FINANCIAL ORIGINS OF UNCERTAINTY

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Abstract. Countercyclical uncertainty could reflect exogenous shocks to uncertainty that drive business cycles. It could also reflect endogenous responses of measured uncertainty to other business cycle shocks. Evidence suggests that the cyclical behaviors of uncertainty depend on financial conditions, with tighter financial conditions associated with more countercyclical uncertainty. A real business cycle model with heterogeneous firms and endogenous default risks can explain these observations. In the model, productive firms face binding borrowing constraints. In a recession, an increase in default risks raises credit spreads, reducing the ex ante borrowing capacity for all firms. Since more productivity firms are more likely to be borrowing constrained, labor and capital are reallocated to firms with lower productivity, reducing aggregate productivity and deepening the recession. Thus, in a recession, a negative shock reduces aggregate output disproportionately more than a positive shock raises output in an expansion. Such state-dependent output responses lead to countercyclical uncertainty measured by the conditional variance of forecast errors. Under calibrated parameters, the model's quantitative predictions are in line with the data. The model also correctly predicts that uncertainty is more countercyclical under tighter financial constraints.

I. Introduction

Following the important contribution of Bloom (2009), a large and growing body of literature studies the relationship between uncertainty and business cycles.[1] A broad consensus

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[1]For recent surveys of this literature, see Bloom (2014) and Fernández-Villaverde and Guerrón-Quintana (2020).

suggests that uncertainty is countercyclical, rising in recessions and falls in booms. It is less clear, however, whether uncertainty is an exogenous source of business cycle fluctuations or an endogenous response to changes in economic conditions.

In a recent study, Ludvigson et al. (2021) present some evidence that countercyclical uncertainty reflects endogenous responses of measured uncertainty to other business cycle shocks. The earlier work by Bachmann et al. (2013) makes a similar point. What causes uncertainty to rise in recessions? Recent literature studies several theoretical channels. Uncertainty can be countercyclical in an environment with labor market search frictions (Bernstein et al., 2022). Countercyclical uncertainty can also arise in a New Keynesian model with nominal rigidities and occasionally binding zero-lower-bound (ZLB) constraints on the short-term nominal interest rates. When the economy is away from the ZLB, monetary accommodation can dampen the recessionary effects of a recessionary shock. When the economy is at the ZLB, no further policy accommodation can be provided, amplifying the recessionary effects (Plante et al., 2018). Information frictions can also lead to countercyclical uncertainty (Fajgelbaum et al., 2017; Benhabib et al., 2016, 2019; Ilut et al., 2018).

In this paper, we argue that financial frictions can be a complementary source of endogenous uncertainty. We first construct an empirical measure of uncertainty following the approach of Jurado et al. (2015) and Ludvigson et al. (2021). Specifically, we measure output uncertainty using the conditional volatility of forecast errors of real GDP growth. Similarly, we construct measures of uncertainty using other macro variables, including consumption, labor hours, and aggregate credit. We then build a "core uncertainty index" by taking the simple average of these four macro uncertainty measures.

We document evidence that, on average, uncertainty is negatively correlated with macro indicators (such as output growth), in line with the literature. More importantly, the correlation of uncertainty with output growth is more negative in periods with greater financial stress, consistent with the firm-level evidence documented by Alfaro et al. (2018). These results are robust to alternative measures of financial conditions, including the Chicago Fed's Adjusted National Financial Conditions Index (or ANFCI) and the financial uncertainty index constructed by Ludvigson et al. (2021).

To understand the theoretical underpinning of the observed correlations between uncertainty and business cycle indicators and the dependence of such correlations on financial conditions, we construct a real business cycle (RBC) model with financial frictions. The model builds on Liu and Wang (2014) and it features heterogeneous firms facing working capital constraints and endogenous default risks. In the model, firms choose the amount of working capital loans after observing aggregate shocks but before observing idiosyncratic productivity shocks. Since firms are ex ante identical, they face an identical borrowing limit determined by the expected equity value of firms. Under constant returns, firms with sufficiently high productivity choose to operate and borrow up to the limit; whereas firms with sufficiently low productivity choose to remain inactive. The firm with the threshold productivity is indifferent between production and inaction, with the threshold productivity determined by the input prices adjusted for aggregate productivity.

After production, each firm observes an idiosyncratic liquidity shock that affects their ability of repaying loans. The liquidity shock in our model can be interpreted as senior debts for which the firm faces a fixed repayment schedule. It can also be interpreted as a fixed cost of staying in business. For simplicity, we do not model the microeconomic foundations of the liquidity shock. After observing the liquidity shock, the firm's maximum available fund for repaying working capital loans equals the difference between the expected equity value and the liquidity shock. If the liquidity shock is sufficiently large, then the firm would not be able to repay working capital loans and chooses to default. The default threshold is just the difference between the expected equity value and the working capital loans. The default probability is then given by the cumulative density of the distribution of liquidity shocks evaluated at the default threshold. The endogenous default risks give rise to an endogenous credit spread, such that risk-neutral lenders can break even.

To close the model, we assume that firms are owned by a risk-averse representative entrepreneur, who receives dividend payments from active firms in each period. In addition, there is a representative household who consumes the goods produced by firms and supplies labor and capital to firms in competitive factor markets. In a competitive equilibrium, the goods market, labor market, and capital market all clear.

We solve the calibrated model based on third-order perturbations around the stochastic steady state. Using simulated data from the calibrated model driven by first-moment shocks to total factor productivity (TFP) and the discount factor, we construct a measure of uncertainty for each macroeconomic variable—including aggregate output, consumption, investment, and labor hours—based on the conditional volatility of forecast errors for each variable. We then take the average of these uncertainty measures to obtain a core uncertainty index, as we do for our empirical analysis.

The model-based uncertainty index is negatively correlated with output growth, with a correlation comparable to that in the data. More importantly, in line with our evidence, the magnitude of the correlation depends on financial conditions: it becomes smaller in the counterfactual with less financial stress. These results suggest that financial frictions are likely important for understanding the observed countercyclical uncertainty.

To further examine the model mechanism, we study impulse responses of several key macroeconomic variables to fundamental shocks, including a TFP shock and a discount factor shock. We find that the responses of aggregate output are state dependent: it responds much more to a negative shock to TFP (or to the discount factor) in a recession than it does to a positive shock in an expansion. This state-dependence stems from procyclical leverage. In a counterfactual with acyclical leverage, we find that the impulse responses of aggregate output are symmetric between recessions and expansions. Leverage is procyclical in our model because the default risks are higher in a recession than in an expansion, such that a negative shock reduces firms' borrowing capacity disproportionately more in a recession than a positive shock can increase the borrowing capacity in an expansion.

Although we focus on the importance of financial frictions as a source of countercyclical movements in endogenous uncertainty, the model does not contradict the empirical observation that exogenous shocks to financial uncertainty can also drive business cycle fluctuations Ludvigson et al. (2021). In the model, we measure financial uncertainty shock by a mean-preserving spread (i.e., the cross-sectional dispersion) of the distribution of the idiosyncratic liquidity shocks. An increase in the dispersion of liquidity shocks raises the tail risks of default, and thus increasing credit spreads and reducing firms' borrowing capacity. The decline in borrowing capacity constrains high-productivity firms' ability to produce, reducing wages and capital rents and allowing low-productivity firms to operate. This reallocation reduces aggregate TFP, creating a recession with synchronized declines in output, consumption, investment, and labor hours. Remarkably, our RBC model with financial frictions can generate business cycle comovements following an uncertainty shock through a reallocation channel that leads to endogenous fluctuations in TFP. Unlike other models without financial frictions, generating such comovements conditional on an uncertainty shock in our model does not require correlated first-moment shocks (Bloom et al., 2018) or the presence of nominal rigidities (Leduc and Liu, 2016; Basu and Bundick, 2017).

Our work is not the first to highlight the importance of financial frictions for explaining the connections between uncertainty and business cycles. In a closely related study, Alfaro et al. (2018) examine the role of financial frictions in amplifying the negative impacts of uncertainty shocks. They identify the effects of uncertainty shocks on firm-level investment by exploiting differential exposures of firms to exchange rate, policy, and energy price risks. They find that, following an uncertainty shock, ex ante financially constrained firms cut investment more than unconstrained firms. They then present a model with heterogeneous firms and show that financial frictions substantially amplify and prolong the negative effects of uncertainty shocks.

