WORKING PAPER

DANMARKS NATIONALBANK

13 APRIL 2023 — NO. 194

When credit expansions become troublesome:

The story of investor sentiments

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Abstract
Identifying the drivers of credit cycles is crucial for prudential regulation. We show in a model that investor sentiments result in excessive asset price movements, leading to sharp credit reversals. Motivated by this, we decompose fluctuations in stock prices into fundamental and noise shocks and estimate their effects on credit. Both shocks lead to a credit expansion, but only a noise shock results in a reversal if the anticipated shock fails to realise. Noise shocks have stronger effects when risk premiums are low. A novel debt overhang channel is important for the propagation of noise shocks.

Resume
Det er er afgørende for prudentiel regulering at identificere faktorerne bag kreditcykler. Vi viser i en model, at ændringer i investortillid resulterer i store bevægelser i aktivpriser, hvilket fører til markante kreditudsving. Motiveret heraf dekomponerer vi prisudsving i aktiekurser i fundamentale stød og stød, som er et udtryk for støj, og estimerer reaktioner i kredit til disse stød. Begge stød fører til en kreditudvidelse, men det er kun stødet indeholdende støj, som resulterer i et fald i kredit. Vi undersøger forskelle i transmissionen i perioder med hhv. høje eller lave risikopræmier. En ny "gældsoverhængskanal" er vigtigt for transmissionen af stød bestående af støj.

Key words
Credit cycles; news shocks; noise shocks; debt overhang; bank lending

JEL classification
E440; G240; G280

Acknowledgements
We thank seminar participants at the Bank of England and Danmarks Nationalbank as well as participants at the 2022 CEBRA conference and the 2022 Money, Macro and Finance conference for comments. This paper represents solely the view of the authors and does not in any way reflect the opinions of Bank of England, PRA, Danmarks Nationalbank, European Central Bank or those of the Eurosystem or ESCB.

When credit expansions become troublesome: The story of investor sentiments*

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April 2023

Abstract

Identifying the drivers of credit cycles is crucial for prudential regulation. We show in a model that investor sentiments result in excessive asset price movements, leading to sharp credit reversals. Motivated by this, we decompose fluctuations in stock prices into fundamental and noise shocks and estimate their effects on credit. Both shocks lead to a credit expansion, but only a noise shock results in a reversal if the anticipated shock fails to realise. Noise shocks have stronger effects when risk premiums are low. A novel debt overhang channel is important for the propagation of noise shocks.

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1 Introduction

Credit growth is a widespread but imperfect indicator of the *actual* risks in the financial system. A popular narrative is that credit is susceptible to non-fundamental increases in asset prices, allowing credit to grow beyond its long-term average.[1] Classic examples are the credit boom and bust in Japan during the 1980s, the telecommunications sector swing in the US in the late 1990s or the mortgage credit booms in the pre-2008 period in countries such as the US, Ireland, Spain, and Denmark.[2] However, several historical episodes deviate from this narrative. One can have a notable increase in corporate credit but without a substantial build-up of systemic risks, like in the case of the US during the 1980s or China during the 2010s.

This paper investigates, theoretically and empirically, how non-fundamental shocks can lead to boom-bust cycles. We present a macroeconomic model of credit demand-driven boom-bust cycles. Agents in the model receive a noisy signal about future productivity. We refer to a signal that turns out to be correct as a news shock, and a signal that turns out to be incorrect as a noise shock. In the model, the leverage of firms and financial intermediaries is endogenous. The key novel element in the model is defaultable long-term debt, which is a realistic assumption, given that most debt of US firms is long-term. Such debt leads to persistent leverage dynamics that can endogenously generate boom-bust cycles in response to noise shocks. Next, we empirically investigate how noise shocks affect credit and the real economy. In line with the model's predictions, news and noise shocks lead to credit booms; however, only noise shocks lead to busts. Thus, credit growth is only an imperfect indicator of the *actual* risks in the financial system.

The theoretical model makes two predictions, which work through a novel debt overhang channel. First, news and noise shocks lead to a boom in credit and the real economy. Credit demand drives this credit boom. In response to higher expected future productivity, firms invest more. Also, future default risk falls, which reduces credit spreads. Consequently, firms issue more debt. Endogenous credit supply amplifies the credit boom because the fall in credit spreads increases the net worth of financial intermediaries, which relaxes their financial constraints. Whether news or noise shocks drive a credit boom is not distinguishable with contemporaneous information available.

Second, noise shocks lead to a bust in credit and the real economy, while news shocks do not. Boom-bust cycles are the result of a debt overhang effect (Myers (1977)) and a leverage ratchet effect (Admati et al. (2018)). These effects arise endogenously because of

1. See, e.g., Mishkin (2008).

2. Kaplan, Mitman, and Violante (2020) discuss the mechanisms behind such a noise-driven housing boom. Commonly, a positive outlook on asset prices assures lenders that it is safe to lend, as the future collateral value more than compensates for the additional default risk of a particular borrower the lenders take on.

defaultable long-term debt. A news shock to productivity leads firms and intermediaries to increase their debt. If the news shock fails to realise, firms maintain a high leverage because of the leverage ratchet effect. The high leverage drags investment down because of the debt overhang effect. Future default risk rises, and credit spreads fall. Endogenous credit supply amplifies the bust, as higher credit spreads reduce the net worth of financial intermediaries.

Empirical evidence reconciles the predictions from the theoretical model and finds support for the novel debt overhang channel. We empirically investigate the effects of news and noise shocks on the US economy. To do so, we build on the literature that extracts news and noise shocks from asset prices (Forni et al. (2017a), Forni et al. (2017b), Chahrour and Jurado (2022)) and use local projections (Jordà (2005), Plagborg-Møller and Wolf (2020b)) to estimate the impulse responses of credit, asset prices and macroeconomic variables to news and noise shocks.[3] We obtain two main results. First, news and noise shocks lead to a rise in credit and a fall in credit spreads. The credit booms following either a news shock or a noise shock are indistinguishable, in line with the model. Second, only noise shocks lead to a credit bust and a recession. We show that a key element in the credit bust is the slow deleveraging of firms, and thereby provide direct evidence for the main mechanism of the model, which operates through persistent leverage dynamics.

In addition, we investigate the state-dependent effects of noise shocks. We find that noise shocks have larger effects during periods of low risk premiums. These results align with our theoretical model. The mechanism behind this stronger amplification during times of lenient credit supply works as follows. If (credit supply) conditions are lenient, financial intermediaries can use more leverage. This ability to use more leverage, in turn, implies that their net worth is more exposed to the fluctuations in the price of debt caused by the noise shock. As a result, credit supply is more responsive to the noise shock.

Our paper contributes to multiple strands of the literature. The first is the literature on credit and asset price booms. We contribute to this literature by showing, theoretically *and* empirically, that noise shocks extracted from asset prices can be powerful drivers of boom-bust cycles. That credit booms predict financial crises is a well-established fact in the empirical literature (e.g. Schularick and Taylor (2012), Jordà, Schularick, and Taylor (2011)). Moreover, the empirical literature has established that there is a mispricing of risks over the business cycle and around financial crises, which some studies have attributed to investor sentiment (López-Salido, Stein, and Zakrajšek (2017)) or credit market froth (Krishnamurthy and Muir (2017)). Likewise, many credit booms are associated with asset price surges, yet that is not a rule. In a cross-country study, Bordo and Landon-Lane (2013) find that "loose" monetary policy - i.e. either interest

3. That allows identifying, ex-post, how close or far a particular economy was from an undesired credit swing.

rate below the target rate or a growth rate of money above the target growth rate - *does* fuel inflation across multiple asset classes, and this correspondence increases during periods of rapid asset prices growth. Mendoza and Terrones (2012) identify a systematic relationship between credit booms and a boom-bust cycle in production and absorption, asset prices, real exchange rates, capital inflows, and external deficits. Illing, Ono, and Schlegl (2018) go a step further to argue that (financially) more deregulated economies are more likely to experience persistent stagnation.

Second, we contribute to the literature on news shocks and business cycles. Our contribution is to present a model in which news shocks that fail to realise can generate boom-bust cycles and to empirically validate the predictions from the model. More specifically, we contribute to this literature by proposing debt overhang as a novel mechanism that can generate boom-bust cycles in response to noise shocks. The closest papers to this are Forni et al. (2017a), Forni et al. (2017b), and Chahrour and Jurado (2022), which investigate the macroeconomic effects of noise shocks. However, they do not focus on credit. Görtz and Tsoukalas (2017) and Görtz, Tsoukalas, and Zanetti (2022) investigate the importance of credit supply for the amplification of news shocks. However, they do not consider noise shocks. Faccini and Melosi (2022) propose a model with labour market frictions in which noise shocks generate boom-bust cycles. However, they do not consider financial frictions. Lagerborg, Pappa, and Ravn (2022) show that sentiment shocks, identified using mass shootings, can have large effects on real activity. However, they do not look at credit as an outcome variable. We link and examine all these outcomes.

In an influential early paper, Beaudry and Portier (2006) show how joint movement in stock prices and TFP represent news about future technological opportunities embedded in stock prices. This shock causes a boom in consumption, investment, and hours worked that precedes productivity growth by a few years. They argue that this news shock can explain about 50% of business cycle fluctuations. Benati et al. (2020) have since refined the method to distinguish news from noise shocks and their macroeconomic impact, building on the criticism of identification equivalence raised by Chahrour and Jurado (2018). Whether news shocks are important drivers of business cycles has since become an active literature, see, e.g., Jaimovich and Rebelo (2009), Barsky and Sims (2012), Schmitt-Grohé and Uribe (2012), Blanchard, L'Huillier, and Lorenzoni (2013), or Barsky, Basu, and Lee (2015).

Moreover, not all noise is born the same. Fraiberger et al. (2021) find a sharp contrast between the effect of local and global news. Whereas local news optimism (pessimism) predicts a small and transitory increase (decrease) in local equity returns, global news sentiment has a larger impact on returns, which does not reverse in the short run. However, large variations in global news sentiment predominantly happen without new information about fundamentals, suggesting they are mainly due to noise. They conclude that global news and noise drive local asset prices.[4]

This paper contributes to the ongoing policy debate in various ways. First, it gives policymakers guidance on how to identify the shocks behind a credit swing and to predict the impact on the future realisation of real variables. The particular attraction is that future outcomes can be linked to current structural elements, allowing early policy design and implementation to prevent undesired outcomes.

Another critical issue policymakers are battling is whether increasing and fostering reliance on market-based finance is desirable. Considering banks' current business model challenges, and low price-to-book ratios over the past decade, many institutions are turning to non-banks or market providers of credit to satisfy their excess credit demand. However, there is a lack of evidence on how stable or reliable those sources are, particularly in the long run. By examining many historical episodes of credit swings and contrasting total financial sector *vis-a-vis* bank credit, this paper can provide some answers to this dilemma.

Finally, this paper contributes to the debate on asset price inflation and credit expansions. There is a broad consensus that strong asset price inflation has preceded most credit expansions and persists for the duration of the credit boom. Our analysis provides the underlying conditions for such boom-bust cycle. We distinguish it from the other possible scenarios including a non-asset price-fueled credit surge, or an asset price boom without a credit expansion. The ability to distinguish between the different mechanisms is essential for deciding whether policymakers should intervene. In the current context of high inflation across asset classes but without a substantial increase in bank credit, policymakers need help in identifying the underlying causal relation.

Section 2 presents the model. Section 3 characterizes the equilibrium. Section 4 shows how noise shocks lead to credit boom-bust cycles, while news shocks do not. The main empirical results about the effects of news and noise shocks are presented in section 5. We discuss the historical importance of noise shocks for the credit cycle in section 6. Section 7 concludes.

2 Model

To explain how defaultable long-term debt can lead to boom-bust cycles in response to noise shocks, we develop a simple, stylised model. The model is simple enough that we can show many important mechanisms in closed form. There are three periods, $t = 1, 2, 3$.

4. Akıncı and Chahrour (2018) show that noise shocks can lead to credit booms with sharp reversals in an open economy model with occasionally binding borrowing constraints. Ozhan (2021) studies the effects of news shocks on credit in a two-country model.

There are workers, entrepreneurs, firms, and financial intermediaries. Workers work and supply deposits to financial intermediaries, and financial intermediaries use deposits and their net worth to finance long-term bonds to entrepreneurs. Entrepreneurs own the capital stock, lend it to firms, and finance it with risky long-term bonds and equity. Firms use capital and labour to produce output. Productivity in period 2 is stochastic. In period 1, agents receive a noisy signal about period 2 productivity.

2.1 Workers

In periods 1 and 2, workers consume C_t and save in the form of risk-free short-term deposits D_t. Deposits earn a risk-free return R_t^D in the subsequent period. In period 3, workers consume. They are risk-neutral and have a discount factor of one. They inelastically supply labour L, which earns a wage W_t. In the initial period, workers hold some deposits from banks.

The problem of a worker in period 1 is

$$V_1 = \max_{C_1, D_1} C_1 + E_1 [V_2],$$

subject to

$$C_1 + D_1 = W_1 L + D_0.$$

The problem of a worker in period 2 is

$$V_2 = \max_{C_2, D_2} C_2 + E_2 [V_3],$$

subject to

$$C_2 + D_2 = W_2 L + R_1^D D_1,$$
$$V_3 = C_3 = W_3 L + R_2^D D_2.$$

2.2 Firms

Firms combine labour from workers and capital from entrepreneurs to produce output according to a production function with constant returns to scale. They choose capital K_{t-1} and labour L_t to maximise profits, taking factor prices W_t and r_t^K as given. The problem of a firm is

$$\max_{K_{t-1},L_t} Z_t K_{t-1}^{\alpha} L_t^{1-\alpha} - W_t L_t - r_t^K K_{t-1}. \tag{2.1}$$

Productivity Z_t evolves as follows. In period 1, productivity is constant and normalised to unity: $Z_1 = 1$. At the beginning of period 1, agents receive a signal S_1 about productivity in period 2.

$$S_1 = a_1 + e_1. \tag{2.2}$$

The signal therefore has a news component $a_1 \sim N(0, \sigma_a)$ and a noise component $e_1 \sim N(0, \sigma_e)$.[5] Productivity in period 2 is

$$Z_2 = 1 + a_1. \tag{2.3}$$

After period 2, there are no more shocks to productivity, such that productivity in period 3 is $Z_3 = Z_2$.

2.3 Entrepreneurs

Like workers, entrepreneurs are risk-neutral. Their discount factor is $\beta^F < 1$. Entrepreneurs own capital k_t, which they finance with risky long-term debt b_t and equity. They rent the capital to firms for a risky return r_t^K.

In periods 2 and 3, entrepreneurs face an idiosyncratic income shock A_t, which has a uniform distribution with bounds $\underline{A}$ and $\overline{A}$. Entrepreneurs have limited liability, such that they can default on their debt and walk away from their firm if the value of their equity falls below zero. In that case, the capital of the entrepreneur is lost. The debt has a state-contingent price $Q_t(k_t, k_t; \mathcal{S}_{t+})$. $\mathcal{S}_{t+}$ is the aggregate state of the economy at the end of the period, which we describe below. The entrepreneur internalises that the debt price depends on her idiosyncratic choices. Entrepreneurs have some initial debt B_0.

The problem of an entrepreneur in period 1 is

$$X_1 = \max_{C_1^F, k_1, b_1} C_1^F + \beta^F E_1 \left[\max(X_2, 0)\right]$$

subject to

$$C_1^F + k_1 = Q_1(k_1, b_1; \mathcal{S}_{1+})(b_1 - B_0)$$

5. Although for simplicity, we assume that both components are normally distributed, they are statistically independent. See more details in section 3.1

The problem of an entrepreneur in period 2 is

$$X_2 = \max_{C_2^F, k_2, b_2} C_2^F + \beta^F E_2 \left[\max(X_3, 0)\right]$$

subject to

$$\begin{aligned} C_2^F + k_2 &= (r_2^K + A_2 + 1)k_1 + Q_2(k_2, b_2; \mathcal{S}_{2+})\,(b_2 - b_1) \\ X_3 = C_3^F &= (r_3^K + A_3 + 1)k_2 - b_2 \\ A_2, A_3 &\sim U(\underline{A}, \overline{A}) \end{aligned}$$

2.4 Financial intermediaries

Financial intermediaries use deposits from workers and their own net worth to finance long-term loans to entrepreneurs. They are risk-neutral and have a discount factor β^I, with $1 > \beta^I > \beta^F$. If they issue equity (i.e. choose negative consumption), they need to pay a quadratic cost with parameter κ. They own a diversified portfolio of loans from entrepreneurs. The recovery rate on defaulting loans is zero.

