Noise-Ridden Lending Cycles[☆]

PRELIMINARY DRAFT

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Elena Afanasyeva[*]

20th Street and Constitution Avenue NW, Washington, D.C. 20551, USA.
Email address: elena.afanasyeva@frb.gov.

Jochen Güntner[**]

Altenberger Straße 69, 4040 Linz, Austria.
Email address: jochen.guentner@jku.at.

Abstract

This paper studies the effect of noise shocks on the credit supply of financial intermediaries. In our model, a risk-neutral competitive "bank" solves a signal extraction problem in order to learn about the state of the economy, which determines the default probability of a given loan. A non-fundamental noise shock lowers the equilibrium interest rate on risky credit, increases the share of riskier loans in the bank's portfolio, and leads thus to higher ex-post default. Given that the reduced-form VAR representation is not invertible, we estimate a general equilibrium version of the model in order to recover the structural shocks and find that noise shocks account for up to 50% of the forecast error variance in credit spreads and credit volumes.

Keywords: Bayesian Maximum Likelihood, Credit Booms, Imperfect Information, Kalman Filter
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[*]Elena Afanasyeva is Economist at the Board of Governors of the Federal Reserve System.

[**]Jochen Güntner is Assistant Professor at the Department of Economics, Johannes Kepler University Linz.

1. Introduction

Do expectations about the current and future state of the economy matter for banks' lending decisions? The *Senior Loan Officer Opinion Survey* conducted by the Board of Governors of the Federal Reserve System gives an unambiguous answer to this question. Figure 1 illustrates that, when commercial banks in the U.S. adjust their lending standards, they report that "economic outlook" is a *somewhat* or *very important* reason for tightening standards in a recession as well as for easing standards in a boom or recovery.

In this paper, we model the lending decision of a risk-neutral competitive financial intermediary subject to a signal extraction problem. While maintaining the assumption of rational expectations, we depart from the frequently associated assumption of full information. Hence, our rational financial intermediary knows the structure of the model, whereas it must forecast the latent state of the economy, which determines the default probability of a given loan next period, based on noisy observables. A positive signal about the current state induces the bank to lend to objectively riskier borrowers in expectation of higher future returns. If the signal is pure noise, however, the expansion of credit is not backed by economic fundamentals and would not occur under full information and rational expectations. To the best of our knowledge, we are the first to analyze the lending decision of financial intermediaries in a noisy information environment.

Building on the partial equilibrium neoclassical investment model in Bordalo et al. (2018), we show that pure noise shocks generate credit booms and busts, if the intermediary cannot observe the true state of the economy and must infer the riskiness of a loan from observables and a noisy public signal. This is costly, as default rates increase when the bank's expectations turn out to be overly optimistic ex post. Importantly, these credit cycles are driven exclusively by imperfect information of financial intermediaries rather than by any kind of financial friction between the borrower and the lender.

Due to this informational friction, the vector-autoregressive (VAR) representation of our model is not invertible. To quantify the role of noise shocks in U.S. credit spreads and volumes, we therefore embed the neoclassical investment model in a general equilibrium setting. We close the partial equilibrium model by assuming that bank lending is funded by accumulated bank net worth and by external funds in the form of risk-free deposits. In order to focus on the propagation of noise shocks through credit supply, we assume the supply of bank deposits to be perfectly elastic, as in a small open economy. Following Blanchard et al. (2013), we solve the linearized general equilibrium model under imperfect information and estimate its equivalent full information representation using Bayesian maximum likelihood techniques.

Figure 1: The importance of "economic outlook" for changes in lending standards of U.S. commercial banks

Notes: Number of banks reporting that "economic outlook" was unimportant, somewhat important, or very important for tightening (if positive) or loosening (if negative) lending standards. **Source:** Senior Loan Officer Opinion Survey on Bank Lending Practices

Calibrating the model's driving processes along the lines of our empirical estimates, we find that noise shocks contribute up to 50% to the forecast error variance of the spread between Moody's seasoned Baa corporate bond yield and the yield on 10-year treasury constant maturity and credit growth at the 5-year horizon. Contrasting our model with the data, we find that it reproduces the historical fluctuations of errors and revisions in Blue Chip survey expectations as well as of U.S. delinquency rates on bank loans.

Our paper is most closely related to the literature on the expectations formation process of investors and financial intermediaries and the literature on the aggregate effects of imperfect information. When modeling the behavior of profit-maximizing financial intermediaries, existing work on the role of expectations in the emergence of lending cycles mostly focuses on deviations from rational expectations. Bordalo et al. (2018), for example, build on insights from cognitive psychology and assume that risk-neutral investors form so-called *diagnostic* rather than rational expectations. De Grauwe and Macchiarelli (2015) instead assume that, due to limited cognitive abilities, banks apply simple extrapolative rules when deciding whether and under which conditions to grant a loan. Similarly, Greenwood et al. (2016) model "credit market sentiment" by assuming that investors extrapolate past defaults when forming expectations about the creditworthiness of their borrowers. Bhattacharya et al. (2015) formalize Minsky's financial instability hypothesis by modeling investors that have incomplete information about the true probability measure when forecasting the future state of the economy. Our model provides an alternative explanation for the emergence of lending cycles based on the rational processing of noisy information by financial intermediaries. Moreover, we are able to quantify the relative importance of noise shocks for fluctuations in credit spreads and volumes.

The signal extraction problem of our representative financial intermediary is similar to that of consumers in Lorenzoni (2009) and Blanchard et al. (2013). We also borrow from Blanchard et al. (2013) a structural identifying strategy that resolves the non-fundamentalness of the VAR representation in models with imperfect information. Cao and L'Huillier (2018) apply this strategy to a small open economy version of the New Keynesian model. In contrast to all of the above, our focus is on the lending conditions and hence on the signal extraction problem of financial intermediaries rather than households. This feature gives rise to a different propagation channel for noise shocks, which operates primarily through financial market rather than consumer expectations, and implies that noise shocks can be interpreted as credit supply rather than aggregate demand shocks (as in Lorenzoni, 2009, for example).

Boz and Mendoza (2014) model the signal extraction problem of households who use Bayesian updating to learn about the risk of a new financial environment. The authors show that the interaction of financial frictions (i.e. a collateral constraint) and imperfect information results in the underpricing of risk in periods following financial innovations, such as 1998–2006. The underpricing of risk also features prominently in our model, where it arises solely from the informational friction on the part of financial intermediaries.

Finally, our work builds on empirical evidence on the role of credit market sentiment for the build-up of financial vulnerability. Greenwood and Hanson (2013) argue that the credit quality of corporate debt issuers helps to identify sentiment-driven credit booms, as narrow spreads predict lower future returns to corporate bondholders. López-Salido et al. (2017) show that time variation in sentiment on the part of credit market investors is an important determinant of the lending cycle, as it reflects changes in the effective risk appetite or beliefs about default probabilities. Accordingly, they identify credit booms using proxies for the expected returns on credit assets rather than balance sheet measures of aggregate credit. The predictions of our theoretical model, where noise-driven lending booms are manifestations of the underpricing of credit risk by financial intermediaries and followed by higher default and reduced returns on credit, are broadly consistent with these empirical regularities.

The rest of the paper is organized as follows. In Section 2, we provide evidence of noisy information in the financial sector. Section 3 uses a neoclassical investment model to illustrate how credit booms emerge

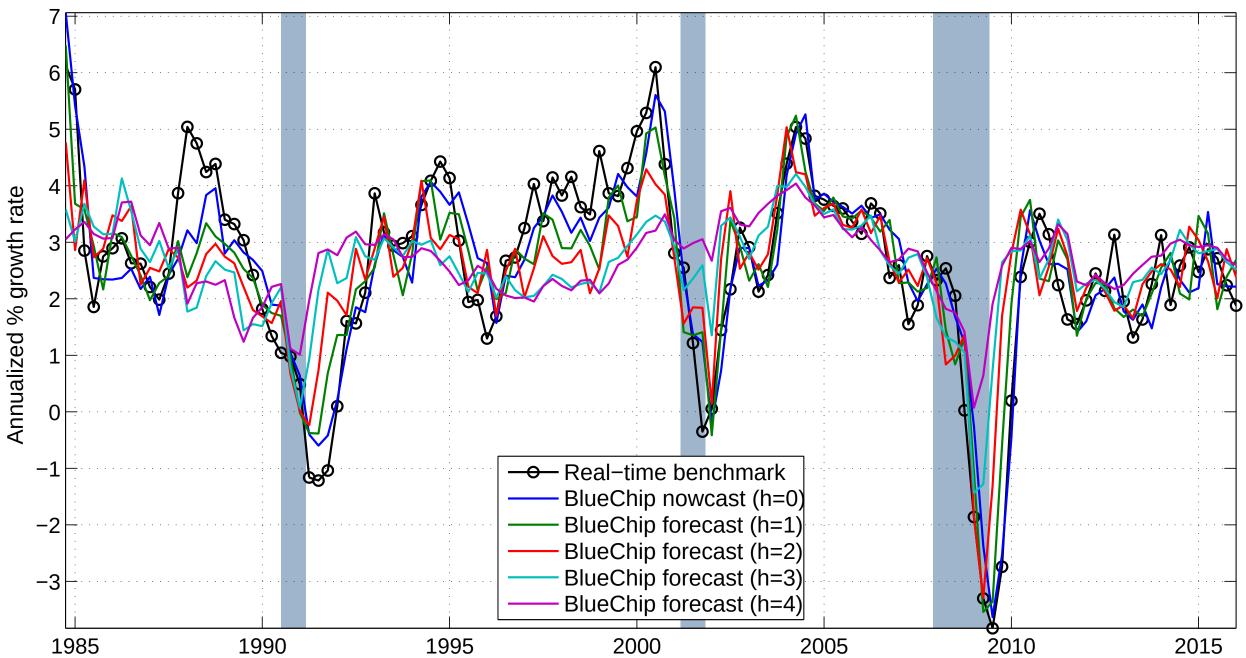

Figure 2: Blue Chip consensus nowcasts and forecasts of year-on-year real GDP growth and $t + 4$ real-time benchmark

in the presence of imperfect information. Section 4 embeds this model in a general equilibrium setting, proposes a simplified version with only two risk types of borrowers, and derives the reduced-form VAR representation of the model. We then estimate the model using Bayesian maximum likelihood techniques and evaluate the relative importance of noise shocks based on the recovered parameters of the forcing processes. Section 5 concludes.

2. Empirical Evidence

In this section, we use survey data on banks' expectations from the Blue Chip Economic Indicators to provide evidence of imperfect information in the financial sector.[1] We focus on the so-called *Blue Chip consensus* forecast, i.e. the simple average of forecasts across all survey participants, of real GDP growth as a key measure of participants' expectations regarding current and future U.S. economic conditions.