Consistent with the firm-level evidence of Alfaro et al. (2018), we find that uncertainty is more negatively correlated with output growth in periods with tighter financial conditions. In line with their theoretical findings, we also find that financial frictions are important for propagating financial uncertainty shocks, although the propagation works through a novel reallocation channel. Our focus is different from theirs. While Alfaro et al. (2018) focus on the propagation mechanism for exogenous shocks to uncertainty, we focus on the drivers of endogenous responses of uncertainty to other business cycle shocks. Thus, we view our work as complementary to theirs and other related recent studies (Gilchrist et al., 2014; Christiano et al., 2014; Arellano et al., 2019; Dong et al., 2021).

I.1. Comparing Model Mechanism.

Consider the following process

$$y_{t+1} = y_t + \phi_t e_{t+1}, \quad e_{t+1} \sim N(0, \sigma_e^2) \tag{1}$$

where y_t is the variable of interest (for example output), e_t denotes exogenous process (for example TFP shock), and ϕ_t captures (potentially time-varying) sensitivity of y_{t+1} to e_{t+1}. In our model, ϕ_t is negatively correlated with y_t due to the fact that financial constraint is disproportionately tightened in recessions and gives rise to larger amplification effect. Therefore, the variance of forecast error

$$var\left(E_t[y_{t+1}|\mathbf{I_t}] - y_{t+1}\right) = [\phi_t]^2 \sigma_e^2 \tag{2}$$

is negatively correlated with y_t since $\phi_t'(y_t) < 0$.

In contrast, models with information friction including Van Nieuwerburgh and Veldkamp (2006) and Straub and Ulbricht (2023) assume that an imperfect signal s_t on e_{t+1} is available at time t to infer e_{t+1} such that

$$s_t = e_{t+1} + u_t, \quad u_t \sim N(0, \frac{1}{\tau_t}) \tag{3}$$

where the signal precision τ_t is endogenous and positively linked to aggregate state y_t. Therefore, the variance of forecast error can be written as

$$var\left(E_t[y_{t+1}|\mathbf{I_t}] - y_{t+1}\right) = \phi^2 \frac{1}{\sigma_e^{-2} + \tau_t} \tag{4}$$

which is negatively correlated with y_t given that ϕ is constant and $\tau_t'(y_t) > 0$.

Our mechanism can be seen as complementary to that of Van Nieuwerburgh and Veldkamp (2006) and Straub and Ulbricht (2023) in that (1) amplification effect ϕ_t is endogenous, while (2) signal precision $\tau_t = 0$ in our model.

II. Data and Facts

II.1. Real uncertainty measures.

Real uncertainty series are constructed following Jurado et al. (2015) (JLN, hereinafter) and Ludvigson et al. (2021), which distinguish between uncertainty and ex-post volatility. For example, a measure of uncertainty about output growth can be constructed as:

$$U^{y}_{t,t+1} = \frac{1}{sd(\Delta y)}\sqrt{E_t\left\{[\Delta y_{t+1} - E_t(\Delta y_{t+1})]^2\right\}} = \frac{1}{sd(\Delta y)}\sqrt{E_t\left\{[y_{t+1} - E_t(y_{t+1})]^2\right\}} \quad (5)$$

where $y_t = log(Y_t)$ and $\Delta y_t = y_t - y_{t-1}$, and is normalized by the standard deviation of output growth (Δy).

Constructing individual uncertainty measures takes four steps. Firstly, a large set of predictors with 132 macro series and 147 financial series is constructed to mimic full information set in estimating rational forecast $(E_t(y_{t+1}))$[2]. In specific, a small number of latent common factors estimated by the method of principal components (PCA) from two large sets of predictors are augmented to an otherwise standard forecasting model, which allows for non-linearity. Secondly, h-period ahead forecast error is defined and computed as $FE^y_t(h) \equiv y_{t+h} - E_t(y_{t+h})$. Thirdly, a conditional volatility of this forecast error based on time t information $E_t[\sqrt{(FE^y_t(h))^2}]$, along with forecast errors of predictors (which also attribute to forecast errors of variable y beyond one-period ahead), is estimated using a parametric stochastic volatility model[3]. The parameters governing stochastic volatility are estimated from least squared residuals using Markov chain Monte-Carlo method.

Similarly, we can measure uncertainty about real consumption, labor hours and credit[4]. We then constructed an index of real uncertainty by simple averaging these four core series ('CORE' real uncertainty index, hereinafter).

[2]Not all of the original series in JLN are regularly updated to 2019. For example, seven NAPM index series were no longer updated at FRED after 2016. We update the series using release by original source, the Institute for Supply Management(ISM). The Cochrane-Piazzesi factor is no longer updated, so we drop this series from the financial set. We replicate uncertainty index following the method of Jurado et al. (2015) based on 132 macro series and 146 financial series, and obtain an extended series that is highly correlated with the original one (correlation = 0.996 over the overlapped sample period).

[3]The stochastic volatility model allows for independence of second moment shocks to first moment ones, consistent with theoretical models of uncertainty. Given auto-correlated nature of predictors and variables, JLN shows that h-period-ahead forecast error variance can be decomposed into four sources: an autoregressive component of forecast errors, a common factor (predictor) uncertainty, a stochastic volatility component, and a covariance term. Eq.(5) defines uncertainty as purely unforecastable component of this forecast error.

[4]Output, consumption, labor and credit correspond to the series of IP:Total, Agg Wkly Hour, Consumption and C&I Loans in JLN, which are also representative for four of five major groups (housing group is irrelevant in our model). See data appendix of Jurado et al. (2015) for details.

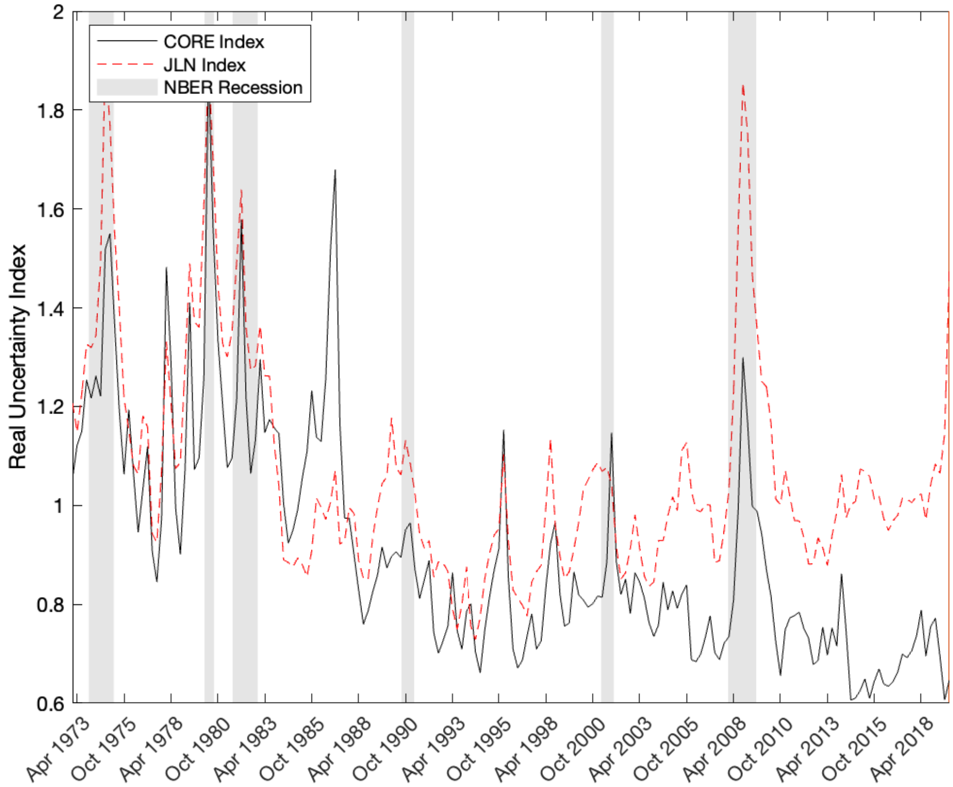

FIGURE 1. Real Uncertainty Series.

Note: The blue line represents real uncertainty index constructed based on four core individual series (output, consumption, hours and credit). The black line represents extended real uncertainty index of Jurado et al. (2015) and Ludvigson et al. (2021). Shaded grey bars are NBER recessions.

