Noisy credit cycles*

Eddie Gerba[†] Danilo Leiva-León[‡] Johannes Poeschl[§]

October 2023

Abstract

Identifying the drivers of credit cycles is crucial for prudential regulation. We show in a model that noise shocks 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 debt overhang channel is important for the propagation of noise shocks.

Keywords: Credit cycles; news shocks; noise shocks; bank lending.

JEL Classification: E440; G240; G280.

*A previous draft of this paper circulated under the title *When credit expansions become troublesome: The story of investor sentiments*. We thank seminar participants at the Bank of England, Danmarks Nationalbank and Ca'Foscari University as well as participants at the 2022 CEBRA conference, the 2022 Money, Macro and Finance conference, the 2023 Barcelona Summer Forum, the 2023 conference of the German Economists' Association and the 2023 IFABS conference in Oxford 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.

[†]Gerba: Prudential Regulation Authority, Bank of England.

[‡]Leiva-León: DG Research, European Central Bank.

[§]Poeschl: Research Department, Danmarks Nationalbank. Corresponding author. Email: jpo@nationalbanken.dk.

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 debt overhang channel that has not been explored in the news shock literature.[3] 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

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.

3. The role of the debt overhang channel for macroeconomic dynamics in settings without news shocks has been explored in Gomes, Jermann, and Schmid (2016), Jungherr and Schott (2021), Jungherr and Schott (2022), and Poeschl (2023). Jungherr, Meier, Reinelt, and Schott (2022), Deng and Fang (2022) and Fabiani, Falasconi, and Heineken (2022) discuss the role of the debt overhang channel for the transmission of monetary policy shocks.

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 defaultable long-term debt. A news shock to productivity leads firms and intermediaries to increase their debt. If the news shock fails to realize, firms maintain 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 increase. 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 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, Gambetti, Lippi, and Sala (2017a), Forni, Gambetti, Lippi, and Sala (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.[4] 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, providing 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 intermediation premiums. These results align with our theoretical model, where we interpret times of low-intermediation premiums as times when the financial constraint of intermediaries is slack. In contrast, times of high-intermediation premiums are times when the financial constraint of intermediaries binds. The mechanism behind this stronger amplification during times of lenient credit supply works as follows. Financial intermediaries can use more leverage if credit supply conditions are lenient. 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

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

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 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. Similar to us, Gorton and Ordoñez (2020) investigate how good and bad credit booms distinguish themselves. In their model, the ultimate driver of credit booms are productivity shocks, not expectations.

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 realize can generate boom-bust cycles and to validate the predictions from the model empirically. 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 greatly affect real activity. Brianti and Cormun (2023) investigate boom-bust cycles in response to shocks in growth expectations as drivers of boom-bust cycles. 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).[5]

This paper contributes to the ongoing policy debate in various ways. First, it gives policymakers guidance on identifying the shocks behind a credit swing and predicting the impact on the future realization 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.

Second, 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 a 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 and 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 4. We discuss the historical importance of noise shocks for the credit cycle in section 5. Section 6 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, $t = 1, 2, 3$.

5. 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. 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. There is aggregate risk in the form of news and noise shocks to productivity and idiosyncratic risk in the form of shocks to the capital quality of entrepreneurs.

2.1 Firms

Firms combine labour from workers and capital from entrepreneurs to produce output according to a production function with constant returns to scale with parameter $\alpha \in [0,1]$. They choose capital K_{t-1} and labour L_t to maximize 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 normalized to unity: $Z_1 = 1$. Productivity in period 2 is equal to productivity in period 1 plus a news shock $a_1 \sim N(0, \sigma_a)$ that is determined in period 1:

$$Z_2 = Z_1 + a_1. \tag{2.2}$$

Agents do not perfectly observe the news shock. Instead, at the beginning of period 1, they receive a signal S_1 about productivity in period 2. The signal consists of the true shock plus a noise shock $e_1 \sim N(0, \sigma_e)$:

$$S_1 = a_1 + e_1. \tag{2.3}$$

The signal, therefore, has a news component a_1 and a noise component e_1.[6] After period 2, there are no more shocks to productivity, such that productivity in period 3 is $Z_3 = Z_2$.

2.2 Workers

In periods 1 and 2, workers consume C_t and save in 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

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

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 t is

$$V_t = \max_{C_t, D_t} C_t + E_t\left[V_{t+1}\right],$$

subject to

$$C_t + D_t = W_t L + R_t^D D_{t-1}.$$

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. New investment is subject to a quadratic capital adjustment cost with parameter θ.[7]

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 $Q_t(k_t, b_t; \mathcal{S}_{t+})$. $\mathcal{S}_{t+}$ is the aggregate state of the economy at the end of the period, which we describe below. The entrepreneur internalizes that the debt price depends on her idiosyncratic choices. Entrepreneurs have some initial debt B_0.

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

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

Appendix A.2.3 shows the entrepreneur's problem in period 1, which looks similar.

7. The capital adjustment cost ensures that the expected return on capital increases in expected future productivity. In its absence, entrepreneurs would adjust the capital stock such that the expected return on capital equals the cost of capital, which is not affected by expected future productivity. In that case, leverage would be counter-cyclical, as Proposition 2 in Jungherr and Schott (2022) shows.

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 must 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 2 is

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

subject to

$$\begin{aligned}
Q_2(K_2, B_2; \mathcal{S}_{2+})B_2^I &= N_2^I + D_2^I - C_2^I \\
N_2^I &= Q_2(K_2, B_2; \mathcal{S}_{2+})B_1^I(1 - F(A_2^*)) - R_1^D D_1^I \\
\psi Q_2(K_2, B_2; \mathcal{S}_{2+})B_2^I &\leq J_2 \\
J_3 = C_3^I = N_3 &= B_2^I(1 - F(A_3^*)) - R_2^D D_2^I
\end{aligned}$$

$1_{C_2^I \leq 0}$ is an indicator function which takes the value of one if the financial intermediary issues equity, i.e. if $C_2^I \leq 0$, and the value of zero if the financial intermediary pays dividends, i.e. if $C_2^I > 0$. The problem of the intermediary in period 1 is in Appendix A.3.2.

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 characterize 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.[8]

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

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

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 explain 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 dramatically amplifies the investment bust. This debt overhang channel is the only financial friction for entrepreneurs, 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 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 emphasizes the importance of default risk for leverage dynamics and credit spreads, 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.

8. We recognize this is a strong assumption, but we do this 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.

2.6.2 Frictions in financial intermediation

The financial frictions we introduce for intermediaries give rise to a time-varying credit intermediation premium. There is ample evidence in the literature for such a credit intermediation 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 intermediation 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 emphasizes 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. The, we discuss how the debt overhang channel can create credit boom-bust cycles in response to such signals. In Appendix A, we derive the optimal decisions of workers, firms, entrepreneurs, and financial intermediaries and characterize the equilibrium of the model in the credit market.

3.1 Signal extraction problem

As in Chahrour and Jurado (2022), the noise representation 2.3 and 2.2 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 $\nu_1 = E\left[Z_2|S_1\right] = \frac{\sigma_a^2}{\sigma_a^2+\sigma_e^2}S_1$. Accordingly, news and noise shocks raise expected productivity in the same way.

The surprise shock in period 2 is

$$
\begin{aligned}
\Delta_2 &= Z_2 - E\left[Z_2|S_1\right] \\
&= a_2 - \frac{\sigma_a^2}{\sigma_a^2+\sigma_e^2}(a_1+e_1) \\
&= \frac{\sigma_e^2}{\sigma_a^2+\sigma_e^2}a_1 - \frac{\sigma_a^2}{\sigma_a^2+\sigma_e^2}e_1.
\end{aligned}
$$

A positive news shock a_1 in period 1 leads to a positive surprise in period 2, consisting of the difference between the true shock and the optimal forecast by the agents. A positive noise shock in period 1 leads to a negative surprise in period 2, namely, minus the optimal forecast in period 1. The surprise 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 Analytical discussion

Equipped with a characterization of how agents optimally update their expectations in response to signal and surprise shocks, we can now characterize how noise shocks can lead to credit boom-bust cycles.

Leverage-driven credit boom We show in Appendix A.2 that leverage in period 1, defined as $\omega_1 \equiv b_1/k_1$, is the solution to the following non-linear equation in ω_1:

$$
\omega_1 = \omega_0\frac{k_0}{k_1} + \frac{E_1\left[\left(\Psi_1-\beta^F\right)\frac{\overline{A}-A_2^*}{\overline{A}-\underline{A}}\Psi_2\frac{\overline{A}-A_3^*}{\overline{A}-\underline{A}}\right]}{E_1\left[\Psi_1\Psi_2\left(f(A_2^*)\frac{\overline{A}-A_3^*}{\overline{A}-\underline{A}}\left(\frac{\partial A_2^*}{\partial\omega_1}+\frac{\partial A_2^*}{\partial\omega_2}\frac{\partial\omega_2}{\partial\omega_1}\right)+\frac{\overline{A}-A_2^*}{\overline{A}-\underline{A}}f(A_3^*)\frac{\partial A_3^*}{\partial\omega_2}\frac{\partial\omega_2}{\partial\omega_1}\right)\right]}. \tag{3.1}
$$

A_2^* and A_3^* are thresholds for the idiosyncratic capital quality shock below which the entrepreneur will default. We show in the appendix that these thresholds are increasing functions of leverage, which implies that default risk is increasing in leverage. Ψ_1 and Ψ_2 are the endogenous discount rates of the intermediary sector in period 1 and period 2, respectively. They are lower, the tighter the intermediary sector's financial constraint.

For the case where there is no period 3 default risk, we can solve for the optimal leverage in closed form:

$$\omega_1 = \max\left(\underbrace{\frac{E_1\left[\left(\Psi_1-\beta^F\right)\Psi_2\left(\overline{A}+(\Psi_2-\beta^F)\omega_2^*+1+(1+r_2^K)+\beta^F(1+r_3^K)\right)\right]}{E_1\left[\left(2\Psi_1-\beta^F\right)\Psi_2^2\right]}}_{\text{Target leverage}}\right.$$

$$\left.+\underbrace{\frac{E_1\left[\Psi_1\Psi_2^2\right]}{E_1\left[\left(2\Psi_1-\beta^F\right)\Psi_2^2\right]}}_{\text{Leverage persistence}}\omega_0\frac{k_0}{k_1},\omega_1^*\right). \tag{3.2}$$

ω_1^* is the maximum attainable risk-free leverage in period 1. Because ω_1 is increasing in $E_1\left[r_2^K\right]$, which is increasing in the productivity signal, equation 3.2 implies that firms will raise leverage in response to a positive signal shock, be it driven by a true news shock or a noise shock. While we assume that the expected default risk in period 3 is zero to derive the result above, we show numerically below that it extends to the case with positive expected default risk in period 2.

Credit bust following a noise shock Equation 3.3 shows the closed-form expression for leverage. It implies that leverage in period 2 is increasing in expected future productivity (through r_3^K) and in lagged leverage ω_1.

$$\omega_2 = \max\left(\underbrace{\frac{\Psi_2-\beta^F}{2\Psi_2-\beta^F}\left(\overline{A}+r_3^K+1\right)}_{\text{Target leverage}}+\underbrace{\frac{\Psi_2}{2\Psi_2-\beta^F}}_{\text{Leverage persistence}}\omega_1\frac{k_1}{k_2},\omega_2^*\right). \tag{3.3}$$

ω_2^* is the maximum attainable risk-free leverage in period 2. Because of the noise shock in period 1, entrepreneurs raise leverage in period 1. Relative to the case without a noise shock, leverage and credit spreads in period 2 are higher, and stock prices are lower following a positive noise shock in period 1. This mechanism implies that default risk is higher, credit spreads are higher, and stock prices are lower than if the shock in period 1 had never happened. Despite the absence of a change in actual productivity, a boom-bust cycle results.

3.3 Numerical example

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 the signal

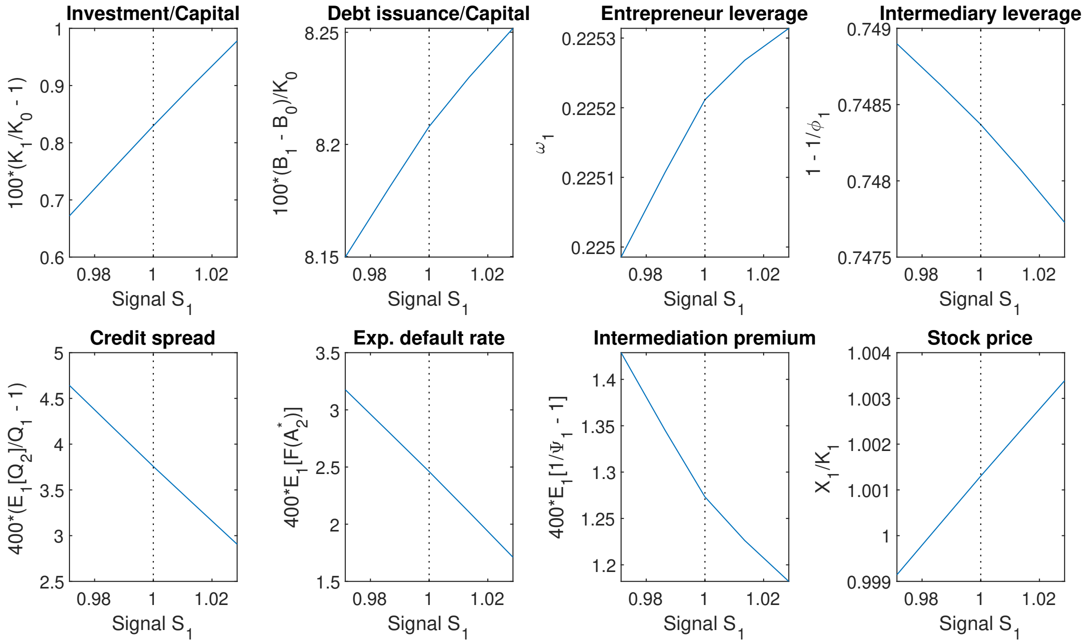

Figure 1: A credit boom in period 1.

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.

was a true news shock. In that case, a small positive surprise shock occurs in period 2. Second, a situation where the surprise shock exactly offsets the signal shock. In that case, the signal shock was a noise shock. We solve the model numerically for this experiment, as even this simple model does not permit a closed-form solution. We analytically discuss the equilibrium of the model in Appendix B. The numerical solution strategy is described in Appendix F.