Figure 2 plots Blue Chip consensus *forecasts* of year-on-year real GDP growth for forecast horizons from 0 to 4 quarters against a real-time benchmark released by the Federal Reserve Bank of Philadelphia

[1]The Blue Chip Economic Indicators is a monthly survey of more than 50 economists employed by some of America's largest manufacturers, banks, insurance companies, and brokerage firms. It was established in 1976 and collects professional forecasts on macroeconomics aggregates for the U.S. economy. What makes it particularly interesting and suitable for our question is that the majority of the survey participants are U.S. commercial and investment banks.

with a lag of four quarters.[2] In general, the Blue Chip consensus forecasts are relatively accurate in real time and track the $t + 4$-benchmark closely. Nevertheless, we detect quantitatively large and persistent deviations during selected historical episodes.[3] During 1987–1990 and during 1997–2000, for example, forecasts were persistently more pessimistic about current real GDP growth than suggested by real-time data. In contrast, forecasts were optimistic relative to the $t + 4$-benchmark during 1990–1992 and during 2005–2010.

The observed persistence in deviations of Blue Chip consensus forecasts from the real-time benchmark is inconsistent with the assumption of full information and rational expectations. The latter implies that forecast errors are *unpredictable* if the underlying disturbances are unpredictable, whereas we find significant positive serial correlation in Blue Chip consensus forecast errors for all forecast horizons. In order to test more formally for the presence of informational frictions in bank expectations, we draw on Coibion and Gorodnichenko (2015), who show that, if agents observe the variable x_t with normally distributed mean-zero noise that is i.i.d. across time and across agents, then the individual forecasts based on agents' information sets and the Kalman filter imply the following relationship between ex-post mean forecast errors and ex-ante mean forecast revisions:

$$x_{t+h} - F_t x_{t+h} = \frac{1 - G}{G} (F_t x_{t+h} - F_{t-1} x_{t+h}) + u_{t+h,t}, \tag{1}$$

where F_t denotes the average forecast across agents at time t, G the so-called Kalman gain, and $u_{t+h,t}$ the rational expectations error. The predictability of average forecast errors reflects the gradual adjustment of conditional expectations to new information by the agents, who don't know whether this information reflects a change in fundamentals or pure noise. Note that the specification in (1) holds for any forecast horizon h as well as for forecasts over multiple horizons (see Coibion and Gorodnichenko, 2015).

Accordingly, models with informational frictions such as noisy information, for example, imply that ex-ante average forecast revisions have predictive power for ex-post average forecast errors, whereas this is not the case under full information and rational expectations (FIRE). We replicate the regression analysis in

[2] We use real-time rather than final data on real GDP growth, because re-classifications and redefinitions might make final data not directly comparable to Blue Chip forecasts (see Croushore, 2010). We use the $t+4$-benchmark rather than the so-called *advance release*, i.e. the $t+1$-benchmark, of the Federal Reserve Bank of Philadelphia, given that a large share of revisions in real-time data occurs within one year after the advance release.

[3] We plot the Blue Chip consensus nowcasts and forecasts based on the *third* monthly round of a given quarter, i.e. from the March, June, September, and December releases, to measure expectations as of quarter I, II, III, and IV, respectively. Releases from the first and second month of each quarter yield similar results.

Table 1: Tests of bank expectations process for real GDP growth based on the regression equation in (2)

		yoy real GDP growth			qoq real GDP growth			
Horizon	Benchmark	c	β	R^2	c	β	R^2	N
$h = 0$	$t+1$	0.038	0.072*	0.013	0.233*	0.145	0.012	125
	$t+2$	0.048	0.098	0.012	0.288*	0.167	0.010	125
	$t+3$	0.045	0.209**	0.040	0.297**	0.087	0.003	125
	$t+4$	0.042	0.192*	0.026	0.272*	0.105	0.004	125
	$t+5$	0.029	0.190	0.022	0.280*	0.170	0.010	125
$h = 1$	$t+1$	0.089**	0.869***	0.673	0.156	1.011***	0.167	124
	$t+2$	0.100*	0.903***	0.560	0.211	1.044***	0.133	124
	$t+3$	0.102	1.008***	0.550	0.212	0.909***	0.101	124
	$t+4$	0.098	0.987***	0.468	0.197	0.979***	0.114	124
	$t+5$	0.092	0.972***	0.430	0.238	1.078***	0.131	124
$h = 2$	$t+1$	0.077	0.974***	0.480	−0.074	1.548***	0.118	123
	$t+2$	0.092	1.021***	0.442	0.010	1.824***	0.131	123
	$t+3$	0.096	1.121***	0.477	0.019	1.633***	0.106	123
	$t+4$	0.096	1.114***	0.445	−0.026	1.751***	0.117	123
	$t+5$	0.091	1.110***	0.410	0.018	1.984***	0.139	123
$h = 3$	$t+1$	0.101	0.911***	0.135	−0.276	0.928	0.019	122
	$t+2$	0.126	1.004***	0.145	−0.210	1.242	0.027	122
	$t+3$	0.141	1.120***	0.169	−0.177	1.180	0.025	122
	$t+4$	0.142	1.119***	0.158	−0.229	1.386	0.034	122
	$t+5$	0.136	1.140***	0.154	−0.213	1.524	0.037	122

Notes: $***/**/*$ indicates statistical significance at the 1/5/10% level based on Newey-West (HAC-robust) standard errors.

Coibion and Gorodnichenko (2015) using Blue Chip consensus forecast errors and revisions as of period t for forecast horizon h:

$$x_{t+h} - F_t x_{t+h} = c + \beta (F_t x_{t+h} - F_{t-1} x_{t+h}) + error_t, \tag{2}$$

where a statistically significant coefficient β indicates a rejection of the null hypothesis of FIRE in favor of the alternative hypothesis of informational frictions in the presence of rational expectations. Table 1 reports our regression results for U.S. bank expectations on year-on-year and quarter-on-quarter real GDP growth, respectively, for 1984Q4 through 2015Q4.

For year-on-year growth rates, the null of FIRE is strongly rejected in favor of informational frictions. The coefficient estimate on forecast revisions, β, is statistically significant (most frequently at the 1% level), whereas the estimated intercept coefficient c is close to zero and not statistically significant. This finding is quantitatively more pronounced for $h = 1, 2, 3$ and also reflected in a higher value of R^2 in these cases. It is important to note that our results are robust to the choice of the real-time benchmark used to evaluate Blue

Chip consensus forecast errors, where $t+1$ corresponds to the so-called *advance release* and $t+l$ to the data on period t made available by the Federal Reserve Bank of Philadelphia with a lag of l quarters.

For quarter-on-quarter growth rates of real GDP growth, the results are qualitatively similar for $h = 1$ and $h = 2$, yet less clear-cut for $h = 0$ and $h = 3$. Given that quarter-on-quarter data displays more unexplained fluctuations, the corresponding R^2 values are lower than their year-on-year counterparts. At the same time, the point estimates of β tend to be larger.

Coibion and Gorodnichenko (2015) show that the point estimate of β translates directly into the degree of informational rigidity in a noisy information model. For $\beta = 1.1$, i.e. the mode of our point estimates, the Kalman gain $G = 1/(1+\beta) = 0.476$ reflects the weight that agents assign to new information relative to their previous forecasts.[4] Based on this evidence, we reject the null hypothesis of FIRE in favor of the alternative hypothesis of informational frictions in Blue Chip consensus forecasts of real GDP growth — a measure of U.S. bank expectations about the current and future state of the economy. While we don't make use of the quantitative estimate of G, the qualitative finding of a rejection of FIRE motivates our analysis of noisy information as a source of lending cycles in a theoretical investment model.

3. The Partial Equilibrium Model

We start by illustrating the intuition in a neoclassical partial equilibrium investment model similar to the one proposed by Bordalo et al. (2018).

3.1. Partial Equilibrium Model under Full Information

Time $t = 1, 2, \dots$ is discrete and the economy's state at time t, $\Omega_t \in \mathbb{R}$ with realization ω_t, follows a Markov process with a normal distribution conditional on Ω_{t-1}, as in the AR(1) case

$$\omega_t - \mu_\omega = b\,(\omega_{t-1} - \mu_\omega) + \epsilon_t^\omega, \tag{3}$$

with $\epsilon_t^\omega \sim N\left(0, \sigma_\omega^2\right)$ and $\mu_\omega \in \mathbb{R}$, $b \in [0, 1]$.

[4]The Kalman gain also reflects the average reduction in the variance of contemporaneous forecast errors relative to the variance of one-step ahead forecast errors (see Coibion and Gorodnichenko, 2015).

3.1.1. Credit demand by firms

A unit measure of atomistic firms uses capital to produce output, where productivity at time t depends on ω_t to a different extent for different firms. Each firm is identified by its *risk type*, $\rho \in \mathbb{R}$. Firms with higher ρ are less likely to be productive in any state ω_t and represent thus a riskier investment. The output of a type-ρ firm at time t is given by

$$y(k|\omega_t, \rho) = \begin{cases} k^\alpha & \text{if} \quad \omega_t \geq \rho \\ 0 & \text{if} \quad \omega_t < \rho \end{cases},$$

where $\alpha \in (0, 1)$.

The capital used for production at time $t+1$ must be installed at time t already, before ω_{t+1} is known. For simplicity, we assume that capital depreciates fully in production. Each firm's risk type ρ is *common knowledge* and distributed across firms according to the continuous density function $f(\rho)$.

Each firm's capital investment is fully debt funded. A firm of type ρ borrows funds $l_t(\rho) = k_{t+1}(\rho)$ from a bank, taking the contractual interest rate $r_t(\rho)$ as given. It repays the loan only if the realized state of the economy allows the firm to be productive. Else, it defaults and repays nothing.

Assuming perfect competition in production, each firm type ρ borrows up to the point where the marginal product of capital equals the cost of borrowing from the bank, i.e.

$$l_t(\rho) = k_{t+1}(\rho) = \left[\frac{\alpha}{r_t(\rho)}\right]^{\frac{1}{1-\alpha}}. \tag{4}$$

3.1.2. Credit supply by banks

Suppose that the credit market is perfectly competitive, while the representative bank owns a stock of net worth that can be used to grant loans. In contrast to the representative household in Bordalo et al. (2018), which elastically supplies any amount of capital at the risk-free interest rate, the lenders in our model do *not* make optimal consumption-saving decisions. Instead, we assume that the risk-neutral representative bank invests all of its net worth, n_t, until it exits the credit market (exogenously) and gets to consume its accumulated net worth.