Source: Sydney Ludvigson's website: https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes. and authors' calculations.

Figure 1 plots the time series of two real uncertainty indices. Both series are negatively correlated with output, consumption, investment, and labor hours[5]. For example, the correlation between CORE uncertainty index and output growth is -0.24 over full sample period from 1973q1 to 2019q4 (see Table 1 for details).

[5]The sample period is from 1973Q1 to 2019Q4. We measure consumption as the sum of real personal consumption expenditures per capita on nondurable goods (FRED series: A796RX0Q048SBEA) and on services (A797RX0Q048SBEA). We measure investment as the sum of real personal consumption expenditures per capita on durable goods (A795RX0Q048SBEA) and real gross private domestic investment per capita on nonresidential fixed investment (constructed with series A008RO1Q156NBEA, PNFIC1 and B230RC0Q173SBEA). Output is measured as sum of real consumption and real investment. We measure

Table 1. Correlation b/w Output Growth and Real Uncertainty Measures

	$U_{t,t+1}^{\text{JLN}}$	$U_{t,t+1}^{\text{CORE}}$	$U_{t,t+1}^{y}$	$U_{t,t+1}^{c}$	$U_{t,t+1}^{n}$	$U_{t,t+1}^{b}$
Normal	-0.4847	-0.2359	-0.3280	-0.1568	-0.1043	-0.2733
Panel A: Financial Regime based on ANFCI						
Loose	-0.0254	0.0979	0.1480	-0.0191	0.2278	0.0529
Tight	-0.6725	-0.4199	-0.4731	-0.2172	-0.3012	-0.4134
Panel B: Financial Regime based on Financial Uncertainty Index						
Loose	-0.0742	0.1361	-0.1237	0.2039	0.1153	0.0043
Tight	-0.5422	-0.2827	-0.3416	-0.1704	-0.1767	-0.3091

Note: This table shows correlation coefficients of uncertainty measures with output growth in the data. $U_{t,t+1}^{JLN}$ represents extended real uncertainty index of Jurado et al. (2015) and Ludvigson et al. (2021). $U_{t,t+1}^{CORE}$ represents real uncertainty index constructed based on four core individual series (output, consumption, hours and credit). $U_{t,t+1}^{y}$, $U_{t,t+1}^{c}$, $U_{t,t+1}^{n}$, $U_{t,t+1}^{b}$ represents real uncertainty of output, consumption, hours and credit.

II.2. **Effect of financial factors on cyclicality of real uncertainty.** How do financial conditions affect the cyclicality of real uncertainty? To answer this question, we first sort the sample period into tight and loose financial regime based on Chicago Fed National Adjusted Financial Conditions Index (ANFCI), which provides a comprehensive estimate on U.S. financial conditions in financial markets and the traditional and "shadow" banking systems[6]. Positive values of the NFCI indicate financial conditions that are tighter than average, while negative values indicate financial conditions that are looser than average. As is shown in panel A of Table 1, the correlation between real uncertainty and output growth is negatively associated with tightness of financial condition. In regimes with looser financial condition, real uncertainty measures are uncorrelated with growth; when financial uncertainty is high, the correlations between real uncertainty measures and economic growth are significantly negative.

For robustness, we consider alternative measures of financial conditions. For example, we use index of financial uncertainty, which by construction is orthogonal to that of real

labor hour as total hours of wage and salary workers on nonfarm payrolls (TOTLQ), normalized by total time endowment.

[6]The adjusted NFCI isolates a component of financial conditions uncorrelated with economic conditions to provide an update on how financial conditions compare with current economic conditions. The data is archived from: https://fred.stlouisfed.org/series/ANFCI.

uncertainty (Ludvigson et al. (2021))[7]. We define loose(tight) regime if financial uncertainty index is lower(higher) than average. The estimates shown in panel B of Table 1 are consistent with results based on previous measure.[8]

The evidence suggests important role of financial factors in generating countercyclical endogenous uncertainty.

III. A RBC Model with Endogenous Debt Contract

III.1. **The firms.** Consider an infinite-horizon economy with a continuum of firms subject to idiosyncratic productivity and liquidity shocks. At the beginning of each period, aggregate shocks are realized. Before observing idiosyncratic productivity shocks (denoted as ε_{jt}), firms optimally choose amount of loan offered by risk-neutral and competitive creditors, which is used to finance working capital. After production, firms are subject to idiosyncratic liquidity shocks (denoted as ϕ_{jt}), and conditional on the realized liquidity shock, firms may choose to either repay the debt or to default. We assume each defaulting firm is replaced by a new entrant, so that total mass of firms is kept fixed over time.

Firms solve the following Bellman equation (suppressing aggregate state variables) by choosing optimal debt (b_t), labor (n_{jt}) and capital (k_{jt}):

$$V_t(\varepsilon_{jt}, \phi_{jt}) = \max_{b_t, k_{jt}, n_{jt}} l_t + A_t \varepsilon_{jt} k_{jt}^{\alpha} n_{jt}^{1-\alpha} - W_t n_{jt} - R_t k_{jt} + \max\{0, E_t M_{t+1} V_{t+1} - b_t - \phi_{jt}\}$$

where A_t is aggregate productivity shock, M_t is stochastic discount factor consistent with entrepreneur's consumption path and preference, ε_{jt} is idiosyncratic productivity shocks that are i.i.d. over time and across firm with cumulative distribution function $F(\varepsilon)$, and ϕ_{jt} is idiosyncratic liquidity shock that is also i.i.d. with C.D.F. $G(\phi)$. If expected value of continuation, net of liquidity shock, is insufficient to cover face value of the debt (denoted as b_t), firm chooses to default[9].

[7]The data is available at Sydney Ludvigson's website: https://www.sydneyludvigson.com/macro-and-financial-uncertainty-indexes.

[8]We also sort credit spread (Moody's seasoned Baa corporate bond yield relative to yield on 10-year treasury constant maturity, FRED series BAA10YM) into different regimes, and compute the conditional correlation. Within the same sample period, the correlations between output growth and two real uncertainty index are -0.10 (CORE) or -0.29(JLN) in low spread regime (below medium), and are -0.32(CORE) or -0.56 (JLN) in high spread regime (above medium). Using credit spread series following Gilchrist and Zakrajšek (2012) obtains consistent results, i.e., the correlations are -0.26 (CORE) or -0.35 (JLN) in low GZ-spread regime and are -0.35 (CORE) or -0.67 (JLN) in high GZ-spread regime. The results are robust when we sort financial regimes into finer regimes based on quartile bins. The results are reported in Table 4in Appendix.

[9]The underlying assumption is that firms can divert the cash from operational income away.

Firms are faced with a working capital constraint, such that they must pay upfront costs of labor and capital before production using external loans,

$$W_t n_{jt} + R_t k_{jt} \leq \int_{\phi_{jt} \in \Phi^n} b_t dG(\phi) \equiv l_t$$

where W_t and R_t denote the wage rate and capital rent that are common to all firms. Denote Φ^n as set of non-default states such that $\forall \phi_{jt} \in \Phi^n$, $E_t M_{t+1} V_{t+1} - b_t - \phi_{jt} \geq 0$.

Lemma III.1. *For a chosen value of b_t, there is a unique threshold of liquidity shock, denoted as ϕ_t^*, above which firm defaults. The cutoff is given as equation* (6).[10]

$$\phi_t^* = E_t M_{t+1} V_{t+1} - b_t \equiv q_t - b_t \tag{6}$$

Taken into account the default risk, risk-neutral and competitive lenders are willing to lend

$$l_t = G(\phi_t^*) b_t$$

to firms to finance their working capital cost, which implies a credit spread as [11]

$$SPR_t = 1 - G(\phi_t^*) \tag{7}$$

Conditional on realization of aggregate productivity shock and chosen value of b_t, the firms' problem can be rewritten as

$$\max_{k_{jt}, n_{jt}} (1 - SPR_t) b_t + A_t \varepsilon_{jt} k_{jt}^{\alpha} n_{jt}^{1-\alpha} - W_t n_{jt} - R_t k_{jt} + \int^{\phi_t^*} [\phi_t^* - \phi] dG(\phi)$$

subject to the following working capital constraint:

$$W_t n_{jt} + R_t k_{jt} \leq (1 - SPR_t) b_t$$

Lemma III.2. *There exists a cut-off productivity, denoted as ε_t^*, above which firms produce. The cut-off is given as equation* (8).

$$\varepsilon_t^* = \frac{1}{A_t} (\frac{R_t}{\alpha})^{\alpha} (\frac{W_t}{1-\alpha})^{1-\alpha} \tag{8}$$

The expected value (before realization of liquidity shock) of a firm with productivity ε_{jt} and predetermined debt b_t is

$$\tilde{V}_t(b_t, \varepsilon_{jt}) = \begin{cases} \frac{\varepsilon_{jt}}{\varepsilon_t^*}(1 - SPR_t) b_t + \int^{\phi_t^*} [\phi_t^* - \phi] dG(\phi), & \text{if} \quad \varepsilon_{jt} \geq \varepsilon_t^* \\ (1 - SPR_t) b_t + \int^{\phi_t^*} [\phi_t^* - \phi] dG(\phi), & otherwise \end{cases} \tag{9}$$

[10]Given that b_t is chosen before realization of i.i.d. ε_{jt} shock, the threshold is not firm-specific.

