	NIPA GDP deflator

Note: $\mathbb{E}(.)$ denotes unconditional mean, $\mathbb{VAR}(.)$ denotes unconditional variance, and $\rho(.)$ denotes the first-order autocorrelation. More details on the data sources can be found in Balke et al. (2017).

Table 3. Simulated and Empirical Business Cycle Volatilities for Various Models

	Data	M1	M2	M3	M4	M5	M6	M7	M8
$stdv\left(z_t\right)$ (%)									
$z_t \equiv \quad 400 \times \ln\left(Y_t\right)$	4.62	4.45	2.57	4.29	4.38	2.95	4.62	2.72	3.69
$stdv\left(z_t\right)/stdv\left(400 \times \ln\left(Y_t\right)\right)$									
$z_t \equiv \quad 400 \times \ln\left(C_t\right)$	0.64	0.38	0.44	0.38	0.36	0.44	0.35	0.52	0.09
$400 \times \ln\left(X_t\right)^*$	4.23	4.20	3.77	3.95	4.24	4.31	3.57	4.13	4.98
$400 \times \ln\left(H_t\right)$	1.66	1.61	1.66	1.61	1.60	1.66	1.56	0.55	1.79
$400 \times \ln\left(\frac{W_t}{P_t}\right)$	0.96	1.54	1.51	1.60	1.56	1.35	1.50	1.19	1.94
$400 \times \ln\left(\Pi_t\right)$	0.14	0.42	0.42	0.44	0.43	0.38	0.41	1.79	0.49
$400 \times \ln\left(I_t\right)$	0.23	0.12	0.12	0.12	0.12	0.12	0.10	0.26	0.17
$100 \times \frac{N_t}{P_t Q_t K_{t+1}}$	0.58	0.32	0.06	0.05	0.32	0.48	0.01	0.52	0.38
$400 \times \mathbb{E}_t\left(\ln\left(\frac{R^e_{t+1}}{I_t}\right)\right)^*$	0.16	0.15	0.02	0.02	0.15	0.23	0.00	0.25	0.19

Note: The endogenous variables included are output, household consumption, investment, hours worked by households, real wages, inflation, and nominal interest rates. We extract the cyclical component of all these series by HP-filtering them with a one-sided filter using a lambda of 1600 and a power of 2, except for the equity ratio that is demeaned instead. More details on the data sources can be found in Balke et al. (2017). The table shows the standard deviation $\sigma(400{\times}ln(Y_t))$ and the standard deviation of all other endogenous variables relative to output $\sigma(z_t)/\sigma(400{\times}ln(Y_t))$. We report the results for the following variants of the model: M1 = benchmark model, M2 = without all stochastic volatilities, M3 = without micro-uncertainty only, M4 = without TFP stochastic volatility only, M5 = without monetary stochastic volatility, M6 = without financial frictions, M7 = without nominal rigidities, and M8 = with high risk aversion.

* $\sigma(400{\times}ln(X_t))/\sigma(400{\times}ln(Y_t))$ and $\sigma(400{\times}\mathbf{E}_t(ln(R^e_{t+1}/I_t)))$ are used to estimate the benchmark model by the simulated method of moments.

Table 4. Simulated and Empirical Business Cycle Persistence for Various Models

	Data	M1	M2	M3	M4	M5	M6	M7	M8
$\rho\left(z_t, z_{t-1}\right)$									
$z_t \equiv$ $400 \times \ln\left(Y_t\right)$	0.91	0.63	0.68	0.64	0.62	0.67	0.63	0.73	0.57
$400 \times \ln\left(C_t\right)^*$	0.90	0.90	0.91	0.89	0.89	0.91	0.89	0.91	0.91
$400 \times \ln\left(X_t\right)$	0.93	0.58	0.58	0.55	0.58	0.64	0.56	0.69	0.58
$400 \times \ln\left(H_t\right)$	0.96	0.56	0.55	0.57	0.56	0.54	0.56	0.54	0.54
$400 \times \ln\left(\frac{W_t}{P_t}\right)$	0.73	0.56	0.59	0.56	0.56	0.60	0.56	0.66	0.57
$400 \times \ln\left(\Pi_t\right)^*$	0.39	0.52	0.51	0.52	0.52	0.51	0.52	0.00	0.51
$400 \times \ln\left(I_t\right)$	0.94	0.75	0.78	0.75	0.75	0.79	0.76	0.48	0.78
$100 \times \frac{N_t}{P_t Q_t K_{t+1}}$	0.96	0.99	0.97	1.00	0.99	0.99	1.00	0.99	0.99
$400 \times \mathbb{E}_t\left(\ln\left(\frac{R^e_{t+1}}{I_t}\right)\right)^*$	0.89	0.88	0.96	0.96	0.88	0.88	0.93	0.88	0.89

Note: The endogenous variables included are output, household consumption, investment, hours worked by households, real wages, inflation, and nominal interest rates. We extract the cyclical component of all these series by HP-filtering them with a one-sided filter using a lambda of 1600 and a power of 2, except for the equity ratio that is demeaned instead. More details on the data sources can be found in Balke et al. (2017). The table shows the first-order autocorrelation $\rho(z_t, z_{t-1})$. We report the results for the following variants of the model: M1 = benchmark model, M2 = without all stochastic volatilities, M3 = without micro-uncertainty only, M4 = without TFP stochastic volatility only, M5 = without monetary stochastic volatility, M6 = without financial frictions, M7 = without nominal rigidities, and M8 = with high risk aversion.