Similar to the behavior of entrepreneurs in Bernanke et al. (1999), the representative bank myopically maximizes its expected net worth in the next period. Given a predetermined amount of bank net worth, n_t, and a risk-free interest rate on deposits, r_t^d, that is assumed to be determined outside the partial equilibrium model (e.g. by monetary policy or household preferences), banks maximize $E_t n_{t+1}$ by optimally choosing the amount of lending $l_t(\rho)$ supplied to each firm type ρ:

$$\begin{aligned} \max_{l_t(\rho)} \quad & Prob_t\left(\omega_{t+1} \geq \rho\right) r_t(\rho) l_t(\rho) - \left[l_t(\rho) - n_t(\rho)\right] r_t^d \\ \frac{\partial E_t n_{t+1}}{\partial l_t(\rho)} &= Prob_t\left(\omega_{t+1} \geq \rho\right) r_t(\rho) - r_t^d = 0 \\ \Leftrightarrow \qquad r_t^*(\rho) &= \frac{r_t^d}{Prob_t\left(\omega_{t+1} \geq \rho\right)}, \end{aligned} \tag{5}$$

where $Prob_t(\bullet)$ denotes the expected repayment probability as of period t, which is assumed to be independent of $r_t(\rho)$. As a result, we have a unique interior solution for the bank's optimal choice of $r_t(\rho)$ for each firm type ρ.[5] Equations (4) and (5) yield a unique interior solution for the firm's optimal demand for credit:

$$l_t^*(\rho) = \left[\frac{\alpha \cdot Prob_t\left(\omega_{t+1} \geq \rho\right)}{r_t^d}\right]^{\frac{1}{1-\alpha}}. \tag{6}$$

From equations (5) and (6), a higher expected probability of repayment translates into a lower interest rate on bank credit, $r_t^*(\rho)$, and thus a higher demand for bank credit and capital, $l_t^*(\rho)$, for each firm type ρ.

Figure 3 plots the equilibrium interest rate in (5) and the demand for capital and bank credit in (6) *by firm type* ρ and illustrates that low-ρ types with a negligible risk of default pay an interest rate on bank credit that is close to the risk-free rate. The figure represents a snapshot of the economy for a given expected value and variance of ω_{t+1} conditional on the information available in period t. The broken lines depict the effect of an increase in $E_t\omega_{t+1} = \mu_\omega$ without any change in $E_t\sigma_{\omega,t+1}$.

In contrast, Figure 4 plots the equilibrium interest rate in (5) and the demand for capital and bank credit in (6) *as a function of the expected repayment probability*. Changes in $E_t\omega_{t+1}$ affect the position of a given firm type ρ on the x-axis rather than shifting graphs (as in Figure 3). Figure 4 illustrates that symmetric increases and decreases in the expected repayment probability have *asymmetric effects* on the equilibrium interest rate and thus on the demand for bank credit for a given firm type ρ. Due to the presence of $Prob_t\left(\omega_{t+1} \geq \rho\right)$ in the denominator of (5), this asymmetry is more pronounced for low expected repayment probabilities, where a decrease in $Prob_t\left(\omega_{t+1} \geq \rho\right)$ raises the equilibrium interest rate by more than a symmetric increase

[5] Our formulation of the representative bank's profit maximization problem implies that the *marginal* unit of credit is financed by deposits rather than bank net worth. Hence, the marginal cost of extending an additional unit of credit equals the risk-free interest rate r_t^d rather than the opportunity cost of bank net worth.

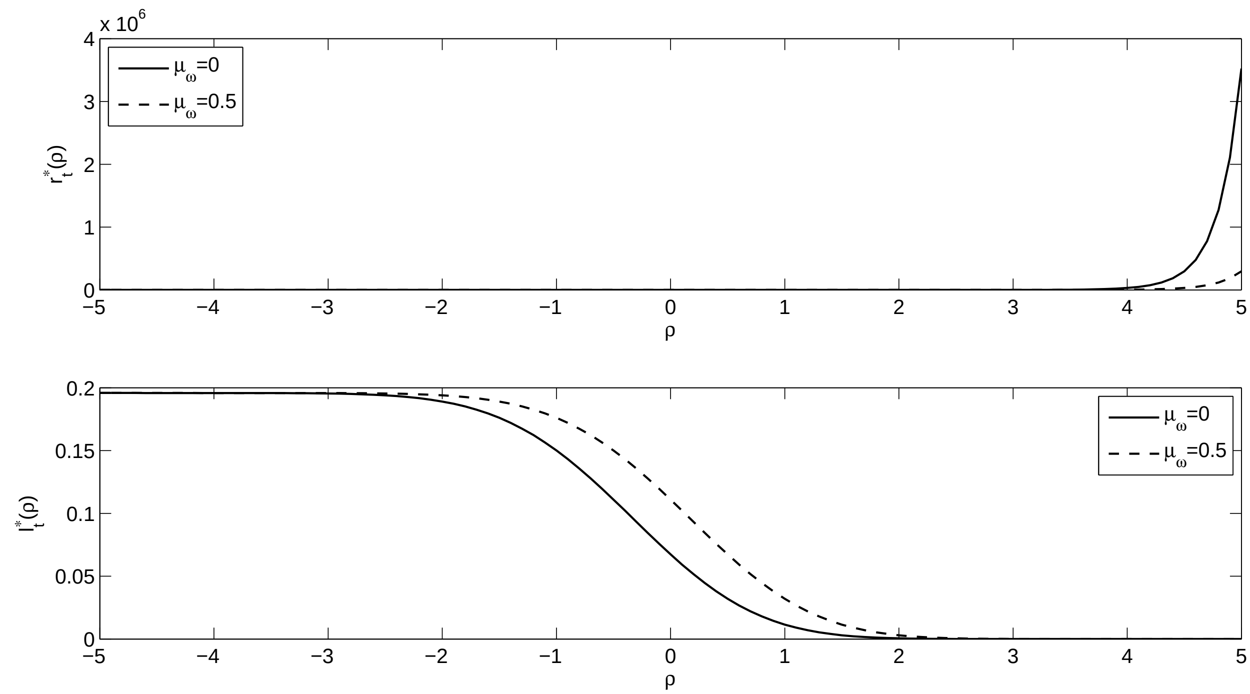

Figure 3: Equilibrium interest rates and demand for bank credit by firm type ρ

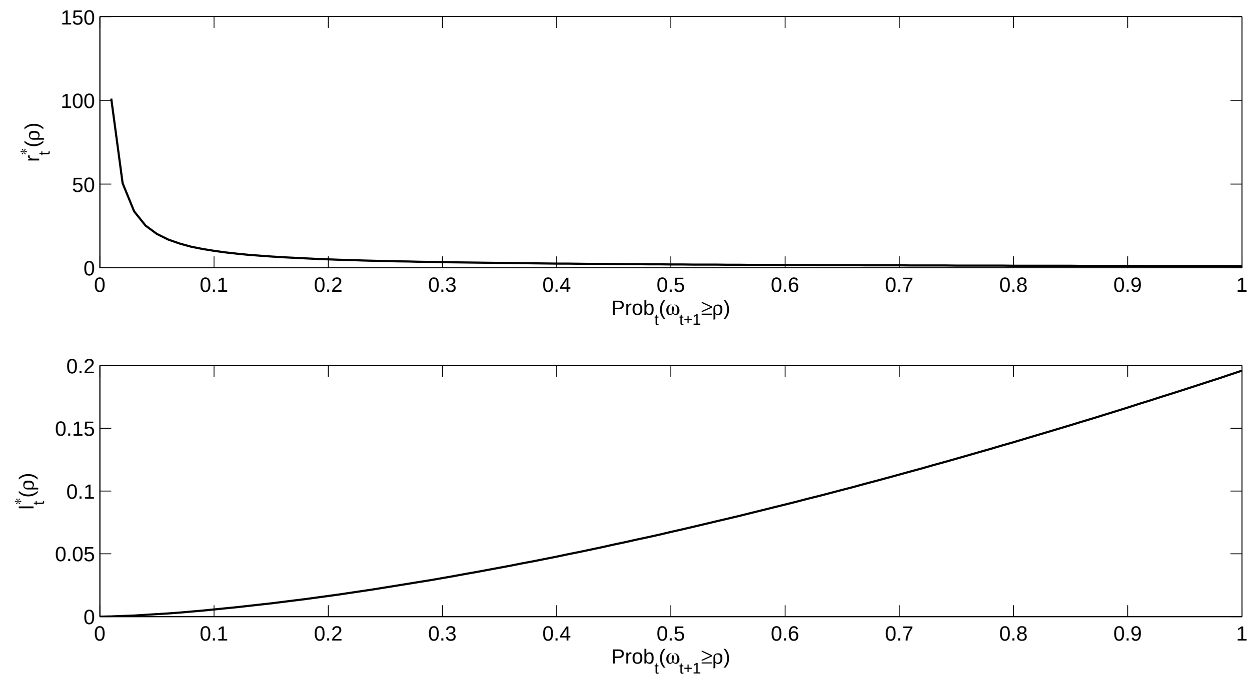

Figure 4: Equilibrium interest rates and demand for bank credit by expected repayment probability

would lower $r^*(\rho)$.

3.2. Partial Equilibrium Model under Imperfect Information

Suppose that the exogenous default threshold ω_t summarizes the persistent and transitory components ν_t and η_t, respectively, which are both *unobservable*. As a consequence, the bank must form expectations about ω_{t+1} based on its nowcast of the unobservable components in period t. Using the above notation, the exogenous processes of the bank's information problem can be written as

$$\begin{aligned} \omega_t &= \nu_t + \eta_t, \\ \nu_t &= \rho_\nu \nu_{t-1} + e_t, \quad e_t \sim N\left(0, \sigma_e^2\right), \\ \eta_t &= \rho_\eta \eta_{t-1} + \epsilon_t, \quad \epsilon_t \sim N\left(0, \sigma_\epsilon^2\right), \end{aligned} \tag{7}$$

where e_t and ϵ_t are assumed to be *contemporaneously* and *serially uncorrelated*, and $\rho_\nu > \rho_\eta$. Following Lorenzoni (2009), we further assume that the bank receives a noisy public signal of the persistent component ν_t at time t, i.e.

$$\tilde{s}_t = \nu_t + \varepsilon_t, \quad \varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right), \tag{8}$$

where ε_t is assumed to be contemporaneously and serially uncorrelated with e_t and ϵ_t.

The disturbance term ε_t in (8) plays two roles. First, it prevents the bank from perfectly observing the persistent component of the aggregate state. Second, it generates an independent source of variation in the bank's beliefs about ν_t. Note that the disturbance terms in η_t and $\tilde{s}_t$ have very different interpretations. While ϵ_t is a shock to the transitory component of the aggregate state and affects thus ω_t, ε_t is a non-fundamental "noise shock", which propagates only through the bank's period-t expectations about ω_{t+1}.

In our partial equilibrium model, the market-clearing interest rate of a loan to firm type ρ thus equals

$$r_t^*(\rho) = \frac{r_t^d}{Prob\left(\omega_{t+1} \geq \rho | \omega_t, \omega_{t-1}, \ldots, \tilde{s}_t, \tilde{s}_{t-1}, \ldots\right)} \quad \forall \rho, \tag{9}$$

where the information set of the bank in period t is confined to current and past realizations of the observable variables ω_t and $\tilde{s}_t$.