[11]Because intra-temporal risk-free interest rate is zero, interest spread in the model corresponds to the default probability.

where firms with productivity below the threshold (ε_t^*) hoard borrowed cash and stay inactive, and repay the debt ($= b_t$) only in non-default states (with probability $(1 - SPR_t) = G(\phi_t^*)$).

At the beginning of each period, firms choose the optimal level of debt to maximize the *ex ante* value of firms:

$$\bar{V}(A_t) = \max_{b_t} \int_{\varepsilon_t^*} (\frac{\varepsilon_{jt}}{\varepsilon_t^*} - 1) dF(\varepsilon)(1 - SPR_t) b_t + \int^{\phi_t^*} (q_t - \phi) dG(\phi) \tag{10}$$

The first order condition w.r.t. b_t gives

$$\int_{\varepsilon_t^*} (\frac{\varepsilon}{\varepsilon_t^*} - 1) dF(\varepsilon)(1 - SPR_t) = \left[\int_{\varepsilon_t^*} (\frac{\varepsilon}{\varepsilon_t^*} - 1) dF(\varepsilon) + 1 \right] g(q_t - b_t) b_t \tag{11}$$

Equation (11) states that benefit and cost of raising additional debt are equalized at the optimum. If a firm increases promise by one unit, credit increases by $G(q_t - b_t)$, which can be used to increase working capital and thus dividend by $(\frac{\varepsilon}{\varepsilon_t^*} - 1)$ per unit of fund. At the same time, one additional unit of promise will increase the default risk and the credit spread (i.e. increase the probability of default by $g(q_t - b_t)$) of existing debt (b_t), plus associated profit loss.

III.2. **The entrepreneur.** The representative entrepreneur owns all the firms, and has the utility function:

$$\mathbf{E} \sum_{t=0}^{\infty} \Phi_t (\beta^e)^t \log C_t^e \tag{12}$$

where β^e is the subjective discount rate of entrepreneurs that is lower than that of the household (β)[12]. Φ_t is intertemporal preference shock. Since entrepreneurs do not accumulate capital, consumption of them is simply aggregate flow profit of firms

$$C_t^e = D_t \tag{13}$$

such that

$$D_t \equiv [\int_{\varepsilon_t^*} (\frac{\varepsilon}{\varepsilon_t^*} - 1) dF(\varepsilon)](1 - SPR_t) b_t \tag{14}$$

The implied stochastic discount factor (SDF) is

$$M_{t+1} = \varphi_{t+1} \beta^e \frac{D_t}{D_{t+1}}, \tag{15}$$

where $\varphi_{t+1} = \frac{\Phi_{t+1}}{\Phi_t}$ is SDF shock (which is different from preference shock of household as it only directly affect firm's stochastic discount factor and borrowing constraint.).

[12]We introduce entrepreneurs with lower discount factor as a sufficient condition to ensure that entrepreneurs do not accumulate capital in equilibrium.

III.3. **The household.** The model economy is populated by a continuum of infinitely lived households with measure one. The representative household has the utility function

$$\mathbf{E}\sum_{t=0}^{\infty}\beta^t\left\{\ln C_t^h-\psi\frac{N_t^{1+\gamma}}{1+\gamma}\right\}, \tag{16}$$

where C_t^h denotes consumption, N_t denotes labor hours. The parameter $\beta\in(0,1)$ is a subjective discount factor, $\psi>0$ measures the relative weight on the disutility of working, and $\gamma\geq 0$ is the inverse Frisch elasticity of labor supply.

All markets are perfectly competitive. The household takes prices as given and maximizes the utility in Eq. (16) subject to investment adjustment cost,

$$K_{t+1}=(1-\delta_t)K_t+[1-\frac{\Omega_k}{2}(\frac{I_t}{I_{t-1}}-1)^2]I_t \tag{17}$$

and the budget constraint,

$$C_t^h+I_t=R_tu_tK_t+W_tN_t, \tag{18}$$

where K_{t+1} denotes the end-of-period capital stock, R_t denotes the capital rental rate, W_t denotes the real wage rate. The capital depreciation rate, denoted as δ_t, varies with capital utilization rate u_t, i.e.,

$$\delta_t=\delta_0\frac{u_t^{1+\eta}}{1+\eta} \tag{19}$$

where δ_0 is a constant and η measures elasticity of depreciation rate with respect to capital utilization rate.

Household's decision rules are characterized by the following equations:

$$\psi N_t^{\gamma}=\frac{1}{C_t}W_t \tag{20}$$

$$R_t=\delta_0u_t^{\eta} \tag{21}$$

$$1=Q_t\left(1-\frac{\Omega_k}{2}\left(\frac{I_t}{I_{t-1}}-1\right)^2-\Omega_k\left(\frac{I_t}{I_{t-1}}-1\right)\frac{I_t}{I_{t-1}}\right)+\beta E_t\frac{C_t^h}{C_{t+1}^h}Q_{t+1}\Omega_k\left(\frac{I_{t+1}}{I_t}-1\right)\left(\frac{I_{t+1}}{I_t}\right)^2 \tag{22}$$

where Q_t is Tobin's q that measures return to capital and it satisfies

$$Q_t=\beta E_t\frac{C_t^h}{C_{t+1}^h}\left(R_{t+1}u_{t+1}+(1-\delta_{t+1})Q_{t+1}\right) \tag{23}$$

III.4. **Stochastic Processes.**

III.4.1. *TFP shock.* Assume that aggregate productivity (A_t) follows an AR(1) process in log:

$$\log(A_t)=\rho_a\log(A_{t-1})+\sigma_a\varepsilon_t^a,\quad \varepsilon_t^a\sim N(0,1) \tag{24}$$

where ρ_a and σ_a denote persistence and volatility of aggregate TFP shocks.

III.4.2. *SDF shock.* Assume that SDF shock of entrepreneurs ($\varphi_t = \frac{\Phi_t}{\Phi_{t-1}}$) follows an AR(1) process in log:

$$\log(\varphi_t) = \rho_\varphi \log(\varphi_{t-1}) + \sigma_\varphi \varepsilon_t^\varphi, \quad \varepsilon_t^\varphi \sim N(0,1) \tag{25}$$

III.4.3. *Idiosyncratic productivity shock.* Assume that idiosyncratic productivity shock ε follows a Pareto distribution over support $[1, +\infty)$ with shape parameter ν:

$$F(\varepsilon) = 1 - \varepsilon^{-\nu} \tag{26}$$

III.4.4. *Idiosyncratic liquidity shock.* Assume that idiosyncratic liquidity shock ϕ follows a Pareto distribution over $[\underline{\phi}, +\infty)$, with shape parameter κ.

$$G(\phi) = 1 - (\frac{\phi}{\underline{\phi}})^{-\kappa} \tag{27}$$

III.5. **Equilibrium.** In a competitive equilibrium, markets for labor, capital, and final consumption goods all clear. The Cobb-Douglas production function implies that labor and capital income constitute constant proportion of productive credit (i.e. credit assigned to active producers), such that

$$W_t N_t = W_t \int n_{jt}(A_t, b_t, \varepsilon_{jt}) dF(\varepsilon) = (1-\alpha)[1 - F(\varepsilon_t^*)](1 - SPR_t) b_t \tag{28}$$

and that

$$R_t u_t K_t = R_t \int k_{jt}(A_t, b_t, \varepsilon_{jt}) dF(\varepsilon) = \alpha[1 - F(\varepsilon_t^*)](1 - SPR_t) b_t \tag{29}$$

Goods market clearing implies that[13]

$$Y_t = C^h + C^e + I_t + E(\phi) \tag{30}$$

where Y_t denote total output by active firms

$$Y_t = \int_{\varepsilon_t^*} \frac{\varepsilon}{\varepsilon_t^*} dF(\varepsilon)(1 - SPR_t) b_t \tag{31}$$

We define an utilization-adjusted measure of endogenous TFP as

$$Z_t = \frac{Y_t}{A_t (u_t K_t)^\alpha N_t^{1-\alpha}} = \frac{\int_{\varepsilon_t^*} \varepsilon F(\varepsilon)}{1 - F(\varepsilon_t^*)} \tag{32}$$

IV. Results

In this section we show that our model with financial friction can generate endogenously countercyclical uncertainty, say, a negative correlation between output growth and expected variance in forecast error (uncertainty), with first-moment TFP and/or SDF shocks.