3.3.1 Credit boom in period 1

Figure 1 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 investment-to-capital ratio. This is because the capital stock is increasing in expected future productivity. Likewise, a higher signal leads to a higher debt issuance-to-capital ratio. This effect is because higher expected future productivity reduces default risk and increases bond prices. The leverage of entrepreneurs increases. Default risk and the intermediation premium decline, leading to a decline in the credit spread. Leverage of intermediaries

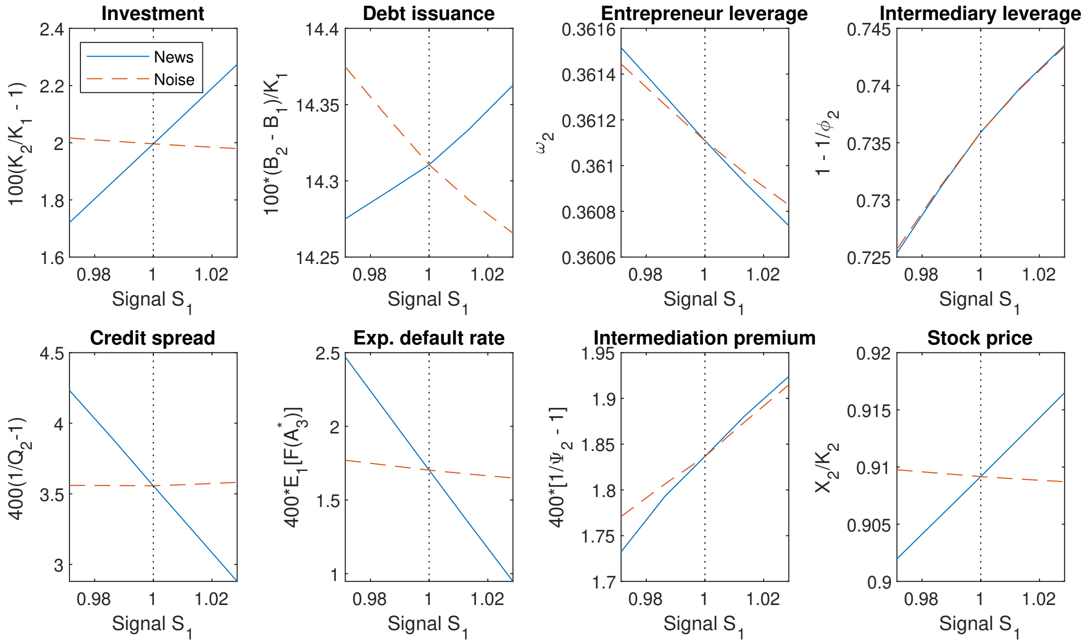

Figure 2: News-driven vs noise-driven credit dynamics in period 2.

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.

declines because of the decline in the credit spread. Stock prices increase.[9]

3.3.2 Sustained credit boom or credit bust in period 2

Figure 2 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 investment-to-capital ratio if the signal in period 1 is higher. This effect is driven by capital being increasing in productivity. Entrepreneurs increase their debt issuance as the current debt choice increases in the lagged debt choice.

The net worth of intermediaries rises, but less than their assets. As a result, intermediaries increase leverage and issue additional equity. 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, entrepreneurs' investment 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

9. An interesting implication of the model is that the leverage of intermediaries and entrepreneurs moves in opposite directions, conditional on the shock. This shows how different financial frictions can lead to different conditional leverage dynamics. The increase in the leverage of entrepreneurs reflects the decline in the default risk of entrepreneurs. The decline in the leverage of intermediaries reflects the decline in the credit spread, which leads to an increase in the value of the outstanding assets of intermediaries.

period 2 is decreasing in the lagged level of debt. In other words, the fall in the capital is driven by a debt overhang effect (e.g. Myers (1977)). The debt issuance falls. 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 the intermediation 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 realize, the high outstanding debt leads entrepreneurs to reduce their capital stock.

3.4 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)). We show in Appendix A.3 that Ψ_1 is increasing in the net worth of intermediaries, which is declining in the default probability. The model thus produces a fall in the intermediation premium Ψ_1 in response to a positive signal and, therefore, a relaxation of credit supply because of increased bond prices and high leverage. It then produces a rise in the intermediation premium Ψ_2 in response to the negative surprise that the shock was noise, resulting in a credit supply contraction.

Notably, according to equation 3.2, the lower is Ψ_1, i.e. the more constrained the financial sector, the less responsive leverage is to changes in expected future productivity. We illustrate in Appendix F.4 that the credit demand channel is muted if the leverage constraint of the intermediary sector is tighter. So, while a constrained financial intermediary sector amplifies the boom-bust dynamics in response to a noise shock, the leverage response of entrepreneurs is ceteris paribus more muted if the intermediary sector is more constrained.

3.5 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, but mute the credit demand channel.

4 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 intermediation premiums.

4.1 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 D describes the econometric procedure to identify the noise shocks.

4.1.1 Identifying signal and surprise 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. A detailed data description is in Appendix C.

We recover signal and surprise shocks from this VAR by applying a simple recursive identification. This first identification step identifies signals and surprise shocks separately from other structural shocks, e.g. shocks to short rates and intermediation premiums. The identification assumptions for the signal and surprise shocks are that first, potential output is on impact only affected by the signal shock, and second, that the S&P500 is on impact affected by short rate shocks, risk premium shocks, signal shocks and surprise shocks. We follow Forni et al. (2017b) in ordering real GDP last, but the main results are robust to ordering real GDP second (see Appendix E.3).

4.1.2 Identifying news and noise shocks

The fundamental (or news) and noise shocks are dynamic rotations of the signal and surprise shocks. These rotations are identified from a semi-structural model, which allows to map the signal and surprise shocks into the news and noise shocks.

The main identification assumption is that the noise shock does not affect potential output at any lead or lag. Under that assumption, the response to a signal shock and the response to a news shock are (up to a scale) identical, while the noise shock is a combination of signal and surprise shocks. This allows us to recover first the impulse response to a news shock and second, by constructing a dynamic rotation based on Blaschke matrices (Lippi and Reichlin (1994)) from the roots of that impulse response, the impulse response to a noise shock.[10]

We use a two-step procedure where we first estimate the news and noise shocks from a VAR and then use the smoothed shocks from the VAR in local projections. The advantage of using local projections is that they leave the long-run effects of the shocks unrestricted, which matters for boom-bust dynamics (Brianti and Cormun (2023)). In Panel (f) of Figure 15 in Appendix E.3, we show that the short-run dynamics and standard errors estimated from a VAR that includes the additional variables of interest are similar to the local projections. As the identification routine is separate from the estimation routine, we could also estimate the signal and surprise shocks using local projections (Plagborg-Møller and Wolf (2020b)).

4.1.3 The recovered noise shocks

Figure 3 displays the resulting noise shock series. It is standardized to zero mean and unit variance. NBER recessions are marked in grey. We also mark the five largest positive 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.

10. Forni et al. (2017b) provide Monte Carlo evidence, based on the model of Blanchard, L'Huillier, and Lorenzoni (2013), that their model can successfully identify news and noise shocks if there is only one signal. Chahrour and Jurado (2022) show that in a Monte Carlo simulation of the same model, but with a different information structure with multiple signals, that the identification procedure of Forni et al. (2017b) may fail to identify the true effects from a noise shock. They point out two issues: first, in response to a noise shock, the Forni et al. (2017b) procedure leads to a negative shock to TFP (or potential output). This is not the case in our empirical application. See Figure 4. Second, by assumption, the Forni et al. (2017b) procedure does not allow for anticipation effects. For example, a signal shock can't have effects before the signal is perceived.

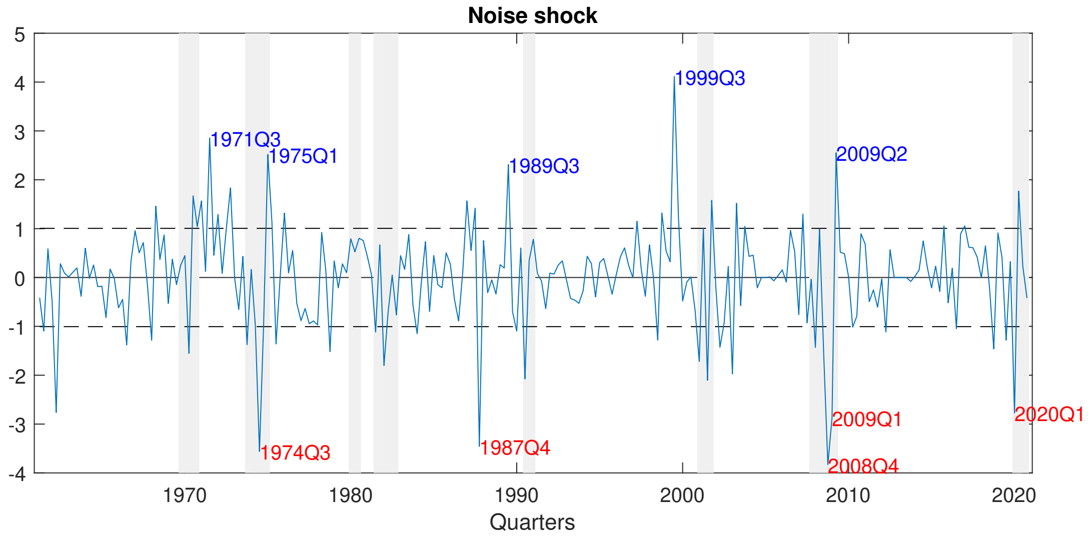

Figure 3: The noise shocks.

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.

4.2 Validating the noise shocks

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)):

$$Y_{t+h} = \alpha^h + \sum_{s=1}^{S} \beta_s^h shock_{t-s} + \sum_{s=1}^{S} \rho_s^h Y_{t-s} + \sum_{s=0}^{S} \Gamma_s^h X_{t-s} + \varepsilon_{t+h} \tag{4.1}$$

$Y_{t+h}, h \in [0, H]$ 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.[11] We set the number of periods over which we estimate the impulse response $H = 30$ quarters.

We choose the specification of the lag-augmented local projections specification to replicate the VAR specification and lag structure that recovers the noise shocks. In particular, by including the other shock, lagged stock prices, potential output and contemporaneous treasury rates and spreads as additional control variables, all VAR shocks also enter the local projections. Therefore, one can interpret these local projections as local projections

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

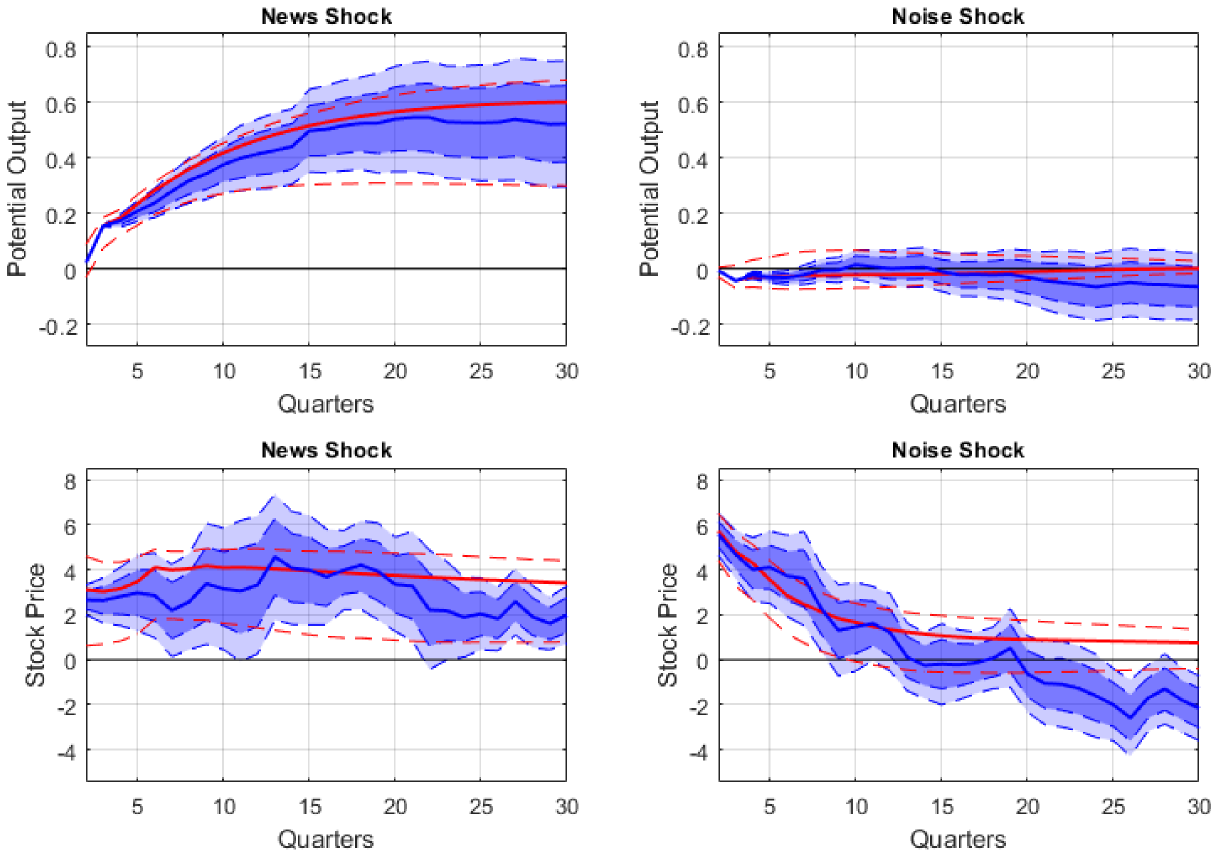

Figure 4: The effect of news and noise shocks on stock prices and potential output.

Note: The blue line in this figure displays the coefficients $\{\beta_0^h\}_{h=0}^{H}$ obtained by estimating equation 4.1. 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.

of outcome variables on an identified structural decomposition of the variables in the original VAR. We show in a robustness check that the results from the local projections look similar to extending the VAR with the credit variable.

Figure 4 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, 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 realizations for potential output. As investors realize that a noise shock drove the signal shock, they correct their stock market pricing downward. This is consistent with the response of agents to signals in the model in section 3.1, where agents eventually learn whether a shock was news or noise.

4.3 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 4.1. In principle, as the main explanatory variable on the right-hand side is a structural 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 5 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 E.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

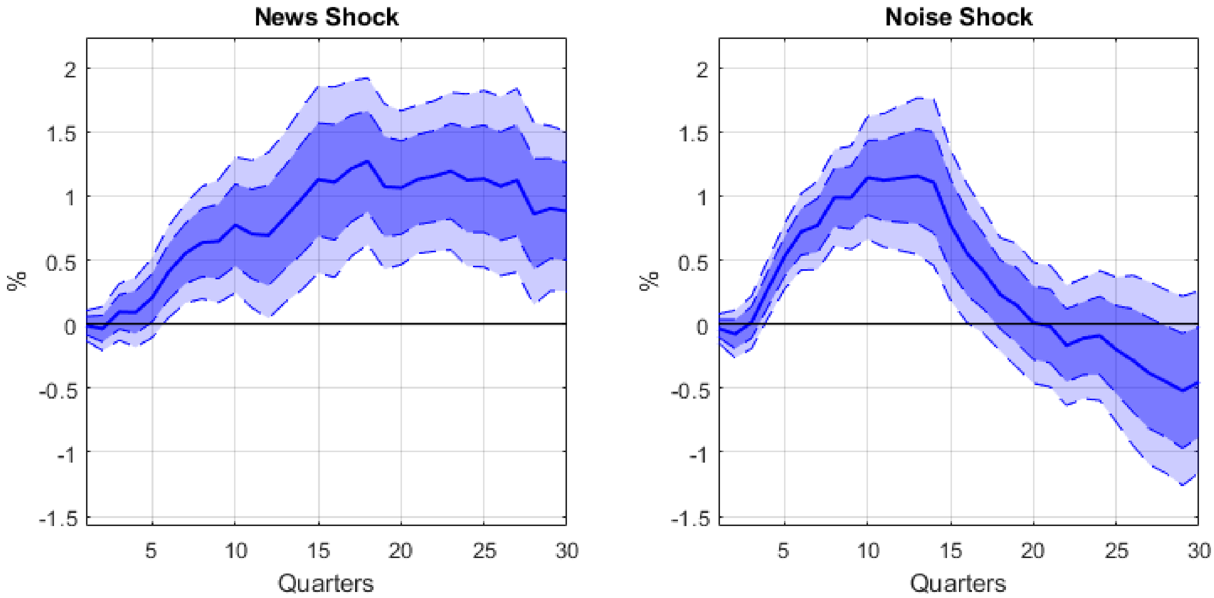

Figure 5: The effect of news and noise shocks on credit to the non-financial sector.