Note that only shocks to the persistent component contribute to fluctuations in $\nu_t = \rho_\nu \nu_{t-1} + e_t$. However, ν_t is not observable either contemporaneously or with a lag. Assuming rational expectations (RE), agents must therefore infer the current value of ν_t from observable variables. Applying Kalman filtering techniques and assuming that $\rho_\eta = 0$ in the transitory component, it can be shown that the optimal period-t nowcast of the persistent component corresponds to the following projection on ω_t, $\tilde{s}_t$, and the period-$t-1$ nowcast of ν_{t-1}:

$$\nu_{t|t} = (1 - \kappa_1 - \kappa_2)\rho_\nu \nu_{t-1|t-1} + \kappa_1 \omega_t + \kappa_2 \tilde{s}_t, \tag{10}$$

where $\kappa_1 \equiv \frac{\sigma_\nu^2 \sigma_\varepsilon^2}{\sigma_\nu^2\sigma_\epsilon^2 + \sigma_\nu^2\sigma_\varepsilon^2 + \sigma_\epsilon^2\sigma_\varepsilon^2}$, $\kappa_2 \equiv \frac{\sigma_\nu^2 \sigma_\epsilon^2}{\sigma_\nu^2\sigma_\epsilon^2 + \sigma_\nu^2\sigma_\varepsilon^2 + \sigma_\epsilon^2\sigma_\varepsilon^2}$, and σ_ν^2 implicitly solves $\sigma_\nu^2 = \rho_\nu^2 \left(\frac{1}{\sigma_\epsilon^2} + \frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_\nu^2}\right)^{-1} + \sigma_e^2$.

Ceteris paribus, the weight on either observable is increasing in the variance of the other observable as well as in the variance of the persistent component. Conversely, $\kappa_1 \to 0$ as $\sigma_\varepsilon^2 \to 0$, $\kappa_2 \to 0$ as $\sigma_\epsilon^2 \to 0$, and $\kappa_1, \kappa_2 \to 0$ as $\sigma_\nu^2 \to 0$. Hence, a higher weight is put on the relatively more precise observable, whereas both observables receive a higher weight if ν_t exhibits more volatility. In Appendix A, we derive the state-space representation of the bank's signal extraction problem and the complete set of Kalman filter updating and forecasting expressions in matrix notation.

3.3. Impulse Response Functions under Imperfect Information

Based on the Kalman filter updating and forecasting expressions in equations (A.1) and (A.2), we can simulate the bank's expectation about ω_{t+1} and thus the expected repayment probability for each firm type ρ as of time t, $Prob\,(\omega_{t+1} \geq \rho | \omega_t, \omega_{t-1}, \ldots, \tilde{s}_t, \tilde{s}_{t-1}, \ldots)$. Using these probabilities in the partial equilibrium model in equations (6) and (9), we can then derive the bank's profit-maximizing interest rate for a given loan and the corresponding credit demand for each firm type ρ.

To compute the *ex-ante* aggregate demand for credit by firms at time t *before the realization of* ω_t, we integrate over the support of the density function of firm types, $f(\rho)$. To compute the *ex-post* aggregate amount of capital available for production *after the realization of* ω_t, we integrate over $f(\rho)$ from the lower bound of the support up to ω_{t+1}. Accordingly, the aggregate demand for credit is computed for *all* firm types ρ, whereas the aggregate amount of capital at time t is computed only for non-defaulting firm types $\rho < \omega_t$.

Due to the non-linearity of the partial equilibrium model in (6) and (9), we compute *generalized impulse response functions* (see Koop et al., 1996) to a shock in the persistent (a.k.a. "trend"), the transitory (a.k.a. "cycle"), and the noise component, respectively, by simulation as follows:

1. Drawing e_t, ϵ_t, and ε_t from their stochastic distributions, we simulate equations (7) and (8) for $T = 250$ periods and save the resulting time series for ω_t and $\tilde{s}_t$. We then impose a unit shock on the persistent, transitory, or noise component at time t_0, i.e. $e_{t_0} = 1$, $\epsilon_{t_0} = 1$, or $\varepsilon_{t_0} = 1$, and save the resulting time series for ω_t' and $\tilde{s}_t'$.

2. Given initial values for $\mathbf{s}_{0|0}$ and $\Sigma_{0|0}$, we compute $\mathbf{s}_{1|0}$, $\Sigma_{1|0}$, and $\mathbf{y}_{1|0}$ and simulate equations (A.1) and (A.2) recursively for $t = 1, ..., T$. Using the Kalman filter forecast of $Prob_t(\omega_{t+1} \geq \rho)$, we compute the equilibrium interest rate and the corresponding credit demand for each firm type ρ and integrate over all firm types.
3. The path-dependent impulse response function to a shock in the persistent, transitory, or noise component can then be computed as the period-by-period difference between the path of a certain ρ-specific or aggregate variable with and without the respective shock for $t = 1, ..., T$.
4. We repeat steps 1-3 a large number (N) of times and take the period-by-period average across the path-dependent impulse response functions for all N replications.

In all simulations, we use $N = 500$ replications and allow for a burn-in of 100 periods to be discarded when computing impulse response functions.

The exogenous processes in (7) and (8) are calibrated in line with our estimates of a general equilibrium version of this model discussed below, i.e. $\rho_\nu = 0.7445$, $\sigma_e = 0.0645$, $\sigma_\epsilon = 1.5432$, and $\sigma_\varepsilon = 0.6415$, while we set $\rho_\eta = 0$ for illustrative purposes. The remaining parameters of our partial equilibrium model are set to conventional values. In particular, we set the elasticity of output with respect to capital to $\alpha = 0.35$ and the gross risk-free interest rate on bank deposits to $r_t^d = r^d = 1.01$. We further assume that firm types ρ are normally distributed with zero mean and unit variance, i.e. $\rho \sim N(0, 1)$.[6]

The impulse responses to a *positive unit shock* in the persistent, transitory, and noise component, respectively, are plotted in Figures 5, 6, and 7. In each case, we simulate and plot impulse response functions under imperfect information ("Kalman") as well as under full information and rational expectations ("FIRE"), where the information set in period t contains the current and past realizations of ω_t, $\tilde{s}_t$, ν_t, and η_t, i.e. the bank separately observes the transitory and persistent components of ω_t under FIRE.

3.3.1. "Trend" shocks

The upper left panel in Figure 5 illustrates that, in response to a unit shock in the persistent component, ω increases by the amount of the disturbance *on impact*.[7] Under imperfect information and rational expectations, the source of this increase is unobservable, whereas ν_t and η_t can be observed separately under

[6] The assumption on the distribution of ρ is not crucial for the results. We get qualitatively similar results under the assumption of a uniform distribution.

[7] Note that the term "trend" shocks in the title is a slight misnomer here, given that the persistent component ν_t is stationary.

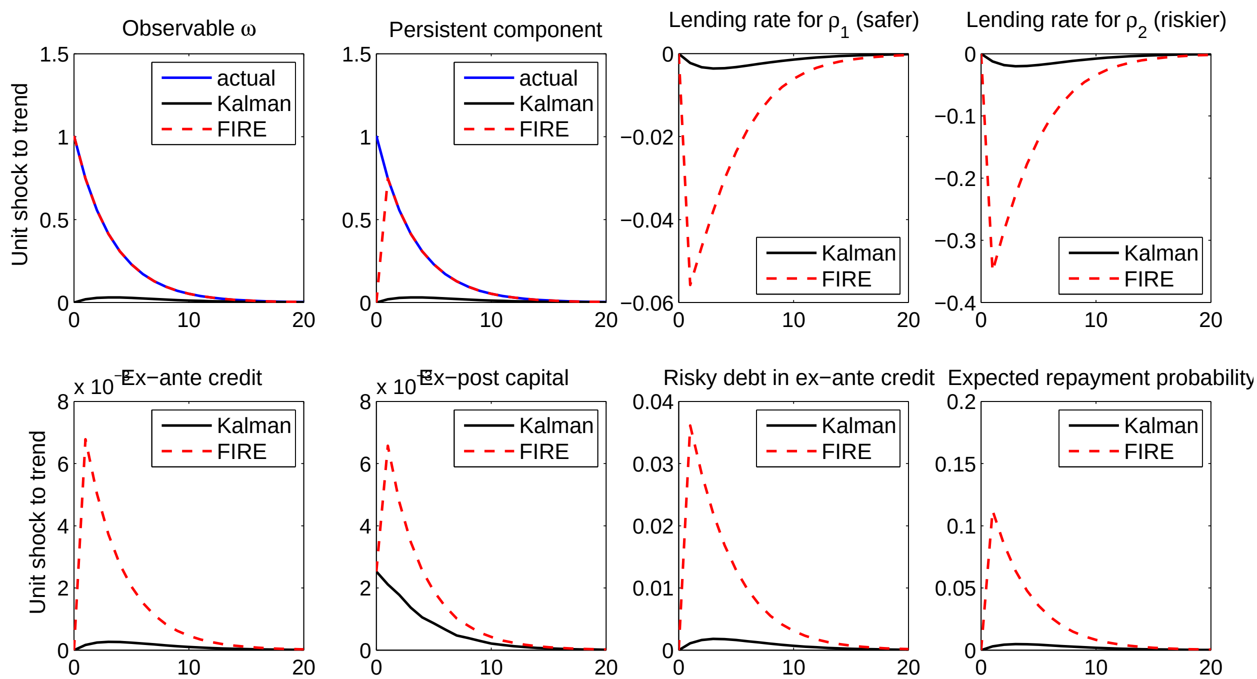

Figure 5: Impulse response functions to a unit shock in the persistent component based on the partial equilibrium investment model

full information and rational expectations. Accordingly, the imperfectly informed bank initially attributes a substantial probability to the possibility that the observed increase in ω_t indicates a transitory (i.e. cycle) or noise shock rather than a shock to the persistent component. As the observable remains positive afterwards, the bank revises its nowcast of the persistent component and thus its forecast of ω_{t+1} upwards, while the uncertainty about the origin of the observed change in ω_t remains. Only as ν_t and ω_t converge to their long-run means of zero, the bank stops making systematic forecast errors. In contrast, the bank immediately knows that the increase in the observable variable is due to its persistent component under FIRE.

For illustrative purposes, we report the responses of two ρ-specific equilibrium lending rates in line with equation (5). We choose $\rho_1 = -3$ and $\rho_2 = -1.5$ in order to represent a relatively safer and a relatively riskier firm type from $\rho \sim N(0, 1)$. In response to a positive shock to the trend component, the bank optimally lowers the lending rate for both ρ_1 and ρ_2. Given the necessity of learning about the actual state of the economy, however, the decrease in $r_t^*(\rho)$ is strongly muted and deferred under imperfect information (Kalman), whereas the equilibrium interest rates under FIRE replicate qualitatively the impulse response function of the persistent component.