After making their borrowing and lending decisions, financial intermediaries can divert a fraction ψ of their assets and run away, with the rest of the assets being lost. To avoid this happening in equilibrium, the creditors of the intermediaries impose an incentive condition that takes the form of an endogenous leverage constraint.

The problem of a financial intermediary in period 1 is

$$J_1 = \max_{C_1^I, B_1^I, D_1^I} C_1^I - \frac{\kappa}{2}\left(\frac{C_1^I}{N_1^I}\right)^2 N_1^I 1_{C_1^I \le 0} + \beta^I E_1\left[J_2\right]$$

subject to

$$\begin{aligned} Q_1(K_1, B_1; \mathcal{S}_{1+})B_1^I &= N_1^I + D_1^I - C_1^I \\ N_1^I &= Q_1(K_1, B_1; \mathcal{S}_{1+})B_0^I - D_0^I \\ \psi Q_1(K_1, B_1; \mathcal{S}_{1+})B_1^I &= \beta^I E_1\left[J_2\right] \end{aligned}$$

$1_{C_1^I \le 0}$ is an indicator function which takes the value of one if the financial intermediary issues equity, i.e. if $C_1^I \le 0$, and the value of zero if the financial intermediary pays dividends, i.e. if $C_1^I > 0$.

The problem of a financial intermediary in period 2 is

$$J_2 = \max_{C_2^I, B_2^I, D_2^I} C_2^I - \frac{\kappa}{2}\left(\frac{C_2^I}{N_2^I}\right)^2 N_2^I 1_{C_2^I \le 0} + \beta^I E_2\left[J_3\right]$$

subject to

$$\begin{aligned}
Q_2(K_2, B_2; \mathcal{S}_{2+})B_2^I &= N_2^I + D_2^I - C_2^I \\
N_2^I &= Q_2(K_2, B_2; \mathcal{S}_{2+})B_1^I(1 - F(A_2^*)) - R_1^D D_1^I \\
\psi Q_2(K_2, B_2; \mathcal{S}_{2+})B_2^I &= \beta^I E_2 [J_3] \\
J_3 &= C_3^I = N_3 = B_2^I(1 - F(A_3^*)) - R_2^D D_2^I
\end{aligned}$$

2.5 Market clearing

In each period $t = 1, 2$, the markets for capital, labour, deposits, and long-term loans need to clear. The aggregate resource constraint needs to hold. As all entrepreneurs make the same decisions, we characterise the problem of a representative entrepreneur. Note that the capital of defaulting entrepreneurs is lost. We assume that defaulting entrepreneurs are replaced with new entrepreneurs with the same level of outstanding debt.[6]

$$\begin{aligned}
L_t^F &= L \\
D_t^I &= D_t \\
B_t^I &= B_t
\end{aligned}$$

$$C_t + C_t^F + C_t^I + \frac{\kappa}{2}\left(\frac{C_t^I}{N_t^I}\right)^2 N_t^I 1_{C_t^I \leq 0} + K_t = \left(Z_2((1 - F(A_t^*))K_{t-1})^\alpha L^{1-\alpha} + (1 - F(A_t^*))K_{t-1}\right)$$

In period 1, the endowment of bankers is added.

2.6 Discussion of the assumptions

Here, we discuss the two key features of the model — first, defaultable long-term debt and second, frictions in financial intermediation. We also briefly motivate why we do not model risk-averse agents and endogenous labour supply.

2.6.1 Defaultable long-term debt

As shown below, risky long-term debt creates a debt overhang channel that amplifies the investment bust. This debt overhang channel is the only financial friction for entrepreneurs in the model, and it is at the heart of the boom-bust cycle in the model.

It is an empirical fact that a large share of firms' debt is long-term, see e.g. Gomes, Jermann, and Schmid (2016). A growing literature in macroeconomics and corporate

6. We recognize this is a strong assumption, but we do this in order to keep the analytics tractable. We could relax this assumption, and have a time-varying distribution of entrepreneurs, but it would complicate the maths without changing the key conclusions of our main mechanism.

finance shows that accounting for this fact matters both for leverage dynamics at the firm level and aggregate dynamics, see e.g. DeMarzo and He (2016), Kuehn and Schmid (2014), Jungherr and Schott (2021), or Jungherr and Schott (2022).

Moreover, extensive literature in macroeconomics and asset pricing emphasises the importance of default risk for leverage dynamics and credit spreads, see e.g. Chen and Manso (2010) or Chen, Collin-Dufresne, and Goldstein (2009).

We abstract from equity issuance costs and, therefore, from the role of financial frictions related to the net worth of entrepreneurs, for two reasons. First, most firms in the US have positive equity payouts and are therefore most likely not financially constrained. Second, we want to focus on the debt overhang channel.

2.6.2 Frictions in financial intermediation

The financial frictions we introduce for intermediaries give rise to a time-varying credit risk premium. There is ample evidence in the literature for such a credit risk premium and that it is related to the net worth of the banking sector, see e.g. Gilchrist and Zakrajšek (2012), He and Krishnamurthy (2012), He, Kelly, and Manela (2017), or Muir (2017).

To obtain such a time-varying credit risk premium, we make two assumptions. First, issuing equity is costly to financial intermediaries. Second, financial intermediaries face a market-imposed leverage constraint. A vast literature in macroeconomics and banking finds support for this assumption. See e.g. Gertler and Kiyotaki (2010).

2.6.3 Risk-neutral agents and fixed labour supply

The literature on news shocks emphasises the role of labour supply and household preferences for the propagation of news shocks, see e.g. Jaimovich and Rebelo (2009), Schmitt-Grohé and Uribe (2012), or Görtz, Gunn, and Lubik (2022). We shut these effects down to focus on the interaction between credit supply and credit demand frictions.

3 Characterisation

We first show how agents optimally respond to a signal. Then, we derive the optimal decisions of workers, firms, entrepreneurs, and financial intermediaries. Finally, we characterise the equilibrium of the model in the credit market.

3.1 Signal extraction problem

As in Chahrour and Jurado (2022), the noise representation 2.2 and 2.3 has an alternative news representation with a news shock ν_1 and a surprise shock Δ_2. To solve the model, we use this latter news representation. The solution to the signal extraction problem yields $\nu_1 = E\left[Z_2|S_1\right] = \frac{\sigma_a^2}{\sigma_a^2+\sigma_e^2}S_1$. The surprise shock in period 2 is

$$\begin{aligned}\Delta_2 &= Z_2 - E\left[Z_2|S_1\right]\\ &= a_2 - \frac{\sigma_a^2}{\sigma_a^2+\sigma_e^2}(a_2+e_2)\\ &= \frac{\sigma_e^2}{\sigma_a^2+\sigma_e^2}a_2 + \frac{\sigma_a^2}{\sigma_a^2+\sigma_e^2}e_2.\end{aligned}$$

This shock is the sum of two normally distributed variables. Let $\zeta = \frac{\sigma_a^2}{\sigma_a^2+\sigma_e^2}$. Then, the surprise shock is normal with mean 0 and variance $\sigma_\Delta^2 = (1-\zeta)^2\sigma_a^2 + \zeta^2\sigma_e^2$. Z_2 has the conditional distribution $Z_2 \sim N(\zeta S_1, \sigma_\Delta)$.

3.2 Workers and firms

The solution to the worker problem yields $R_1^D = R_2^D = 1$. Optimal choice of inputs yields a wage $W_t = (1-\alpha)Z_t K_{t-1}^{\alpha} L^{-\alpha}$ and a return on capital $r_t^K = \alpha Z_t K_{t-1}^{\alpha-1} L^{1-\alpha}$ for $t = 1, 2, 3$.

3.3 Entrepreneurs

We solve the problem of entrepreneurs backwards.

3.3.1 Period 2

Period 2 choices are a function of the idiosyncratic period 1 debt of the entrepreneur b_1 and the aggregate state at the beginning of the period $\mathcal{S}_2 = B_1, N_2, Z_2$. The bond price is a function of the entrepreneur's choices k_2 and b_2 and the aggregate state at the end of the period $\mathcal{S}_{2+} = K_2, B_2, D_2, Z_2$. Plugging in the expression for C_2^F from the budget constraint and taking derivatives yields as optimality conditions for $k_2(b_1;\mathcal{S}_2)$ and $b_2(b_1;\mathcal{S}_2)$:

$$1 - \frac{\partial Q_2(k_2,b_2;\mathcal{S}_{2+})}{\partial k_2}(b_2-b_1) = \beta^F\left[r_3^K + \frac{\overline{A}+A_3^*}{2} + 1\right](1-F(A_3^*)) \quad (3.1)$$

$$Q_2(k_2,b_2;\mathcal{S}_{2+}) + \frac{\partial Q_2(k_2,b_2;\mathcal{S}_{2+})}{\partial b_2}(b_2-b_1) = \beta^F\left(1-F(A_3^*)\right). \quad (3.2)$$

The default threshold in period 3, $A_3^*(k_2, b_2, Z_2)$, is

$$A_3^* = \frac{b_2}{k_2} - (r_3^K + 1) \tag{3.3}$$

Notice that the default threshold is a function of idiosyncratic leverage only. We conjecture here, and verify below, that the bond price is a function of the default probability of the firm and a time-varying wedge that is independent of firm decisions:

$$Q_2(k_2, b_2; \mathcal{S}_{2+}) = \Psi_2(1 - F(A_3^*)) = \Psi_2 \frac{\overline{A} - A_3^*}{\overline{A} - \underline{A}}.$$

This implies that the bond price derivatives are

$$\frac{\partial Q_2(k_2, b_2; \mathcal{S}_{2+})}{\partial k_2} = \frac{\Psi_2}{\overline{A} - \underline{A}} \frac{b_2}{k_2^2} \tag{3.4}$$

$$\frac{\partial Q_2(k_2, b_2; \mathcal{S}_{2+})}{\partial b_2} = -\frac{\Psi_2}{\overline{A} - \underline{A}} \frac{1}{k_2} \tag{3.5}$$

The period 3 expected value function is

$$E_2 \left[X_3 | A > A_3^* \right] = (1 - F(A_3^*)) \left[\left(r_3^K + \frac{\overline{A} + A_3^*}{2} + 1 \right) k_2 - b_2 \right] \tag{3.6}$$

3.3.2 Period 1

The optimal choices of the entrepreneur in period 1 depend on the initial level of debt b_0 and the aggregate state at the beginning of the period $\mathcal{S}_1 = B_0, N_1, S_1$.. The bond price in period 1 depends on the idiosyncratic choices of the entrepreneur k_1 and b_1 and the end of period aggregate state $\mathcal{S}_{1+} = K_1, B_1, D_1, S_1$. In period 1, the optimality conditions for $k_1(S_1)$ and $b_1(S_1)$ are

$$1 - \frac{\partial Q_1(k_1, b_1; \mathcal{S}_{1+})}{\partial k_1}(b_1 - b_0) = \beta^F E_1 \left[\left(r_2^K + \frac{\overline{A} + A_2^*}{2} + 1 \right) (1 - F(A_2^*)) \right] \tag{3.7}$$

$$Q_1(k_1, b_1; \mathcal{S}_{1+}) + \frac{\partial Q_1(k_1, b_1; \mathcal{S}_{1+})}{\partial b_1}(b_1 - b_0) = \beta^F E_1 \left[Q_2(k_2, b_2; \mathcal{S}_{2+}) \left(1 - F(A_2^*)\right) \right]. \tag{3.8}$$

It is useful to define the continuation policy of the firm as

$$\begin{aligned} \tilde{X}_2(b_1; \mathcal{S}_2) = & -k_2(b_1; \mathcal{S}_2) + Q_2(k_2(b_1; \mathcal{S}_2), b_2(b_1; \mathcal{S}_2); \mathcal{S}_{2+}) b_2(b_1; \mathcal{S}_2) \\ & + E_2 \left[X_3(k_2(b_1; \mathcal{S}_2), b_2(b_1; \mathcal{S}_2); \mathcal{S}_{2+}) | A_3 > A_3^* \right] \end{aligned}$$

The default threshold in period 2, $A_2^*(k_1, b_1; \mathcal{S}_2)$, is then

$$A_2^* = Q_2(k_2(b_1; \mathcal{S}_2), b_2(b_1; \mathcal{S}_2); \mathcal{S}_{2+}) \frac{b_1}{k_1} - (r_2^K + 1) - \frac{\tilde{X}_2(b_1; \mathcal{S}_2)}{k_1} \tag{3.9}$$

Similar to period 2, the bond price is

$$Q_1(k_1, b_1; \mathcal{S}_{1+}) = E_1 \left[\Psi_1 Q_2(k_2, b_2; \mathcal{S}_{2+}) \frac{\overline{A} - A_2^*}{\overline{A} - \underline{A}} \right].$$

The bond price derivatives are

$$\frac{\partial Q_1(k_1, b_1; \mathcal{S}_{1+})}{\partial k_2} = \frac{1}{\overline{A} - \underline{A}} E_1 \left[\Psi_1 Q_2(k_2, b_2; \mathcal{S}_{2+}) \frac{b_1 - \tilde{X}_2}{k_1^2} \right] \tag{3.10}$$

$$\begin{aligned} \frac{\partial Q_1(k_1, b_1; \mathcal{S}_{1+})}{\partial b_1} &= -\frac{1}{\overline{A} - \underline{A}} E_1 \left[\Psi_1 Q_2(k_2, b_2; \mathcal{S}_{2+}) \frac{1}{k_1} \right] \\ &\quad + E_1 \left[\Psi_1 \frac{\overline{A} - A_2^*}{\overline{A} - \underline{A}} \left(\frac{\partial Q_2(k_2, b_2; \mathcal{S}_{2+})}{\partial k_2} \frac{\partial k_2}{\partial b_1} + \frac{\partial Q_2(k_2, b_2; \mathcal{S}_{2+})}{\partial b_2} \frac{\partial b_2}{\partial b_1} \right) \right] \end{aligned} \tag{3.11}$$

Notice the presence of the derivatives of the policy functions with respect to the current debt policy. The creditors internalise that the entrepreneur's current debt choice affects future policy functions. To find these derivatives, we apply the implicit function theorem to equations 3.2 and 3.1. This yields

$$\begin{aligned} \frac{\partial b_2}{\partial b_1} &= \frac{\frac{\partial Q_2(k_2, b_2; \mathcal{S}_{2+})}{\partial b_2}}{2\frac{\partial Q_2(k_2, b_2; \mathcal{S}_{2+})}{\partial b_2} + \beta^F f(A_3^*)} = \frac{-\Psi_2}{-2\Psi_2 + k_2 \beta^F} > 0. \\ \frac{\partial k_2}{\partial b_1} &= -\frac{\frac{\partial Q_2(k_2, b_2; \mathcal{S}_{2+})}{\partial k_2}}{\beta^F f(A_3^*)} = -\frac{\Psi_2 \frac{b_2}{k_2^2}}{\beta^F} < 0. \end{aligned}$$

That is, a higher level of debt b_1 increases future debt b_2 and reduces future capital k_2. This shows the leverage ratchet effect and the debt overhang effect at play.

3.4 Financial intermediaries

As for entrepreneurs, we solve the decision problem of financial intermediaries backwards.