* $\rho(400 \times ln(C_t))$, $\rho(400 \times ln(\Pi_t))$, and $\rho(400 \times \mathbf{E}_t(ln(R^e_{t+1}/I_t)))$ are used to estimate the benchmark model by the simulated method of moments.

Table 5. Simulated and Empirical Business Cycle Cyclicality for Various Models

		Data	M1	M2	M3	M4	M5	M6	M7	M8
$\rho\left(z_t, 400 \times \ln\left(Y_t\right)\right)$										
$z_t \equiv$	$400 \times \ln\left(Y_t\right)$	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	$400 \times \ln\left(C_t\right)$	0.90	0.70	0.80	0.77	0.69	0.67	0.75	0.73	0.49
	$400 \times \ln\left(X_t\right)$	0.93	0.94	0.95	0.96	0.94	0.92	0.97	0.89	0.97
	$400 \times \ln\left(H_t\right)$	0.88	0.79	0.55	0.77	0.83	0.54	0.80	−0.10	0.73
	$400 \times \ln\left(\frac{W_t}{P_t}\right)$	0.04	0.94	0.96	0.97	0.94	0.89	0.97	0.89	0.93
	$400 \times \ln\left(\Pi_t\right)$	0.35	0.83	0.69	0.84	0.86	0.62	0.84	−0.12	0.85
	$400 \times \ln\left(I_t\right)$	0.65	−0.78	−0.94	−0.93	−0.77	−0.62	−0.93	−0.55	−0.69
	$100 \times \frac{N_t}{P_t Q_t K_{t+1}}$	−0.02	0.06	−0.03	−0.09	0.06	0.11	−0.06	0.11	0.08
	$400 \times \mathbb{E}_t\left(\ln\left(\frac{R^e_{t+1}}{I_t}\right)\right)$	−0.51	−0.07	0.06	0.09	−0.07	−0.12	0.01	−0.11	−0.07
$\rho\left(z_t, 400 \times \mathbb{E}_t\left(\ln\left(\frac{R^e_{t+1}}{I_t}\right)\right)\right)$										
$z_t \equiv$	$400 \times \ln\left(Y_t\right)$	−0.51	−0.07	0.06	0.09	−0.07	−0.12	0.00	0.01	−0.11
	$400 \times \ln\left(C_t\right)$	−0.51	−0.04	0.09	0.10	−0.05	−0.06	0.00	0.00	−0.03
	$400 \times \ln\left(X_t\right)$	−0.42	−0.10	0.03	0.08	−0.10	−0.15	0.00	0.01	−0.16
	$400 \times \ln\left(H_t\right)$	−0.44	−0.03	0.14	0.15	−0.03	−0.05	0.00	0.01	−0.15
	$400 \times \ln\left(\frac{W_t}{P_t}\right)$	−0.04	−0.01	0.07	0.11	−0.01	−0.04	0.00	0.01	−0.02
	$400 \times \ln\left(\Pi_t\right)$	−0.18	0.00	0.12	0.13	0.00	−0.01	0.00	0.01	−0.00
	$400 \times \ln\left(I_t\right)$	−0.53	−0.07	−0.02	−0.07	−0.07	−0.09	0.00	−0.00	−0.06
	$100 \times \frac{N_t}{P_t Q_t K_{t+1}}$	0.02	0.18	−0.99	−0.99	0.18	0.18	0.00	−0.10	0.19
	$400 \times \mathbb{E}_t\left(\ln\left(\frac{R^e_{t+1}}{I_t}\right)\right)$	1.00	1.00	1.00	1.00	1.00	1.00	0.00	1.00	1.00

Note: The endogenous variables included are output, household consumption, investment, hours worked by households, real wages, inflation, and nominal interest rates. We extract the cyclical component of all these series by HP-filtering them with a one-sided filter using a lambda of 1600 and a power of 2, except for the equity ratio that is demeaned instead. More details on the data sources can be found in Balke et al. (2017). The table shows the contemporaneous correlation with output $\rho(z_t, y_t)$. We report the results for the following variants of the model: M1 = benchmark model, M2 = without all stochastic volatilities, M3 = without micro-uncertainty only, M4 = without TFP stochastic volatility only, M5 = without monetary policy stochastic volatility, M6 = without financial frictions, M7 = without nominal rigidities, and M8 = with high risk aversion.