The lower left panels in Figure 5 illustrate the effects of a trend shock on ex-ante aggregate credit and ex-post aggregate capital. The reduction in equilibrium lending rates induces all firm types ρ to purchase more capital financed by bank credit. This increase in the demand for credit is driven exclusively by the increase in the bank's expected probability of repayment in the lower right panel, which follows the same qualitative pattern as $\nu_{t|t}$.

Finally, the lower next-to-right panel in Figure 5 illustrates that the share of loans to objectively riskier firm types in the bank's portfolio *increases* in response to a positive innovation in the persistent component. Due to the fact that a relatively riskier firm type, such as $\rho_2 = -1.5$, is generally more likely to default than a firm type $\rho_1 = -3$, a change in $\omega_{t+1|t}$ has a relatively larger effect on $Prob\left(\omega_{t+1} \geq \rho_2 | \omega_t, \omega_{t-1}, \ldots, \tilde{s}_t, \tilde{s}_{t-1}, ...\right)$ than on $Prob\left(\omega_{t+1} \geq \rho_1 | \omega_t, \omega_{t-1}, \ldots, \tilde{s}_t, \tilde{s}_{t-1}, ...\right)$. Note that this result is not sensitive to our assumptions about $f(\rho)$.

3.3.2. "Cycle" shocks

The upper left panels of Figure 6 illustrate that, although the effect of a shock in the "cycle" component is purely transitory, the bank still attributes part of the observed increase in ω to the persistent component. Accordingly, the bank expects a higher probability of repayment and expands its supply of credit to both the relatively safer and the relatively riskier firm type. From the upper right panels, the decrease in $r_t^*(\rho_2)$ is quantitatively more pronounced than the decrease in $r_t^*(\rho_1)$. As a consequence, firms' aggregate demand for credit increases, replicating the pattern in ρ-specific equilibrium lending rates with an opposite sign.

The slow learning process under imperfect information implies that the bank's perceived probability of repayment for each firm type ρ remains elevated for an extended period before converging back to the long-run equilibrium. Accordingly, equilibrium lending rates and ex-ante aggregate credit slowly converge back to the long-run equilibrium. In contrast, neither the lending rates nor ex-ante aggregate credit respond to a cycle shock under FIRE at all. Once the agent observes the shock, its transitory nature ($\rho_\eta = 0$) implies that it is too late to expand the supply of credit by lowering lending rates. Under FIRE, it is therefore optimal to "let bygones be bygones", if a shock to fundamentals is purely transitory.

Both under imperfect information and under FIRE, ex-post aggregate capital increases on impact due to the transitory increase in the observable ω_t and the corresponding decrease in ex-post firm default, while its impulse response function remains quantitatively below that of ex-ante aggregate credit from period 2 onwards. The vertical distance between the response of ex-ante credit and the response of ex-post capital corresponds to ex-post aggregate default of credit due to imperfect information.

From the lower right panels of Figure 6, a positive shock to the cycle component results in a persistent

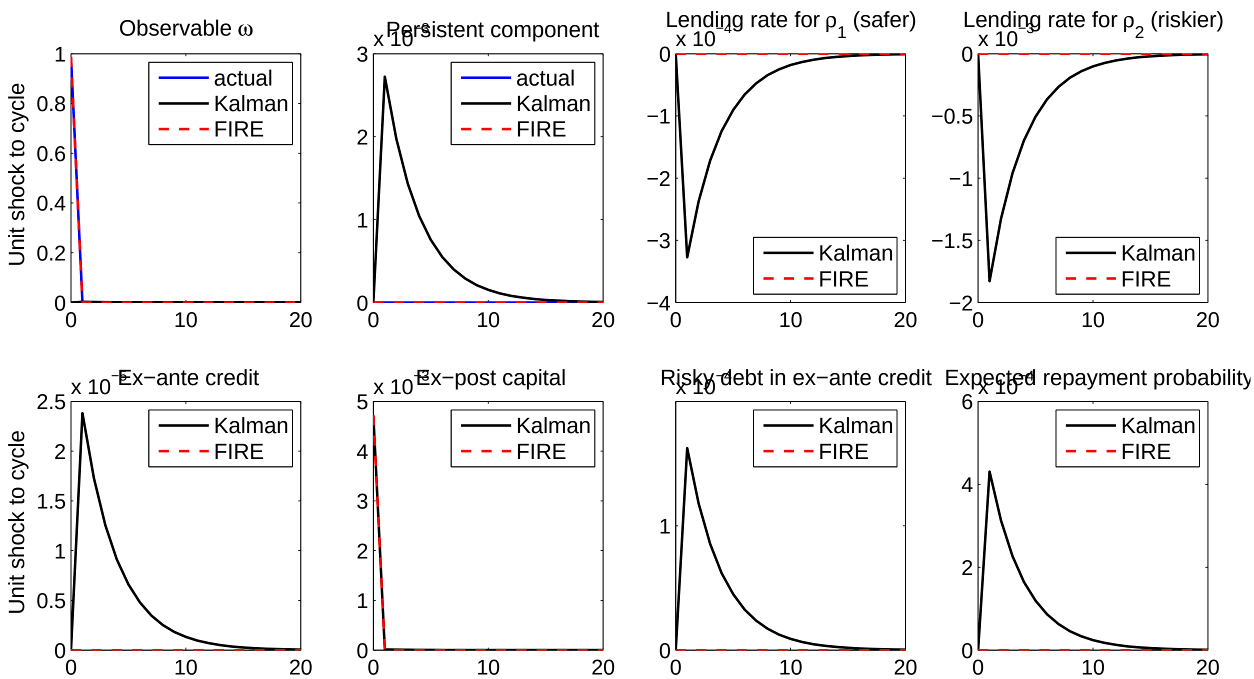

Figure 6: Impulse response functions to a unit shock in the transitory component based on the partial equilibrium investment model

increase in the share of loans to *objectively* riskier (i.e. higher-ρ) firm types and in the *subjectively* expected probability of repayment of the bank's loan portfolio at the same time.

3.3.3. Noise shocks

Figure 7 plots the impulse responses to a unit shock in the noise component of the public signal in (8). From the upper left panel, a pure noise shock does not have any impact on the observable ω_t. Nevertheless, the positive signal induces the bank to attribute a nonzero probability to the possibility of an increase in the persistent component and thus in the Kalman-filter forecast of ω_t under imperfect information.

Given its expectation of a higher value for ω_{t+1}, the bank revises its expected probability of repayment upwards and expands its supply of credit to relatively safer firm types, such as $\rho_1 = -3$, and even more so to relatively riskier firm types, such as $\rho = -1.5$. As a consequence, the corresponding equilibrium lending rates decrease, while firms' demand for credit increases, replicating the pattern in ρ-specific lending rates with an opposite sign. In contrast, neither the lending rates nor aggregate credit respond to a cycle shock under FIRE, where the bank realizes that the increase in $\tilde{s}_t$ represents pure noise.

In order to illustrate the role of imperfect information as a possible driver of credit booms in our partial equilibrium model, Figure 8 plots the impulse responses of ex-ante credit and ex-post capital to a pure noise

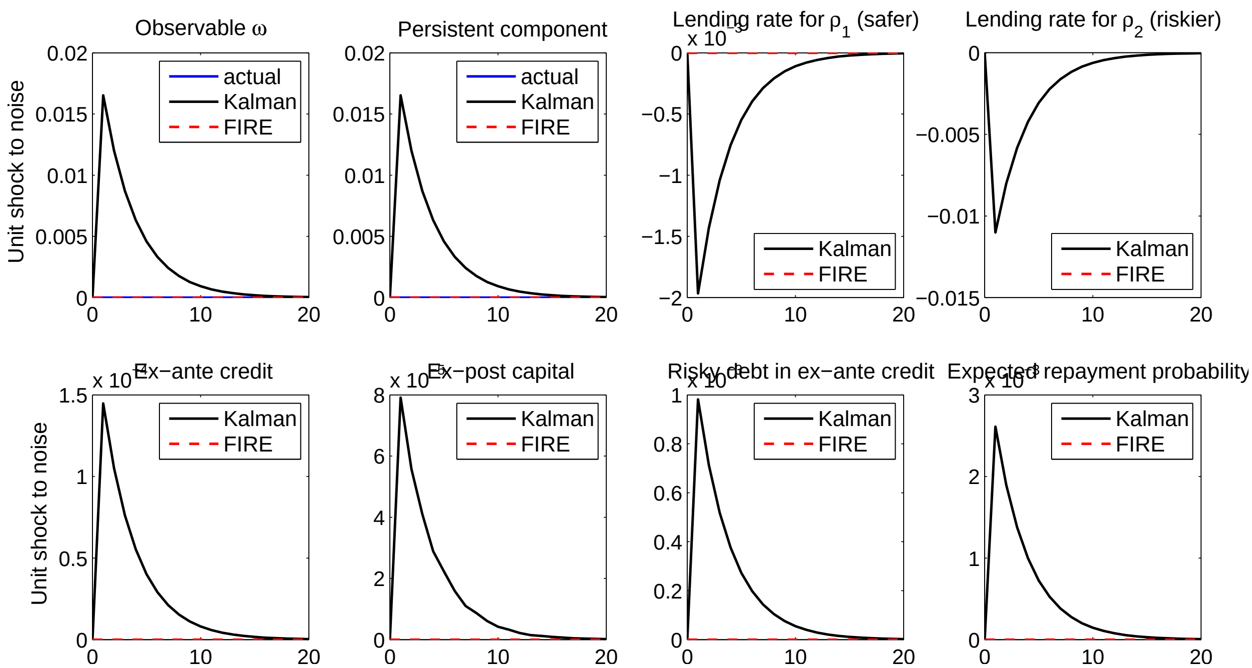

Figure 7: Impulse response functions to a unit shock in the noise component based on the partial equilibrium investment model

shock and indicates ex-post aggregate default as the shaded area between the two responses. Accordingly, the learning process in this simple model implies that the bank might become more optimistic in response to misleading news about the state of the economy, lower its lending rates accordingly to attract borrowers, and cause thus an aggregate credit expansion accompanied by an increase in firm default. Note that a similar noise-ridden credit boom does not occur under FIRE.