Note: The blue line in this figure displays the coefficients $\{\beta_0^h\}_{h=0}^H$ obtained by estimating equation 4.1. 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.

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.

4.4 Noise shocks and credit spreads

Figure 6 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 6a). For the Gilchrist and Zakrajšek (2012) spread, we see a similar impact (Panel 6b).

There are two reasons why credit spreads may fall in response to a noise shock: antic-

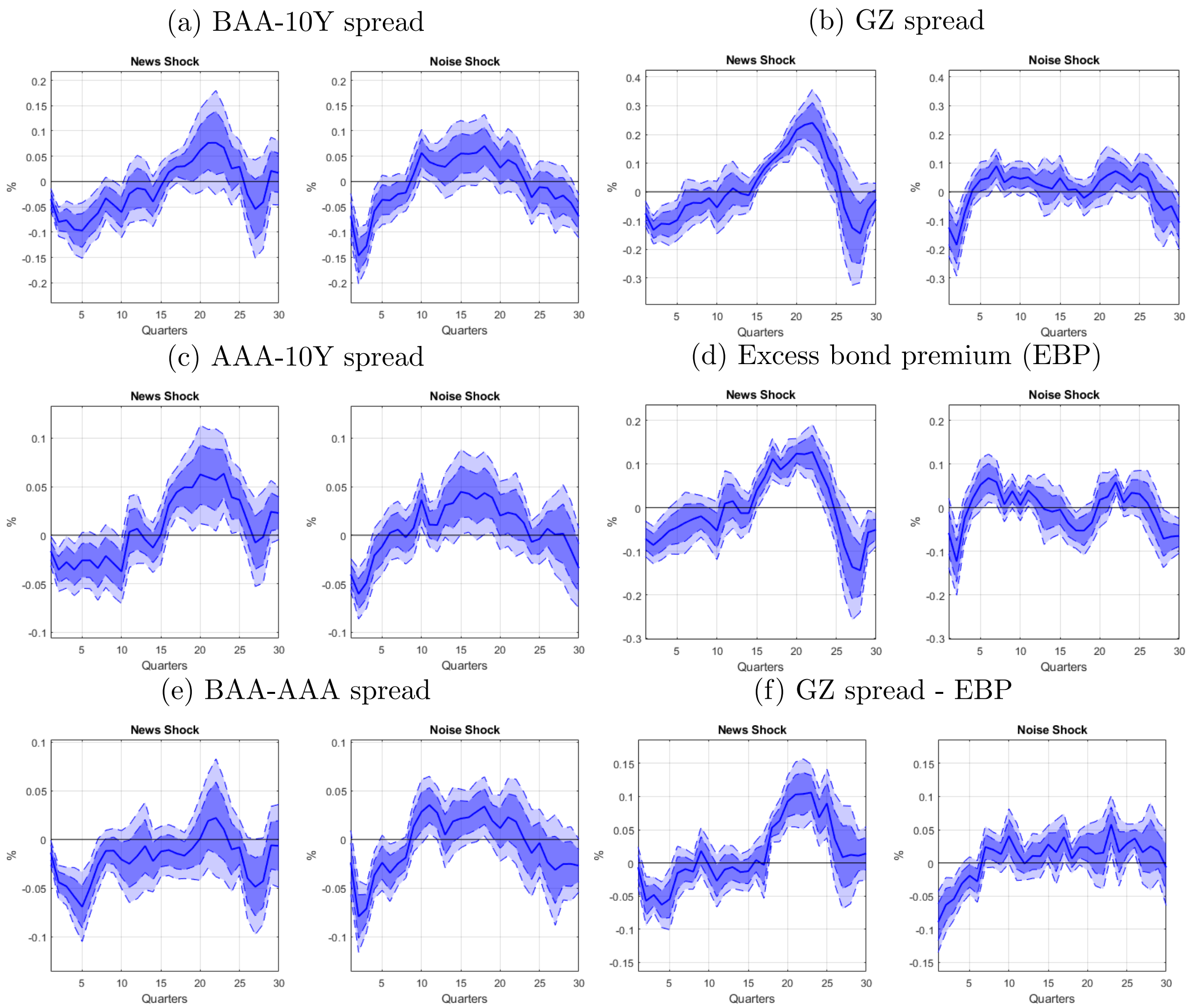

Figure 6: The effect of news and noise shocks on credit spreads.

Note: The blue line in this figure displays the coefficients $\{\beta_0^h\}_{h=0}^H$ obtained by estimating equation 4.1. 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.

ipating good news, creditors perceive firms as less risky, which would lead to a fall in expected defaults. Alternatively, creditors may charge a lower intermediation 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 intermediation 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).

4.5 Transmission channels

Appendices E.1 and E.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.

4.6 Noise shocks and real activity

We next investigate the effects of news and noise shocks on real activity. Figure 7 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

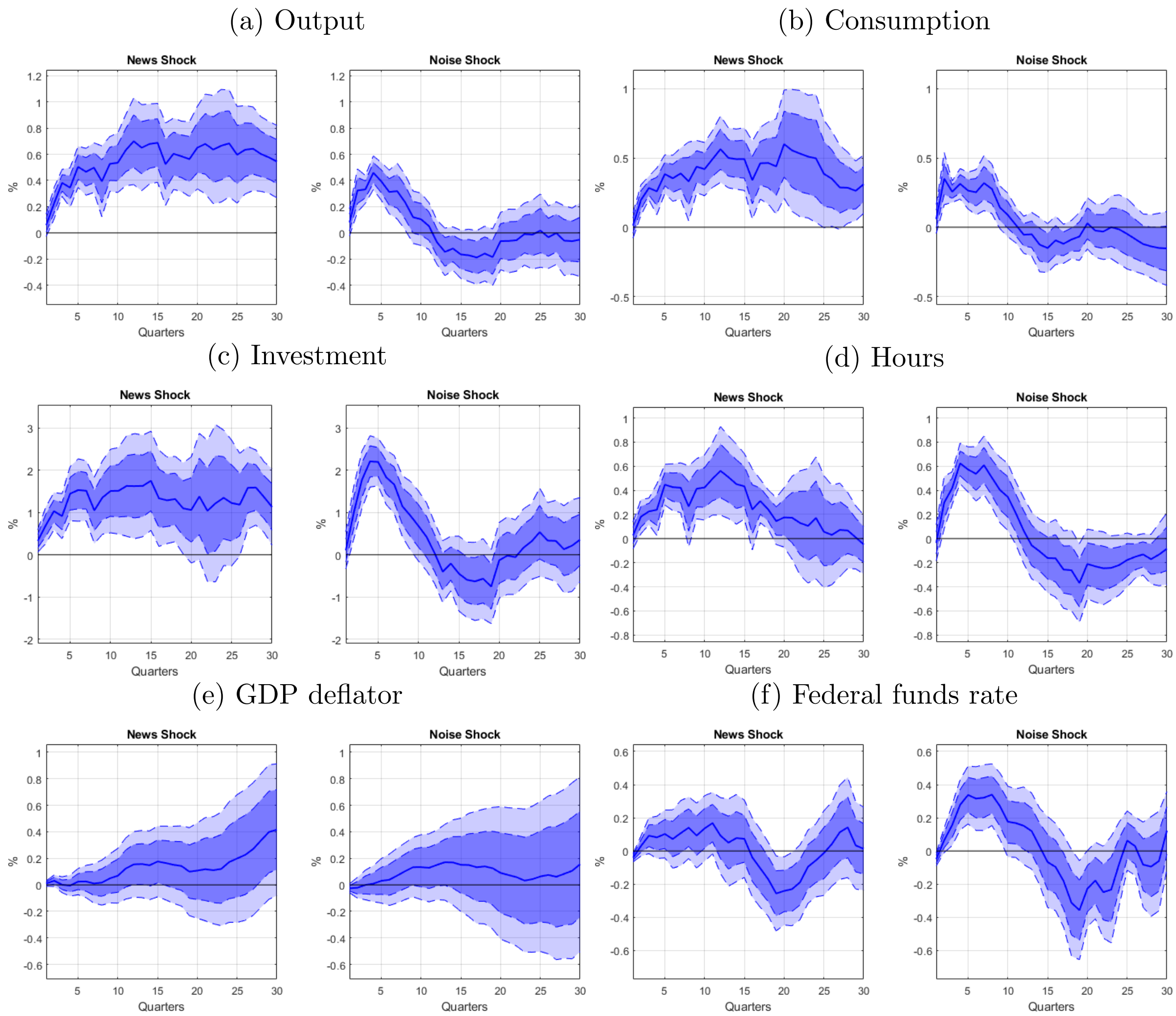

Figure 7: The effect of news and noise shocks from the stock market on the macroeconomy.

This figure displays the coefficients $\{\beta_0^h\}_{h=0}^{H}$ obtained by estimating equation 4.1. The confidence levels depicted are 68 per cent (shaded area). Standard errors correct for autocorrelation of the residuals using a Newey-West estimator.

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 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 Time-varying Effects of Noise Shocks

According to the model, the strength of the transmission of noise shocks is state-dependent and varies with credit supply conditions. In particular, noise shocks lead to stronger leverage booms if credit supply conditions are lenient and more pronounced credit busts if credit supply conditions are tight. Here, we test this prediction of the model. First, we show that noise shocks have stronger effects on credit and real activity during times of low credit spreads but imply stronger boom-bust cycles during times of high credit spreads. Second, we use an unobserved component model to show that the effects of noise shocks on the credit cycle are stronger during credit cycle booms and weaker during credit cycle busts.

5.1 State-dependent transmission

Next, we study the state dependence of the response of leverage dynamics to both shocks. We hypothesise that the level of intermediation premiums affects the propagation of news and noise shocks. To test this prediction, we estimate the following regression:

$$\begin{aligned} Y_{t+h} = \alpha^h &+ f(RP_t)\left[\sum_{s=1}^{S}\beta_s^h shock_{t-s} + \sum_{s=1}^{S}\rho_s^h Y_{t-s} + \sum_{s=0}^{S}\Gamma_s^h X_{t-s}\right] \\ &+ (1-f(RP_t))\left[\sum_{s=1}^{S}\tilde{\beta}_s^h shock_{t-s} + \sum_{s=1}^{S}\tilde{\rho}_s^h Y_{t-s} + \sum_{s=0}^{S}\tilde{\Gamma}_s^h X_{t-s}\right] + \varepsilon_{t+h} \end{aligned} \tag{5.1}$$

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

We distinguish between times of high and low intermediation premiums. Following Auerbach and Gorodnichenko (2011), we transform the intermediation premium using the function $f(x) = \frac{\exp(-\gamma x)}{1+\exp(-\gamma x)}$, with $\gamma = 10$. Our measure of the intermediation premium is the one-quarter-lagged, linearly detrended AAA-10Y corporate bond spread. Figure 8

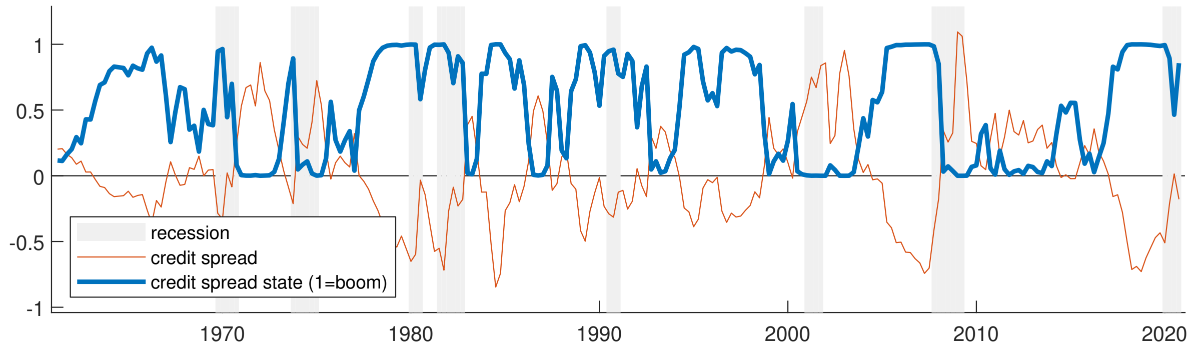

Figure 8: The intermediation premium state.

displays the corporate bond spread RP_t (in red), as well as the intermediation premium state $f(RP_t)$ (in blue). The shaded areas are the NBER recession dates. While recessions are typically times of low intermediation premiums, the mapping is not one-for-one. In particular, intermediation premiums were high during the Euro Area sovereign debt crisis in the early 2010s and in the mid-1980s.

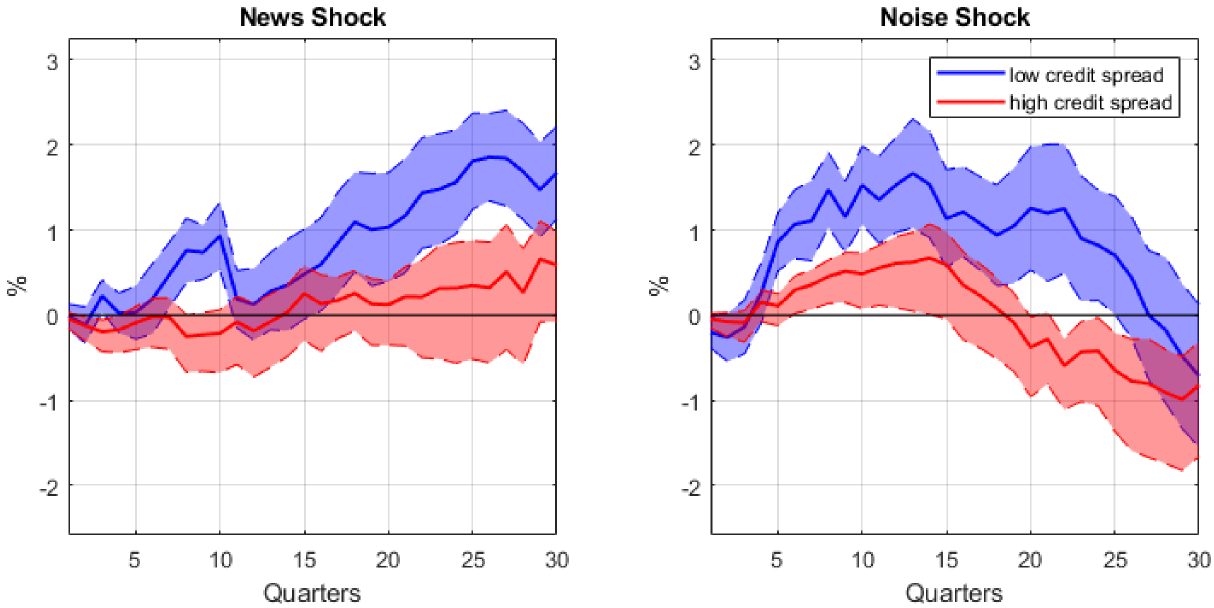

Figure 9: The effect of news and noise shocks on total credit – state-dependent results.