[13]We keep total liquidity cost $E(\phi)$ fix over-time for clean exposition. To do so we implicit assume that liquidity cost due to defaulting firms is paid by entrants replacing them.

Table 2. Calibration

	Parameter Description	Value	Target/ Reference
β	Discount factor: Household	0.99	Risk-free interest rate
β^e	Discount factor: Entrepreneur	0.98	Excess equity return
γ	Inverse Frisch elasticity	0	Hansen (1985) and Rogerson (1988)
ψ	Utility weight on leisure	3.00	Average hours of 1/3 of time endowment
α	Capital share	0.35	Labor income share of 0.65
$\delta_0/(1+\eta)$	Steady state depreciation	0.025	Annual depreciation rate of 10%
η	Elasticity of DP to utilization	0.40	Wen (1998) and Liu and Wang (2014)
Ω_k	Inv. adjustment cost	0.71	Estimated using GMM
ν	Shape parameter of F()	5.7	Avg. economic profit
κ	Shape parameter of G()	2.8	Debt to quarterly GDP ratio
$\bar{\phi}/Y$	Fixed cost to output	0.12	Corporate Bond Spread
ρ_a	Persistence: TFP	0.95	Cooley and Prescott (1995)
σ_a	Volatility: TFP	0.0075	Cooley and Prescott (1995)
ρ_φ	Persistence: SDF	0.9741	Albuquerque et al. (2016)
σ_φ	Volatility: SDF	0.0017	Albuquerque et al. (2016)

IV.1. **Solution and Calibration.** The ergodic mean can vary a lot from deterministic steady state, thus each time we simulate the model for 500 periods to obtain the ergodic distribution, after which we simulate the model for 2000 periods to calculate the simulated moments [14].

To maintain comparability with the RBC literature with credit friction, we perform a standard calibration following Liu and Wang (2014) wherever possible. Table 2 summarises calibrated parameters. Each period equals a quarter in the model. Subjective discount factor for household is set to 0.99 to match risk-free annual rate of 4%. Discount factor for entrepreneurs is then set to 0.98 at the steady state, which implies excess return of about 4 percent on average (Liu et al. (2013), Liu and Wang (2014) etc.). We assume that $\gamma = 0$, following Hansen (1985) and Rogerson (1988). Utility weight on leisure, ψ, is set to match average hours of 1/3. α is set to 0.35 to match the labor income share of 65 percent in the US data. We set δ_0 to match quarterly rate of depreciation at 2.5%, with steady state capital utilization rate normalized to 1. We estimate parameter on investment adjustment cost Ω_k using GMM to match volatility and autocorrelation of investment, and obtain a value of 0.71

[14]Because the simulated shocks are randomly drawn, simulating the model for longer period reduces sampling errors and standard errors of estimation. Simulating for 1000 or 4000 periods gives similar results.

(within the range estimated in the literature with credit friction including Liu et al. (2013)). Shape parameter of Pareto distribution of idiosyncratic productivity shock, ν, is set to 5.7 to match average economic profit of 7% following Basu and Fernald (1997) and Liu and Wang (2014). Finally, Steady state κ and $\bar{\phi}$ are set to jointly match average quarterly bond spread (=0.60%) (corresponding to equation (7) in the model) and debt in non-financial corporate business to quarterly output ratio in the data (= 1.6) following Gilchrist et al. (2014), Chen et al. (2018) etc.[15].

The parameters governing the aggregate shock processes are calibrated following the literature. For example, the persistence and volatility of TFP shocks are set to 0.95 and 0.0075, consistent with the value in Cooley and Prescott (1995) and Gilchrist et al. (2014) etc. The discount factor shock corresponds to the valuation shock in Albuquerque et al. (2016), which directly affects the continuation value of firms. Thus, we set the persistence and volatility of this shock to 0.9741 and 0.0017 accordingly[16].

IV.2. **Endogenous Uncertainty.** We define uncertainty about output growth as Eq. (5), which is normalized by the standard deviation of output growth (Δy) in the ergodic distribution. Similarly, we can define uncertainty about growth rates of labor ($U^n_{t,t+1}$), capital($U^k_{t,t+1}$), endogenous component of TFP ($U^z_{t,t+1}$) and exogenous component of TFP($U^a_{t,t+1}$).

According to upper panel of Table 3, the baseline model with credit friction is promising to be explanatory to this endogenous uncertainty replying on first-moment shocks alone[17]. Uncertainty measures based on endogenous component of TFP ($U^z_{t,t+1}$) and labor ($U^n_{t,t+1}$) are also significantly countercyclical, while uncertainty about the exogenous process of TFP ($U^a_{t,t+1}$) does *not* show any statistically significant cyclicality. As second moment shocks are absent in the model, the negative correlation between uncertainty and output must be driven by an endogenous response to first moment shocks.

To understand the mechanism that generate endogenous uncertainty, we investigate the effect of TFP shock and SDF shock.

IV.2.1. *Effects of TFP Shock.* Figure 2 shows the impulse response of the model to a 1 s.d. positive TFP shock.

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[15]The data on bond spread is based on Moody's seasoned Baa corporate yield relative to yield on 10-year treasury with constant maturity, and debt-to-GDP is measured based on total non-financial corporate business outstanding debt.

[16]We translate the monthly values of 0.991 and 0.0006 in Albuquerque et al. (2016) to quarterly frequency.

[17]The baseline model contains both aggregate productivity and SDF shocks. In appendix I show the results are robust with TFP shock or SDF shock alone.

Table 3. Simulated Correlation b/w Output Growth and Real Uncertainty

	$U_{t,t+1}^{CORE}$	$U_{t,t+1}^{y}$	$U_{t,t+1}^{c}$	$U_{t,t+1}^{n}$	$U_{t,t+1}^{b}$
Benchmark	-0.3234	-0.3152	-0.1993	-0.4638	-0.3152
		(0.0385)	(0.0410)	(0.0371)	(0.0385)
Counterfactual: Loose financial condition with lower $\bar{\phi}$					
Loose	-0.2077	-0.1566	-0.0831	-0.4344	-0.1566
		(0.0385)	(0.0386)	(0.0341)	(0.0385)

Note: This table shows correlation coefficients of uncertainty measures with output growth from simulated benchmark model with aggregate TFP and SDF shocks. $U_{t,t+1}^{y}$, $U_{t,t+1}^{c}$, $U_{t,t+1}^{n}$, and $U_{t,t+1}^{b}$ represent real uncertainty measures of output, consumption, hours, credit, endogenous TFP and exogenous productivity respectively. $U_{t,t+1}^{CORE}$ represents the core index of real uncertainty as simple average of four individual series. The standard errors are shown in the parentheses. In counterfactual economy of loose financial regime, we set $\bar{\phi}$ to be 25% lower than benchmark value.

A positive TFP shock generates a synchronized increase in aggregate variables through two channels. A persistent and positive productivity shock directly raises firm value. Higher equity price relaxes the credit constraint for productive firms, pushing up factor prices and crowding out low-productivity firms. The reallocation effects towards high-productivity firms, manifested as lower output dispersion, raise endogenous TFP and amplify the expansion output (This is the reallocation channel highlighted in Liu and Wang (2014)). At the same time, high aggregate productivity increases continuation value of firms, and reduces the default risk. Thus, firms can choose debt contract with higher face value and lower spread. The endogenous leverage channel generate a credit boom and further expansion in output. The two channels compounds each other in generating amplified expansion in credit and production with two-way feedback loop.