Figure 1. Unconditional generalized impulse responses for the baseline model

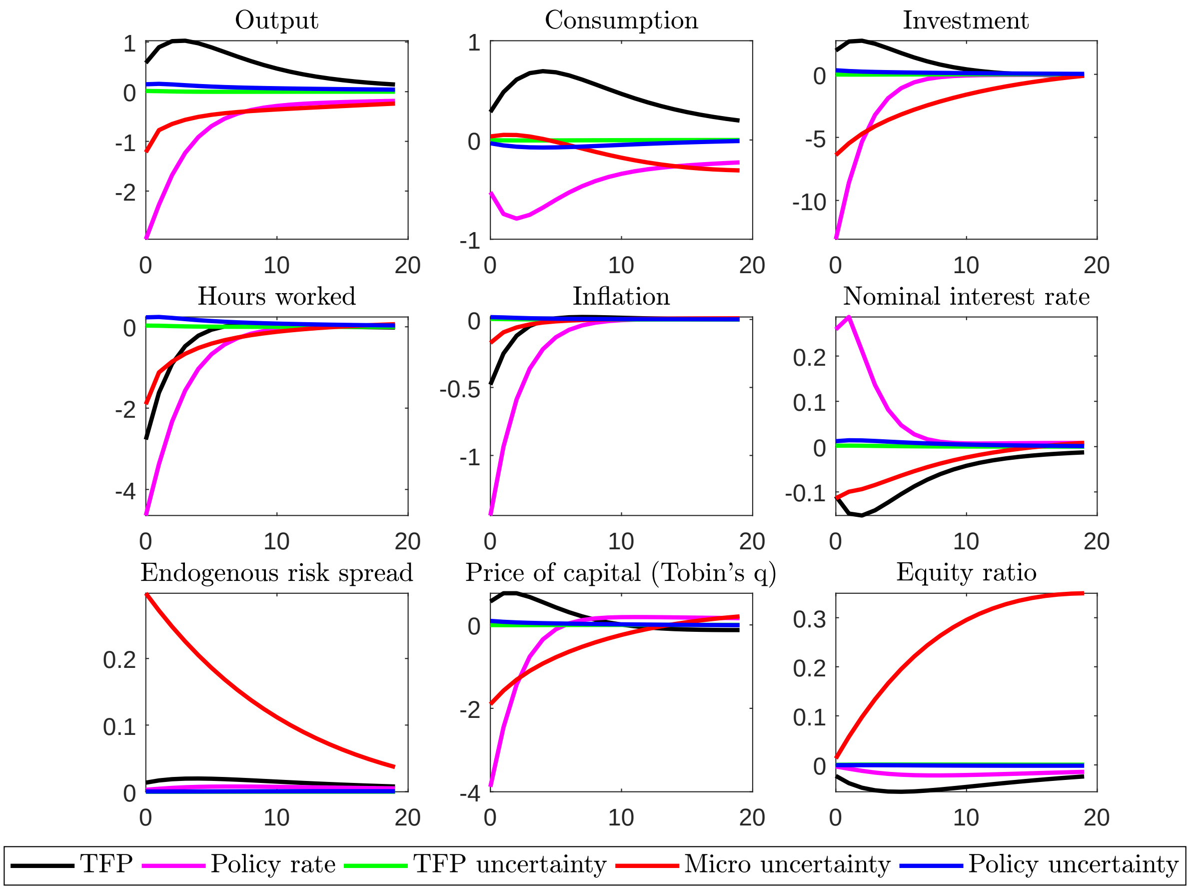

Figure 2. Unconditional generalized impulse responses for alternative models

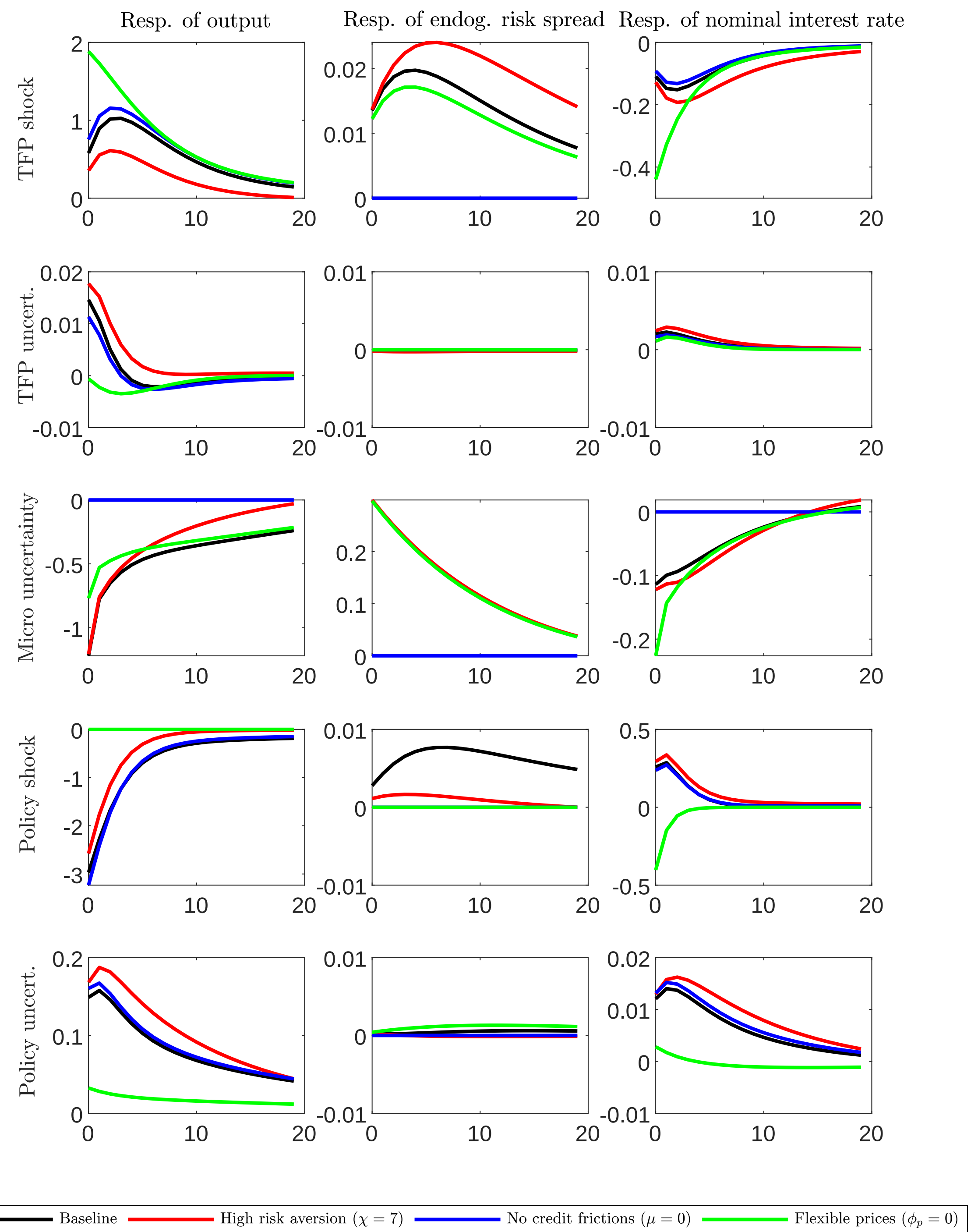

Figure 3. Generalized impulse response of output to alternative shock sizes and directions