3.4.1 Period 2

The balance sheet constraint gives

$$D_2^I = Q_2(K_2, B_2; \mathcal{S}_{2+}) B_2^I - N_2^I + C_2^I.$$

Plugging this expression for D_2 into the law of motion for net worth yields

$$N_3^I = B_2^I(1 - F(A_3^*)) - \left(Q_2(K_2, B_2; \mathcal{S}_{2+})B_2^I - N_2^I + C_2^I\right).$$

The problem of the intermediary reduces to

$$J_2 = \max_{C_2^I, B_2^I} C_2^I - \frac{\kappa}{2}\left(\frac{C_2^I}{N_2^I}\right)^2 N_2^I 1_{C_2^I \leq 0} + \beta^I \left[B_2^I(1 - F(A_3^*)) - \left(Q_2(K_2, B_2; \mathcal{S}_{2+})B_2^I - N_2^I + C_2^I\right)\right] \tag{3.12}$$

subject to

$$\psi Q_2(K_2, B_2; \mathcal{S}_{2+})B_2^I = \beta^I \left[B_2^I(1 - F(A_3^*)) - \left(Q_2(K_2, B_2; \mathcal{S}_{2+})B_2^I - N_2^I + C_2^I\right)\right]. \tag{3.13}$$

Solving this maximisation problem gives an expression for the multiplier on the incentive constraint μ^I

$$\mu^I = \frac{1}{\beta^I}\left(1 - \kappa\frac{C_2^I}{N_2^I}\right) - 1, \tag{3.14}$$

and the bond price $Q_2(K, B; \mathcal{S}_{2+})$:

$$\begin{aligned} Q_2(K, B; \mathcal{S}_{2+}) &= \beta^I \frac{1 + \mu^I}{\mu^I\psi + \beta^I(1 + \mu^I)}(1 - F(A_3^*)) \\ &= \underbrace{\beta^I \frac{1 + \mu^I}{\mu^I\psi + \beta^I(1 + \mu^I)}}_{\equiv \Psi_2} \frac{A_3^* - \underline{A}}{\overline{A} - \underline{A}}. \end{aligned} \tag{3.15}$$

If $\kappa = 0$, this becomes

$$Q_2(K, B; \mathcal{S}_{2+}) = \beta^I \frac{\beta^I}{\psi + \beta^I(1 - \psi)} \frac{A_3^* - \underline{A}}{\overline{A} - \underline{A}}.$$

When $\psi = 1$, the intermediary needs to finance B to 100 per cent with her own equity. The relevant discount factor for the bond price is β^I. When $\psi = 0$, the intermediary can finance B to 100 per cent with household deposits. The discount factor is 1. We call the case with $\kappa = 0$ and $\psi = 0$ the case without credit supply frictions.

3.4.2 Period 1

We solve the period 1 problem of the financial intermediary similarly to the period 2 problem. We define $\Omega_2 \equiv J_2/N_2$. Net worth in period 1 is

$$N_1 = Q_1 B_0 - D_0. \tag{3.16}$$

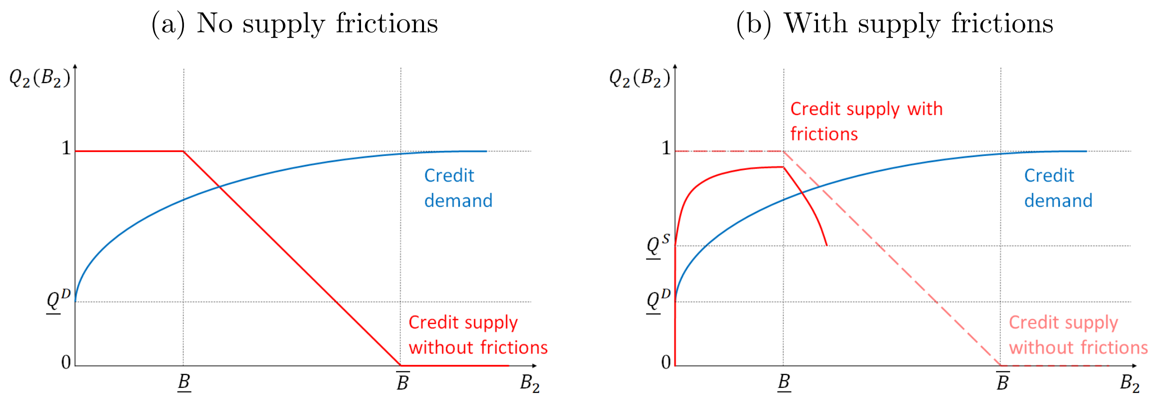

Figure 1: Equilibrium in the credit market.

The incentive constraint is

$$\psi Q_1 B_1^I = \beta^I E_1 \left[\Omega_2 \left(Q_2 B_1^I (1 - F(A_2^*)) - \left(Q_1 B_1^I - N_1^I + C_1^I\right)\right)\right]. \tag{3.17}$$

The Lagrange multiplier μ_1^I for period 1 is:

$$\mu_1^I = \frac{1}{\beta^I E_1 [\Omega_2]} \left(1 - \kappa \frac{C_1^I}{N_1^I}\right) - 1. \tag{3.18}$$

The bond price $Q_1(K_1, B_1; \mathcal{S}_{1+})$ is:

$$Q_1(K_1, B_1; \mathcal{S}_{1+}) = E_1 \left[\underbrace{\beta^I \frac{1 + \mu_1^I}{\mu_1^I \psi + \beta^I E_1 [\Omega_2] (1 + \mu_1^I)}}_{\equiv \Psi_1} \Omega_2 \left(Q_2(K_2, B_2; \mathcal{S}_{2+}) \frac{\overline{A} - A_2^*}{\overline{A} - \underline{A}} \right) \right]. \tag{3.19}$$

3.5 Equilibrium in the credit market

We characterise market clearing in the credit market. In period 2, the solution to the entrepreneur problem, equations 3.2 to 3.5, determines credit demand. The solution to the intermediary problem, equations 3.13 to 3.15, determines credit supply.

3.5.1 Equilibrium without credit supply frictions

Consider first the case without credit supply frictions, $\psi = \kappa = 0$. In that case, the Lagrange multiplier $\mu_2^I = 0$ and $\Psi_2 = 1$ for all values of B. Credit supply is simply

$$Q_2(B_2) = 1 - F(A_3^*). \tag{3.20}$$

There is some value $\underline{B}$, such that there is no default for $B \leq \underline{B}$. In that case, $Q_2(B_2) = 1$. There is some other value $\overline{B} > \underline{B}$, such that for $B \geq \overline{B}$, the entrepreneurs will default with certainty. In that case, $Q_2(B_2) = 0$. For B in between $\underline{B}$ and $\overline{B}$, the bond price is linearly decreasing in B. The supply schedule is displayed in red in Panel 1a of Figure 1.

The credit demand schedule is determined as follows. There is some price $\underline{Q}^D$, such that $Q \leq \underline{Q}^D$, credit demand is zero. As the bond price approaches 1, credit demand approaches infinity from below. This implies that credit demand is convex in the bond price. The demand schedule is displayed in blue in Panel 1a of Figure 1.

The equilibrium is where the credit demand and the credit supply schedule intersect. This must be in the region with some positive credit risk. If there were no credit risk, the bond price would be 1, and credit demand would be infinite.

3.5.2 Equilibrium with credit supply frictions

Consider next the case with credit supply frictions, i.e. with $\psi > 0, \kappa > 0$. The credit demand schedule remains unchanged. The credit supply schedule is, however, much more complicated.

There is a value of the bond price $\underline{Q}^S$, such that for $Q \leq \underline{Q}^S$, the net worth of the financial intermediaries is zero. In that case, credit supply is also zero. For $Q > \underline{Q}^S$, the credit supply curve is increasing in the bond price, as a higher bond price increases the net worth of financial intermediaries, relaxing the credit supply constraint. For $B > \underline{B}$, the bond price becomes decreasing in B because of the credit risk of entrepreneurs. With credit supply frictions, the bond price decreases more than in the case without credit supply frictions, as a fall in the bond price reduces the net worth of financial intermediaries.

Panel 1b of Figure 1 depicts the equilibrium in the case with credit supply frictions. The equilibrium is again where the credit demand and the credit supply schedules intersect. Note that there are at least two equilibria. First, the equilibrium with positive credit risk. Second, a trivial equilibrium with zero debt. In principle, there could be many more equilibria, if the credit supply and credit demand schedule intersect more often. However, there is only one equilibrium with positive credit risk, i.e. in the downward sloping area of the credit supply schedule.

With credit supply frictions, equilibrium credit and the equilibrium bond price are lower than in the case without credit supply frictions. This is because the bond price contains an additional liquidity premium that reflects the financial constraints of financial intermediaries. This liquidity premium, the distance between the credit supply schedule without frictions and the credit supply frictions with frictions, varies with the bond price. In particular, for positive credit risk, it is increasing in credit risk.

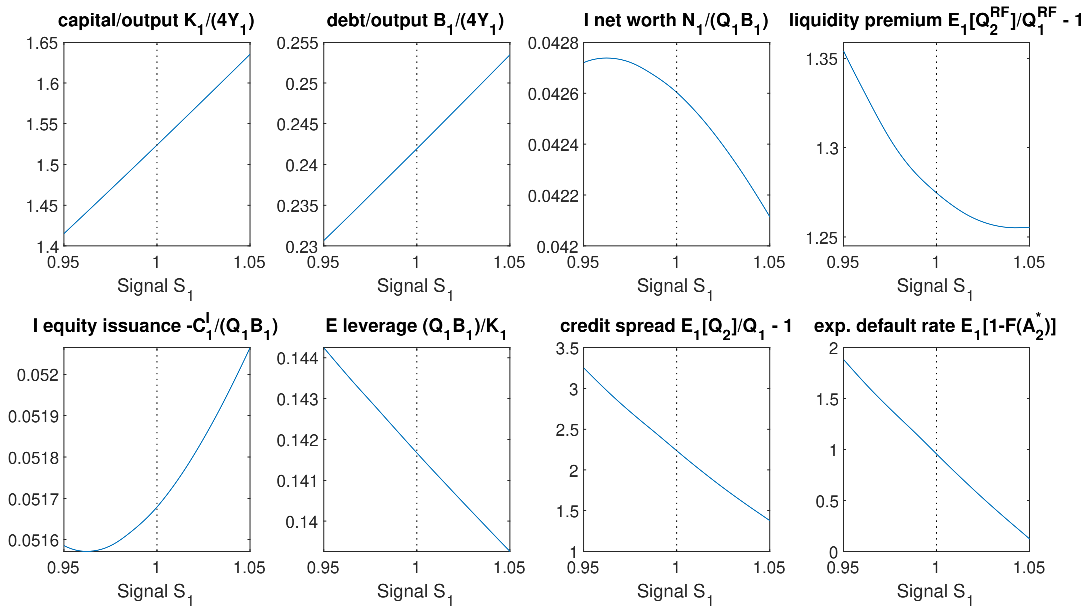

Figure 2: A credit boom in period 1.

Note: This figure shows model variables in period 1 as a function of the signal size in period 1. A signal of 1 means that there is no shock. A signal less than 1 means that agents receive a negative news shock about future productivity, and a signal above 1 means that agents receive a positive news shock about future productivity.

4 A noise-driven credit boom-bust cycle

We do the following experiment: We shock the economy with a signal of size S_1 in period 1. In period 2, we consider two situations. First, we discuss a situation where there is no surprise shock. In that case, the signal shock was a genuine news shock. Second, a situation where the surprise shock exactly offsets the signal shock. In that case, the signal shock was a noise shock. For this experiment, we solve the model numerically, as even this simple model does not permit a closed form solution. The numerical solution strategy is described in Appendix E.

4.1 Credit boom in period 1

Figure 2 shows the effect of the news shock in period 1 in the credit boom period. A signal of 1 means that there is no shock. A signal less than 1 means that agents receive a negative news shock about future productivity, and a signal above 1 means that agents receive a positive news shock about future productivity.

The higher the signal about future productivity, the higher the capital-to-output ratio. This is because the capital stock is increasing in expected future productivity; see equation 3.7. Likewise, a higher signal leads to a higher debt-to-output ratio. This effect is because higher expected future productivity reduces future default risk and increases future bond

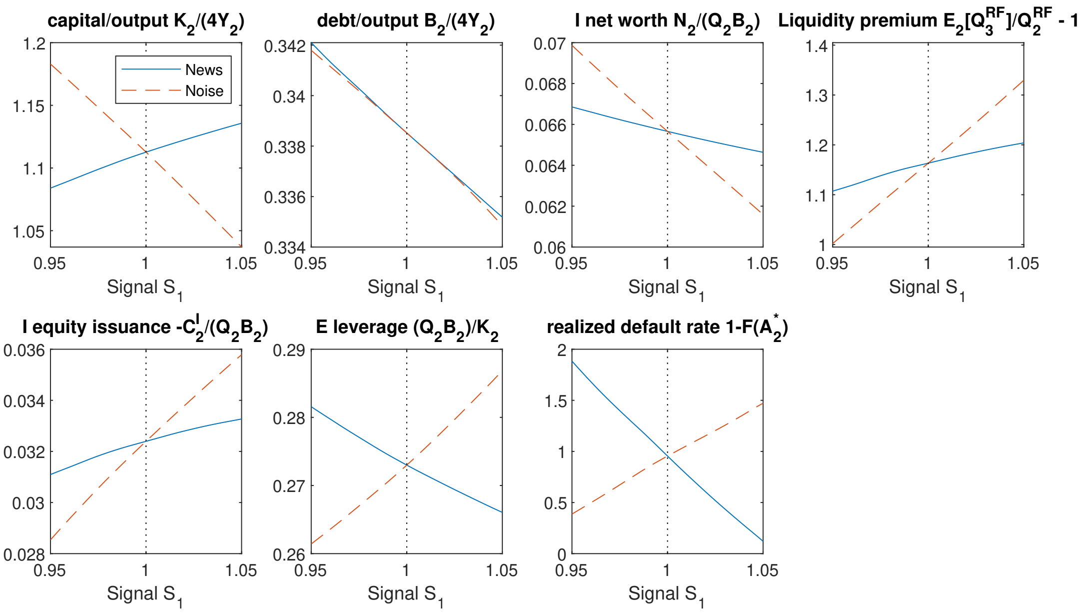

Figure 3: News-driven vs noise-driven credit dynamics in period 2.

Note: This figure shows model variables in period 2 as a function of the signal size in period 1. The blue line is where the news shock ex-post turns out to be correct. The red line is where the news shock ex-post turns out to be noise.

prices, see equation 3.19.

The net worth of intermediaries rises, but it rises less than assets. As a result, intermediaries issue additional equity and deposits, see equations 3.18 and 3.17. Leverage increases slightly. This result starkly contrasts a model where banks would directly hold the economy's capital stock. In such a model, a positive news shock raises the price of capital, which increases net worth relative to assets. Default risk and the liquidity premium decline, leading to a decline in the credit spread.

4.2 Credit bust in period 2

Figure 3 shows the effect of news and noise shocks in period 2. Consider first a situation where the news shock ex-post turns out to be true. In that case, agents choose a higher capital-to-output ratio if the signal in period 1 is higher. This effect is driven by capital being increasing in productivity; see equation 3.1. Entrepreneurs increase their level of debt, as the current debt choice is increasing in the lagged debt choice; see equation 3.2. However, the debt-to-output ratio falls as output increases more than debt, and realised default rates fall.

The net worth of intermediaries rises, but less than their assets. As a result, intermediaries again increase leverage and issue additional equity; see equations 3.14 and 3.13. Credit spreads fall, but primarily due to lower future default rates.

Consider next a situation where the news shock ex-post turns out to be false. In that case, the capital of entrepreneurs falls relative to a situation without a shock. This fall in capital occurs because entrepreneurs have increased their debt in period 1, and capital in period 2 is decreasing in the lagged level of debt; see equation 3.1. In other words, the fall in the capital is driven by a debt overhang effect (e.g. Myers (1977)). The debt-to-output ratio falls less than when the news shock is genuine. This smaller fall occurs because debt is increasing in lagged debt, leading to a leverage ratchet effect (e.g. Admati et al. (2018), DeMarzo and He (2016)).

Net worth falls, but less than intermediary assets. As a consequence, intermediaries issue less equity. Credit spreads rise, driven by an increase in future default risk and the liquidity premium.