. The impulse responses to TFP shock feature overshooting, which usually arises due to complex eigenvalue but is quite common in the literature (i.e. Rios-Rull and Santaeulalia-Llopis (2010) and Liu and Wang (2014)), and is desirable for being able to generate boom-bust cycles even absent of additional shocks.

IV.2.2. *Effects of SDF Shock.* Figure 3 shows the impulse response of the model to a 1 s.d. positive SDF shock.

A positive shock to intertemporal preference of entrepreneurs increases the continuation value of firms. Given chosen face value of debt, higher continuation value reduces the probability of default and credit spread, raising the value of debt contract. Relaxed borrowing

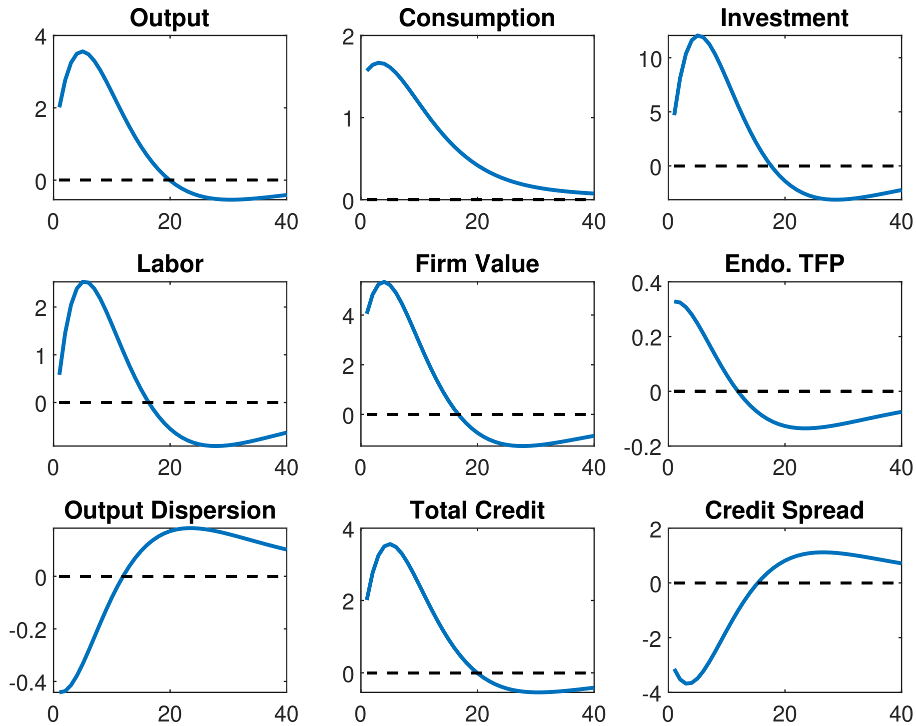

FIGURE 2. IRFs to TFP Shock

Note: This figure shows the impulse responses to a one-standard-deviation shock to TFP in calibrated model. The horizontal axis shows the periods (quarters) since the impact of the shock. The vertical axis shows the percent deviations of each variable from its stochastic steady-state level.

constraint pushes up the factor prices, reallocates resources towards more productive firms and reduces cross-sectional output dispersion. Thus, the SDF shock can generate a boom with synchronized expansion in output, consumption, investment and labor hours [18].

IV.3. **State-dependent effects and procyclical leverage.** Countercyclical uncertainty, that precision of rational forecasts is lower in bad times than in good times, stems from state-dependent effects from the same shocks. If the shocks have equally large impact across states, uncertainty should be a-cyclical. In current theory the key mechanism to generate this asymmetric response is procyclical leverage. With presence of liquidity shock in our model, the borrowing constraint is disproportionately tighter in bad times relative to boom times, generating larger response to negative shocks.

To illustrate the state-dependent effect, consider two economies initially at the steady state. The first economy is hit by a negative, transitory TFP shock, while the second is hit by a positive one. The upper left panel of Figure 4 shows the response of leverage, defined

[18] Similar to those from TFP shock, the effects are also asymmetric between positive and negative shock.

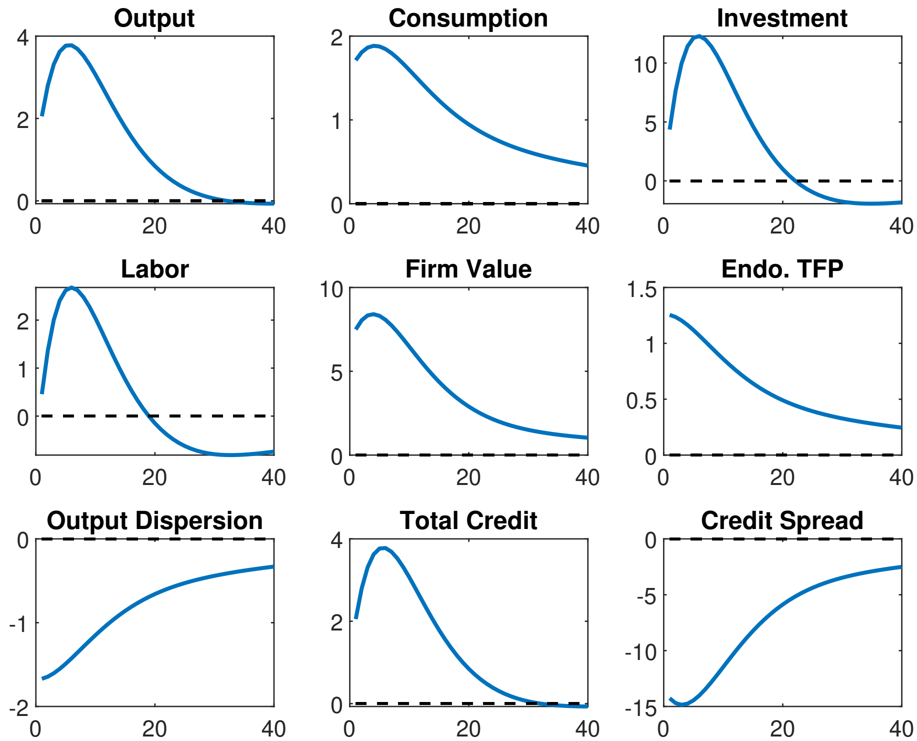

Figure 3. IRFs to SDF Shock

Note: This figure shows the impulse responses to a one-standard-deviation shock to stochastic discount factor of entrepreneurs in the calibrated benchmark model. The horizontal axis shows the periods (quarters) since the impact of the shock. The vertical axis shows the percent deviations of each variable from its stochastic steady-state level.

as ratio of loan granted to continuation value of firm, in two states. It's obvious that the leverage drops in the recession, and the drop from the steady state level is larger than the increase in boom. We then simulate the two economies with an additional TFP shock of the same magnitude, and compare the response of output between two states. As is shown in the upper right plot, the response measured as percentage deviation from steady state is dramatically larger in recession state when credit constraint is disproportionately tightened.

Pro-cyclical leverage, for example higher loan to value ratio in boom than recession, implies that the amplification effect due to credit constraint is weaker in good times when since tightness of borrowing constraint is relaxed. It is consistent with the stylized facts that rational forecast is less precise in recession. The state-dependent effects will be mitigated if the loan-to-value ratio is time-invariant. To show it, we perform the same simulation in a counterfactual economy, where loan-to-value ratio is fixed at the steady state level of the baseline economy. The lower panel of Figure 4 plots the responses of leverage and output