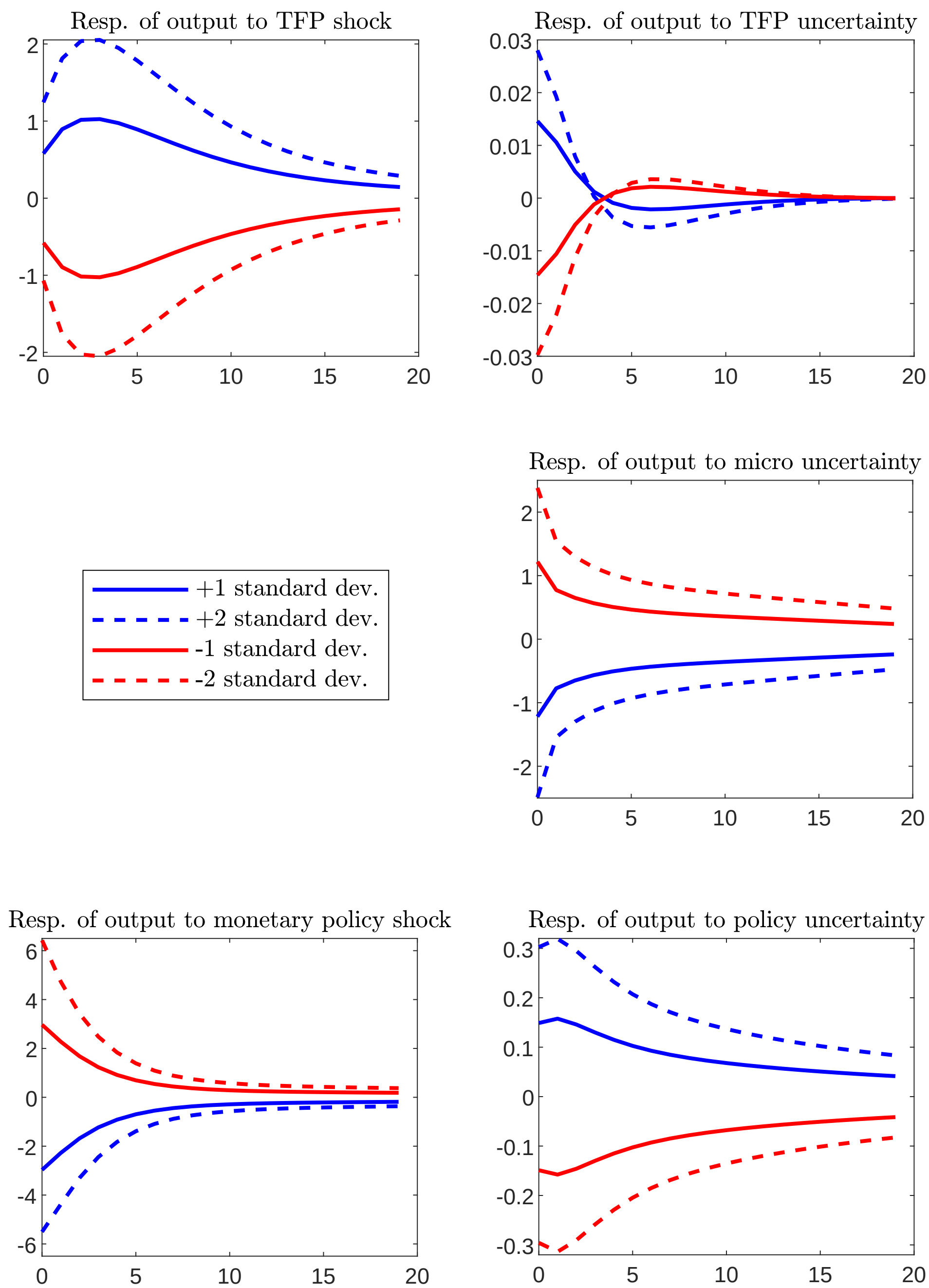

Figure 4.A Generalized impulse response of output to shocks
conditional on the value of the spread