This figure displays the coefficients $\{\beta_0^h\}_{h=0}^{H}$ obtained by estimating equation 4.1. The confidence levels depicted are 68 per cent (shaded area). Standard errors correct for autocorrelation of the residuals using a Newey-West estimator.

Figure 9 displays the results. The red impulse response is the response during periods of high intermediation premiums, while the blue plots the response during periods of low intermediation premiums. The figure shows impulse responses of total credit to the non-financial sector.

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-intermediation premium state); for a news shock, the increase is statistically significant only in a low-intermediation premium state. Conversely, total credit growth reverts and falls below trend in both states following a noise shock, although almost 10 quarters sooner in a high intermediation premium state. Overall, general credit conditions matter, and the boom-bust cycle generated by a noise shock is more pronounced in a high-intermediation 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 intermediation premium, in turn, amplifies the credit boom and, in the case of a noise shock, the subsequent bust.

5.2 Unobserved Components Model

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.

$$C_t = \tau_t + c_t. \tag{5.2}$$

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 4.1.3, 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

$$\tau_t = \delta_{t-1} + \tau_{t-1} + \varepsilon_t, \tag{5.3}$$
$$\delta_t = \delta_{t-1} + \upsilon_t, \tag{5.4}$$
$$c_t = \phi_1 c_{t-1} + \phi_2 c_{t-2} + \alpha_t shock_t + \epsilon_t, \tag{5.5}$$

where α_t denotes the sensitivity of the credit cycle to noise shocks and the corresponding innovations are normally distributed, that is, $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$, $\upsilon_t \sim N(0, \sigma_\upsilon^2)$, and $\epsilon_t \sim N(0, \sigma_\epsilon^2)$. 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,

$$y_t = \beta_0 + \beta_1 y_{t-1} + \beta_{2,t} c_{t-1} + u_t, \tag{5.6}$$

where $u_t \sim N(0, \sigma_u^2)$ 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,

$$\alpha_t = \alpha_{t-1} + u_{\alpha,t}, \tag{5.7}$$
$$\beta_{2,t} = \beta_{2,t-1} + u_{\beta_2,t}, \tag{5.8}$$

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 10 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 10 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.[12]

6 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

12. Charts A and B of Figure 16 in Appendix E.4 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.

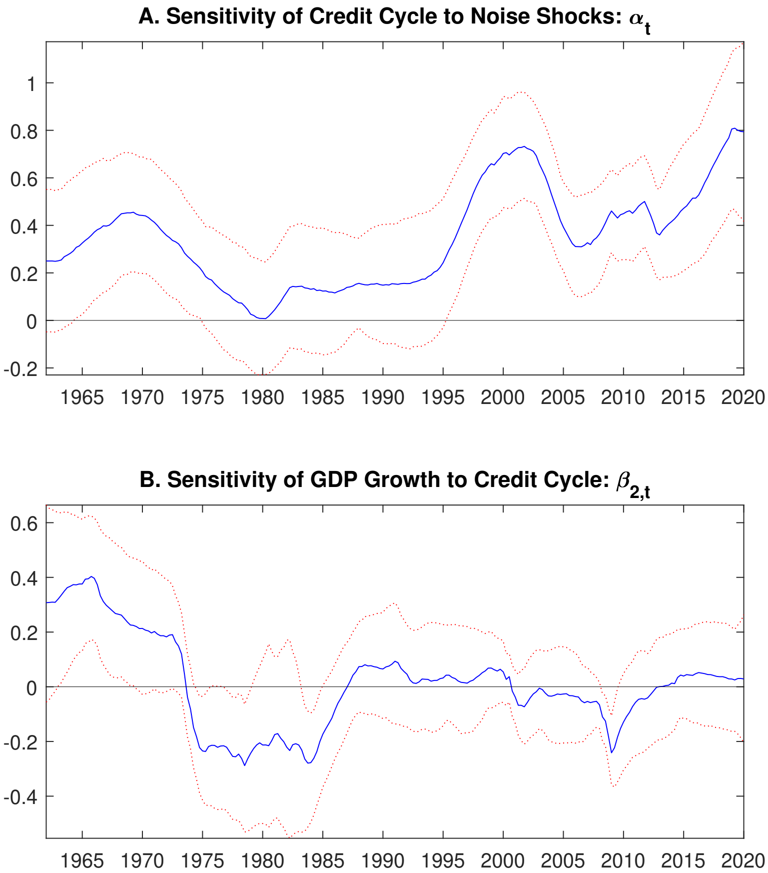

Figure 10: Time-varying effects of noise shocks on credit and GDP growth.

Note: This figure shows the results from the estimation of the unobserved components model given by equations 5.3 to 5.8. The credible sets (red, dashed lines) represent the 16th and 84th percentiles of the corresponding posterior densities.

can lead to unsustainable credit booms, especially when intermediation 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.

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.

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Appendix

For online publication

A Characterization of the decision problems

A.1 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 $t = 1, 2, 3$.

A.2 Entrepreneurs

We solve the problem of entrepreneurs backwards.

A.2.1 Preliminaries

The capital quality shock follows a uniform distribution. The cumulative distribution function of a uniform distribution on $\underline{A}, \overline{A}$ is $F(A) = \frac{A-\underline{A}}{\overline{A}-\underline{A}}$ for $A \in \left[\underline{A}, \overline{A}\right]$. The density function is $f(A) = \frac{1}{\overline{A}-\underline{A}}$ for $A \in \left[\underline{A}, \overline{A}\right]$ and 0 else. The conditional expectation $E\left[A|A > A^*\right]$ is

$$\begin{aligned} E\left[A|A > A^*\right] &= \int_{A^*}^{\overline{A}} A f(A) dA \\ &= \underbrace{\frac{\overline{A} - A^*}{\overline{A} - \underline{A}}}_{1-F(A^*)} \frac{\overline{A} + A^*}{2}. \end{aligned}$$

A.2.2 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

$b_2(b_1; \mathcal{S}_2)$:

$$1 + \theta \left(\frac{k_2}{k_1} - 1 \right) - \frac{\partial Q_2(k_2, b_2; \mathcal{S}_{2+})}{\partial k_2} (b_2 - b_1) = \beta^F \left[r_3^K + \frac{\overline{A} + A_3^*}{2} + 1 \right] (1 - F(A_3^*)) \tag{A.1}$$

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

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

$$A_3^* = \max \left(\frac{b_2}{k_2} - (r_3^K + 1), \underline{A} \right) \tag{A.3}$$

The default threshold cannot fall below the lowest possible value of the idiosyncratic capital quality shock. This implies that there is a value for leverage, call it ω_2^*, below which the entrepreneur issues risk-free debt. This threshold is

$$\omega_2^* = \underline{A} + r_3^K + 1 \tag{A.4}$$

It is not optimal for the entrepreneur to have a lower leverage than ω_2^*.

The derivatives of the default policy with respect to the entrepreneur's debt and capital choice are

$$\begin{aligned} \frac{\partial A_3^*}{\partial b_2} &= \frac{1}{k_2} \\ \frac{\partial^2 A_3^*}{(\partial b_2)^2} &= 0 \\ \frac{\partial A_3^*}{\partial k_2} &= -\frac{b_2}{k_2^2} \\ \frac{\partial^2 A_3^*}{(\partial k_2)^2} &= 2\frac{b_2}{k_2^3} \end{aligned}$$

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

$$\frac{\partial Q_2(k_2, b_2; \mathcal{S}_{2+})}{\partial k_2} = \Psi_2(-f(A_3^*))\frac{\partial A_3^*}{\partial k_2} = \frac{\Psi_2}{\overline{A} - \underline{A}}\frac{b_2}{k_2^2} \tag{A.5}$$

$$\frac{\partial Q_2(k_2, b_2; \mathcal{S}_{2+})}{\partial b_2} = \Psi_2(-f(A_3^*))\frac{\partial A_3^*}{\partial b_2} = -\frac{\Psi_2}{\overline{A} - \underline{A}}\frac{1}{k_2} \tag{A.6}$$

The period 3 expected value function is

$$E_2\left[X_3 | A > A_3^*\right] = (1 - F(A_3^*))\left[\left(r_3^K + \frac{\overline{A} + A_3^*}{2} + 1\right)k_2 - b_2\right] \tag{A.7}$$

Plugging the bond price into the first order conditions, we get

$$1 + \theta\left(\frac{k_2}{k_1} - 1\right) - \frac{\Psi_2}{\overline{A} - \underline{A}}\frac{b_2}{k_2^2}(b_2 - b_1) = \beta^F\left[r_3^K + \frac{\overline{A} + A_3^*}{2} + 1\right]\frac{\overline{A} - A_3^*}{\overline{A} - \underline{A}} \tag{A.8}$$

$$\left(\Psi_2 - \beta^F\right)\frac{\overline{A} - A_3^*}{\overline{A} - \underline{A}} - \frac{\Psi_2}{\overline{A} - \underline{A}}\frac{1}{k_2}(b_2 - b_1) = 0. \tag{A.9}$$

This implies for the leverage policy

$$\frac{b_2}{k_2} = \frac{\Psi_2 - \beta^F}{2\Psi_2 - \beta^F}\left(\overline{A} + (r_3^K + 1)\right) + \frac{\Psi_2}{2\Psi_2 - \beta^F}\frac{b_1}{k_1}\frac{k_1}{k_2}. \tag{A.10}$$

Defining leverage as $\omega_t \equiv b_t/k_t$, we get

$$\omega_2 = \max\left(\frac{\Psi_2 - \beta^F}{2\Psi_2 - \beta^F}\left(\overline{A} + r_3^K + 1\right) + \frac{\Psi_2}{2\Psi_2 - \beta^F}\omega_1\frac{k_1}{k_2}, \omega_2^*\right). \tag{A.11}$$

Notice that because $\Psi_2 \geq \beta^F$, the leverage policy is increasing in lagged leverage ω_1 and in the expected future return on capital r_3^K.

The first-order condition for the capital policy is

$$1 + \theta\left(\frac{k_2}{k_1} - 1\right) - \frac{\Psi_2}{\overline{A} - \underline{A}}\omega_2\left(\omega_2 - \omega_1\frac{k_1}{k_2}\right) = \beta^F\left[r_3^K + \frac{\overline{A} + \omega_2 - (r_3^K + 1)}{2} + 1\right]\frac{\overline{A} - \omega_2 + (r_3^K + 1)}{\overline{A} - \underline{A}} \tag{A.12}$$

We have now characterized the period 3 default decision (A.3) and the period 3 value function (A.7). The solution to the second period problem is characterized by the optimal leverage policy A.11. Next, we need to characterize the period 2 value function and default decision, before finally determining the optimal period 1 leverage policy.

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

$$\frac{\tilde{X}_2(\omega_1;\mathcal{S}_2)}{k_1} = -1 - \frac{\theta}{2}\left(\frac{k_2}{k_1} - 1\right)^2 + Q_2(\omega_2(\omega_1;\mathcal{S}_2);\mathcal{S}_{2+})\omega_2(\omega_1;\mathcal{S}_2)$$
$$+ \beta^F \frac{k_2}{k_1} E_2\left[\frac{X_3(\omega_2(\omega_1;\mathcal{S}_2);\mathcal{S}_{2+})}{k_2} | A_3 > A_3^*\right].$$

This equation shows that the value function and the policy functions of the entrepreneur are linear homogeneous in k_1. This allows us to characterize them as a function of only one idiosyncratic state variable, namely leverage ω_1.

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

$$A_2^* = \max\left(Q_2(\omega_2(\omega_1;\mathcal{S}_2);\mathcal{S}_{2+})\omega_1 - (r_2^K + 1) - \frac{\tilde{X}_2(\omega_1;\mathcal{S}_2)}{k_1}, \underline{A}\right).$$

Plugging in the bond price and the continuation value function gives

$$A_2^* = \min\left(Q_2(\omega_2(\omega_1;\mathcal{S}_2);\mathcal{S}_{2+})\omega_1 - (r_2^K + 1) - \frac{\tilde{X}_2(\omega_1;\mathcal{S}_2)}{k_1}, \underline{A}\right)$$
$$= \min\Bigg(\underbrace{\Psi_2 \frac{\overline{A} - A_3^*}{\overline{A} - \underline{A}}\omega_1}_{\text{Debt repayment}} - \underbrace{(\Psi_2 - \beta^F)\frac{\overline{A} - A_3^*}{\overline{A} - \underline{A}}\omega_2}_{\text{Value of debt issuance}} \underbrace{-1 - \frac{\theta}{2}\left(\frac{k_2}{k_1} - 1\right)^2}_{\text{Investment}}$$
$$- \underbrace{\left((r_2^K + 1) + \beta^F \frac{\overline{A} - A_3^*}{\overline{A} - \underline{A}}\left(r_3^K + 1 + \frac{\overline{A} + A_3^*}{2}\right)\right)}_{\text{Value of discounted cash flows}}, \underline{A}\Bigg). \tag{A.13}$$

Together with ω_2 and A_3^*, A.13 defines the period 2 default policy of the entrepreneur. A.13 also defines the risk-free leverage ω_1^* of the entrepreneur as the solution to the non-linear equation

$$\underline{A} = \Psi_2 \frac{\overline{A} - A_3^*}{\overline{A} - \underline{A}}\omega_1^* - (\Psi_2 - \beta^F)\frac{\overline{A} - A_3^*}{\overline{A} - \underline{A}}\omega_2 - 1 - \frac{\theta}{2}\left(\frac{k_2}{k_1} - 1\right)^2$$
$$- \left((r_2^K + 1) + \beta^F \frac{\overline{A} - A_3^*}{\overline{A} - \underline{A}}\left(r_3^K + 1 + \frac{\overline{A} + A_3^*}{2}\right)\right). \tag{A.14}$$

Next and finally, we need to characterize the period 1 leverage policy of the firm.