In summary, noise shocks lead to a boom-bust cycle. This boom-bust cycle arises despite no fundamental change in productivity, and a debt overhang channel drives it. Because of a positive news shock, entrepreneurs increase their debt. If the news fails to realise, the high outstanding debt leads entrepreneurs to reduce their capital stock.

4.3 The role of credit supply

In the baseline calibration, the credit boom-bust cycle is due to credit demand. However, the literature has shown that news shocks are amplified by a relaxation in credit supply as well (e.g. Görtz and Tsoukalas (2017), Görtz, Tsoukalas, and Zanetti (2022)). The model produces a fall in the liquidity premium, and therefore a relaxation of credit supply, because of an increase in bond prices and high leverage. Under what conditions can the model increase credit supply in response to a news shock?

The stance of credit supply is determined by how much the net worth of intermediaries changes relative to their assets. If net worth increases more than assets, intermediaries become less financially constrained, and the liquidity premium falls. In that case, the relaxation of the credit supply amplifies the credit boom.

What, then, can amplify the response of net worth relative to assets? One crucial factor is leverage. The more highly levered intermediaries are, the more a fluctuation in asset prices will increase their net worth.

Another crucial factor is the sensitivity of the prices of the assets that banks hold to the news shock. In the current model, the assets of intermediaries are only corporate bonds. In an extended model, where intermediaries also hold some capital directly, credit supply would be more responsive to news shocks. Such direct capital holdings could, for example, represent direct stock or securities investments of banks.

4.4 Testable hypotheses

To sum up, the model delivers the following testable predictions for the empirical investigation. First, news and noise shocks lead to a boom that results in an expansion of the real economy and a rise in credit. Second, noise shocks lead to an economic bust, while news shocks do not. Third, lenient credit supply conditions amplify these boom-bust cycles.

5 Empirical evidence

We proceed in five steps to test the hypotheses developed in the previous section. **First**, we decompose fluctuations that jointly drive stock prices and dividends into underlying noise and fundamental shocks following Forni et al. (2017b). **Second**, we examine the impact of these shocks on financial variables applying local projections. However, this only depicts the unconditional dynamics. **Third**, we extend the investigation to include the impact of the same shocks on real economic activity. To understand the state-contingent dynamics, we **lastly** decompose the previous into episodes of high and low risk premiums.

5.1 Identifying noise shocks

We extract a news and a noise shock from stock price and dividend data, following the approach of Forni et al. (2017b). Intuitively, noise shocks are identified as shocks to asset prices unrelated to past, current and future potential output. Appendix B describes the econometric procedure to identify the noise shocks.

As a first step for estimating the noise shocks, we estimate a VAR with the following variables: potential real GDP from the CBO, the 3-month treasury bill yield, Moody's AAA corporate bond yield, the S&P500, and real GDP. Potential GDP and real GDP are expressed in per capita terms by dividing them by the civilian population above age 16. All data are expressed in quarterly frequency. We recover signal and surprise shocks from this VAR by applying a simple recursive identification. The fundamental (or news) and noise shocks are dynamic rotations of these signal and surprise shocks. We could also estimate the signal and surprise shocks using local projections.

5.2 The recovered noise shocks

Figure 4 displays the resulting noise shock series. It is standardised to zero mean and unit variance. NBER recessions are marked in grey. We also mark the five largest positive

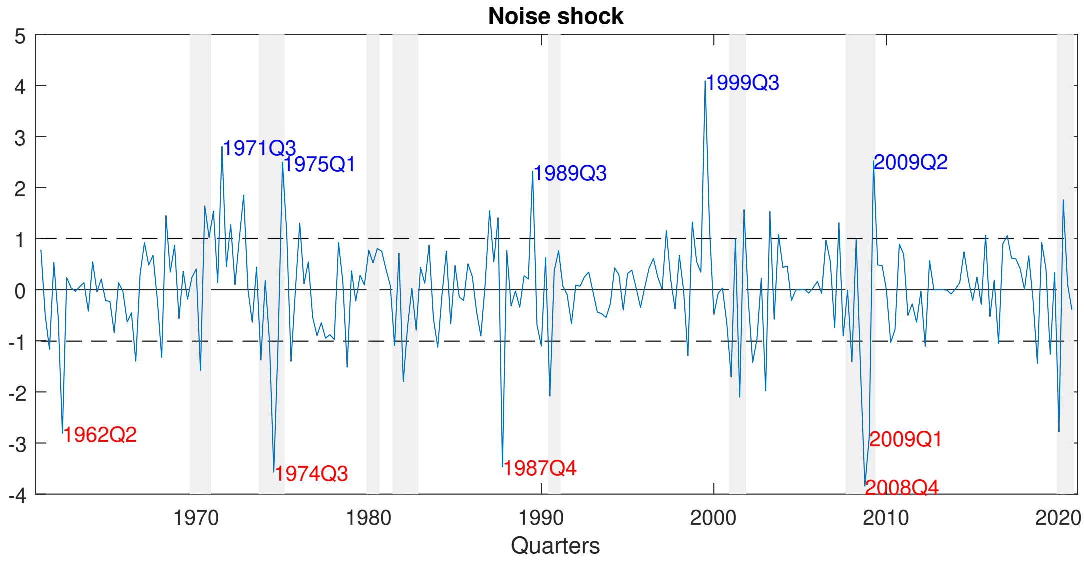

Figure 4: The noise shocks.

Note: This figure shows the noise shocks recovered using the estimation procedure of Forni et al. (2017b). The shaded grey areas mark NBER recession dates. The five largest positive (negative) shocks are marked in blue (red). The dashed, horizontal lines are +/- one standard deviation.

and negative noise shocks. Noise shocks are plausibly related to events that moved stock prices, but had a smaller than expected or no effect on dividends ex post. For example, the 1974Q3 noise shock is contemporaneous to the Nixon resignation, the 1987Q4 shock coincides with the boom and bust around the 1987 stock market crash. The positive 1999Q3 noise shock marks the peak of the dotcom bubble. The 2008Q4 shock happens at the same time as the peak of the Great Financial Crisis, the 2009Q2 shock marks its end in the US.

5.3 Validating the noise shocks as instrument for investor sentiments

To validate the shocks, we run the following lag-augmented local projection (Jordà (2005), Stock and Watson (2018), Olea and Plagborg-Møller (2020), Plagborg-Møller and Wolf (2020a)):

$$Y_{t+h} = \alpha^h + \sum_{s=1}^{S} \beta_s^h shock_{t-s} + \sum_{s=1}^{S} \rho_s^h Y_{t-s} + \sum_{s=0}^{S} \Gamma_s^h X_{t-s} + \varepsilon_{t+h} \tag{5.1}$$

$Y_{t+h}, h \in [0, H]$ is the outcome of interest h periods ahead, $shock_t$ is the shock of interest, which is either the news shock a_t or the noise shock e_t. As control variables X_t, we include the variables that were also included in the VAR, namely the respective other shock, the lagged stock price and potential output series, the 3-month treasury rate, and the Moody's AAA corporate bond spread. The β_s^h coefficients measure the impulse response to the shock. As in the VAR, we include 4 lags of Y_t, $shock_t$, and X_t in the regression, to capture the full annual effect.[7] We set the number of periods over which we estimate the impulse response $H = 30$ quarters.

Figure 5 displays the results. The left two panels display the impulse response of potential output (top) and stock prices (bottom) to a news shock, the two panels on the right the impulse response to a noise shock. The blue, solid line is the point estimate for the local projections, the shaded areas are the 90 per cent (dark shading) and 68 per cent (light shading) confidence intervals, respectively. For comparison, we include impulse responses estimated from the original VAR to the same shocks. The red, solid line is the point estimate from the VAR, the red, dashed lines are the 90 per cent confidence interval, obtained using a Kilian (1998) bootstrap. The inclusion of the VAR facilitates the comparison with the results in Forni et al. (2017a). The point estimate and the confidence interval from the VAR are similar to the ones estimated with local projections.

A one standard deviation **news shock** leads to a 0.6 per cent permanent increase in potential output and a permanent increase in stock prices of roughly 4 per cent. Despite the fact that we use 10 more years of data, these effects are of the same magnitude as the ones estimated in Forni et al. (2017b). The impact effect in the VAR is permanent, while the impulse response estimated from the local projections implies a smaller long-run effect than the VAR.

On the other hand, a one standard deviation **noise shock** has by construction no effect on potential output. However, it leads to a large, roughly 6 per cent, impact on stock prices. This impact on stock prices vanishes over time. After 15 quarters, the impact of noise shocks on the stock market is no longer significantly different from zero at the 10 per cent confidence level.

The intuition behind these results is that while investors do not know at the time when they observe a news shock whether it is a "fundamental" news shock or a noise shock, they learn over time by observing more and more realisations for potential output. As investors realise that a noise shock drove the signal shock, they correct their stock market pricing downward.

5.4 Noise shocks and credit to the non-financial sector

We now estimate the impact of the noise shocks on credit to non-financial firms.

We estimate lag-augmented local projections similar to the specification in equation 5.1. In principle, as the main explanatory variable on the right-hand side is a structural

7. Here, we follow Forni et al. (2017b).

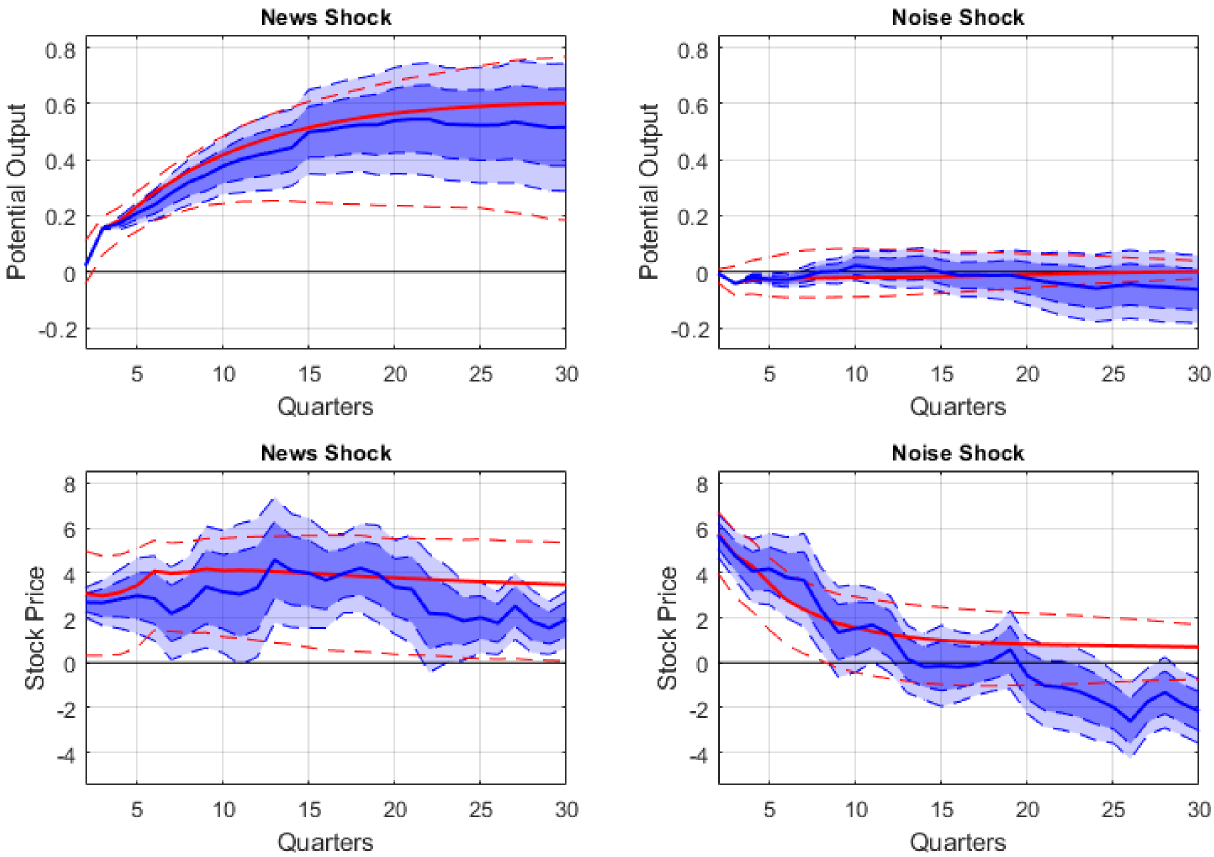

Figure 5: The effect of news and noise shocks on stock prices and potential output.

Note: The blue line in this figure displays the coefficients $\{\beta_0^h\}_{h=0}^H$ obtained by estimating equation 5.1. For comparison, the red line displays the impulse responses obtained from the VAR used to identify the shocks. The confidence levels depicted are 68 per cent (dark shaded area) and 90 per cent (light shaded area). The red, dashed lines are the 90 per cent confidence interval from the VAR. Standard errors in the local projections correct for autocorrelation of the residuals using a Newey-West estimator.

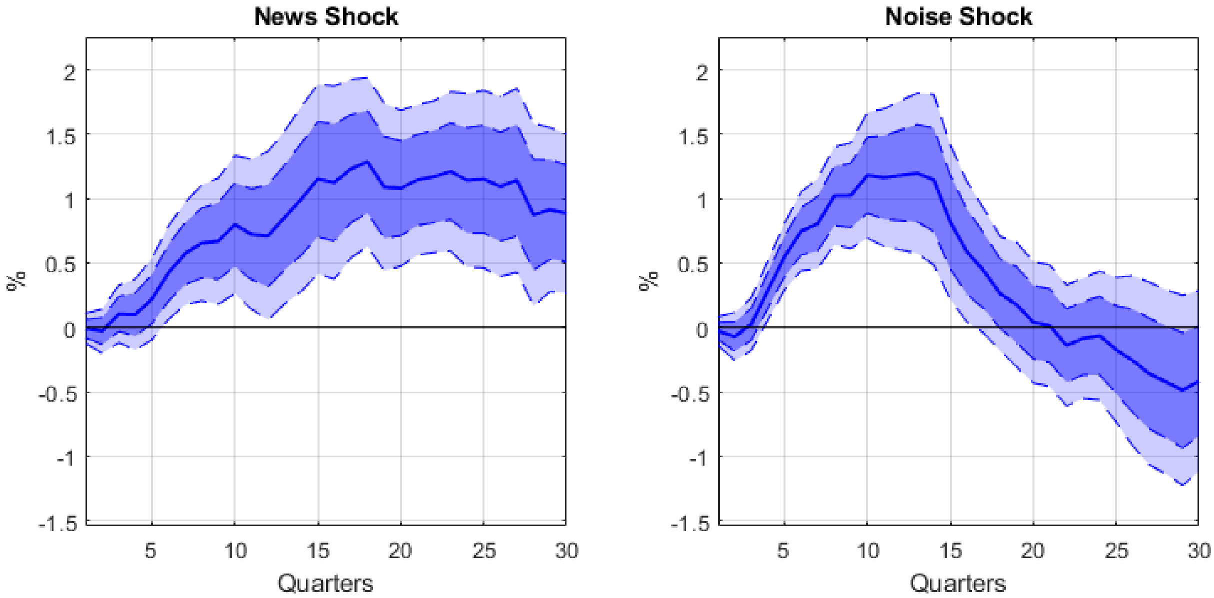

Figure 6: The effect of news and noise shocks on credit to the non-financial sector.

Note: The blue line in this figure displays the coefficients $\{\beta_0^h\}_{h=0}^H$ obtained by estimating equation 5.1. The confidence levels depicted are 68 per cent (dark shaded area) and 90 per cent (light shaded area). Standard errors correct for autocorrelation of the residuals using a Newey-West estimator. Estimation sample: 1961Q1-2020Q4.

shock, it is not necessary to include any control variables. We nonetheless control for the variables included in the VAR used in the estimation of the shock, as well as the lagged outcome variable, as this improves the estimator's efficiency (see Olea and Plagborg-Møller (2020)). We set the number of lags equal to $S = 4$. We set the number of periods over which we estimate the impulse response to $H = 30$.