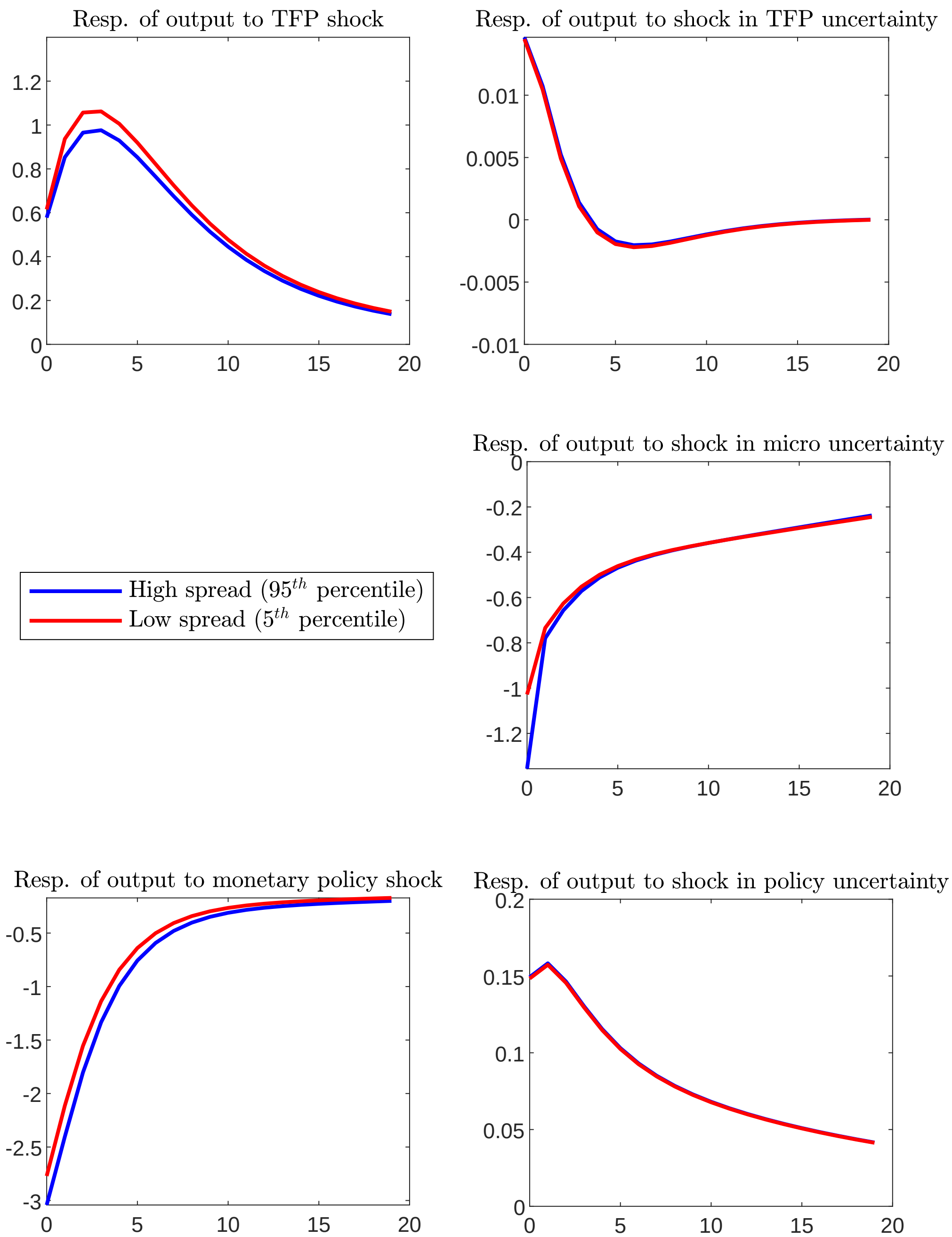

Figure 4.B Generalized impulse response of risk spread to shocks conditional on the value of the spread