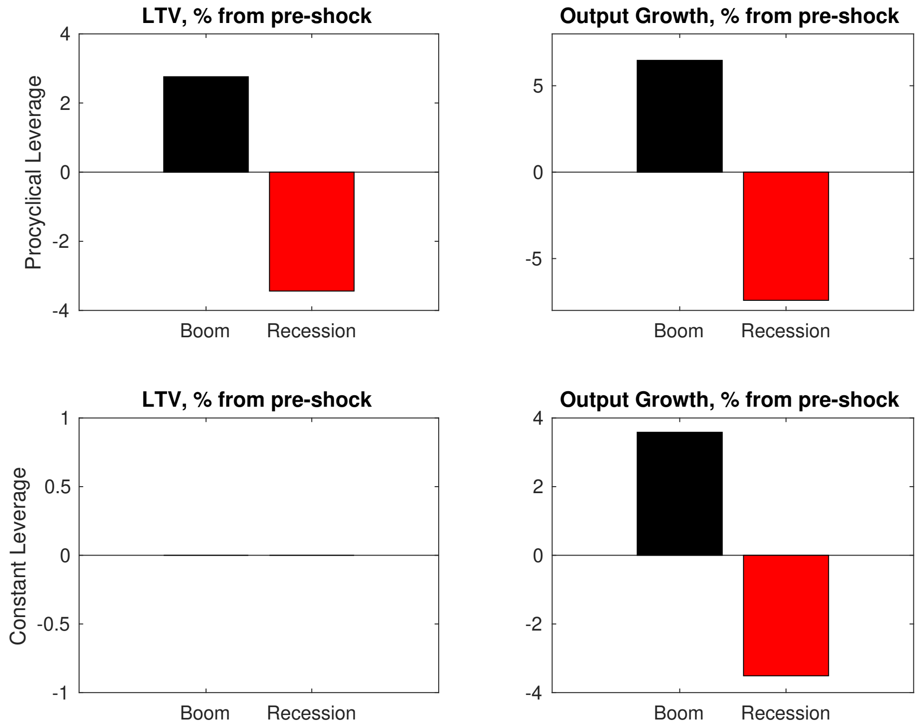

FIGURE 4. Pro-cyclical leverage and state-dependent effects

Note: The upper (lower) panel plots the response of leverage and output in the baseline (counterfactual) economy from the pre-shock level to a one-standard-deviation TFP shock in boom and recession state. Black bars show the responses at the impact period when the aggregate economy is in good state, and red bars represent the responses in bad state. Adjustment cost is removed to facilitate comparison at the impact period.

in the counterfactual economy. When the leverage is kept constant, output's responses from boom or recession state are of same magnitude, suggesting that procyclical leverage is crucial to generate state-dependent effects.

IV.4. **The role of financial friction.** Our evidence suggests that financial friction, especially procyclical leverage, is crucial to generate countercyclical response of endogenous uncertainty. We now illustrate the quantitative importance of credit constraint by showing that uncertainty is less countercyclical in a less constrained economy.

The value of $\bar{\phi}$ in counterfactual economy is 25% lower than that in the benchmark economy, implying a lower steady-state credit spread(i.e. less financial friction). As is shown in the bottom panel of Table 3, in the counterfactual economy correlations (in absolute value) between output growth and uncertainty measures are lower than those in the baseline model. In appendix, we plot the impulse response of to TFP and SDF shock, and the responses are dampened in this counterfactual economy with less financial friction. The results suggest that credit constraint amplifies the counter-cyclicality of real uncertainty, echoing the stylized facts documented in Table 1.

IV.5. **Effects of Financial Uncertainty Shocks.** While our model produces endogenous response of uncertainty to fundamental shocks, it doesn't debunk the theory that second-moment uncertainty shocks can drive business fluctuations. Ludvigson et al. (2021) find that positive shocks to financial uncertainty, a type of 'second moment' variable that could arise because of expected volatility in financial markets such as fear of bankruptcy, are a driving force of declines in real activity. We illustrate that our model is consistent with such observation by showing the effects of a second moment shock on liquidity risk.

To do so, assume that κ is time-varying and follows an AR(1) process in log:

$$\log(\kappa_t) = (1-\rho_f)\log(\kappa) + \rho_f \log(\kappa_{t-1}) + \sigma_f \varepsilon_t^F, \quad \varepsilon_t^f \sim N(0,1) \tag{33}$$

where ρ_f and σ_f measure the persistence and volatility of financial uncertainty shock. We set $\underline{\phi}_t = \bar{\phi}\frac{\kappa_t}{\kappa_t - 1}$ to ensure that $E(\phi) = \bar{\phi}$ is constant. We set the persistence of uncertainty shock ρ_f to 0.76 following Leduc and Liu (2016), and normalize the volatility σ_f to 0.01.

Figure 5 shows the impulse response of the model to this financial uncertainty shock. The model is able to qualitatively generate realistic output fluctuations following a financial uncertainty shock. An expected rise in dispersion of idiosyncratic liquidity shock increases the risk of default, and thus the credit spread. Taken this into consideration, the firms optimally choose to reduce level of debt, thus total credit capacity shrinks. The decline in credit reduces equilibrium wage and capital rent, inducing more low-productivity firms to produce. Therefore, endogenous TFP declines, and the model generates synchronized decline in output, consumption and investment.

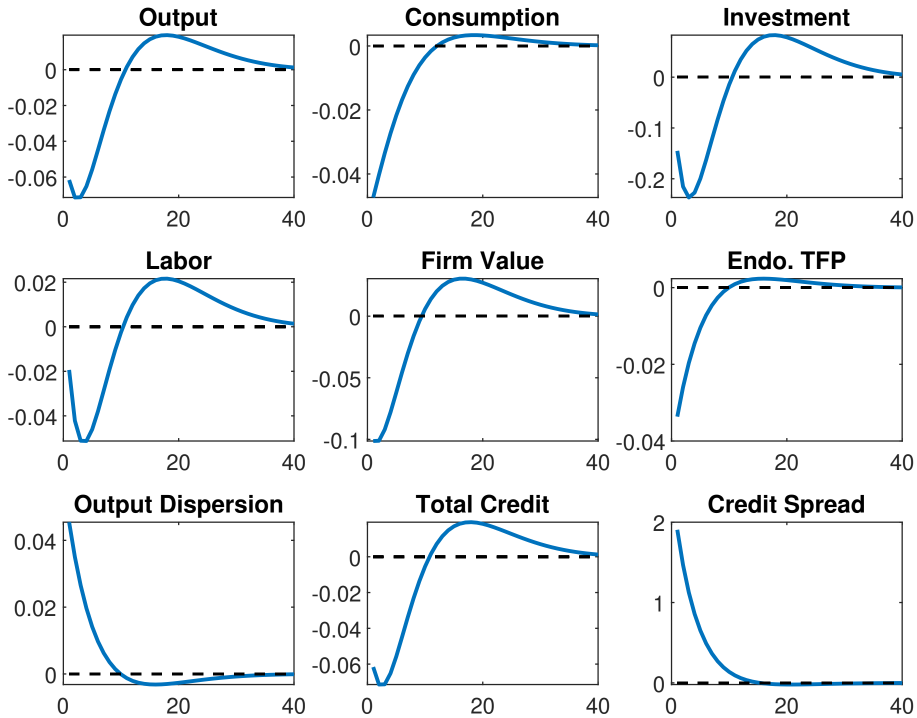

Figure 5. IRFs to Financial Uncertainty Shock

Note: This figure shows the impulse responses to a one-standard-deviation mean-preserving shock to liquidity shock in the calibrated benchmark model. The horizontal axis shows the periods (quarters) since the impact of the shock. The vertical axis shows the percent deviations of each variable from its stochastic steady-state level.

V. Conclusion

We have studied an RBC model with heterogeneous firms, in which financial frictions give rise to countercyclical uncertainty, as observed in the data. In the model, firms face working capital constraints, and default risks limit the access of productive firms to external credit. In a recession, a negative first-moment shock (such as a TFP shock or a discount factor shock) reduces firms' borrowing capacity and production disproportionately more than a positive shock raises the borrowing capacity and production in a boom. Such asymmetric (or state dependent) responses of aggregate variables imply a larger conditional variance of forecast errors in a recession than in a boom, giving rise to countercyclical uncertainty. Consistent with empirical evidence, the model predicts that uncertainty is less negatively correlated with aggregate output growth in periods with less financial stress. Furthermore, following an exogenous increase in financial uncertainty, our model can generate a recession with synchronized declines in output, consumption, investment, and labor hours without requiring correlated first-moment shocks or the presence of nominal rigidities. The key to generating such business cycle comovements in our model is a reallocation channel stemming from financial frictions.

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VI. Appendix

VI.1. **Empirical Appendix.** For robustness, we sort the sample period into tight and loose financial regime based on different measures of credit spread. High values of the credit spread indicate financial conditions that are tighter than average. As is shown in three panels of Table 4, the correlation between real uncertainty and output growth is negatively associated with tightness of financial condition. In regimes with looser financial condition, real uncertainty measures are less correlated with growth; when financial uncertainty is high, the correlations between real uncertainty measures and economic growth are significantly negative.