Figure 6 displays the results. A one standard deviation **news shock** leads to a permanent long-run increase in credit of around 1 per cent. The impact effect of the shock on the level of firm credit is 0. It increases over time and peaks after 10 quarters. This implies that the shock leads to increased credit growth for around 10 quarters.

A one standard deviation **noise shock** leads to a transitory increase in the level of credit which also peaks after around 10 quarters, but then decreases thereafter. This implies that a noise shock leads to around 10 quarters of credit growth, followed by around 10 quarters of negative credit growth. In Appendix C.3, we show that this result is not driven by the financial crisis, and not driven by the COVID crisis. The result is moreover robust to various changes in model specification. We obtain similar results if we use dividends instead of potential output as fundamental, the BAA yield instead of stock prices as expectation, if we include credit in the VAR, if we order output right after potential output instead of last, and if we include the Jurado, Ludvigson, and Ng (2015)-uncertainty measure in the VAR.

The intuition behind these results is that economic agents expect that *news shocks are* *informative about future business conditions of firms.* The level of credit is a slow-moving variable, so adjusting takes a while. Similarly, a noise shock leads to positive credit growth for around 10 quarters. As investors slowly become more and more certain that a noise shock drove the news, credit growth is negative for the subsequent 10 quarters.

5.5 Noise shocks and credit spreads

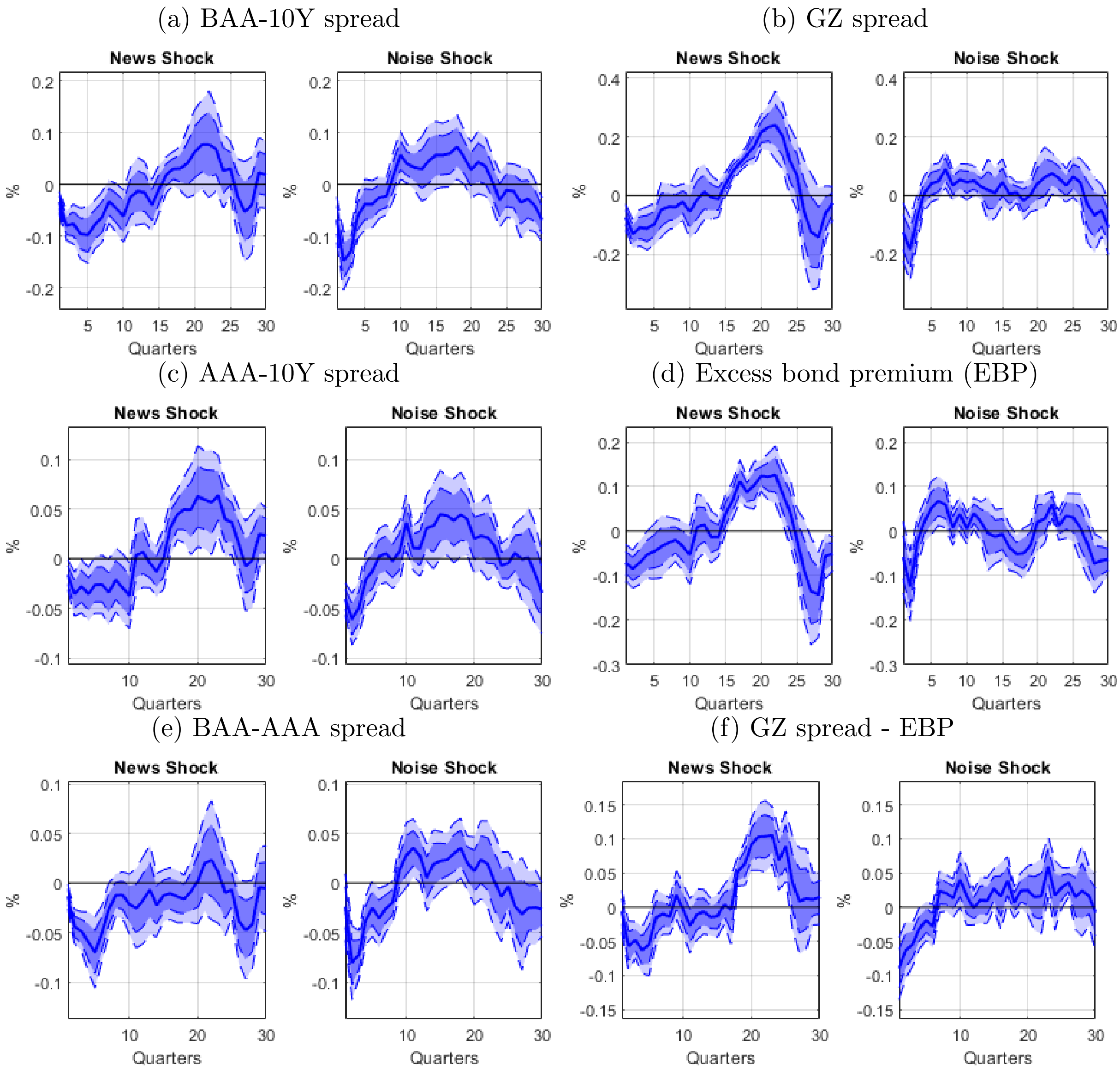

Figure 7: The effect of news and noise shocks on credit spreads.

Note: The blue line in this figure displays the coefficients $\{\beta_0^h\}_{h=0}^H$ obtained by estimating equation 5.1. The confidence levels depicted are 68 per cent (dark shaded area) and 90 per cent (light shaded area). Standard errors correct for autocorrelation of the residuals using a Newey-West estimator. Estimation sample: 1961Q1-2020Q4.

Figure 7 shows the effect of news and noise shocks on various credit spreads. Credit spreads are often used as a measure of corporate borrowing conditions, see e.g. Gilchrist and Zakrajšek (2012) or López-Salido, Stein, and Zakrajšek (2017). In response to both a news and a noise shock, the BAA-10Y credit spread falls. A one standard deviation positive noise shock leads to a 0.1 percentage point fall in the BAA-10Y credit spread (Panel 7a). For the Gilchrist and Zakrajšek (2012) spread, we see a similar impact (Panel 7b).

There are two reasons why credit spreads may fall in response to a noise shock: anticipating good news, creditors perceive firms as less risky, which would lead to a fall in expected defaults. Alternatively, creditors may charge a lower liquidity premium, for example because they expect good news about their own future balance sheets (e.g. He and Krishnamurthy (2012)). To decompose which channel is the more likely to drive the results, we furthermore investigate the dynamics of two additional credit spreads: The BAA-AAA credit spread, which measures the difference in credit spreads of investment-grade firms with relatively high default risk (BAA firms) and low default risk (AAA firms). This spread can be interpreted as a default premium. The AAA-10Y spread measures the spread between corporate bonds with a low default risk and government bonds. This spread can be interpreted as a liquidity premium. (e.g. Krishnamurthy and Vissing-Jorgensen (2012)).

In response to a positive one standard deviation noise shock, the BAA-AAA spread falls by around 0.1 percentage points and stays low for around ten quarters before reverting back to zero. The AAA-10Y spread falls by around 0.05 percentage points and stays low for around five quarters before turning positive and increasing above zero after around 15 quarters. This evidence favours the hypothesis that investors interpret the positive noise shock as good news about the corporate non-financial sector, thus charging lower default premiums, which in turn leads to an increase in bond financing (or issuance).

5.6 Transmission channels

Appendices C.1 and C.2 investigate how noise shocks affect credit supply and demand in more detail. We investigate the effects of news and noise shocks on indicators of credit demand, like the credit demand reported by loan officers in the senior loan officer opinion survey (SLOOS) or the business loan delinquency rate, as well as indicators of credit supply, like the fraction of senior loan officers reporting tighter credit standards or bank balance sheet indicators. In summary, we find that both indicators of credit demand and credit supply improve in response to a positive shock. The boom-bust dynamics appear mostly in indicators of credit demand, supporting the view that credit demand frictions, for example because of defaultable long-term debt, are important for the propagation of noise shocks.

5.7 Noise shocks and real activity

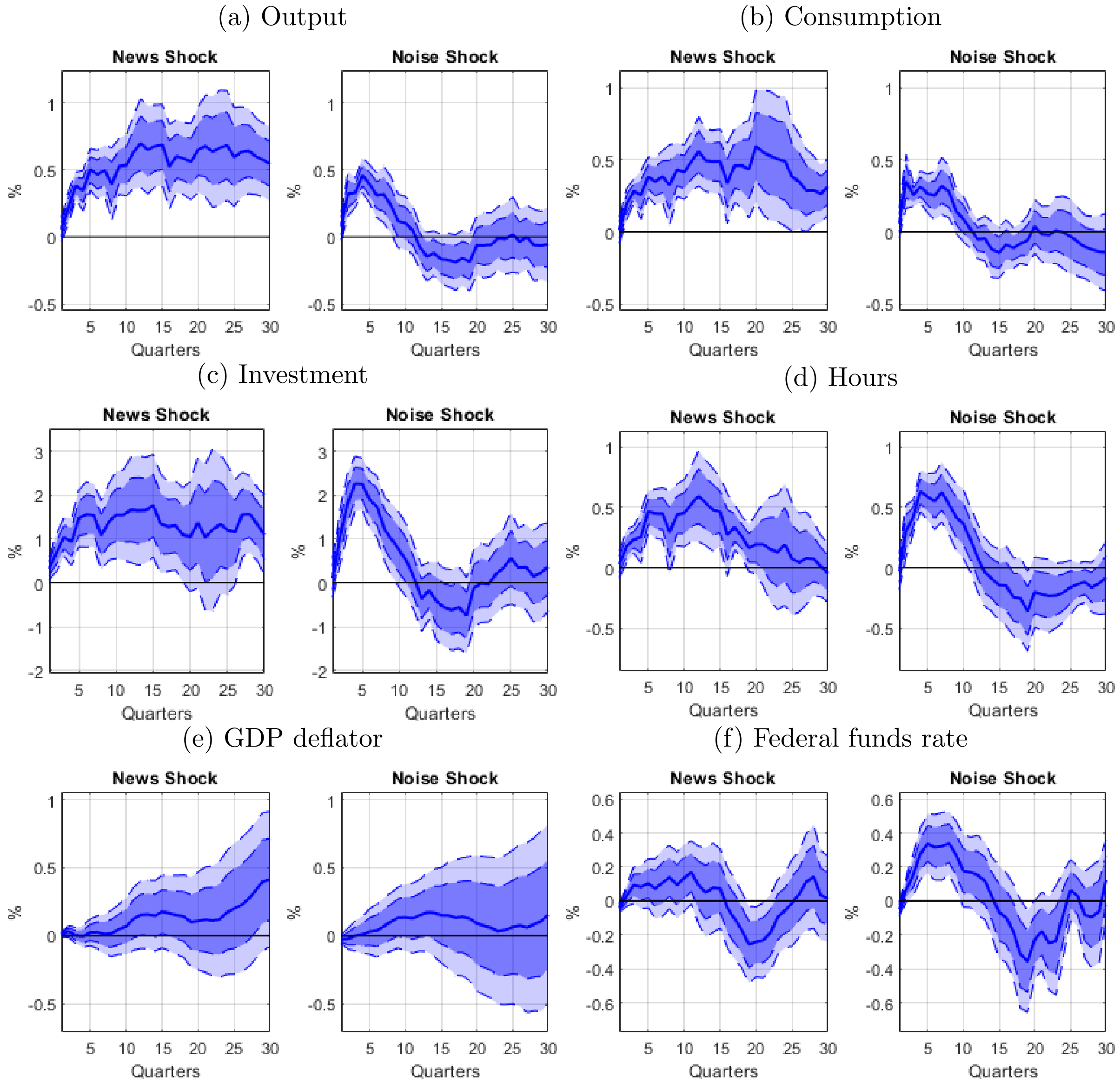

Figure 8: The effect of news and noise shocks from the stock market on the macroeconomy.

This figure displays the coefficients $\{\beta_0^h\}_{h=0}^{H}$ obtained by estimating equation 5.1. The confidence levels depicted are 68 per cent (shaded area). Standard errors correct for autocorrelation of the residuals using a Newey-West estimator.

We next investigate the effects of news and noise shocks on real activity. Figure 8 displays the results. The top row shows unconditional impulse responses of GDP, consumption, investment, hours, prices, and the policy rate to news shocks (left) and noise shocks (right). Both news and noise shocks lead to economic expansions. In the case of news shocks, the expansion leads to a permanent increase in the level of GDP. GDP growth is positive and permanent. For noise shocks, the expansion is short-lived, lasting around 5 quarters. Thereafter, there is a prolonged decline in GDP growth as the effect of the noise shock partially mean-reverts. This is similar for all other macroeconomic aggregates. In

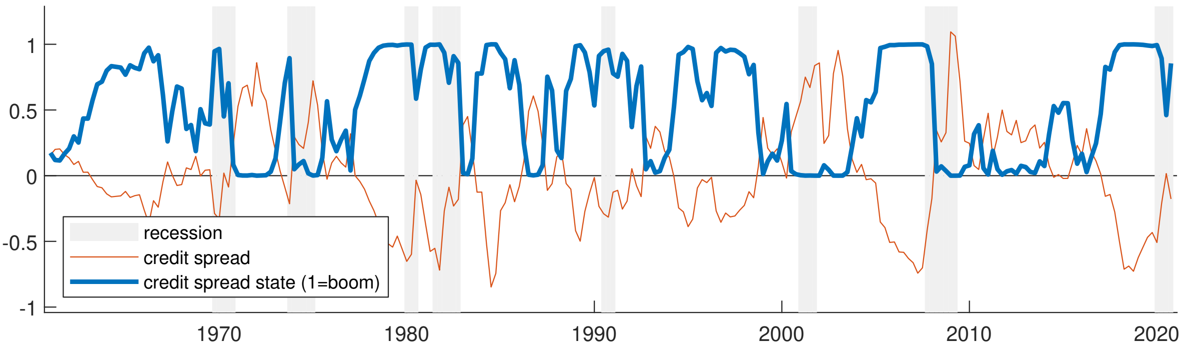

Figure 9: The risk premium state.

particular, both news and noise shocks lead to co-movement of output, consumption, investment, hours, interest rates, and credit. News and noise shocks do not lead to a response of inflation.

5.8 State-dependent transmission

Next, we study the state dependence of the response of leverage dynamics to both shocks. Our hypothesis is that the level of risk premiums has an effect on the propagation of news and noise shocks. To test this prediction, we estimate the following regression:

$$\begin{aligned} Y_{t+h} = \alpha^h + f(RP_t) &\left[\sum_{s=1}^{S} \beta_s^h shock_{t-s} + \sum_{s=1}^{S} \rho_s^h Y_{t-s} + \sum_{s=0}^{S} \Gamma_s^h X_{t-s} \right] \\ + (1 - f(RP_t)) &\left[\sum_{s=1}^{S} \tilde{\beta}_s^h shock_{t-s} + \sum_{s=1}^{S} \tilde{\rho}_s^h Y_{t-s} + \sum_{s=0}^{S} \tilde{\Gamma}_s^h X_{t-s} \right] + \varepsilon_{t+h} \end{aligned} \tag{5.2}$$

Now β_h^0 measures the response of leverage in period $t + h$ to a fundamental news shock that realises in period t during times of low risk premiums, while $\tilde{\beta}_h^0$ measures the same response during times of high risk premiums.

We distinguish between times of high and low risk premiums. Following Auerbach and Gorodnichenko (2011), we transform the risk premium using the function $f(x) = \frac{\exp(-\gamma x)}{1+\exp(-\gamma x)}$, with $\gamma = 10$. Our measure of the risk premium is the one quarter-lagged, linearly detrended AAA-10Y corporate bond spread. Figure 9 displays the corporate bond spread RP_t (in red), as well as the risk premium state $f(RP_t)$ (in blue). The shaded areas are the NBER recession dates. While recessions are typically times of low risk premiums, the mapping is not one for one. In particular, risk premiums were high during the Euro Area sovereign debt crisis in the early 2010s and in the mid-1980s.