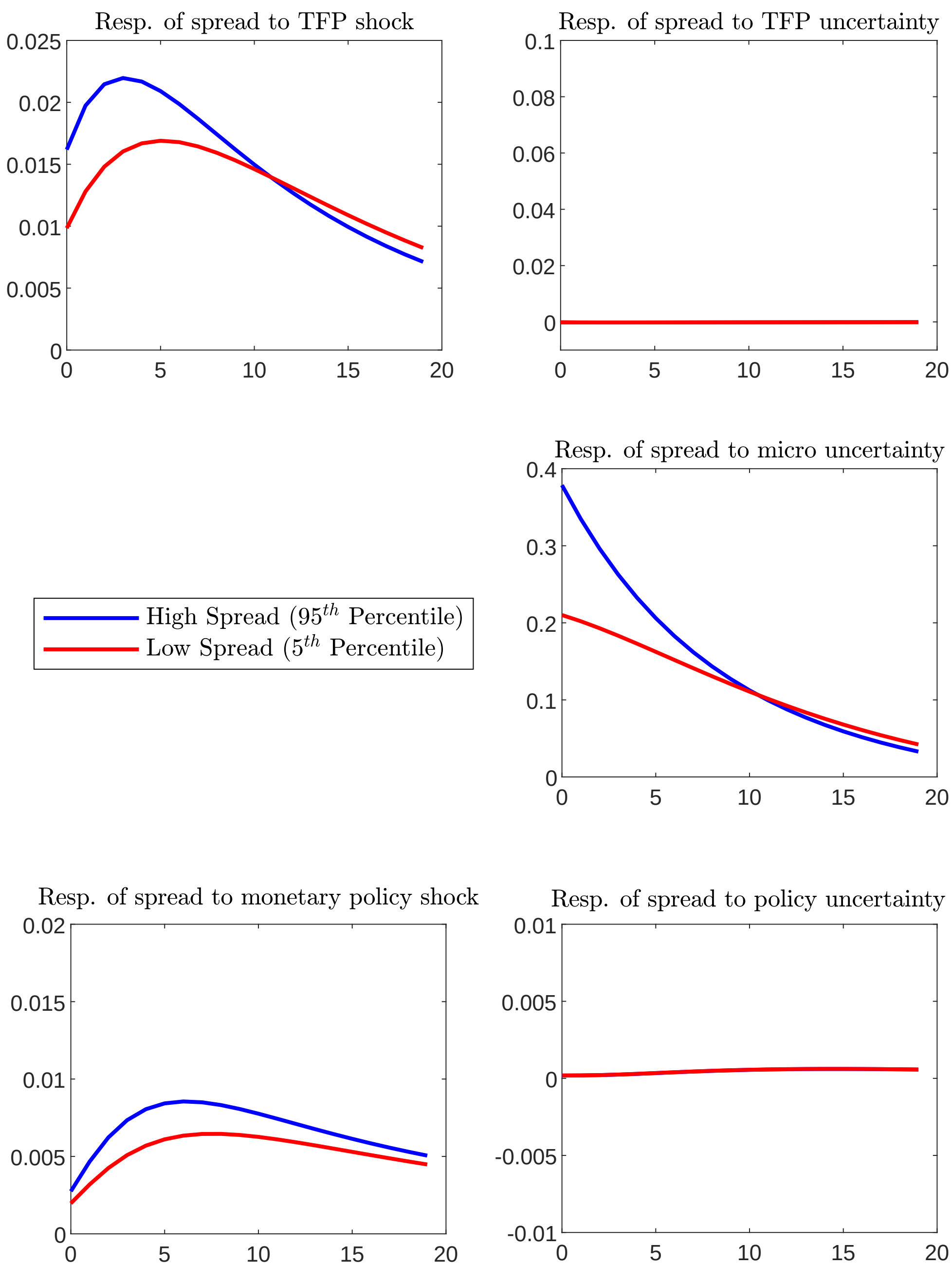

Figure 5. Generalized impulse response of output, risk spread, and nominal interest rate to shocks conditional on the value of endogenous financial factors