A.2.3 Period 1

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

$$C_1^F + k_1 + \frac{\theta}{2}\left(\frac{k_1}{k_0} - 1\right)^2 k_0 = Q_1(k_1, b_1; \mathcal{S}_{1+})(b_1 - B_0).$$

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

$$1 + \theta\left(\frac{k_1}{k_0} - 1\right) - \frac{\partial Q_1(k_1, b_1; \mathcal{S}_{1+})}{\partial k_1}(b_1 - b_0) = \beta^F E_1 \left[\left(r_2^K + \frac{\overline{A} + A_2^*}{2} + 1\right)(1 - F(A_2^*))\right] \tag{A.15}$$

$$Q_1(k_1, b_1; \mathcal{S}_{1+}) + \frac{\partial Q_1(k_1, b_1; \mathcal{S}_{1+})}{\partial b_1}(b_1 - b_0) = \beta^F E_1 \left[Q_2(k_2, b_2; \mathcal{S}_{2+})\left(1 - F(A_2^*)\right)\right]. \tag{A.16}$$

Similar to period 2, the bond price is

$$\begin{aligned} Q_1(\omega_1; \mathcal{S}_{1+}) &= E_1 \left[\Psi_1 Q_2(\omega_2; \mathcal{S}_{2+}) \frac{\overline{A} - A_2^*}{\overline{A} - \underline{A}}\right] \\ &= E_1 \left[\Psi_1 \Psi_2 \frac{\overline{A} - A_2^*}{\overline{A} - \underline{A}} \frac{\overline{A} - A_3^*}{\overline{A} - \underline{A}}\right]. \end{aligned}$$

The bond price derivative is

$$\begin{aligned} \frac{\partial Q_1(\omega_1; \mathcal{S}_{1+})}{\partial \omega_1} &= E_1 \left[\Psi_1 \Psi_2 \left((-f(A_2^*)) \frac{\partial A_2^*}{\partial \omega_1} \frac{\overline{A} - A_3^*}{\overline{A} - \underline{A}} + (-f(A_2^*)) \frac{\partial A_2^*}{\partial \omega_2} \frac{\partial \omega_2}{\partial \omega_1} \frac{\overline{A} - A_3^*}{\overline{A} - \underline{A}}\right)\right] \\ &+ E_1 \left[\Psi_1 \Psi_2 \frac{\overline{A} - A_2^*}{\overline{A} - \underline{A}} (-f(A_3^*)) \frac{\partial A_3^*}{\partial \omega_2} \frac{\partial \omega_2}{\partial \omega_1}\right] \end{aligned} \tag{A.17}$$

Notice the presence of the derivative of the policy function with respect to the current leverage policy. The creditors internalise that the entrepreneur's current debt choice affects future policy functions. Further, note that, because A_2^* is implicitly defined through the value function and because ω_2 is optimally chosen in period 2, $\frac{\partial A_2^*}{\partial \omega_2} = 0$. The bond price derivative simplifies to

$$\frac{\partial Q_1(\omega_1;\mathcal{S}_{1+})}{\partial \omega_1} = E_1\left[\Psi_1\Psi_2(-f(A_2^*))\frac{\partial A_2^*}{\partial \omega_1}\frac{\overline{A}-A_3^*}{\overline{A}-\underline{A}}\right] + E_1\left[\Psi_1\Psi_2\frac{\overline{A}-A_2^*}{\overline{A}-\underline{A}}(-f(A_3^*))\frac{\partial A_3^*}{\partial \omega_2}\frac{\partial \omega_2}{\partial \omega_1}\right] \tag{A.18}$$

Plugging the bond price and its derivative into the first order condition of the entrepreneur gives

$$\begin{aligned} &E_1\left[\left(\Psi_1-\beta^F\right)\frac{\overline{A}-A_2^*}{\overline{A}-\underline{A}}\Psi_2\frac{\overline{A}-A_3^*}{\overline{A}-\underline{A}}\right] - \left[E_1\left[\Psi_1\Psi_2\left(f(A_2^*)\frac{\overline{A}-A_3^*}{\overline{A}-\underline{A}}\left(\frac{\partial A_2^*}{\partial \omega_1}+\frac{\partial A_2^*}{\partial \omega_2}\frac{\partial \omega_2}{\partial \omega_1}\right)\right)\right]\right.\\ &\left.+E_1\left[\Psi_1\Psi_2\frac{\overline{A}-A_2^*}{\overline{A}-\underline{A}}f(A_3^*)\frac{\partial A_3^*}{\partial \omega_2}\frac{\partial \omega_2}{\partial \omega_1}\right]\right](\omega_1-\omega_0)=0. \end{aligned} \tag{A.19}$$

This implies that ω_1 is the solution to the following non-linear equation in ω_1:

$$\omega_1 = \omega_0 + \frac{E_1\left[\left(\Psi_1-\beta^F\right)\frac{\overline{A}-A_2^*}{\overline{A}-\underline{A}}\Psi_2\frac{\overline{A}-A_3^*}{\overline{A}-\underline{A}}\right]}{E_1\left[\Psi_1\Psi_2\left(f(A_2^*)\frac{\overline{A}-A_3^*}{\overline{A}-\underline{A}}\left(\frac{\partial A_2^*}{\partial \omega_1}+\frac{\partial A_2^*}{\partial \omega_2}\frac{\partial \omega_2}{\partial \omega_1}\right)+\frac{\overline{A}-A_2^*}{\overline{A}-\underline{A}}f(A_3^*)\frac{\partial A_3^*}{\partial \omega_2}\frac{\partial \omega_2}{\partial \omega_1}\right)\right]}. \tag{A.20}$$

For a special case, we can still characterize the leverage policy in closed form. Assume that there is no period 3 default risk, i.e. that $A_3^* = \underline{A}$. Then, $\omega_2 = \omega_2^*$, $\frac{\partial \omega_2}{\partial \omega_1} = 0$. We get that

$$\omega_1 = \frac{E_1\left[\Psi_1\Psi_2^2\right]}{E_1\left[\left(2\Psi_1-\beta^F\right)\Psi_2^2\right]}\omega_0 + \frac{E_1\left[\left(\Psi_1-\beta^F\right)\Psi_2\left(\overline{A}+(\Psi_2-\beta^F)\omega_2^*+1+(1+r_2^K)+\beta^F(1+r_3^K)\right)\right]}{E_1\left[\left(2\Psi_1-\beta^F\right)\Psi_2^2\right]}. \tag{A.21}$$

Equation A.21 shows that leverage in period 1, like leverage in period 2, is increasing in expected future productivity and in initial period 0 leverage. Moreover, the equation shows that it is increasing in the value of future debt issuance. That is, the higher $(\Psi_2-\beta^F)\omega_2^*$, the more leverage entrepreneurs take on already today. This mechanism arises, because the possibility to issue debt in the future lowers the incentive to default, which raises the incentive to issue leverage today. If Ψ_2 rises endogenously in response to a news shock, e.g. because of expectations of less tight financial intermediary financial constraints, the value of future debt issuance amplifies the response of leverage to the news shock.

A.2.4 Debt overhang

Leverage and credit spreads in period 2 are increasing, stock prices decreasing in an entrepreneur's idiosyncratic leverage in period 1.

We want to show that debt in period 2 is increasing in debt in period 1. To find these derivatives, we apply the implicit function theorem to equations A.2 and A.1. This yields

$$\frac{\partial b_2}{\partial b_1} = \frac{\Psi_2}{2\Psi_2 - \beta^F} > 0. \tag{A.22}$$

$$\frac{\partial k_2}{\partial b_1} = -\frac{\Psi_2}{2\Psi_2\left(\frac{b_2}{k_2} - \frac{b_1}{k_1}\frac{k_1}{k_2}\right) + \beta^F A_3^* + \beta^F\left[r_3^K + 1\right]}. \tag{A.23}$$

The derivative of the second period investment policy with respect to leverage is negative, if

$$\frac{b_2}{k_2} > \frac{b_1}{k_1}\frac{k_1}{k_2} - \frac{1}{2\Psi_2}\left(\beta^F A_3^* + \beta^F\left[r_3^K + 1\right]\right).$$

This is the case, because the higher leverage, the more sensitive is the bond price to the capital choice of the firm, and the bigger is the potential for a debt overhang effect.

A.3 Financial intermediaries

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

A.3.1 Period 2

The balance sheet constraint states that end of period assets must equal $Q_2(K_2, B_2; \mathcal{S}_{2+})B_2^I$ must equal end of period liabilities D_2^I plus net worth $N_2^I - C_2^I$. Solving this constraint for liabilities 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^I 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

$$J_2 = \max_{C_2^I, B_2^I} C_2^I - \frac{\kappa}{2}\left(\frac{C_2^I}{N_2^I}\right)^2 N_2^I 1_{C_2^I \leq 0} + \beta^I\left[B_2^I(1 - F(A_3^*)) - \left(Q_2 B_2^I - N_2^I + C_2^I\right)\right] \tag{A.24}$$

subject to

$$\psi Q_2 B_2^I \leq \beta^I\left[B_2^I(1 - F(A_3^*)) - \left(Q_2 B_2^I - N_2^I + C_2^I\right)\right]. \tag{A.25}$$

The Lagrangian of this problem is

$$\mathcal{L} = C_2^I - \frac{\kappa}{2}\left(\frac{C_2^I}{N_2^I}\right)^2 N_2^I 1_{C_2^I \leq 0} + \beta^I \left[B_2^I(1-F(A_3^*)) - \left(Q_2 B_2^I - N_2^I + C_2^I\right)\right](1+\mu_2^I) - \psi Q_2 B_2^I.$$

Notice that the intermediaries take bond prices as given. Defining leverage $\phi_2 \equiv \frac{Q_2(K_2,B_2;\mathcal{S}_{2+})B_2^I}{N_2^I}$ and dividing by N_2, the incentive constraint becomes

$$\psi\phi_2 = \beta^I\left[\left(\frac{1}{\Psi_2}-1\right)\phi_2 + 1 - \frac{C_2^I}{N_2}\right].$$

The Lagrangian becomes

$$\mathcal{L} = \frac{C_2^I}{N_2^I} - \frac{\kappa}{2}\left(\frac{C_2^I}{N_2^I}\right)^2 1_{\frac{C_2^I}{N_2^I}\leq 0} + \beta^I\left[\phi_2\left(\frac{1}{\Psi_2}-1\right) + 1 - \frac{C_2^I}{N_2^I}\right](1+\mu_2^I) - \psi\phi_2.$$

If the incentive constraint binds, optimal leverage ϕ_2 and equity issuance C_2^I/N_2^I are given by the incentive constraint and a first-order condition for equity issuance. Solving the incentive constraint for leverage yields

$$\phi_2 = \frac{\beta^I\left[1-\frac{C_2^I}{N_2}\right]}{\psi - \beta^I\left(\frac{1}{\Psi_2}-1\right)}. \tag{A.26}$$

This expression allows us to write Ω_2 as

$$\begin{aligned}\Omega_2 &= \frac{J_2}{N_2^I}\\ &= \frac{C_2^I}{N_2^I} - \frac{\kappa}{2}\left(\frac{C_2^I}{N_2^I}\right)^2 + \psi\phi_2.\end{aligned}$$

Differentiating the Lagrangian with respect to $\frac{C_2^I}{N_2^I}$ and ϕ_2 yields

$$1 - \kappa\frac{C_2^I}{N_2^I} - \beta^I(1+\mu^I) = 0.$$

$$\beta^I E_2\left[(1-F(A_3^*)) - Q_2\right](1+\mu^I) - \mu^I\psi Q_2 = 0$$

Solving this maximisation problem gives an expression for optimal equity issuance:

$$\frac{C_2^I}{N_2^I} = \frac{1}{\kappa}\left(1-\beta^I(1+\mu^I)\right), \tag{A.27}$$

This equation states that intermediaries issue more equity (i.e. C_2^I/N_2^I becomes more negative), the higher is the multiplier on the financial constraint.

The derivative with respect to leverage ϕ_2 yields an expression for the bond price $Q_2(K, B; \mathcal{S}_{2+})$:

$$
\begin{aligned}
Q_2(K, B; \mathcal{S}_{2+}) &= \beta^I \frac{1+\mu^I}{\mu^I \psi + \beta^I(1+\mu^I)}(1 - F(A_3^*)) \\
&= \underbrace{\beta^I \frac{1+\mu^I}{\mu^I \psi + \beta^I(1+\mu^I)}}_{\equiv \Psi_2} \frac{A_3^* - \underline{A}}{\overline{A} - \underline{A}}.
\end{aligned}
\tag{A.28}
$$

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.

A.3.2 Period 1

The problem of a financial intermediary in period 1 is

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

subject to

$$
\begin{aligned}
Q_1(K_1, B_1; \mathcal{S}_{1+})B_1^I &= N_1^I + D_1^I - C_1^I \\
N_1^I &= Q_1(K_1, B_1; \mathcal{S}_{1+})B_0^I - D_0^I \\
\psi Q_1(K_1, B_1; \mathcal{S}_{1+})B_1^I &\leq J_1.
\end{aligned}
$$

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

$$
N_1 = Q_1 B_0 - D_0. \tag{A.29}
$$

The incentive constraint is

$$
\psi Q_1 B_1^I = \beta^I E_1 \left[\Omega_2 \left(Q_2 B_1^I (1 - F(A_2^*)) - \left(Q_1 B_1^I - N_1^I + C_1^I\right)\right)\right]. \tag{A.30}
$$

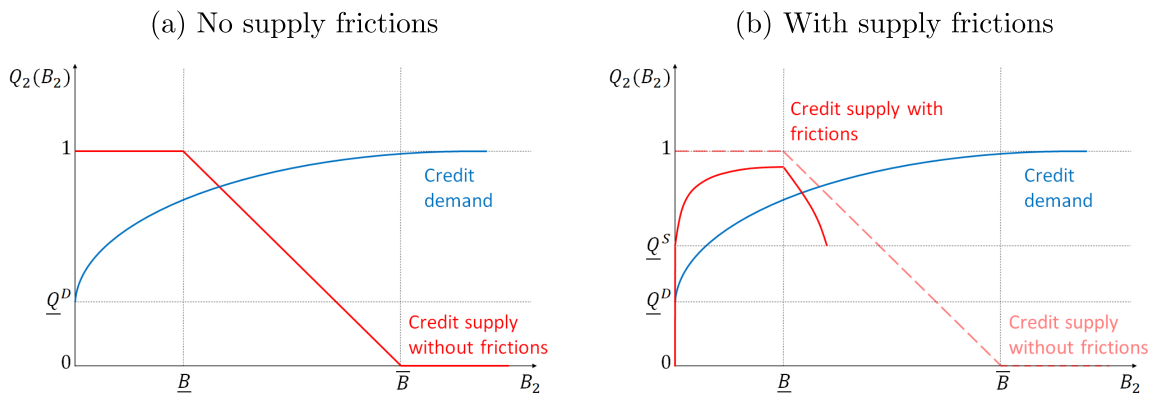


Figure 11: Equilibrium in the credit market.