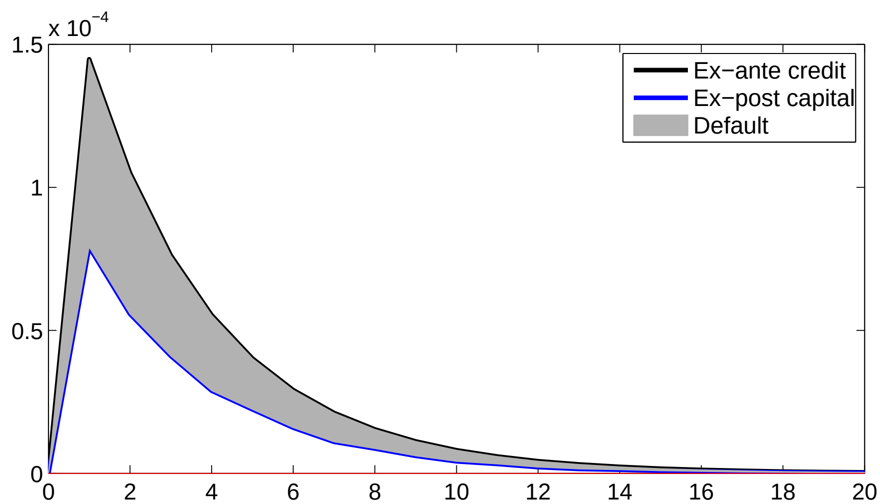

Figure 8: Impulse response function of ex-post credit default to a unit shock in the noise component

4. The General Equilibrium Model

4.1. A General Version

Suppose that lending to firms is undertaken by a continuum of perfectly competitive financial intermediaries, which are endowed with aggregate bank equity N_t and collect aggregate deposits D_t in each period t. Assuming that firm credit represents the only asset, while bank equity and deposits represent the only liabilities, the financial sector's aggregate balance sheet identity is given by

$$L_t \equiv N_t + D_t, \tag{11}$$

where L_t denotes ex-ante aggregate credit at the *end of period t*. The sole purpose of bank equity is to shield depositors from unexpected fluctuations in the aggregate return on firm credit and guarantee them a risk-free rate of return on deposits in each state of the world, ω_t. To avoid that bank equity N_t grows without bound, each period a constant fraction δ is assumed to be consumed exogenously by the financial sector. Assuming a uniform distribution for firm types $\rho \in \left[\underline{\rho}, \bar{\rho}\right]$, aggregate bank equity evolves according to

$$N_t = (1-\delta)\left[\int_{\underline{\rho}}^{\omega_t} r_{t-1}(\rho)\, k_t^*(\rho)\, d\rho - R_{t-1}^d D_{t-1}\right] = (1-\delta)\left[\int_{\underline{\rho}}^{\omega_t} r_{t-1}(\rho)\, k_t^*(\rho)\, d\rho - R_{t-1}^d \left(L_{t-1} - N_{t-1}\right)\right],$$

where R_{t-1}^d denotes the *gross* risk-free rate of return on bank deposits between period $t-1$ and period t.

In order to isolate the propagation of noise shocks via the supply of bank credit from potential demand-side effects (e.g. consumption and savings), we assume that bank deposits are supplied perfectly elastically by risk-neutral foreign depositors that demand the exogenous interest rate R_t^w, a.k.a. the "world interest rate". Accordingly, the economy-wide resource constraint must account for the payments of principal and interest on maturing period-$t-1$ deposits as well as for the inflows of new deposits in period t, i.e.

$$Y_t = C_t + L_t - D_t + R_{t-1}^d D_{t-1}, \tag{12}$$

where aggregate consumption C_t captures any residual demand for domestic output. Given that we abstract from the possibility of bank failure, deposits are effectively risk-free and pay the gross rate of return $R_t^d = R_t^w$ *in all states* of the economy. Without loss of generality, we further abstract from exogenous fluctuations in the world interest rate and assume that $R_t^w = R^w$ *in each period t*.

Note that aggregate *ex-ante* credit in period t,

$$L_t = \int_{\underline{\rho}}^{\bar{\rho}} l_t^* (\rho) \, d\rho,$$

is weakly larger than aggregate *ex-post* capital available for production in period $t + 1$,

$$K_{t+1} = \int_{\underline{\rho}}^{\bar{\omega}_{t+1}} k_{t+1}^* (\rho) \, d\rho.$$

Making use of the bank's balance sheet identity in (11) and the production function for firm type ρ,

$$y_t^* (\rho) = \begin{cases} k_t^* (\rho)^{\alpha} & \text{if } \omega_t \geq \rho \\ 0 & \text{if } \omega_t < \rho \end{cases},$$

we can rewrite the resource constraint in (12) as

$$Y_t = \int_{\underline{\rho}}^{\omega_t} k_t^* (\rho)^{\alpha} \, d\rho = C_t + \int_{\underline{\rho}}^{\bar{\rho}} l_t^* (\rho) \, d\rho - D_t + R_{t-1}^d D_{t-1},$$

where $\rho \in [\underline{\rho}, \omega_t]$ contains only firm types that are productive in period t, whereas $\rho \in [\underline{\rho}, \bar{\rho}]$ indicates that *all* types demand bank loans in period t which may or may not turn into productive capital in period $t + 1$.

Under these assumptions, we get the following set of equilibrium conditions for period t:

$$R_t^d = R^w, \tag{13}$$

$$Y_t = C_t + N_t + R_{t-1}^d D_{t-1}, \tag{14}$$

$$L_t = N_t + D_t, \tag{15}$$

$$K_t = \int_{\underline{\rho}}^{\omega_t} k_t^* (\rho) \, d\rho, \tag{16}$$

$$Y_t = \int_{\underline{\rho}}^{\omega_t} k_t^* (\rho)^{\alpha} \, d\rho, \tag{17}$$

$$L_t = \int_{\underline{\rho}}^{\bar{\rho}} l_t^* (\rho) \, d\rho, \tag{18}$$

$$N_t = (1 - \delta) \left[\int_{\underline{\rho}}^{\omega_t} r_{t-1}^* (\rho) \, l_{t-1}^* (\rho) \, d\rho - R_{t-1}^d D_{t-1} \right], \tag{19}$$

where

$$l_t^*(\rho) = \left[\frac{\alpha}{r_t^*(\rho)}\right]^{\frac{1}{1-\alpha}} \quad \text{and} \quad r_t^*(\rho) = \frac{R_t^d}{Prob\,(\omega_{t+1} \geq \rho | \omega_t, \omega_{t-1}, \ldots, \tilde{s}_t, \tilde{s}_{t-1}, \ldots)}.$$

Equations (13)–(19) yield a system of seven equilibrium conditions in the seven endogenous variables C_t, Y_t, K_t, L_t, D_t, N_t, and R_t^d. Given exogenous processes for the observable variables ω_t and $\tilde{s}_t$, we can investigate the general-equilibrium implications of imperfect information for credit spreads, lending, and output.

4.2. A Simplified Version with Two Risk Types

Now suppose that the economy accommodates *only two risk types*, ρ_1 and ρ_2, where $\rho_2 > \rho_1$ implies that the second type has a higher probability of defaulting in each state of the world. Both risk types consist of a unit-mass continuum of firms. As before, $\omega_t = \nu_t + \eta_t$ contains the persistent component $\nu_t = \rho_\nu \nu_{t-1} + e_t$, $e_t \sim N\left(0, \sigma_e^2\right)$, and the transitory component $\eta_t = \rho_\eta \eta_{t-1} + \epsilon_t$, $\epsilon_t \sim N\left(0, \sigma_\epsilon^2\right)$, which are not separately observable, while the noisy signal of the trend component $\tilde{s}_t = \nu_t + \varepsilon_t$, $\varepsilon_t \sim N\left(0, \sigma_\varepsilon^2\right)$, is publicly observable.

Given that ω_{t+1} is normally distributed conditional on Ω_t, the ex-ante expected repayment probability of a firm of type ρ_i, $i = 1, 2$, in period $t + 1$ is given by

$$E_t Prob_{t+1}^i \equiv E_t Prob\,(\omega_{t+1} \geq \rho_i) = 1 - F\left(\rho_i | E_t \omega_{t+1|t}, E_t \sigma_{\omega,t+1}^2\right), \tag{20}$$

where $E_t \omega_{t+1}$ denotes the expected value of ω_{t+1} conditional on information available in period t, $E_t \sigma_{\omega,t+1}^2$ the corresponding variance, and $F(\bullet)$ the normal CDF. In what follows, we fix the risk type and vary $E_t \omega_{t+1}$.

Panel (a) of Figure 9 plots the expected repayment probability of two arbitrarily chosen risk types $\rho_1 = 0$ and $\rho_2 = 1$ as a function of $E_t \omega_{t+1}$. It illustrates that $E_t Prob_{t+1}^i$, $i = 1, 2$, increases with $E_t \omega_{t+1}$ and that ρ_2 is "riskier" than ρ_1, as it implies a lower expected repayment probability and thus a higher expected default probability for all $\omega_{t+1|t}$.

Now consider the marginal effect of a change in $E_t \omega_{t+1}$ on the expected repayment probability of either risk type. Partially differentiating the CDF in (20) yields

$$\frac{\partial E_t Prob_{t+1}^i}{\partial E_t \omega_{t+1}} = \frac{\partial}{\partial E_t \omega_{t+1}} \left\{-F\left(\rho_i | E_t \omega_{t+1}, E_t \sigma_{\omega,t+1}^2\right)\right\} = f\left(\rho_i | E_t \omega_{t+1}, E_t \sigma_{\omega,t+1}^2\right), \tag{21}$$

where $f(\bullet)$ denotes the PDF of the normal distribution evaluated at ρ_i. Panel (b) of Figure 9 illustrates that the sensitivity of $E_t Prob_{t+1}^2$ with respect to $E_t \omega_{t+1}$ is shifted to the right relative to that of $E_t Prob_{t+1}^1$.

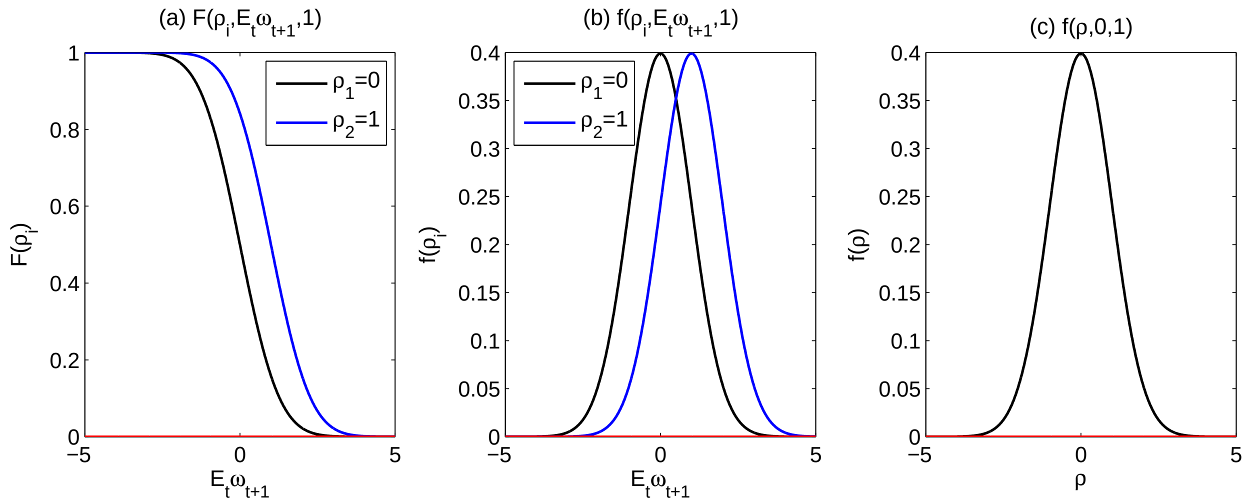

Figure 9: Continuous mappings from $\omega_t \in \mathbb{R}$ onto $Prob_t^1 \in (0, 1)$ and $Prob_t^2 \in (0, 1)$

In what follows, we assume that the mapping in (20) and (21) holds *ex ante* in expected future as well as *ex post* in the realized states of the economy, i.e.

$$Prob_t^i = 1 - F\left(\rho_i|\omega_t, \sigma^2_{\omega,t}\right) \quad \text{and} \quad \frac{\partial Prob_t^i}{\partial \omega_t} = f\left(\rho_i|\omega_t, \sigma^2_{\omega,t}\right). \tag{22}$$

Recall that, in the partial equilibrium model, default occurs *at the risk type level*. All firms of type $\rho \leq \omega_t$ become productive and repay the full amount of credit, while all firms of type $\rho > \omega_t$ "burn down" and default *deterministically* on their full amount of credit. If the state of the economy is sufficiently bad and ω_t is sufficiently low, then all firms of type ρ_2 default if $\omega_t < \rho_2$, while all firms of either type default if $\omega_t < \rho_1 < \rho_2$.