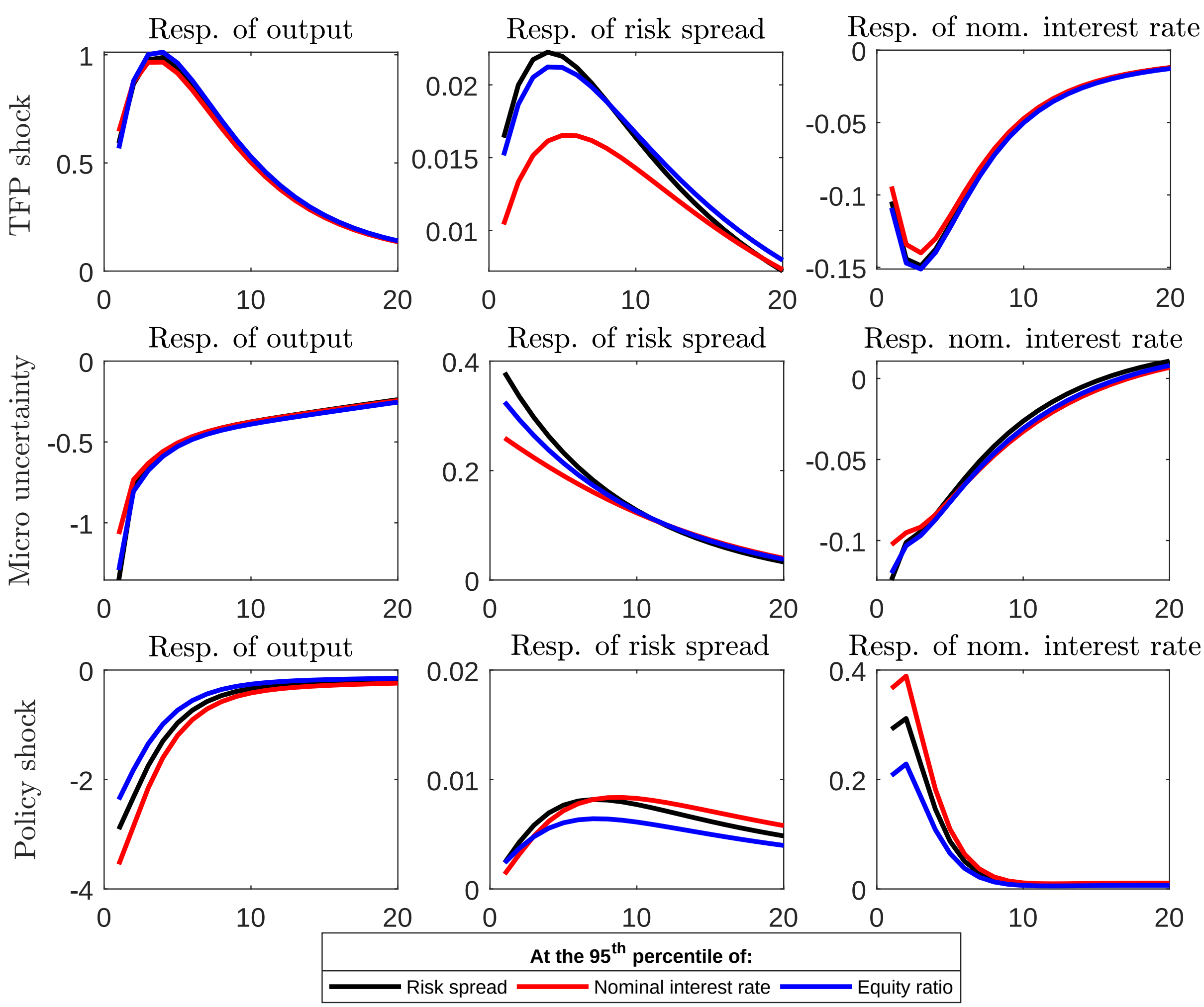

Figure 6. Scatterplot of the unconditional distribution for the baseline model

Figure 7. Joint distribution of the endogenous spread risk (external finance premium) and the nominal short-term interest rate