With leverage defined as $\phi_1 = Q_1 B_1^I / N_1$, the constraint simplifies to

$$\psi\phi_1 = \beta^I E_1 \left[\Omega_2 \left(\left(\frac{Q_2(1 - F(A_2^*))}{Q_1} - 1 \right) \phi_1 + 1 - \frac{C_1^I}{N_1^I} \right) \right].$$

Solving this constraint for leverage yields

$$\phi_1 = \frac{\beta^I E_1 \left[\Omega_2 \left(1 - \frac{C_1^I}{N_1^I} \right) \right]}{\psi - \beta^I E_1 \left[\Omega_2 \left(\frac{Q_2(1-F(A_2^*))}{Q_1} - 1 \right) \right]} \tag{A.31}$$

The Lagrange multiplier μ_1^I for period 1 is:

$$\mu_1^I = \frac{1}{\beta^I E_1 [\Omega_2]} \left(1 - \kappa \frac{C_1^I}{N_1^I} \right) - 1. \tag{A.32}$$

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

$$Q_1(K_1, B_1; \mathcal{S}_{1+}) = E_1 \left[\underbrace{\beta^I \frac{1 + \mu_1^I}{\mu_1^I \psi + \beta^I E_1 [\Omega_2] (1 + \mu_1^I)} \Omega_2}_{\equiv \Psi_1} \left(Q_2(K_2, B_2; \mathcal{S}_{2+}) \frac{\overline{A} - A_2^*}{\overline{A} - \underline{A}} \right) \right]. \tag{A.33}$$

B Equilibrium in the credit market

We characterise market clearing in the credit market. In period 2, the solution to the entrepreneur problem, equations A.2 to A.6, determines credit demand. The solution to the intermediary problem, equations A.25 to A.28, determines credit supply.

B.1 Equilibrium with non-binding intermediary constraint

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

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

Period 2 The equilibrium is where the credit demand and the credit supply schedule intersect. It is determined by the expression for leverage A.10, the first-order condition for capital A.12, and the expression for the default threshold A.3, plus the expression of the return on capital from the firm problem. For convenience, we list the system of equations here:

$$\begin{aligned}
r_3^K &= \alpha Z_3 K_2^{\alpha-1}, \qquad\qquad (B.2)\\
A_3^* &= \max\left(\omega_2 - (r_3^K + 1), \underline{A}\right),\\
\omega_2^* &= \underline{A} + r_3^K + 1,\\
\omega_2 &= \max\left(\frac{\Psi_2 - \beta^F}{2\Psi_2 - \beta^F}\left(\overline{A} + r_3^K + 1\right) + \frac{\Psi_2}{2\Psi_2 - \beta^F}\frac{\omega_1}{\Delta_2^K}, \omega_2^*\right),\\
1 + \theta\left(\Delta_2^K - 1\right) - \frac{\Psi_2}{\overline{A} - \underline{A}}\omega_2\left(\omega_2 - \frac{\omega_1}{\Delta_2^K}\right) &= \beta^F\left[r_3^K + \frac{\overline{A} + A_3^*}{2} + 1\right]\frac{\overline{A} - A_3^*}{\overline{A} - \underline{A}},\\
E_2\left[x_3(\omega_2; \mathcal{S}_{2+})|A > A_3^*\right] &= (1 - F(A_3^*))\left[\left(r_3^K + \frac{\overline{A} + A_3^*}{2} + 1\right) - \omega_2\right],\\
\Psi_2 &= 1,\\
\tilde{x}_2(\omega_1; \mathcal{S}_2) &= -1 - \frac{\theta}{2}\left(\Delta_2^K - 1\right)^2 + \Psi_2\frac{\overline{A} - A_3^*}{\overline{A} - \underline{A}}\omega_2\\
&\quad + \beta^F \Delta_2^K E_2\left[x_3(\omega_2(\omega_1; \mathcal{S}_2); \mathcal{S}_{2+})|A_3 > A_3^*\right],\\
Q_2(\omega_1; \mathcal{S}_2) &= \Psi_2\frac{\overline{A} - A_3^*}{\overline{A} - \underline{A}},\\
Z_3 &= Z_2.
\end{aligned}$$

$\Delta_2^K \equiv k_2/k_1$ is the change in the idiosyncratic capital stock of an entrepreneur. The state variables of the equilibrium are leverage ω_1, capital K_1, and productivity Z_2. The solution yields policy functions $\Delta_2^K(\omega_1; K_1, Z_2)$ and $\omega_2(\omega_1; K_1, Z_2)$.

Panel 11a of Figure 11 illustrates the equilibrium with a non-binding intermediary constraint. 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.

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.

Period 1 The system of equations that pins down the period 1 equilibrium is

$$
\begin{aligned}
r_2^K &= \alpha Z_2 K_1^{\alpha-1}, \qquad\qquad (B.3)\\
A_2^* &= \max\left(Q_2(\omega_1;\mathcal{S}_2)\frac{\omega_1}{\Delta_2^K(\omega_1;\mathcal{S}_2)} - (r_2^K+1) - \tilde{x}_2(\omega_1;\mathcal{S}_2), \underline{A}\right),\\
0 &= E_1\left[\left(\Psi_1 - \beta^F\right)\frac{\overline{A}-A_2^*}{\overline{A}-\underline{A}}Q_2(\omega_1;\mathcal{S}_2)\right] + \frac{\partial Q_1(\omega_1;\mathcal{S}_{2+})}{\partial \omega_1}\left(\omega_1 - \frac{\omega_0}{\Delta_1^K}\right),\\
\underline{A} &= Q_2(\omega_1^*;\mathcal{S}_2)\frac{\omega_1^*}{\Delta_2^K(\omega_1^*;\mathcal{S}_2)} - (r_2^K+1) - \tilde{x}_2(\omega_1^*;\mathcal{S}_2)\\
\omega_1 &= \max\left(\omega_1, \omega_1^*\right),\\
0 &= -1 - \theta\left(\Delta_1^K - 1\right) + \frac{\partial Q_1(\omega_1;\mathcal{S}_{1+})}{\partial \omega_1}(-\omega_1)\left(\omega_1 - \frac{\omega_0}{\Delta_1^K}\right)\\
&\quad + \beta^F E_1\left[\left(r_2^K + \frac{\overline{A}+A_2^*}{2} + 1\right)(1 - F(A_2^*))\right],\\
\frac{\partial Q_1(\omega_1;\mathcal{S}_{1+})}{\partial \omega_1} &= E_1\left[\Psi_1(-f(A_2^*))Q_2(\omega_1;\mathcal{S}_2)^2\right] + E_1\left[\Psi_1\Psi_2\frac{\overline{A}-A_2^*}{\overline{A}-\underline{A}}(-f(A_3^*))\frac{\partial \omega_2}{\partial \omega_1}\right],\\
\frac{\partial \omega_2}{\partial \omega_1} &= \frac{\Psi_2}{2\Psi_2 - \beta^F}\left(1 - \frac{\omega_1}{K_2}\frac{\partial K_2}{\partial \omega_1}\right)\frac{1}{\Delta_2^K},\\
\frac{\partial K_2}{\partial \omega_1} &= -\frac{\Psi_2 K_1}{2\Psi_2\left(\omega_2 - \frac{\omega_1}{\Delta_2^K}\right) + \beta^F A_3^* + \beta^F\left[r_3^K + 1\right]},\\
\Psi_1 &= \Psi_2 = 1,\\
E_1\left[Z_2\right] &= \frac{\sigma_a^2}{\sigma_a^2 + \sigma_e^2}S_1.
\end{aligned}
$$

The first equation pins down the return on capital, the second the default threshold, the third the risky leverage choice, the fourth the risk-free leverage choice, the fifth the actual leverage choice, the sixth the capital choice, the seventh the bond price derivative, the eighth and ninth the derivatives of the leverage and capital policies with respect to lagged leverage, the tenth the excess return on capital, and the eleventh expected future productivity.

The state space of this economy is the aggregate capital stock K_0, aggregate leverage ω_0 and the signal S_1. It yields policy functions $\Delta_1^K(\omega_0; K_0, S_1)$ and $\omega_1(\omega_0; K_0, S_1)$.

B.2 Equilibrium with binding intermediary constraint

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.

Period 2 Entrepreneurs and intermediaries are connected only through the term Ψ_t, which is determined in equilibrium to equate credit supply and credit demand. The relevant equations that pin down credit supply are the leverage constraint A.25, the definition of the bond price A.28 and the first order condition for equity issuance A.27. We report the equations here for convenience:

$$\begin{aligned}\phi_2 &= \frac{\beta^I\left[1-\frac{C_2^I}{N_2}\right]}{\psi-\beta^I\left(\frac{1}{\Psi_2}-1\right)}, \\ \frac{C_2^I}{N_2^I} &= \frac{1}{\kappa}\left(1-\beta^I\left(1+\mu^I\right)\right), \\ \Psi_2 &= \beta^I\frac{1+\mu^I}{\mu^I\psi+\beta^I(1+\mu^I)}.\end{aligned} \tag{B.4}$$

In equilibrium, credit supply must equal credit demand. Credit supply is $B_2^{supply} = \frac{\phi_2 N_2}{Q_2(\omega_2;\mathcal{S}_{2+})}$. Credit demand is $B_2^{demand} = \omega_2 K_1 \Delta_2^K$. To close the model, we need to determine the law of motion for net worth N_2, which is

$$\begin{aligned}N_2 &= Q_2 B_1 - D_1 \\ &= Q_2\omega_1 K_1 - D_1.\end{aligned}$$

The market clearing condition therefore reads

$$\omega_2 K_1 \Delta_2^K = \frac{\phi_2\left(Q_2(\omega_2;\mathcal{S}_{2+})\omega_1 K_1 - D_1\right)}{Q_2(\omega_2;\mathcal{S}_{2+})}. \tag{B.5}$$

The state space of the model with a binding intermediary constraint is $\mathcal{S}_2 = \{\omega_1, K_1, D_1, Z_2\}$. The solution of the model consists of the system of equations for credit demand B.2, the system of equations for credit supply B.4, and the market clearing condition B.5. Together, these equations yield policy functions for entrepreneurs for leverage $\omega_2(\omega_1;\mathcal{S}_2)$ and capital growth $\Delta_2^K(\omega_1;\mathcal{S}_2)$, a policy function for intermediaries for leverage $\phi_2(\mathcal{S}_2)$ and a market price for credit $\Psi_2(\mathcal{S}_2)$.

Panel 11b of Figure 11 depicts the equilibrium in the case with credit supply frictions. 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.

The equilibrium is 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 intermediation premium that reflects the financial constraints of financial intermediaries. This intermediation 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.

Period 1 The problem of intermediaries in period 1 looks similar, and is given by the incentive constraint A.30, the first-order condition for dividend payments A.32, and the first-order condition for debt A.33. The system of equations that pins down credit supply is

$$\begin{aligned}
\phi_1 &= \frac{\beta^I E_1\left[\Omega_2\left(1-\frac{C_1^I}{N_1^I}\right)\right]}{\psi-\beta^I E_1\left[\Omega_2\left(\frac{\Psi_2(1-F(A_3^*))(1-F(A_2^*))}{E_1\left[\Psi_1\Psi_2(1-F(A_3^*))(1-F(A_2^*))\right]}-1\right)\right]}, \qquad \text{(B.6)}\\
\frac{C_1^I}{N_1^I} &= \frac{1}{\kappa}\left(1-\beta^I E_1\left[\Omega_2\right]\left(1+\mu_1^I\right)\right),\\
\Psi_1 &= \beta^I\frac{1+\mu_1^I}{\mu_1^I\psi+\beta^I E_1\left[\Omega_2\right](1+\mu_1^I)}\Omega_2,\\
\Omega_2 &= \frac{C_2^I}{N_2^I}-\frac{\kappa}{2}\left(\frac{C_2^I}{N_2^I}\right)^2+\psi\phi_2.
\end{aligned}$$

The last equation is the value function of the intermediary. Like in period 2, Ψ_1 adjusts such that the market clears. The market clearing condition is

$$\omega_1 K_0\Delta_1^K = \frac{\phi_1\left(Q_1(\omega_1;\mathcal{S}_{1+})\omega_0 K_0 - D_0\right)}{Q_1(\omega_1;\mathcal{S}_{1+})}. \qquad \text{(B.7)}$$

Together with the system of equations for credit demand B.3 and the system of equations for credit supply B.6, equation B.7 determines the equilibrium of the model in period 1.

C Data

C.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.

C.2 Data included in the VAR

The shocks and the underlying variables are displayed in Figure 12. Table 1 presents further summary statistics for the shocks.

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

Table 1: Summary statistics

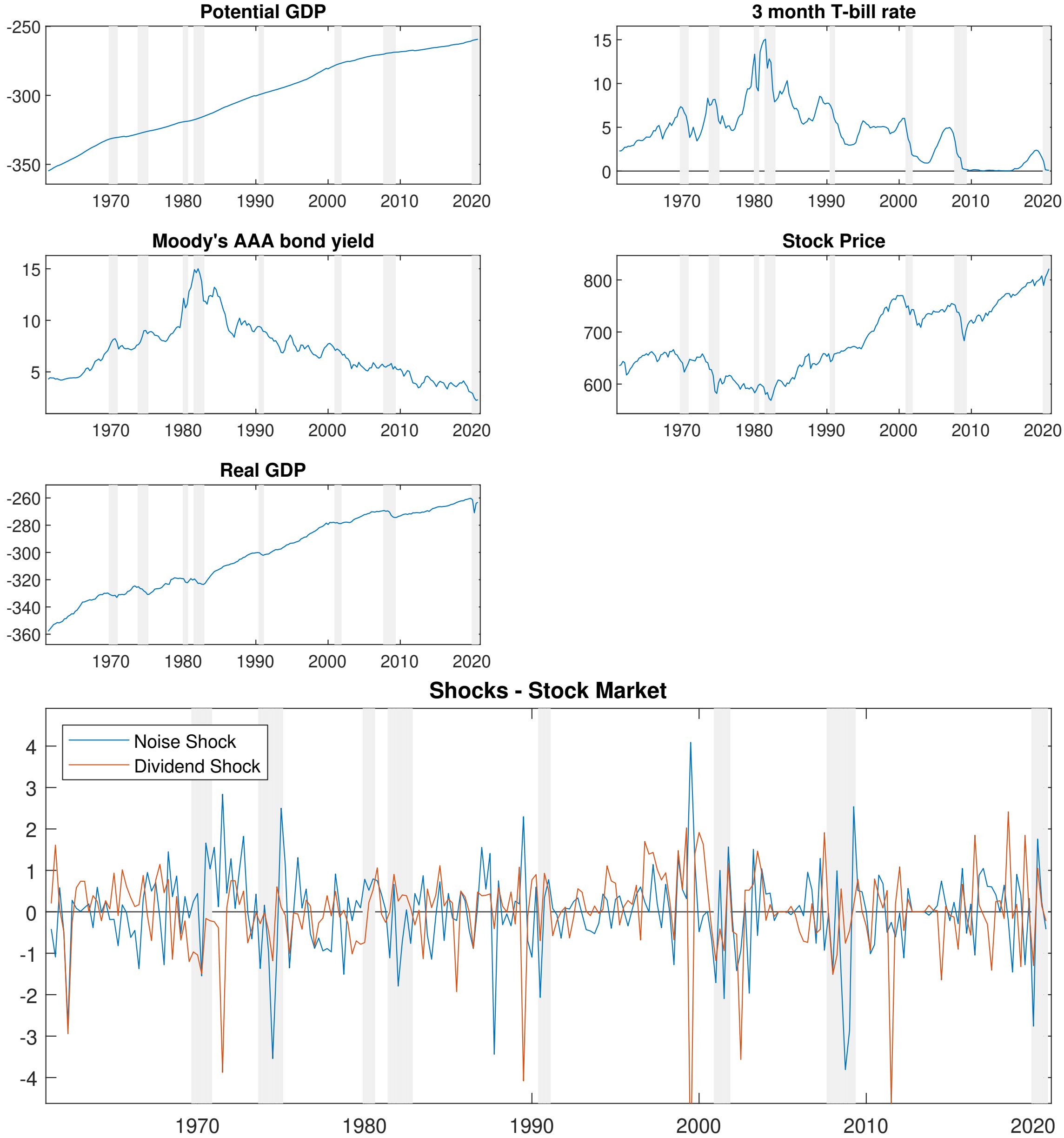


Figure 12: The shocks and the variables used to identify them in the VAR.