In contrast, the ex-post mapping in equation (22) implies that default occurs *at the firm level*. Assuming a continuum of type-1 and type-2 firms with repayment probabilities $Prob_t^1$ and $Prob_t^2$, respectively, a fraction $1 - Prob_t^i$, $i = 1, 2$, of firms of either risk type defaults *stochastically*, while the rest becomes productive and repays the full amount of credit.[8] The ex-post mapping in (20) allows us to model firms with different risk profiles, while avoiding that an entire type is wiped out in a sufficiently bad state of the economy. For each ω_t, there will be a nonzero mass of firms of either risk type that becomes productive and repays its loans.

[8]Alternatively, suppose that a single representative firm of each risk type engages in a continuum of investment projects with different success probabilities. Hence, either firm defaults on *part of* its loans and *repays the rest*. In our model, both interpretations are admissible and observationally equivalent.

A log-linear approximation of $E_t Prob^i_{t+1}$ (and $Prob^i_t$) i.t.o. *absolute* deviations from steady state yields

$$E_t Prob^i_{t+1} - Prob^i_{ss} = f\left(\rho_i | \omega_{ss}, \sigma^2_{\omega,ss}\right) \cdot \left(E_t \omega_{t+1} - \omega_{ss}\right), \quad i = 1, 2.$$

Panel (c) of Figure 9 plots the sensitivity of this log-linear approximation at the steady state as a function of ρ. Note that the sensitivity is low for very risky ($\rho >> E_t\omega_{t+1}$) *and* very safe ($\rho << E_t\omega_{t+1}$) risk types. This is due to the fact that fluctuations in $E_t\omega_{t+1}$ around its steady state are largely irrelevant for ρ's far away from ω_{ss}, as these risk types have virtually zero chance of surviving or defaulting at the margin. If we considered only risk types $\rho < \omega_{ss}$ with a steady-state repayment probability larger than 50%, then the sensitivity of $E_t Prob_{t+1}(\rho)$ w.r.t. $E_t\omega_{t+1}$ increases monotonically with ρ. This is consistent with the finding in López-Salido et al. (2017) that fluctuations in "credit-market sentiment" have a stronger effect on the cost of borrowing and thus on the investment behavior of firms with relatively lower credit ratings.

Based on the ex-ante expected probabilities of repayment, the equilibrium lending rates of type-i firms can then be computed as

$$R^i_t = \frac{R^d_t}{E_t Prob^i_{t+1}}, \quad i = 1, 2,$$

which pins down the corresponding demand for *expected* productive capital by either firm type in period t:

$$E_t K^i_{t+1} = E_t Prob^i_{t+1} L^i_t = \left(\frac{\alpha}{R^i_t}\right)^{\frac{1}{1-\alpha}}, \quad i = 1, 2.$$

Note that the aggregate demand for *ex-ante* bank credit by either firm type in period t is thus given by

$$L^i_t = \frac{E_t K^i_{t+1}}{E_t Prob^i_{t+1}}, \quad i = 1, 2,$$

while the actual amount of *ex-post* productive capital in period $t + 1$ depends on the realized probability of repayment of a firm of type i, i.e.

$$K^i_{t+1} = Prob^i_{t+1} L^i_t, \quad i = 1, 2.$$

The equilibrium conditions of the simplified model with two risk types can be summarized as follows:

$$R_t^d = R^w, \tag{23}$$

$$R_t^1 = \frac{R_t^d}{E_t Prob_{t+1}^1}, \tag{24}$$

$$R_t^2 = \frac{R_t^d}{E_t Prob_{t+1}^2}, \tag{25}$$

$$E_t Prob_{t+1}^1 L_t^1 = \left(\frac{\alpha}{R_t^1}\right)^{\frac{1}{1-\alpha}}, \tag{26}$$

$$E_t Prob_{t+1}^2 L_t^2 = \left(\frac{\alpha}{R_t^2}\right)^{\frac{1}{1-\alpha}}, \tag{27}$$

$$L_t = L_t^1 + L_t^2, \tag{28}$$

$$K_t^1 = Prob_t^1 L_{t-1}^1, \tag{29}$$

$$K_t^2 = Prob_t^2 L_{t-1}^2, \tag{30}$$

$$K_t = K_t^1 + K_t^2, \tag{31}$$

$$Y_t = \left(K_t^1\right)^\alpha + \left(K_t^2\right)^\alpha, \tag{32}$$

$$Y_t = C_t + N_t + R_{t-1}^d D_{t-1}, \tag{33}$$

$$L_t = N_t + D_t, \tag{34}$$

$$N_t = (1-\delta)\left(R_{t-1}^1 K_t^1 + R_{t-1}^2 K_t^2 - R_{t-1}^d D_{t-1}\right). \tag{35}$$

Equations (23)–(35) yield a system of 13 equilibrium conditions in the 13 endogenous variables C_t, Y_t, K_t, K_t^1, K_t^2, L_t, L_t^1, L_t^2, D_t, N_t, R_t^d, R_t^1, and R_t^2, while the ex-ante expected repayment probabilities $E_t Prob_{t+1}^i$, $i = 1, 2$, are defined in (20). Given exogenous processes for ω_t and $\tilde{s}_t$, we can investigate the implications of imperfect information for credit spreads, lending, and output.[9] Equation (36) defines the aggregate lending rate R_t as the average of type-specific interest rates weighted by the respective loan volumes, while equation (37) defines the aggregate credit spread as the ratio of R_t to the risk-free rate on deposits:

$$R_t \equiv \frac{R_t^1 L_t^1 + R_t^2 L_t^2}{L_t^1 + L_t^2}, \tag{36}$$

$$spread_t \equiv \frac{R_t}{R_t^d}. \tag{37}$$

[9] Appendix B summarizes the log-linearized equilibrium conditions of the simplified model with two risk types in (23)–(35).

4.3. Reduced Form VAR Representation of the Model

Given our assumptions about the exogenous processes, the reduced-form VAR(1) representation of the model takes the following form:

$$\omega_t = A^{\omega} L_{t-1} + \epsilon_t^{\omega}, \tag{38}$$

$$L_t = B^L L_{t-1} + \epsilon_t^L, \tag{39}$$

where the scalar coefficients A^{ω} and B^L represent convolutions of the model's parameters, while ϵ_t^{ω} and ϵ_t^L are mean-zero reduced-form disturbances. The details of the derivation can be found in Appendix C.

From the first equation in (38), it is obvious that past lending helps in predicting current values of the fundamental ω_t. The reason is that ex-ante aggregate lending reflects the bank's additional information about the persistent component of the fundamental process, as it observes the informative public signal $\tilde{s}_t$. The second equation in (39) shows that ex-ante credit follows an AR(1)-process, even though the decision problem of the bank is static and there are no frictions inducing this kind of backward-looking dynamic. Note that the baseline model features no investment adjustment costs and assumes perfect depreciation of the productive capital stock. The persistence in ex-ante credit arises solely from the persistence in bank expectations about the state of the economy.

Finally, the VAR representation illustrates that it is not possible to recover the three structural shocks (i.e. “trend”, “cycle’, and noise shocks) from two reduced-form innovations. This non-invertibility problem is due to the informational friction in financial intermediation and common to this class of models with noisy information.[10]

4.4. Moment-Based Identification

The system in (7) implies that the fundamental process ω_t, which represents the sum of an AR(1) and an i.i.d. process, can be written as an ARMA(1,1) process. In what follows, we use these restrictions and moments in the data to identify the structural shocks of interest. For this purpose, we start by estimating an ARMA(1,1) model on a proxy for ω_t:

$$\omega_t = \rho_{\omega} \omega_{t-1} + \varepsilon_t^{\omega} - \theta_{\omega} \varepsilon_{t-1}^{\omega}.$$

[10]See Blanchard et al. (2013) for a more comprehensive discussion.

The ARMA(1,1) representation of the structural model in (7) then implies the following conditions:

$$\sigma_\epsilon^2 = \frac{\theta_\omega}{\rho_\omega},$$
$$\sigma_e^2 = 1 - 2\theta_\omega\rho_\omega + \theta_\omega^2 - \left(1 - \rho_\omega^2\right).$$

The above conditions identify the variances of cycle and trend shocks for given estimates of the ARMA(1,1) coefficients.[11] Note that, ceteris paribus, the variance of the cycle shock increases in the coefficient of the MA component and decreases in the coefficient of the AR component of the fundamental process. Given the recovered estimates of cycle and trend shock, we can identify the variance of noise shocks.

In order to identify the variance of the noise shock, we exploit the correlation between the reduced-form residuals of the VAR representation of the structural model in the previous section. Note that there is a monotonic relationship between this correlation and the variance of noise shocks. To help the intuition, consider first the limiting case, where the variance of noise shocks goes to infinity. In this case, the reduced-form VAR representation simplifies to

$$L_t = \rho_v L_{t-1} + u_t,$$
$$\omega_t = \rho_v \omega_{t-1} + u_t,$$

and the contemporaneous correlation of the reduced-form residuals reaches its upper bound of unity.

On the contrary, the lower bound of this correlation obtains, when the variance of noise shocks decreases to zero. The corresponding reduced-form VAR representation is given by

$$L_t = \rho_v L_{t-1} + B^L e_t,$$
$$\omega_t = A^\omega L_{t-1} + e_t + \epsilon_t,$$

where $B = \frac{\alpha}{1-\alpha}\rho_v\zeta$ and the correlation of the reduced-form residuals is equal to $0 < \frac{1}{\sqrt{1+\sigma_\epsilon^2/\sigma_e^2}} < 1$.