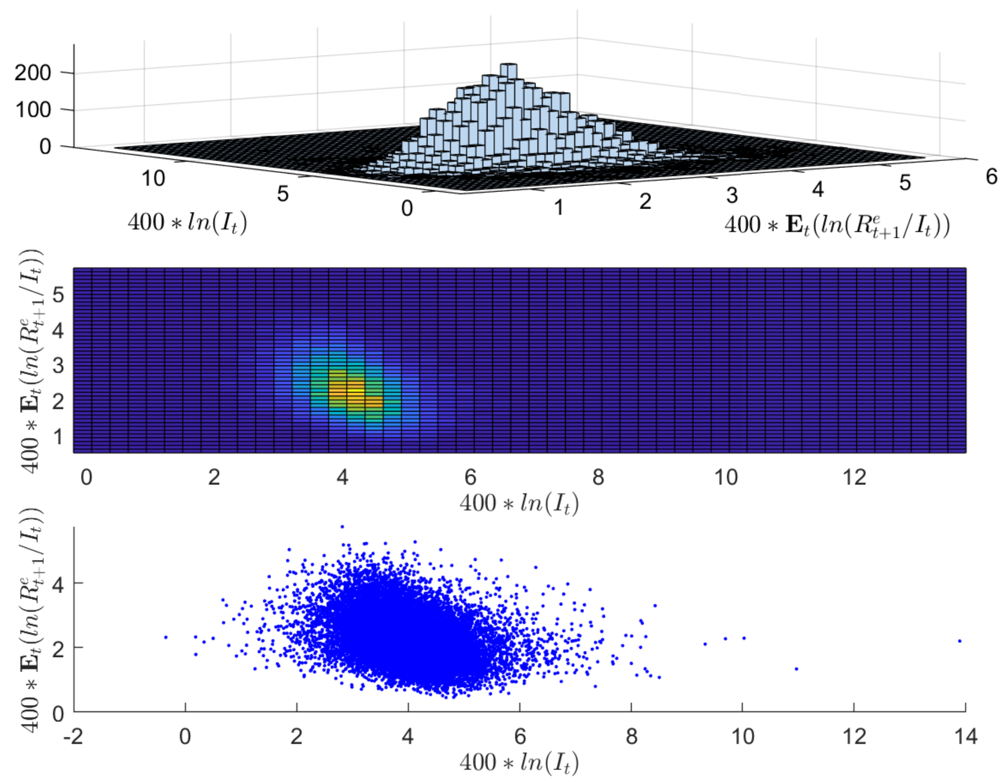

Figure 8.A Generalized impulse response of output, risk spread, and interest rate to shocks conditional on the value of own uncertainty type

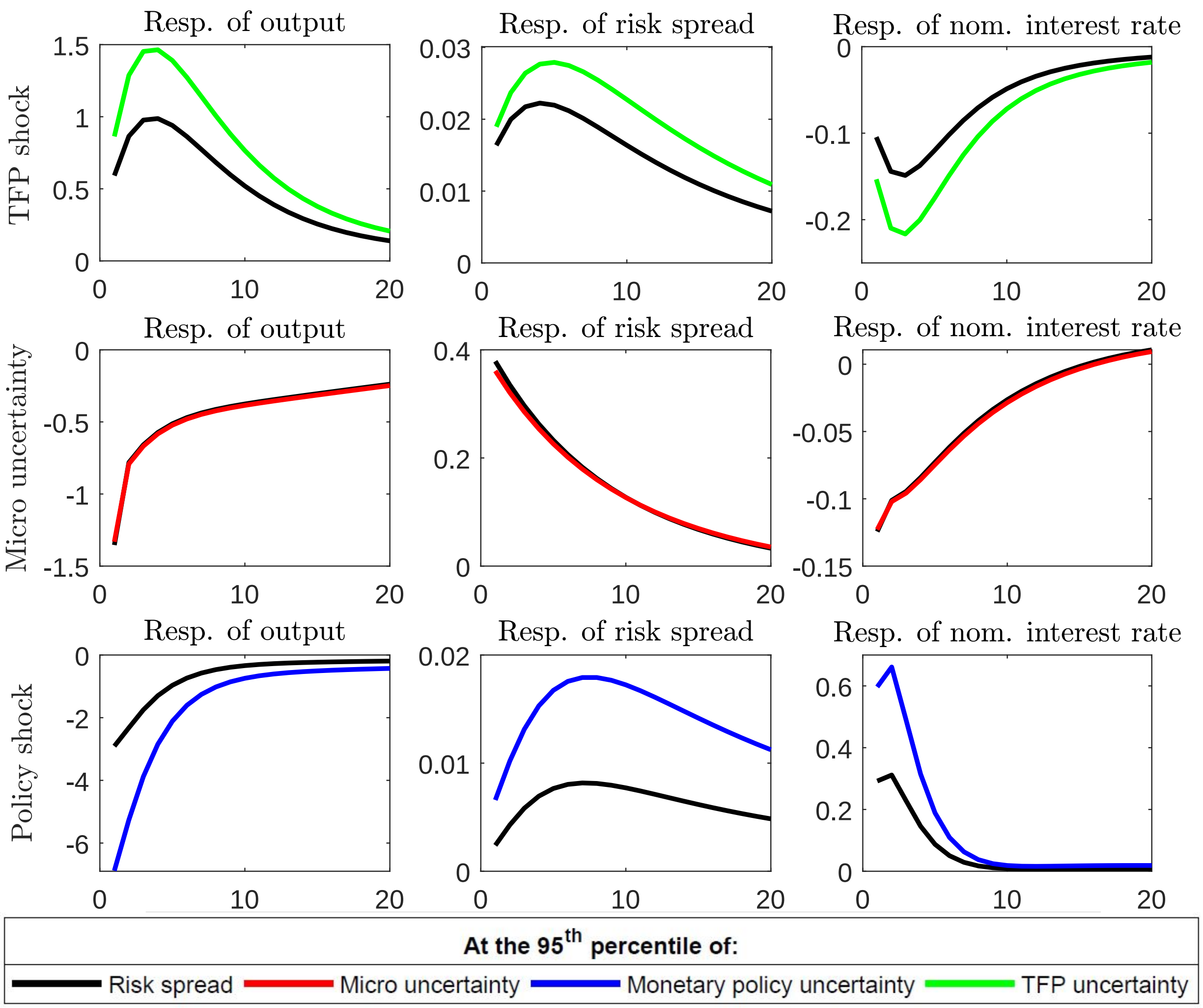

Figure 8.B Generalized impulse response of output, risk spread, and interest rate to shocks conditional on the value of other uncertainty types