Figure 10 displays the results. The red impulse response is the response during periods of high risk premiums, while the blue plots the response during periods of low risk premiums. The figure shows impulse responses of total credit to the non-financial sector.

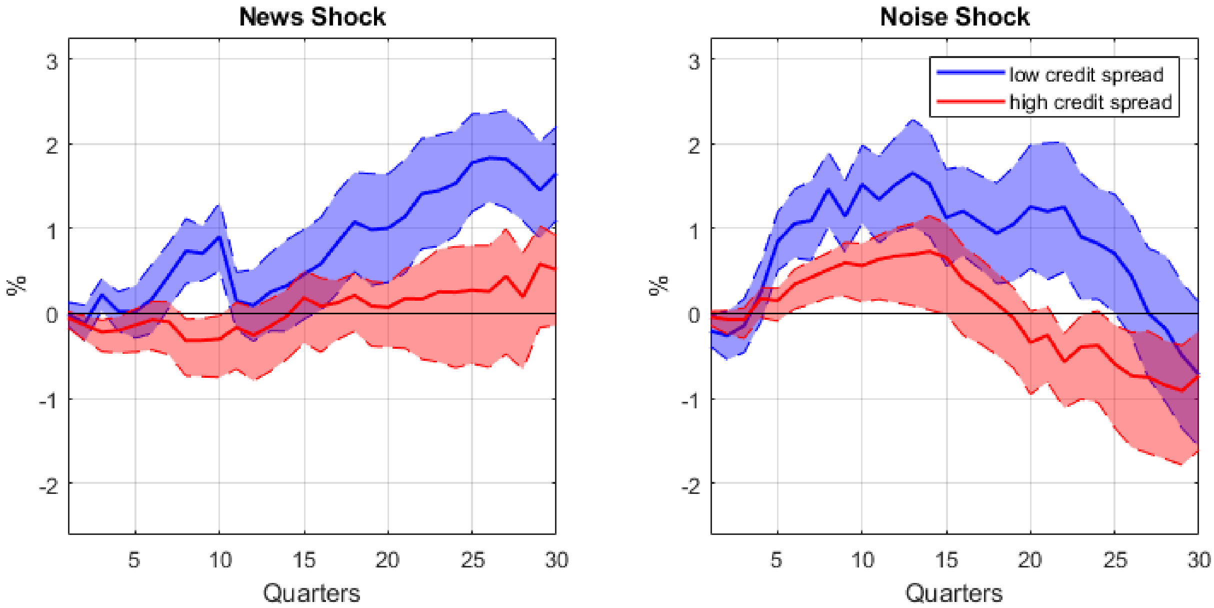

Figure 10: The effect of news and noise shocks on total credit – state-dependent results.

This figure displays the coefficients $\{\beta_0^h\}_{h=0}^H$ obtained by estimating equation 5.1. The confidence levels depicted are 68 per cent (shaded area). Standard errors correct for autocorrelation of the residuals using a Newey-West estimator.

The main result is that state contingency matters. Meanwhile for the noise shock, total credit rises in both states (albeit by more in a low risk premium state), for a news shock, the increase is statistically significant only in a low risk premium state. On the opposite end, total credit growth reverts and falls below trend in both states following a noise shock, although almost 10 quarters sooner in a high risk premium state. Overall, general credit conditions matter, and the boom-bust cycle generated by a noise shock is more pronounced in a high risk premium state.

A possible explanation is that investors are able to leverage in response to news and noise shocks if credit conditions are lenient, but not if credit conditions are tight. This is in line with the model. There, news and noise shocks only lead to a decline in liquidity premiums if the leverage capacity of financial intermediaries is high. The decline in the liquidity premium in turn amplifies the credit boom and, in the case of a noise shock, the subsequent bust.

6 The historical importance of noise shocks for credit cycles

The previous section showed that noise shocks could lead to boom-bust cycles in credit and real outcomes. One important question from this evidence is how important noise shocks were historically for the dynamics of credit and GDP. Appendix D shows the results of estimating an unobserved component model for credit and GDP, where we embed the identified noise shock as an observable. The model decomposes credit into a trend component and a cycle component. We allow the impact of noise shocks on the credit cycle and the impact of the credit cycle on GDP growth to vary over time.

There are two main results. First, the importance of noise shocks for the credit cycle dynamics has increased since the late 1990s. Second, the impact of the credit cycle on GDP growth was especially large during the late 1970s, the early 1980s, and the Great Recession. These results imply that noise shocks have become increasingly important for the credit cycle, while their impact on GDP growth is the largest during large recessions.

7 Conclusion

We provide a theoretical and empirical framework to distinguish sustainable from unsustainable credit booms. First, we use a macro-financial model to show that noise shocks can lead to unsustainable credit booms, especially when risk premiums are low. The key transmission mechanism is a novel debt overhang channel. Second, we empirically identify noise shocks and show that they lead to persistent credit boom-bust cycles, in line with the debt overhang channel. Third, we show that noise shocks have become more prominent in driving the credit cycle since the 1990s.

Our findings have implications for the conduct of macroprudential policy since only some credit booms require regulatory tightening. In particular, even when asset prices are high relative to fundamentals, credit growth does not necessarily warrant a regulatory response, as high asset prices and credit growth might be driven by news about the future.

An important avenue for future research is to study the role of firm debt structure in the propagation of noise shocks. We find suggestive evidence of the following mechanism. Banks initially supply credit to fund firms after they receive a positive signal. However, over time, firms shift from loan financing to bond financing if the signal is a news shock. In this case, bond markets are more liquid and efficient in providing the necessary external financing. Nevertheless, the bond market will not supply funding in the case of a noise shock, in which case firms cannot offset the fall in bank lending, such that total credit will decrease. That has become a crucial consideration in the current Basel 3.1 regulatory context.

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Appendix

For online publication

A Data

A.1 Data description

We use the following data series:

- **Real GDP**, obtained from FRED (identifier GDPC1). The series is log-transformed, and then the log of population (identifier CNP16OV) is subtracted.
- **Dividends**, obtained from FRED (identifier DIVIDEND). Dividends are deflated with the GDP deflator (identifier GDPDEF) and log-transformed, and then the log of population (identifier CNP16OV) is subtracted.
- **Stock prices**, the S&P500, obtained from datastream. The series is deflated with the GDP deflator and log-transformed.
- **3-month treasury rate**, obtained from FRED (identifier TB3MS).
- **10-year treasury rate**, obtained from FRED (identifier GS10)
- **Moody's AAA corporate bond yield**, obtained from FRED (identifier AAA)
- **Moody's BAA corporate bond yield**, obtained from FRED (identifier BAA)
- **GZ spread**, obtained from the homepage of Simon Gilchrist (quarterly data up until 2016) and the homepage of the Atlanta Fed (daily data from 2002 onwards)
- **Loans to non-financial business**, obtained from FRED (identifier NCBLL). The series is deflated with the GDP deflator and then log-transformed. We also use an alternative definition that includes the sum of loans to non-financial corporate and non-corporate business (identifiers NCBLL and NNBLL).
- **Bonds to non-financial business**, obtained from FRED (identifier NCBDBIQ027S). The series is deflated with the GDP deflator and then log-transformed.
- **Total credit**, sum of loans and bonds (NCBLL + NCBDBIQ027S). The series is deflated with the GDP deflator and then log-transformed.

- **Book equity, banks**, obtained from the Financial Accounts of the United States (FRB Z1, identifier FL763164103.Q). Our baseline specification uses the book equity of US-chartered depository institutions. We also use an alternative definition, which is the sum of the book equity of US-chartered depository institutions and broker-dealers (identifier FL663164103.Q). We use a further alternative definition, which cumulates the book equity from flows (identifier FA763164103.Q). The series is deflated with the GDP deflator and then log-transformed.

- **Book assets, banks**, obtained from the Financial Accounts of the United States (FRB Z1, identifier FL764095005.Q). Our baseline specification uses the book assets of US-chartered depository institutions. We also use an alternative definition, which is the sum of the book assets of US-chartered depository institutions and broker-dealers (identifier FL664095005.Q). We use a further alternative definition, which cumulates the book assets from flows (identifier FA764095005.Q). The series is deflated with the GDP deflator and then log-transformed.

- **Book leverage, banks**, the log of book assets minus the log of book equity.

- **Market equity, banks**, obtained from CRSP-Compustat. The series is constructed by summing up, within each quarter, the closing price with the number of outstanding shares (prccq $\times$ cshoq), across all firms with SIC codes 602, 603, and 671. We use an alternative specification that also includes firms with SIC codes 620 and 621. The series is deflated with the GDP deflator and then log-transformed.

- **Market assets, banks**, obtained from CRSP-Compustat. The series is constructed by summing up, within each quarter, the sum of the market value of equity and the book value of debt and deposits (prccq $\times$ cshoq + dlcq + dlttq + apq), across all firms with SIC codes 602, 603, and 671. We use an alternative specification that also includes firms with SIC codes 620 and 621. The series is deflated with the GDP deflator and then log-transformed.

- **Market leverage, banks**, the log of market assets minus the log of market equity.

A.2 Data included in the VAR

The shocks and the underlying variables are displayed in Figure 11. Table 1 presents further summary statistics for the shocks.

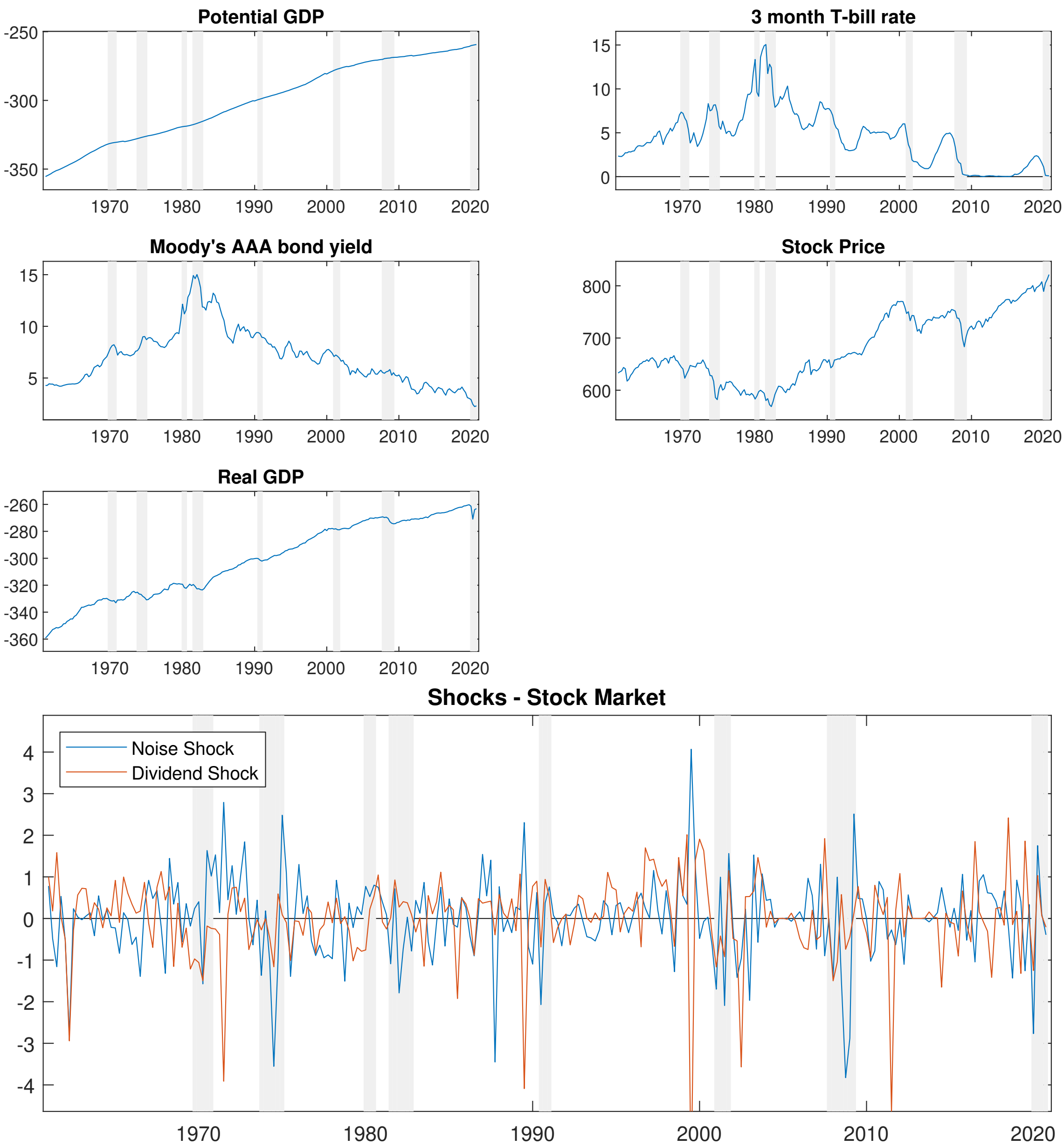

Figure 11: The shocks and the variables used to identify them in the VAR.

	Mean	St.dev.	Autocorr.
Noise (stocks)	0.00	1.01	-0.01
Fund. (stocks)	-0.00	0.99	-0.02

Table 1: Summary statistics

	Noise (stocks)	Fund. (stocks)
Noise (stocks)	1.00	-0.01
Fund. (stocks)	-0.01	1.00

Table 2: Correlation of shocks

B Identifying noise shocks

B.1 Economic environment

This section outlines a simplified version of the economic model developed in Forni et al. (2017a). The model assumes that dividends d_t are given by

$$d_t = d_{t-1} + c(L)a_{t-1} + h(L)v_t, \tag{B.1}$$

where a_t is a dividend shock, v_t is a vector of other disturbances, and $c(L)$ and $h(L)$ are lag polynomials. a_t is assumed to be a news shock that only affects dividends with a lag, i.e. $c(0) = 0$. Agents only receive a noisy signal s_t about the true news shock a_t:

$$s_t = a_t + e_t, \tag{B.2}$$

where e_t is the noise shock.

B.2 Information set of investors

The information set of the agents when determining stock prices is given by $\{\Delta d_\tau, s_\tau, v_\tau\}_{\tau \leq t}$. The relationship between the observable information and the structural shocks a_t, e_t, v_t is given by

$$\begin{bmatrix} \Delta d_t \\ s_t \\ v_t \end{bmatrix} = \begin{bmatrix} c(L) & 0 & h(L) \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} a_t \\ e_t \\ v_t \end{bmatrix}. \tag{B.3}$$

Importantly, it is not possible to recover the structural shocks from the information set of the agents: due to the assumption that a_t is a news shock, $c(0) = 0$, which implies that the matrix in equation B.3 is not invertible. The intuition is that, a_t being a news shock that does not affect dividends contemporaneously, it is not part of the information set of the agents.

B.3 An alternative information set: signal and surprise shocks

However, there is an alternative set of shocks, u_t, s_t, v_t, that can be recovered from the information set of the agents, with

$$\begin{bmatrix} \Delta d_t \\ s_t \\ v_t \end{bmatrix} = \begin{bmatrix} c(L)/b(L) & c(L)\frac{\sigma_a^2}{\sigma_s^2} & h(L) \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u_t \\ s_t \\ v_t \end{bmatrix}. \tag{B.4}$$

u_t is defined as $u_t = -\frac{\sigma_a^2}{\sigma_s^2} b(L) e_t + \frac{\sigma_e^2}{\sigma_s^2} b(L) a_t$. The matrix in equation B.4 is invertible. Thus, it is possible to recover the shocks u_t, s_t, v_t from the residuals of the VAR. Moreover, the shocks u_t, s_t, v_t are related to the shocks a_t, e_t, v_t in the following way:

$$\begin{bmatrix} a_t \\ e_t \\ v_t \end{bmatrix} = \begin{bmatrix} b(F) & \frac{\sigma_a^2}{\sigma_s^2} & 0 \\ -b(F) & \frac{\sigma_e^2}{\sigma_s^2} & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u_t \\ s_t \\ v_t \end{bmatrix} = B(L)^{-1} \begin{bmatrix} u_t \\ s_t \\ v_t \end{bmatrix}. \tag{B.5}$$

F is the forward operator. This equation states that the shocks a_t, e_t, v_t can be recovered using future shocks u_t, s_t, v_t. The intuition is that future information about dividend growth reveals whether signal shocks were indeed news shocks or whether they were only noise.