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

Table 2: Correlation of shocks

D Identifying noise shocks

D.1 Economic environment

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

$$Z_t = Z_{t-1} + c(L)a_{t-1} + h(L)v_t, \tag{D.1}$$

where a_t is a permanent productivity 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:

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

where e_t is the noise shock.

D.2 Information set of investors

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

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

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 D.3 is not invertible, and therefore nonfundamental in the sense of Hansen and Sargent (1980). 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.

D.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

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

u_t is defined as $u_t = -\frac{\sigma_a^2}{\sigma_s^2} b(L) e_t + \frac{\sigma_e^2}{\sigma_s^2} b(L) a_t$. $b(L)$ is a Blaschke matrix, which has the properties that $b(L)^{-1} = b(L^{-1})$, where $L^{-1} = F$ is the forward operator. A transformation $b(L)e_t$ of an orthonormal white noise process e_t is itself an orthonormal white noise process if and only if the matrix $b(L)$ is a Blaschke matrix (Lippi and Reichlin (1994), though Chahrour and Jurado (2022) show that this is only the case for causal shocks).[13] Finally, a Blaschke matrix can transform a nonfundamental representation like D.3 into a fundamental representation like D.4.

The matrix in equation D.4 is invertible, as $b(L)$ is defined in a way such that $c(0)/b(0)$ does not vanish at 0. This is achieved by defining $b(L) = \prod_{j=1}^{n} \frac{L - r_j}{1 - \bar{r}_j L}$, where r_j are the roots of $c(L)$ that are inside the unit disk (i.e. the ones that make D.3 non-fundamental) and $\bar{r}_j$ their complex conjugates, i.e. the complex values with the opposite sign on the complex part (Forni et al. (2017b)).

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:

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

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.

D.4 Estimating signal and surprise shocks from a VAR

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

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

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

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

13. Causual shocks are shocks that have no effect before they occur. This is the case for the shocks we consider in the model.

Together, equations D.5, 4.1, and D.7 imply the following autoregressive system:

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

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 D.8 using a VAR model. The model is as follows:

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

where Y_t contains, in that order, the log of potential output, 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.

D.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, implied by the structural model, is that potential output responds in the same way to technology news shocks a_t as to signal shocks s_t. Accordingly, one can use the estimated impulse response coefficients to a signal shock to infer the estimated impulse response coefficients to a technology news shock, $c(L)$. This, in turn, allows us to estimate the lag polynomial $b(L)$, as it is computed from the roots of $c(L)$. Finally, with estimates of $c(L)$ and $b(L)$, we can back out estimates of the relative standard deviations of news and noise shocks.

E Additional results

E.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.

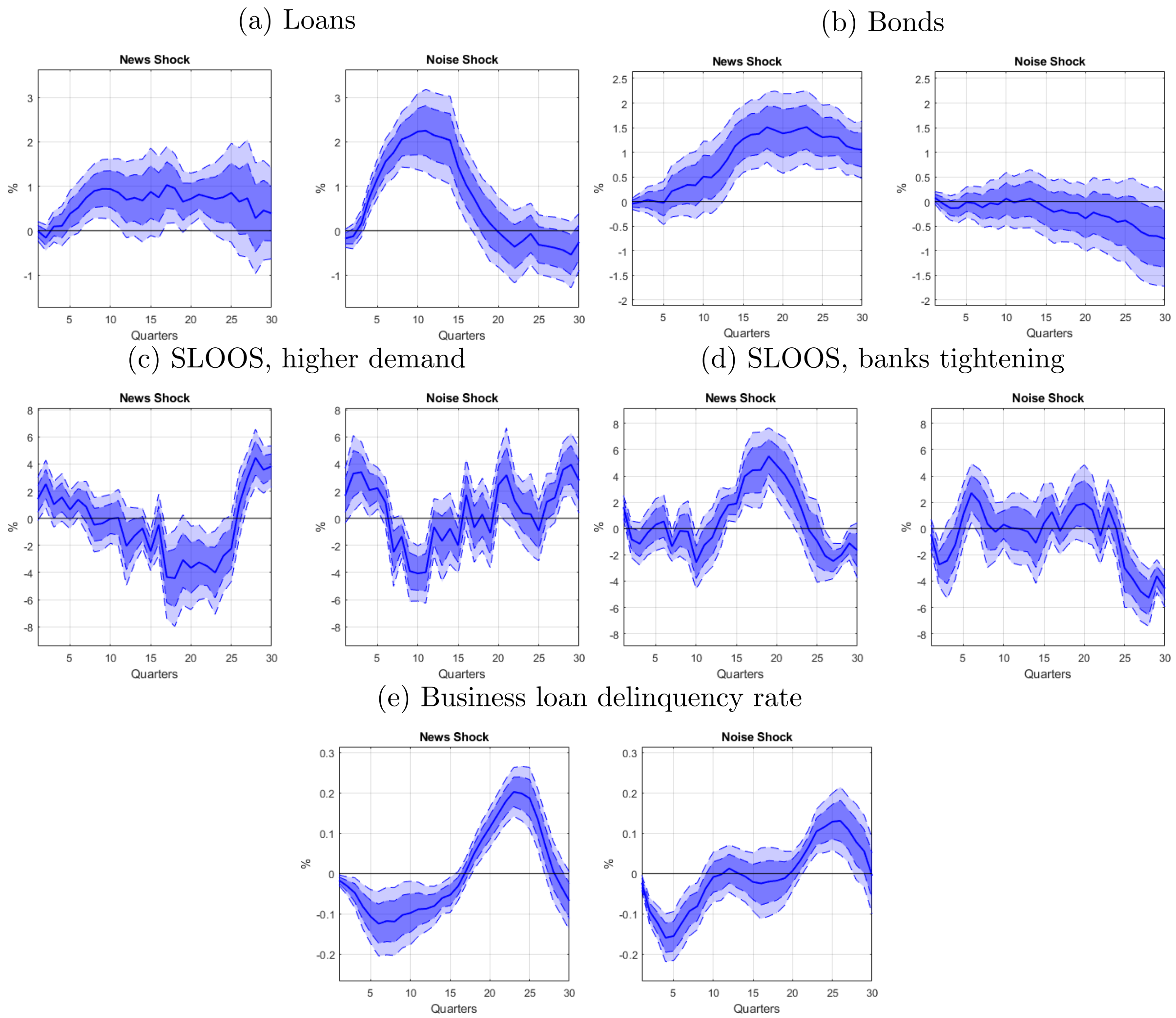


Figure 13: The effect of news and noise shocks on various financial indicators.

Note: The blue line in this figure displays the coefficients $\{\beta_0^h\}_{h=0}^{H}$ obtained by estimating equation 4.1. 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.

Figure 13 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 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.

E.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 14 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

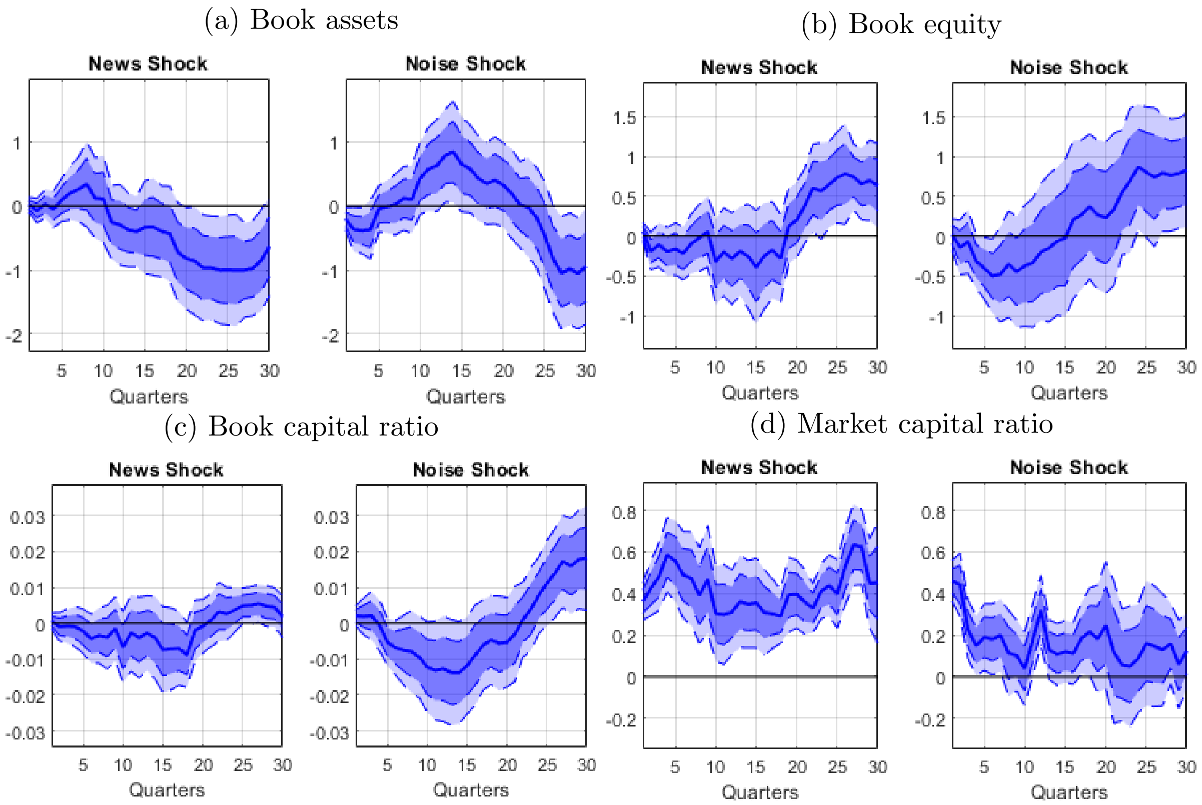


Figure 14: Impulse responses of bank balance sheets to news and noise shocks.

Note: The blue line in this figure displays the coefficients $\{\beta_0^h\}_{h=0}^{H}$ obtained by estimating equation 4.1. 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.

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 4.3 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 14 investigated the effects of news and noise shock on bank book leverage. There 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 14d 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.

E.3 Robustness

Figure 15 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.

E.4 Additional Figures

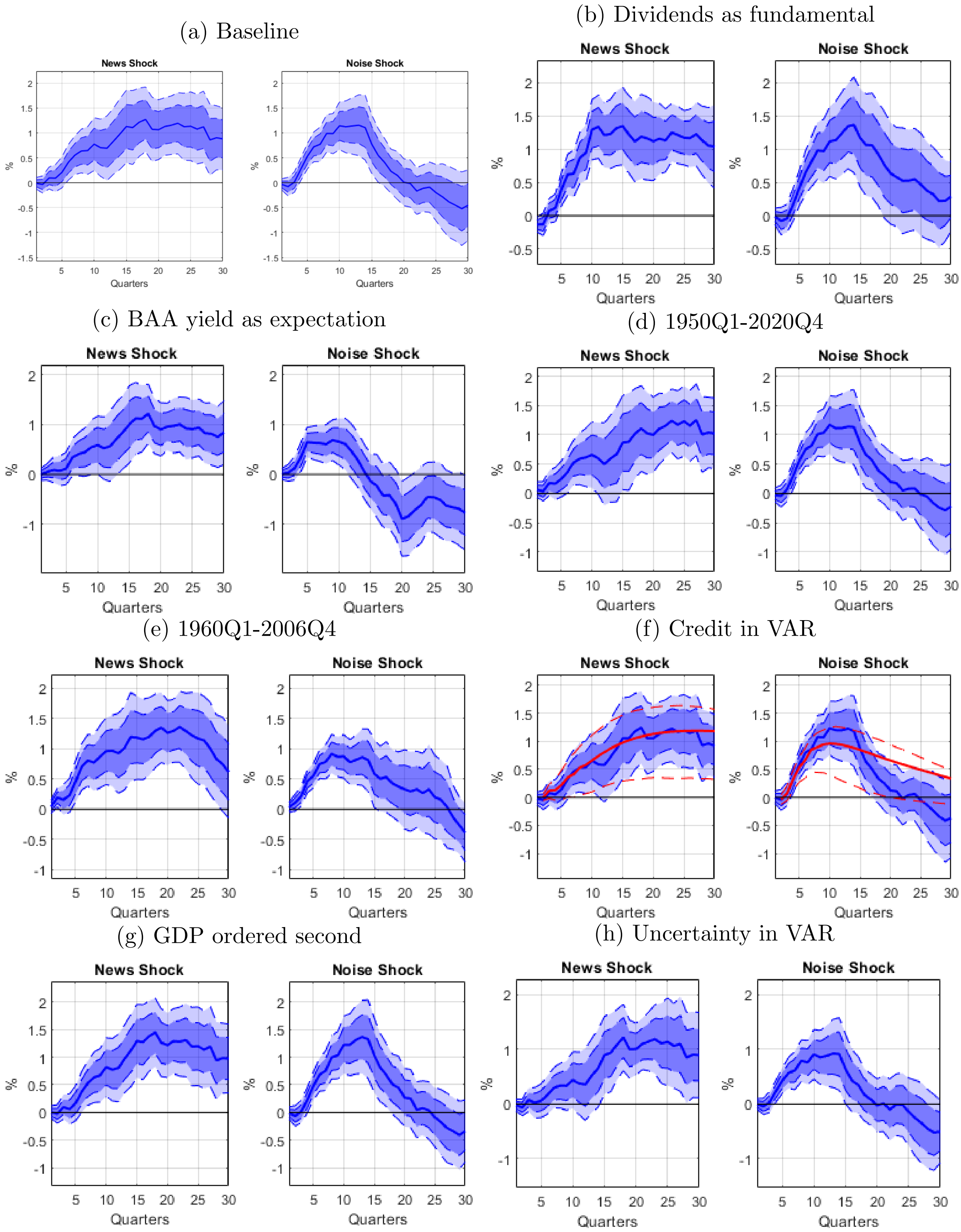


Figure 15: Various robustness checks.