Table 4. Correlation b/w Output Growth and Real Uncertainty

	$U_{t,t+1}^{\text{JLN}}$	$U_{t,t+1}^{\text{CORE}}$	$U_{t,t+1}^{y}$	$U_{t,t+1}^{c}$	$U_{t,t+1}^{n}$	$U_{t,t+1}^{b}$
Average	-0.4847	-0.2359	-0.3280	-0.1568	-0.1043	-0.2733
Panel A: Financial Regime Based on Credit Spread (Baa)						
Loose	-0.2944	-0.0997	-0.1533	-0.1404	0.0643	-0.0708
Tight	-0.5560	-0.3126	-0.4018	-0.1882	-0.2131	-0.3592
Panel B: Financial Regime Based on GZ Credit Spread Index						
Loose	-0.3474	-0.2617	-0.3071	-0.2653	-0.0897	-0.1170
Tight	-0.6719	-0.3475	-0.5213	-0.1591	-0.3433	-0.3813
Panel C: Financial Regime Based on GZ Excess Bond Premium						
Loose	-0.3452	-0.1502	-0.3015	-0.1125	-0.0514	-0.0610
Tight	-0.5205	-0.2137	-0.3173	-0.0821	-0.1318	-0.3331

Note: This table shows correlation coefficients of uncertainty measures with output growth in the data. $U_{t,t+1}^{JLN}$ represents extended real uncertainty index of Jurado et al. (2015) and Ludvigson et al. (2021). $U_{t,t+1}^{CORE}$ represents real uncertainty index constructed based on four core individual series (output, consumption, hours and credit). $U_{t,t+1}^{y}$, $U_{t,t+1}^{c}$, $U_{t,t+1}^{n}$, $U_{t,t+1}^{b}$ represents real uncertainty of output, consumption, hours and credit. Credit spread (Baa) is Moody's seasoned Baa corporate bond yield relative to yield on 10-Year treasury constant maturity (FRED series BAA10Y), GZ credit spread and excess bond premium are constructed based on Gilchrist et al. (2014).

VI.2. **Model Appendix.**

VI.2.1. *Simulated correlation b/w output growth and real uncertainty (TFP shock).* Table 5 reports correlation b/w output growth and real uncertainty in a simulated model with TFP shock alone.

TABLE 5. Simulated Correlation b/w Output Growth and Real Uncertainty (TFP Shock)

	$U^{CORE}_{t,t+1}$	$U^{y}_{t,t+1}$	$U^{c}_{t,t+1}$	$U^{n}_{t,t+1}$	$U^{b}_{t,t+1}$
Benchmark	-0.2099	-0.1726	-0.1083	-0.3860	-0.1726
		(0.0383)	(0.0386)	(0.0354)	(0.0383)
Counterfactual: Loose financial condition with lower $\bar{\phi}$					
Loose	-0.1413	-0.1215	-0.0731	-0.3225	-0.1215
		(0.0384)	(0.0386)	(0.0358)	(0.0384)

Note: This table shows correlation coefficients of uncertainty measures with output growth from simulated benchmark model with aggregate TFP shocks. $U^{y}_{t,t+1}$, $U^{c}_{t,t+1}$, $U^{n}_{t,t+1}$, and $U^{b}_{t,t+1}$ represent real uncertainty measures of output, consumption, hours, credit, endogenous TFP and exogenous productivity respectively. $U^{CORE}_{t,t+1}$ represents the core index of real uncertainty as simple average of four individual series. The standard errors are shown in the parentheses. In counterfactual economy of loose financial regime, we set $\bar{\phi}$ to be 25% lower than benchmark value.

VI.2.2. *Simulated correlation b/w output growth and real uncertainty (SDF shock).* Table 6 reports correlation b/w output growth and real uncertainty in a simulated model with SDF shock alone.

Table 6. Simulated Correlation b/w Output Growth and Real Uncertainty (SDF Shock)

	$U_{t,t+1}^{CORE}$	$U_{t,t+1}^{y}$	$U_{t,t+1}^{c}$	$U_{t,t+1}^{n}$	$U_{t,t+1}^{b}$		
Benchmark	-0.2715	-0.2219	-0.1524	-0.4900	-0.2219	-0.1385	-0.0260
		0.0401)	(0.0416)	(0.0312)	(0.0401)	(0.0418)	(0.0473
Counterfactual: Loose financial condition with lower $\bar{\phi}$							
Loose	-0.1472	-0.1241	-0.0825	-0.4047	-0.1241	-0.0755	0.0525
		(0.0391)	(0.0394)	(0.0329)	(0.0391)	(0.0394)	(0.0451)

Note: This table shows correlation coefficients of uncertainty measures with output growth from simulated benchmark model with aggregate SDF shocks. $U_{t,t+1}^{y}$, $U_{t,t+1}^{c}$, $U_{t,t+1}^{n}$, and $U_{t,t+1}^{b}$ represent real uncertainty measures of output, consumption, hours, credit, endogenous TFP and exogenous productivity respectively. $U_{t,t+1}^{CORE}$ represents the core index of real uncertainty as simple average of four individual series. The standard errors are shown in the parentheses. In counterfactual economy of loose financial regime, we set $\bar{\phi}$ to be 25% lower than benchmark value.

VI.2.3. *Impulse response of counterfactual economy.* Figure 6 and 7 plot impulse response of counterfactual economy(red dashed lines) with lower $\bar{\phi}$ against benchmark economy(blue solid lines) under TFP shocks and SDF shocks respectively. Fluctuations are dampened in the counterfactual economy with less severe financial friction. (A in counterfactual economy is re-scaled to ensure two economies has the same steady state output.)

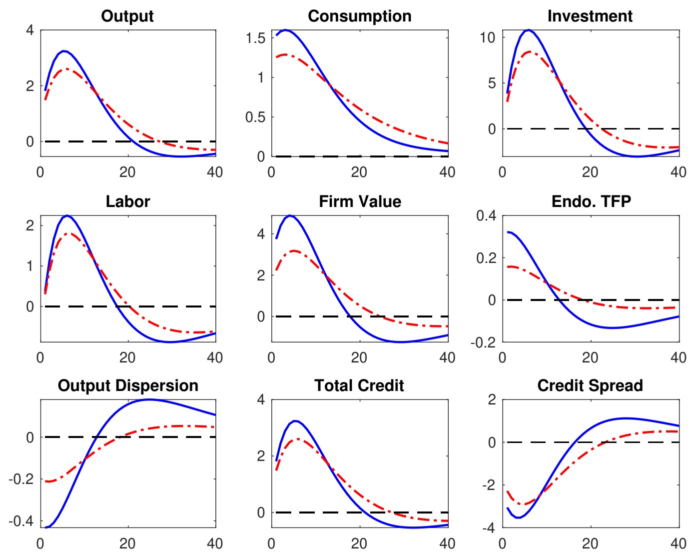

FIGURE 6. Counterfactual Economy: IRFs to TFP Shock

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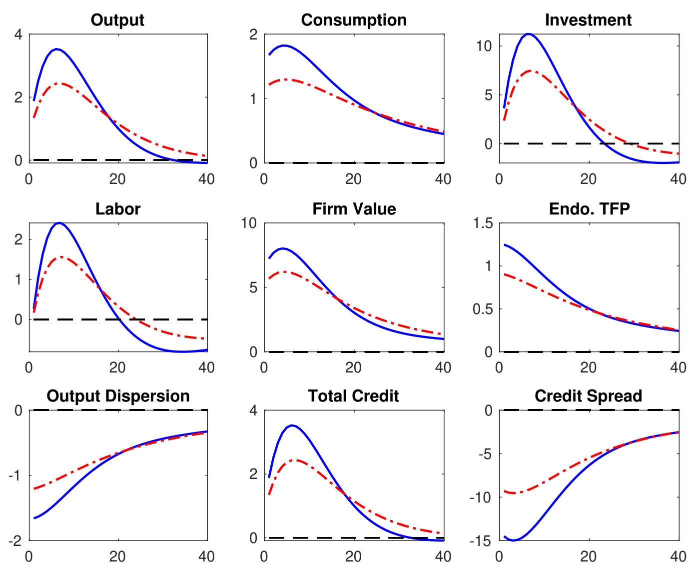

FIGURE 7. Counterfactual Economy: IRFs to SDF Shock

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