B.4 Estimating signal and surprise shocks from a VAR

Stock prices are assumed to respond to shocks in the following way:

$$p_t = p_{t-1} + m(L)u_t + d(L)s_t + n(L)v_t. \tag{B.6}$$

Finally, there is a set of additional variables y_t such that

$$\Delta y_t = N(L)v_t + f(L)u_t + g(L)s_t. \tag{B.7}$$

Together, equations B.5, 5.1, and B.7 imply the following autoregressive system:

$$\begin{bmatrix} \Delta y_t \\ \Delta d_t \\ \Delta p_t \end{bmatrix} = \begin{bmatrix} N(L) & f(L) & g(L) \\ n(L) & a_{11}(L) & a_{12}(L) \\ h(L) & a_{21}(L) & a_{22}(L) \end{bmatrix} \begin{bmatrix} v_t \\ u_t \\ s_t \end{bmatrix} = A(L) \begin{bmatrix} v_t \\ u_t \\ s_t \end{bmatrix}. \tag{B.8}$$

We impose that the shocks u_t, s_t do not affect interest rates contemporaneously, i.e. that $f(0) = g(0) = 0$.

To identify the shocks $[u_t, s_t, v_t]$, we first estimate the system of equations B.8 using a VAR model. The model is as follows:

$$\Delta Y_t = \Gamma(L)\varepsilon_t, \tag{B.9}$$

where Y_t contains, in that order, the log of dividends, the log of the S&P 500, the 3-month US treasury yield, and the Moody's AAA corporate bond yield. The S&P 500 is deflated with the GDP deflator and logged. Potential output is divided by population. To estimate the model, we use quarterly data from 1960Q1 to 2020Q4. We use $p = 4$ lags, as recommended by the Akaike information criterion. With the crucial assumption that dividends do not respond to contemporaneous dividend shocks, it is possible to recover the shocks $\hat{u}_t, \hat{s}_t, \hat{v}_t$ and the impulse response coefficients $\hat{A}(L)$ from the reduced form estimates.

B.5 Recovering the news and noise shocks from signal and surprise shocks

With the information contained in the estimate $\hat{A}(L)$ as well as the estimated shocks $\hat{u}_t, \hat{s}_t, \hat{v}_t$, it is possible to recover the first $\hat{B}(L)$ and then the shocks $\hat{a}_t, \hat{e}_t, \hat{v}_t$. The crucial assumption is that dividends respond in the same way to dividend shocks a_t as to signal shocks s_t.

C Additional results

C.1 Investigating possible transmission channels

To understand what drives the increase in credit to the non-financial sector, we decompose the response of total credit to non-financial firms into loans and bonds.

Figure 12 shows the impulse response of bank loans (top row) and bonds (bottom row) to the non-financial corporate sector to a news shock (left column) and a noise shock (right column). Both shocks lead to a temporary increase in the level of loans, that peaks after around 10 quarters. The peak response to a 1 standard deviation news shock is a **2 per cent increase in the level** of loans. Thereafter, the level of loans decreases back to its original level for both the news shock and the noise shock.

The initial impact of news and noise shocks on the level of bonds to non-financial firms is zero, but starts to increase after around 10 quarters. In the case of a news shock, we find two interesting patterns: 1) The rise in bonds coincides with the relative drop in bank loans, which points to a substitution away from bank-based to market-based credit. 2) The total rise in bonds is higher than that of bank loans, which points to a higher elasticity of non-bank credit to a fundamental shock. For a noise shock, both bank credit and bonds start to decrease after around 10 to 15 quarters.

The intuition behind this result is that banks initially supply credit to fund firms after they receive a positive signal. But over time, firms shift from loan financing to bond financing if the signal turns out to be a news shock. In this case, bond markets are more liquid and efficient in providing the necessary external financing. Yet the bond market will not supply funding in the case of a noise shock, in which case firms cannot offset the

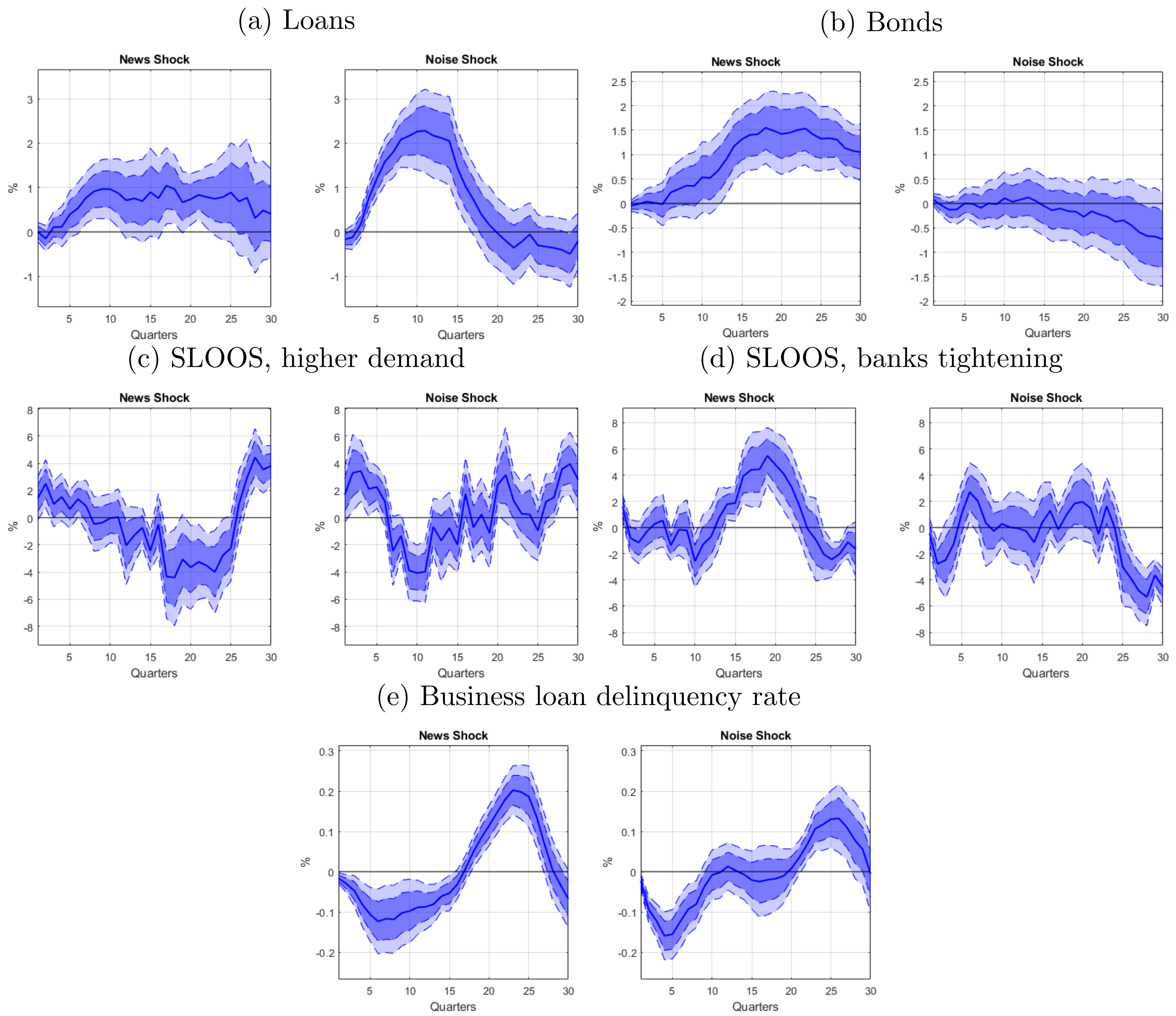

Figure 12: The effect of news and noise shocks on various financial indicators.

Note: The blue line in this figure displays the coefficients $\{\beta_0^h\}_{h=0}^{H}$ obtained by estimating equation 5.1. The confidence levels depicted are 68 per cent (dark shaded area) and 90 per cent (light shaded area). Standard errors correct for autocorrelation of the residuals using a Newey-West estimator.

fall in bank lending, such that total credit will decrease.

We further look at the impact of news and noise shocks on the senior loan officer opinion survey (SLOOS). In response to news and noise shocks, senior loan officers report that their institutions experience higher credit demand. For noise shocks, credit demand falls below the initial level after around 5 quarters and then recovers slowly. Senior loan officers also report slightly lower credit standards, though the response is only significant in the case of noise shocks.

Finally, we investigate the impact of news and noise shocks on business loan delinquency rates. In response to both types of shocks, the delinquency rate falls. For news shocks, it stays low for a long time and then increases, while for noise shocks, it increases back to the initial level quite rapidly. The results in this section suggest that default risk and the sluggish adjustment of credit to news shocks are important transmission channels for fundamental shocks.

C.2 Noise shocks and bank leverage dynamics

Are these results driven by a balance sheet expansion of banks? And is this balance sheet expansion driven by higher leverage or more equity financing of banks? Answering these question is important for regulators: If banks finance credit expansions driven by noise shocks with more debt, these credit expansions could pose substantial financial stability risks. Thus, in this section, we investigate the effects of news and noise shocks on bank leverage.

Figure 13 shows the effects of news and noise shocks on the book assets of private depository institutions (top left panel), as well as book equity (top right panel) and their capital ratio (bottom left panel). A news shock leads to a balance sheet expansion by private depository institutions, which is initially driven by an increase in leverage and later by an increase in equity. The intuition is that banks increase borrowing in response to the positive news shock. Initially, they finance this balance sheet expansion by borrowing themselves. After a while, they deleverage and use equity funding to finance additional assets. This substitution is not one for one: Assets decrease slightly, as banks use more equity.

In contrast, noise shocks do not lead to asset expansions. Thus, the increase in loans documented in Section 5.4 is driven by a reallocation from other lending activities towards lending to non-financial firms. This implies that the asset side of banks' balance sheet becomes riskier following a noise shock. At the same time, firms reduce their equity, such that the liability side of their balance sheet also becomes riskier.

Figure 13 investigated the effects of news and noise shock on bank book leverage. There

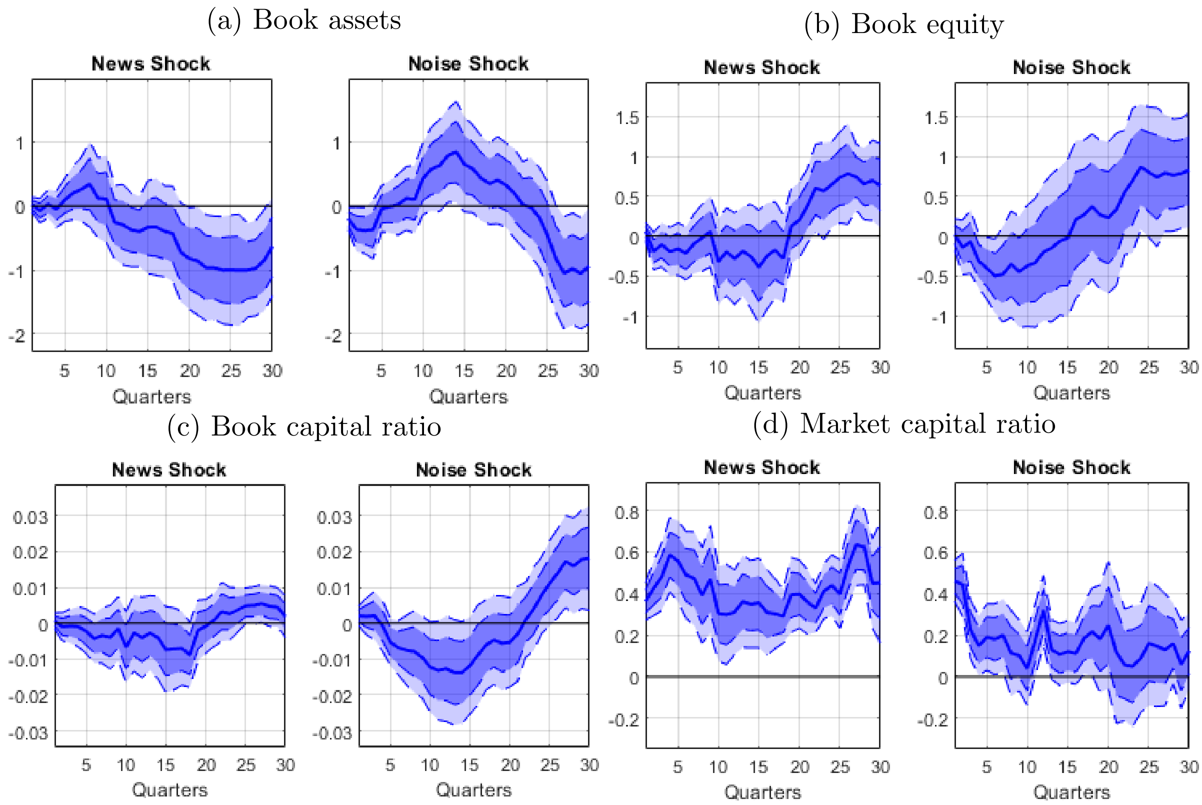

Figure 13: Impulse responses of bank balance sheets to news and noise shocks.

Note: The blue line in this figure displays the coefficients $\{\beta_0^h\}_{h=0}^{H}$ obtained by estimating equation 5.1. The confidence levels depicted are 68 per cent (dark shaded area) and 90 per cent (light shaded area). Standard errors correct for autocorrelation of the residuals using a Newey-West estimator.

is, however, still an active debate about which leverage measure is the most useful to draw conclusions about bank behaviour. The bottom right panel of Figure 13d therefore investigates the dynamics of another leverage measure, market leverage. In response to both news and noise shocks, there is on impact a fall in market leverage, as the market value of banks' equity rises more than the market value of its assets. As banks adjust their debt upwards, market leverage rises back to its initial level in response to a news shock, while it only partially reverts to its previous level in response to a noise shock.

C.3 Robustness

Figure 14 shows various robustness checks. Overall, our main result that credit increases permanently in response to news shocks, while there is a credit boom-bust cycle in response to noise shocks, is robust across specifications.

Dividends as fundamental In a rational model, stock prices reflect the value of the discounted stream of dividends. It could be that potential output is not the right fundamental variable. We therefore follow Forni et al. (2017a) and use dividends as an alternative fundamental.

BAA yield as expectation Some papers have argued that credit spreads are more informative about future economic developments than stock prices (e.g., López-Salido, Stein, and Zakrajšek (2017)). We therefore consider Moody's BAA bond yield as an alternative expectation variable.

Different samples We can extend the sample back to 1950Q1, or we can consider a pre-crisis sample that stops in 2006Q4. The results are unchanged.

Credit in VAR An alternative approach to first estimating the shocks and then estimating the response of credit in local projections would be to directly include credit in the VAR. This also changes the shocks used in the local projections. We do, however, get similar responses to the baseline model.

GDP ordered second In the baseline model, we follow Forni et al. (2017b) in ordering GDP last in the VAR. One criticism is that this implies that GDP responds contemporaneously to financial variables, which is an unusual assumption in the VAR literature. Therefore, we try an alternative specification, whereby we order GDP second, right after potential GDP. This does not change the results.

Uncertainty in VAR It could be that news and noise shocks reflect times of increased uncertainty. Therefore, we include the macroeconomic uncertainty index of Jurado, Ludvigson, and Ng (2015) in the VAR. We order it second, such that uncertainty shocks can contemporaneously affect asset prices and GDP, but not potential GDP. We need to shorten the sample by two periods, as the uncertainty index only becomes available in 1960Q3. The results do not change much.