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).

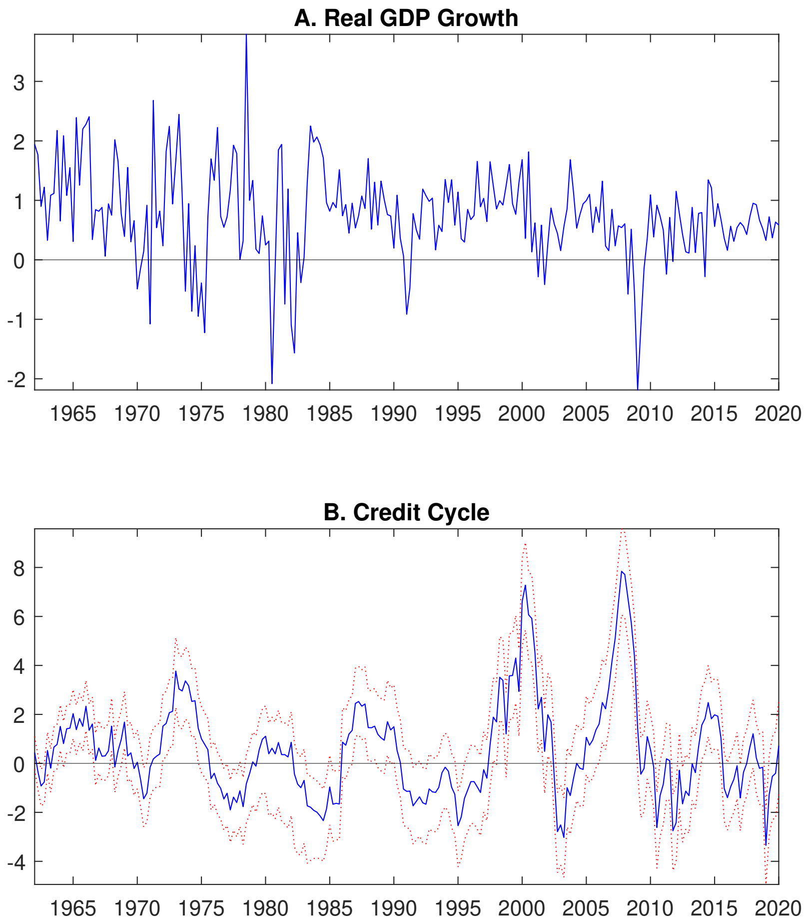


Figure 16: Estimates from an unobserved component model.

Note: This figure shows the results from the estimation of the unobserved components model given by equations 5.3 to 5.8. The credible sets (red, dashed lines) represent the 16th and 84th percentiles of the corresponding posterior densities.

F 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 $\Delta_2 = Z_2 - S_1$.

F.1 Solution strategy

Equipped with the expressions for $\frac{C_2^I}{N_2^I}$, Ψ_2, and μ_2^I, from equations A.28, A.27, and A.25, and the default threshold A.3, solving the period 2 equilibrium boils down to solving a system of the two non-linear equations A.2 and A.1 for Δ_2^K and ω_2 as a function of the aggregate state K_1, ω_1, D_1, and Z_2.

From solving the period 2 equilibrium, we obtain policy functions $\Delta_2^K(K_1, \omega_1, D_1, Z_2)$ and $\omega_2(K_1, \omega_1, D_1, Z_2)$ that allow us to compute value functions and bond prices $\Omega_2(K_1, \omega_1, D_1, Z_2)$,

$Q_2(K_1, \omega_1, D_1, Z_2)$, and $E_2\left[x_3(K_1, \omega_1, D_1, Z_2)|A > A_3^*\right]$ from equations A.7, and A.24. 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 Δ_1^K and ω_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 distribution $Z_2 \sim N(\zeta S_1, \sigma_\Delta)$. We again obtain expressions for $\frac{C_1^I}{N_1^I}$, Ψ_1, and μ_1^I from equations A.33, A.32 and A.25, and the default threshold from equation A.13. Then, solving the period 1 equilibrium boils down to solving a system of the two non-linear equations A.19 and A.15 for Δ_1^K and ω_1.

F.2 Calibration strategy

The model has the following parameters: α, L, β^F, β^I, $\overline{A}_2$, $\overline{A}_3$, κ, ψ, σ^a, σ^e. The model further has initial conditions K_0, D_0, ω_0. We calibrate the parameters to target a leverage of intermediaries of 4 (ψ), a period 2 leverage of entrepreneurs of 0.3 (β^F), an quarterly entrepreneur default rate of 0.025/4 ($\overline{A}_2$,$\overline{A}_3$), a quarterly intermediary component of the credit spread in period 2 of 0.01/4 (β^I), and a quarterly equity issuance rate of intermediaries of 0.01 (κ). The equity issuance rate is in line with the empirical evidence in Gertler, Kiyotaki, and Prestipino (2020). The default rate corresponds to the average delinquency rate on business loans reported by the Federal Reserve Board and available on FRED (identifier DRBLACBS). We set $\alpha = 0.87$, $L = 1$, $\sigma^a = 0.005$, and $\sigma^e = 0.005$, 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 intermediary component of the credit spread of 0.01/4.

F.3 Policy functions

Figure 17 shows that despite its simplicity and the many linear function form assumptions, the policy functions of the model are highly non-linear. Capital is decreasing, leverage is increasing, and the default probability is increasing in the lagged leverage of the entrepreneur. The bond price is non-monotonic in leverage, in line with the intuition in section B. The multiplier on the leverage constraint of the banking sector is increasing, and the bond price is declining in the lagged leverage of the banking sector, reflecting a higher intermediation premium. The period 2 policy functions look qualitatively similar.

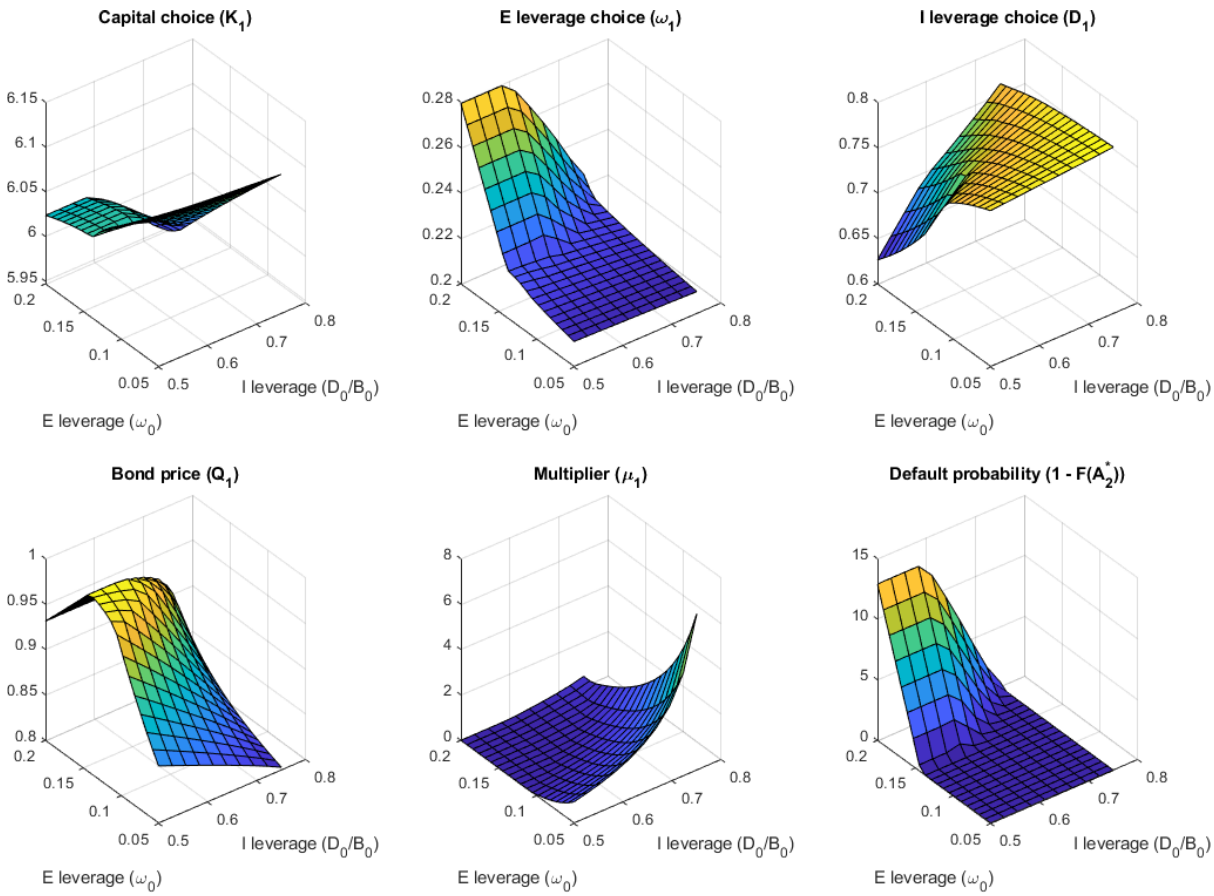


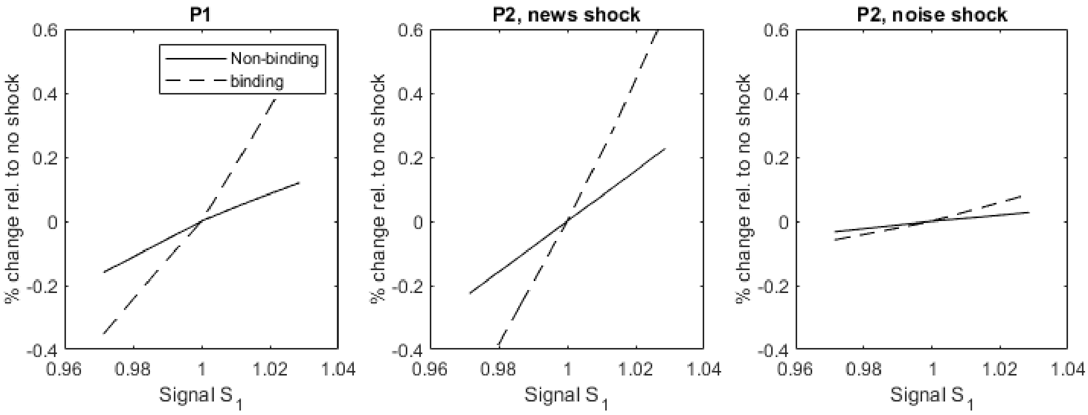
Figure 17: Equilibrium policy functions in period 1

Note: This figure shows the policy functions as a function of entrepreneur leverage (ω_0) and intermediary leverage (D_0/B_0) in period 1. The productivity signal and capital are kept constant, with productivity set to 1 and capital to an intermediate value.

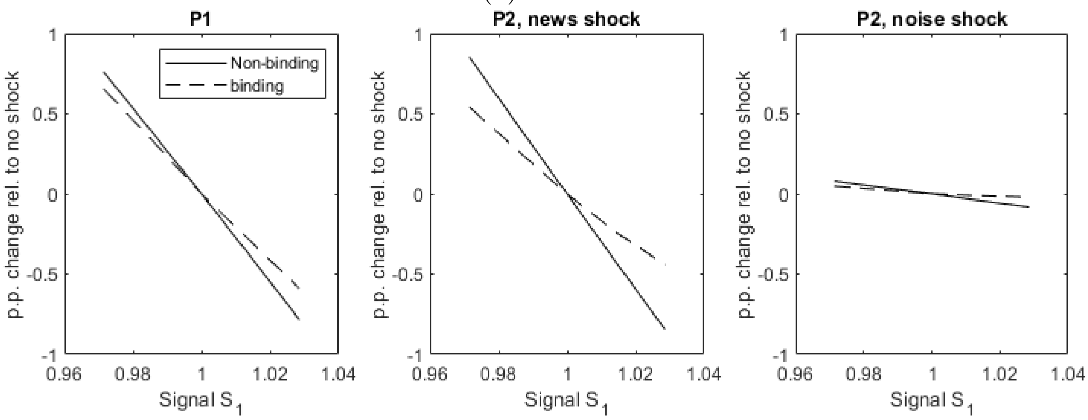
F.4 State-dependent dynamics

Figure 18 shows that binding financial leverage constraints amplify credit dynamics, but mute the credit supply channel that operates through default risk. In particular, it shows how the response of credit, default rates and credit spreads is different for different values of intermediaries initial deposits D_0. The lower initial deposits, the less binding is the financial intermediaries' leverage constraint.

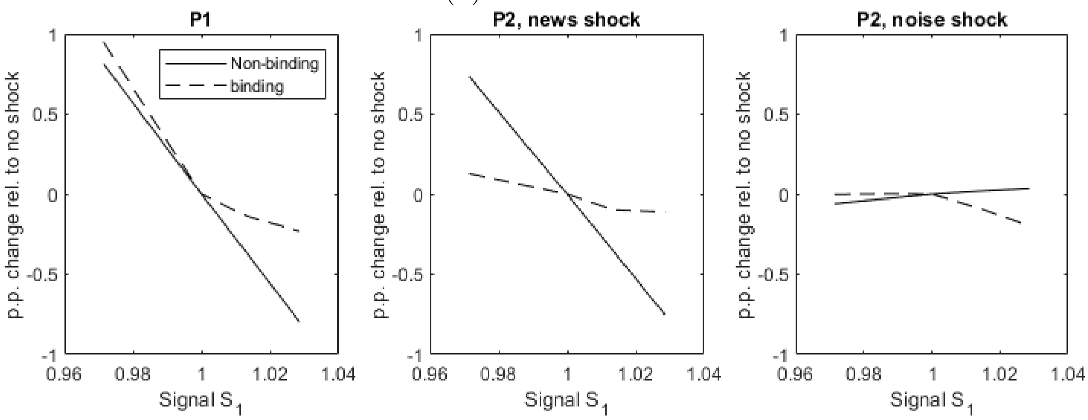
For the case of a binding constraint, credit is more responsive to the signal. This is because credit supply loosens in response to a positive signal, which lowers the intermediation premium and increases the incentive of entrepreneurs to use credit. In contrast, default rates are less responsive to the signal in case of a binding constraint. This is because the higher intermediation premium mutes the incentive of entrepreneurs to take on default risk, making default risk less cyclical. This is reflected in credit spreads, which are less responsive in response to a signal if the leverage constraint binds. Note also that the interplay of the default premium and the intermediation premium leads to non-linear responses of credit spreads to the signal shock.



(a) Credit



(b) Default rate



(c) Credit spread

Figure 18: State-dependent dynamics

Note: This figure shows credit, default rates, and credit spreads as a function of the signal shock and different financial constraints. All series are normalized relative to the case of no shock. The left column shows period 1, the middle column period 2 in the case of a true news shock and the right column period 2 in case of a noise shock. The dashed line shows responses if the initial debt D_0 of intermediaries is four per cent above steady state, the solid line responses if it is four per cent below steady state.