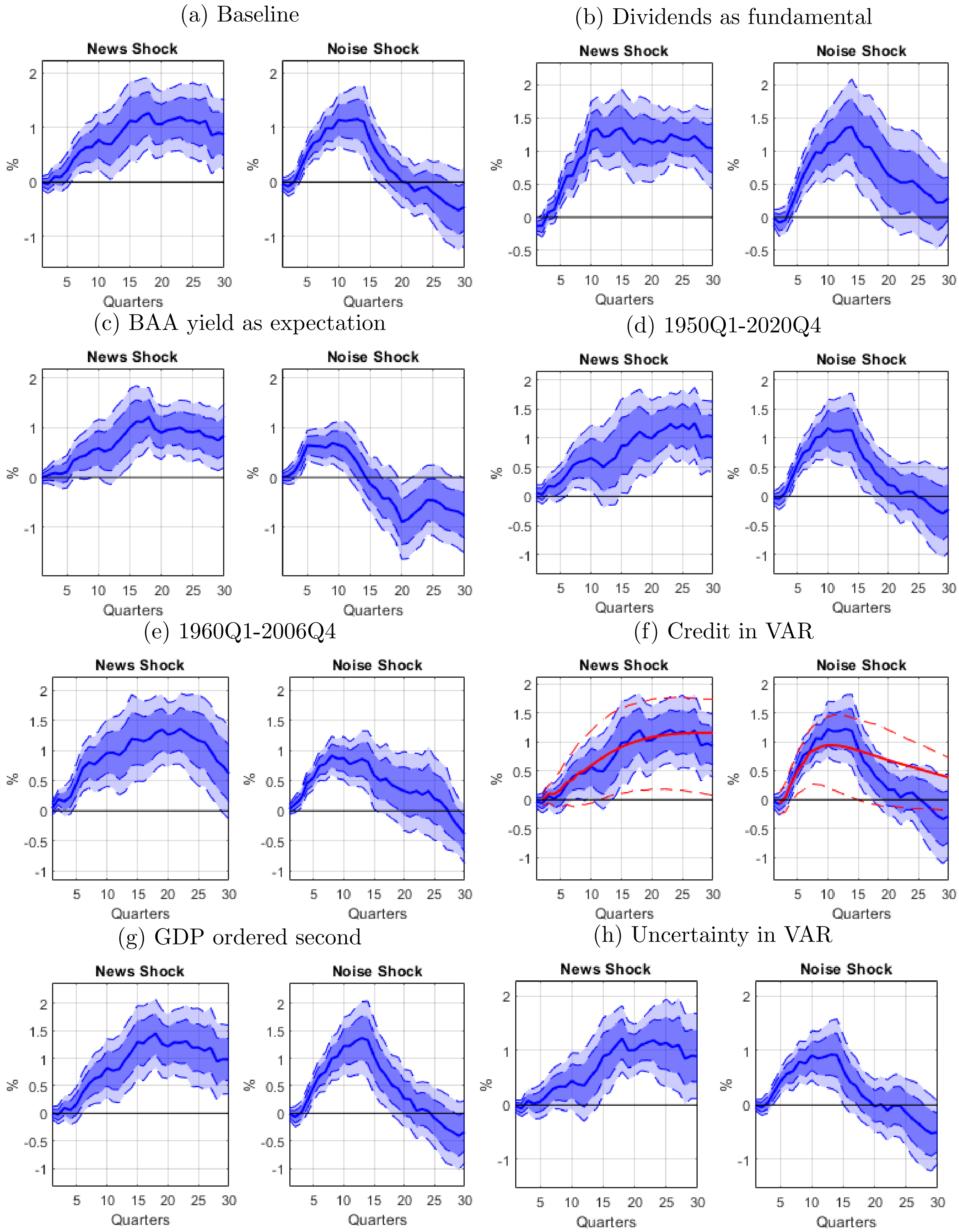

Figure 14: Various robustness checks.

Note: All panels show the responses of credit to news and noise shocks, for various models. First, we consider an alternative identification that uses dividends as a fundamental, as in Forni et al. (2017a). Second, we consider an alternative identification that uses the BAA bond yield as expectation. Third, we extend the sample to 1950Q1-2020Q4. Fourth, we cut off the sample before the financial crisis in 2006Q4. Fifth, we include credit as a variable in the VAR used to identify the shocks. Sixth, we order GDP second in the VAR and the local projections, right after potential GDP. Seventh, we add Jurado, Ludvigson, and Ng (2015) uncertainty to the VAR and the local projections, ordered second. The confidence levels depicted are 68 per cent (dark shaded area) and 90 per cent (light shaded area).

D Time-varying Effects of Noise Shocks

In order to illustrate the evolving role of noise shocks in determining the relationship between fluctuations in credit and real activity, we employ an unobserved component model. In particular, we are interested in inferring changes over time associated with two types of elasticities. The first elasticity corresponds to the effect of noise shocks on the credit cycle, and the second elasticity corresponds to the effect of the credit cycle on real activity. Accordingly, the estimates isolate periods when credit expansions, fueled by noise shocks, negatively affect real activity.

The level of credit, C_t, is decomposed into a trend, τ_t, and a cyclical component, c_t. The variable used to measure C_t, is the amount of total financial assets in the US economy.

$$C_t = \tau_t + c_t. \tag{D.1}$$

On the one hand, since a persistently increasing stochastic process drives the level of credit, the trend component is assumed to follow a random walk with a time-varying drift, δ_t. This drift, which is also assumed to follow a random walk, can be interpreted as a measure of credit's evolving medium-term growth. On the other hand, the cyclical component of credit, c_t, is assumed to follow an autoregressive process of order two. Most importantly, we also allow noise shocks, denoted by $shock_t$, to potentially influence the credit cycle in a time-varying fashion. The employed measure of noise shocks, based on the work by Forni et al. (2017b) and explained in detail in Section 5.2, are innovations to stock prices unrelated to past, current and future potential output. Hence, the dynamics of the trend and cyclical components of credit are

$$\tau_t = \delta_{t-1} + \tau_{t-1} + \varepsilon_t, \tag{D.2}$$

$$\delta_t = \delta_{t-1} + \upsilon_t, \tag{D.3}$$

$$c_t = \phi_1 c_{t-1} + \phi_2 c_{t-2} + \alpha_t shock_t + \epsilon_t, \tag{D.4}$$

where α_t denotes the sensitivity of the credit cycle to noise shocks and the corresponding innovations are normally distributed, that is, $\varepsilon_t \sim N(0, \sigma^2_\varepsilon)$, $\upsilon_t \sim N(0, \sigma^2_\upsilon)$, and $\epsilon_t \sim N(0, \sigma^2_\epsilon)$. In addition, we also evaluate the time-varying effect that the credit cycle may have on GDP growth, y_t, by relying on the following relationship,

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_{2,t} c_{t-1} + u_t, \tag{D.5}$$

where $u_t \sim N(0, \sigma^2_u)$ and $\beta_{2,t}$ measures the changing sensitivity of real activity to the credit cycle. Lastly, the dynamics of both time-varying coefficients are assumed to follow independent random walks,

$$\alpha_t = \alpha_{t-1} + u_{\alpha,t}, \tag{D.6}$$

$$\beta_{2,t} = \beta_{2,t-1} + u_{\beta_2,t}, \tag{D.7}$$

where $u_{\alpha,t} \sim N(0, \sigma_\alpha^2)$ and $u_{\beta_2,t} \sim N(0, \sigma_{\beta_2}^2)$. The model is cast into a state space representation and estimated with Bayesian methods.

Chart A of Figure 15 shows the time-varying sensitivity of the credit cycle to noise shock, α_t, suggesting that since the "Dot-com Bubble", credit has largely been driven by these type of innovations. Chart B of Figure 15 shows the time-varying sensitivity of GDP growth to the lagged credit cycle. The estimates identify two periods when credit expansions could have been detrimental for real activity; Between 1975 and 1985, and during the "Great Recession". During this second episode, a high sensitivity to noise shocks accompanied credit expansion. In other words, large noise shocks lead to deep contraction in economic activity.[8]

E Numerical solution strategy

Even this simple model is too non-linear to allow for a closed-form solution. We, therefore, calibrate the model and show a numerical example. As a numerical experiment, we show the equilibrium as a function of the signal S_1 and the surprise $\Delta_2 = Z_2 - S_1$.

Equipped with the expressions for C_2^I, Q_2, and μ_2^I, from equations 3.15, 3.14, and 3.13, and the default threshold 3.3, solving the period 2 equilibrium boils down to solving a system of the two non-linear equations 3.2 and 3.1 for K_2 and B_2 as a function of the aggregate state K_1, B_1, D_1, and Z_2.

From solving the period 2 equilibrium, we obtain policy functions $K_2(K_1, B_1, D_1, Z_2)$ and $B_2(K_1, B_1, D_1, Z_2)$ that allow us to compute value functions and bond prices $J_2(K_1, B_1, D_1, Z_2)$, $Q_2(K_1, B_1, D_1, Z_2)$, and $E_2\left[X_3(K_1, B_1, D_1, Z_2)|A > A_3^*\right]$ from equations 3.6, and 3.12. We solve for the period 2 equilibrium for various values of Z_2, given by the quadrature nodes used to compute the expectations in period 1.

Next, we solve the period 1 equilibrium as a system of two non-linear equations in K_1 and B_1. We need to compute expectations over Z_2 conditional on the period 1 signal. To do so, we use Gauss-Hermite quadrature. Remember that $\zeta = \frac{\sigma_a^2}{\sigma_a^2 + \sigma_e^2}$. Then, the surprise shock is normal with mean 0 and variance $\sigma_\Delta^2 = (1-\zeta)^2\sigma_a^2 + \zeta^2\sigma_e^2$. Z_2 has the conditional

8. Charts A and B of Figure 16 show the quarterly GDP growth and the cyclical component of credit, respectively. The credit cycle exhibits four expansionary regimes associated with the early 1970s, the late 1980s, the "Dot-com Bubble", and the "Great Recession", where the last two are much more prominent than the previous.

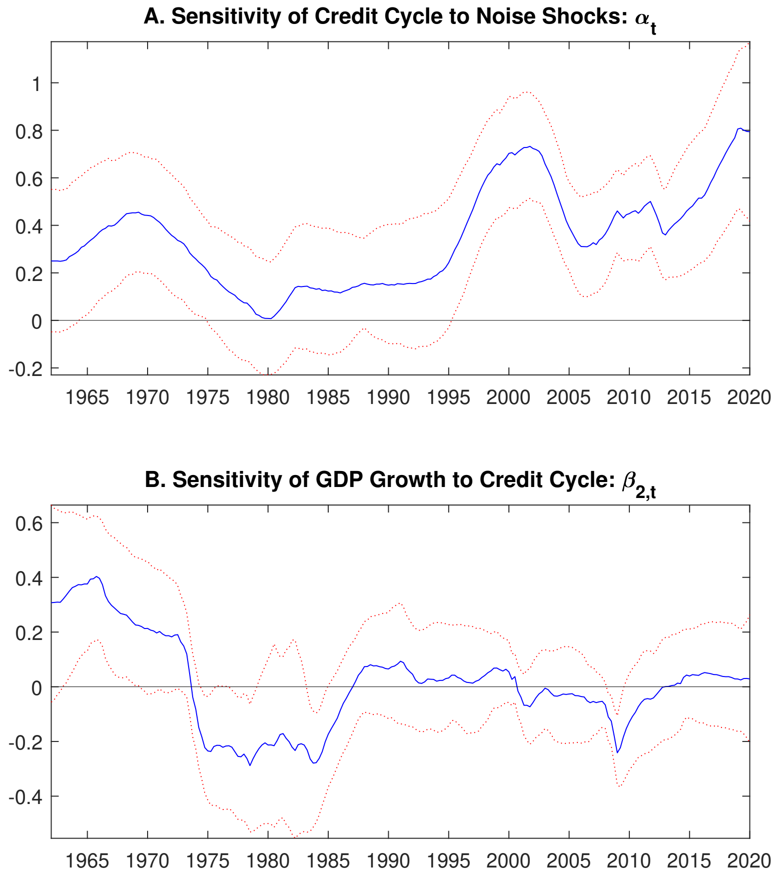

Figure 15: Time-varying effects of noise shocks on credit and GDP growth.

Note: This figure shows the results from the estimation of the unobserved components model given by equations D.2 to D.7. The credible sets (red, dashed lines) represent the 16th and 84th percentiles of the corresponding posterior densities.

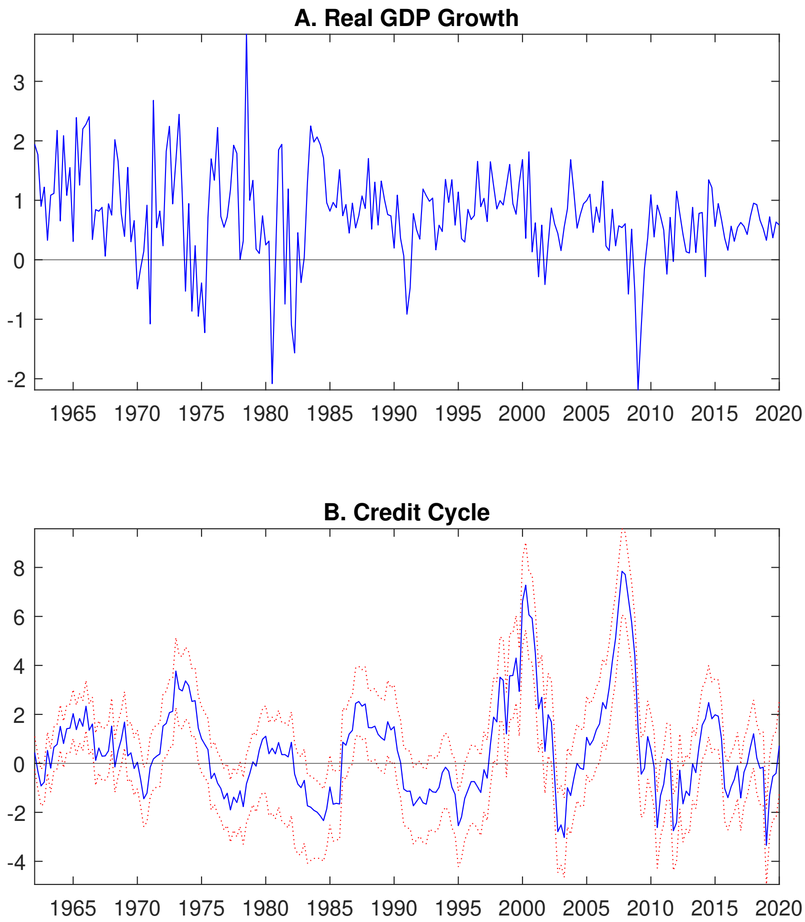

Figure 16: Estimates from an unobserved component model.

Note: This figure shows the results from the estimation of the unobserved components model given by equations D.2 to D.7. The credible sets (red, dashed lines) represent the 16th and 84th percentiles of the corresponding posterior densities.

distribution $Z_2 \sim N(\zeta S_1, \sigma_\Delta)$. We again obtain expressions for C_1^I, Q_1, and μ_1^I from equations 3.19, 3.18 and 3.13, and the default threshold from equation 3.9. Then, solving the period 1 equilibrium boils down to solving a system of the two non-linear equations 3.8 and 3.7 for K_1 and B_1.

The model has the following parameters: α, L, β^F, β^I, $\underline{A}$, $\overline{A}$, κ, ψ, N_1, σ^a, σ^e. We calibrate the parameters to target a leverage of intermediaries of 0.9 (ψ), a period 2 leverage of entrepreneurs of 0.3 (β^F), an entrepreneurs default rate of 0.01 ($\underline{A}$,$\overline{A}$), an intermediary component of the credit spread of 0.01 (β^I), and an equity issuance rate of intermediaries of 0.03 (κ). We set $\alpha = 0.33$, $L = 1$, $\sigma^a = 0.01$, and $\sigma^e = 0.01$, which are conventional values from the literature. We set B_0 to target a period 1 leverage of entrepreneurs of 0.15, and D_0 to target an initial equity issuance rate of intermediaries of 0.05.

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