For intermediate cases, the correlation of the reduced-form residuals is monotonically increasing in the variance of the noise shock, implying a non-trivial learning problem of economic agents.

[11] In order to avoid scaling effects on the recovered estimates of σ_ϵ^2 and σ_e^2, we standardize the empirical counterpart of ω_t to have zero mean and unit variance.

To illustrate this identifying strategy, we use TFP growth as a proxy for ω_t (see Fernald, 2014) and Gilchrist and Zakrakšek's (2012) *excess bond premium* (EBP) as a proxy for the credit spread, i.e. the bank's relevant choice variable in the model. Note that the reduced-form VAR representation of the spread is the same as for ex-ante credit, except for the sign of the residual correlation coefficient. The reason is that a higher expected value of ω_{t+1} is associated with *higher* ex-ante credit volumes but a *lower* credit spread.

Using quarterly data of TFP growth and the EBP during 1982–2017, we find that the fundamental process exhibits considerable persistence ($\rho_\omega = 0.78$), while the coefficient of the MA component is quantitatively similar ($\theta_\omega = 0.71$). These estimates imply that $\sigma_\epsilon^2 = 0.86$ and $\sigma_e^2 = 0.05$. The residual correlation of the reduced-form VAR representation equals -0.34, which corresponds to a variance of the noise shock equal to $\sigma_\varepsilon^2 = 0.04$. Accordingly, the variance of cycle shocks is an order of magnitude larger than that the noise shock, suggesting a potential role of noise shocks for credit spreads and volumes in our model. While this identification is straightforward and transparent, it relies on an empirical proxy for ω_t, which is difficult to find. Moreover, moment-based identification does not exploit all the theoretical restrictions implied by the model. For this reason, we turn to a maximum-likelihood identifying strategy in what follows.

4.5. *Estimation of the Simplified Model*

In order to identify the structural shocks in (7) and (8) and to quantify their importance for aggregate fluctuations, we estimate the simplified version of the general equilibrium model with two risk types while allowing for imperfect information about the underlying state of the economy.[12] The aim of this section is to quantify the role of noise shocks in the financial cycle by matching the general equilibrium model to economic data. For this purpose, we draw on the approach to estimating DSGE models with a signal extraction problem proposed by Blanchard et al. (2013).

4.5.1. *Equivalent full information representation*

Suppose that the simplified general equilibrium model can be expressed in terms of the following system of stochastic difference equations:

$$\mathbf{D}E_t\left[\mathbf{x}_{t+1}\right] + \mathbf{F}\mathbf{x}_t + \mathbf{G}\mathbf{x}_{t-1} + \mathbf{M}\mathbf{y}_t + \mathbf{N}E_t\left[\mathbf{y}_{t+1}\right] = 0,$$

[12] In contrast to the dynamic stochastic general equilibrium (DSGE) exercise in Blanchard et al. (2013), as a starting point, we allow only for the three structural shocks in Section 3 rather than adding additional shocks that are standard in the DSGE literature.

where $\mathbf{x}_t$ denotes a vector of *endogenous* state variables, $\mathbf{D}, \mathbf{F}, \mathbf{G}, \mathbf{M}$, and $\mathbf{N}$ are parameter matrices, and the *unobservable* exogenous state vector $\mathbf{s}_t$ only enters the system through the observable vector $\mathbf{y}_t$.[13] Suppose further that the model has the unique stable solution

$$\mathbf{x}_t = \mathbf{O}\mathbf{x}_{t-1} + \mathbf{P}\mathbf{s}_t + \mathbf{R}\mathbf{s}_{t|t},$$

where, as in Section 3, $\mathbf{s}_{t|t}$ denotes the agents' expectation of the state vector conditional on all information available in period t, i.e. $\mathbf{x}_{t|t} \equiv E\left[\mathbf{s}_t|\mathbf{y}_t, \mathbf{y}_{t-1}, \ldots\right]$, and the matrices $\mathbf{O}, \mathbf{P}$, and $\mathbf{R}$ can be found by solving

$$\mathbf{D}\mathbf{O}^2 + \mathbf{F}\mathbf{O} + \mathbf{G} = 0, \quad (\mathbf{D}\mathbf{O} + \mathbf{F})\,\mathbf{P} + \mathbf{M} = 0, \quad (\mathbf{D}\mathbf{O} + \mathbf{F})\,\mathbf{R} + \left[\mathbf{D}\,(\mathbf{P}\mathbf{Z} + \mathbf{R}) + \mathbf{N}\mathbf{Z}\right]\mathbf{T} = 0,$$

where the matrices $\mathbf{Z}$ and $\mathbf{T}$ are defined in Section 3. While the second and third equation are linear in $\mathbf{P}$ and $\mathbf{R}$ and thus straightforward to solve, Uhlig (1995) provides solution techniques for the first equation in $\mathbf{O}$.

Making use of the Kalman filter updating and forecasting expressions for the state vector $\mathbf{s}_t$ in (A.1) and (A.2), respectively, we can express the joint dynamics of $\mathbf{s}_{t|t}$ and the vector of observables $\mathbf{y}_t$ as

$$\begin{aligned}
\mathbf{s}_{t|t} &= \mathbf{T}\mathbf{s}_{t-1|t-1} + \mathbf{K}\left(\mathbf{y}_t - \mathbf{y}_{t|t-1}\right) = \mathbf{T}\mathbf{s}_{t-1|t-1} + \mathbf{K}\left(\mathbf{y}_t - \mathbf{Z}\mathbf{T}\mathbf{s}_{t-1|t-1}\right), \\
\mathbf{y}_t &= \mathbf{Z}\mathbf{T}\mathbf{s}_{t-1|t-1},
\end{aligned}$$

where $\mathbf{K} \equiv \Sigma_{t|t-1}\mathbf{Z}'\left(\mathbf{Z}\Sigma_{t|t-1}\mathbf{Z}' + \mathbf{H}\right)^{-1}$ denotes the Kalman filter gain and $\Sigma_{t|t-1} \equiv \mathrm{Var}_{t-1}\left(\mathbf{y}_t\right)$ the variance-covariance matrix of $\mathbf{y}_t$ conditional on the information available in period t.

Suppose that the latter can be factorized as $\Sigma_{t|t-1} = \mathbf{F}\mathbf{F}'$ for some matrix $\mathbf{F}$ and consider the model

$$\begin{aligned}
\hat{\mathbf{s}}_t &= \mathbf{T}\hat{\mathbf{s}}_{t-1} + \mathbf{K}\mathbf{F}\hat{\mathbf{v}}_t, \\
\mathbf{y}_t &= \mathbf{Z}\mathbf{T}\hat{\mathbf{s}}_{t-1} + \mathbf{F}\hat{\mathbf{v}}_t,
\end{aligned} \tag{40}$$

where $\hat{\mathbf{v}}_t$ is an m-dimensional vector of mutually independent standard normal shocks. *Lemma 2* in Blanchard et al. (2013) states that, identifying $\mathbf{s}_t$ with $\mathbf{s}_{t|t}$ and $\mathbf{v}_t$ with $\mathbf{y}_t - \mathbf{Z}\mathbf{T}\mathbf{s}_{t-1|t-1}$, the original signal extraction model is *observationally equivalent* to the model in (40) with the assumption that the agent perfectly ob-

[13] This reflects the assumption that the information set of the representative agent contains past and current values of $\mathbf{y}_t$ and $\mathbf{x}_t$ rather than current and past values of $\mathbf{s}_t$ (see Blanchard et al., 2013).

serves $\hat{\mathbf{s}}_t$ and $\hat{\mathbf{v}}_t$ for any matrix $\mathbf{F}$. Hence, we can estimate the equivalent full information model subject to a restriction on the correlation matrix of shocks and recover the parameters of the signal extraction model.

4.5.2. Bayesian maximum likelihood estimation

In the absence of additional shocks, the equivalent full information representation of the simplified general equilibrium model with imperfect information in (40) allows for $m = 2$ mutually independent shock series. Hence, we estimate the parameters of the exogenous processes in (7) and (8) by matching aggregate output, Y_t, and the aggregate spread between lending rates and the risk-free rate on deposits, $spread_t$, to their empirical counterparts. For the log-difference of aggregate output, we use the seasonally adjusted quarter-on-quarter growth rate of U.S. real GDP growth. For $spread_t$, we employ the difference between Moody's seasoned Baa corporate bond yield and the yield on 10-year treasury constant maturity.[14] The variables are transformed as proposed by Pfeifer (2017).

We use Dynare to solve and estimate the model by maximizing the likelihood function at the posterior mode for the vector of parameter values. Following Blanchard et al. (2013), the impulse response functions of the economic variables to the $n = 3$ shocks in the original signal extraction model can then be backed out from the impulse responses to the $m = 2$ mutually orthogonal shocks in the vector $\hat{\mathbf{v}}_t$ of the equivalent full information representation in (40). While we estimate the parameters of the exogenous processes in (7) and (8), we calibrate the two risk types to $\rho_1 = -3$ and $\rho_2 = -1$, implying steady-state repayment probabilities of $Prob^1_{ss} = 0.99$ and $Prob^2_{ss} = 0.79$ and sensitivities of $f\left(\rho_1|\omega_{ss}, \sigma^2_\omega\right) = 0.016$ and $f\left(\rho_2|\omega_{ss}, \sigma^2_\omega\right) = 0.234$.

4.5.3. Bayesian priors and parameter estimates

Table 2 reports the posterior mode of the parameter estimates in equations (7) and (8) as well as the type and mean of the corresponding Bayesian priors. The latter are standard in the DSGE literature. We assume a beta-distributed prior with a mean of 0.6 and a standard deviation of 0.2 for both ρ_ν and ρ_η, while we set the means of the inverse gamma-distributed priors for σ_e, σ_ϵ, and σ_ε to 0.5, 1.0, and 1.0, respectively, and the corresponding standard deviations to unity.

We find substantial serial correlation in the estimated persistent component ν_t and virtually zero serial correlation in the estimated transitory component η_t. While the posterior mode of the coefficient ρ_ν is equal to 0.7717 and highly statistically significant, the posterior mode of ρ_η hits its imposed lower bound of 0.01

[14]In Appendix D, we show that the parameter estimates and results discussed below are robust to using Gilchrist and Zakrakšek's (2012) EBP as a proxy for $spread_t$.

Table 2: Bayesian priors and maximum likelihood posterior estimates of the parameters in equations (7) and (8)

Parameter	Prior type	Prior mean	Prior s.d.	Posterior mode	Posterior s.d.
ρ_ν	beta	0.600	0.200	0.7717	0.0331
ρ_η	beta	0.600	0.200	0.0100	0.0006
σ_e	inverse gamma	0.500	1.000	0.0670	0.0058
σ_ϵ	inverse gamma	1.000	1.000	1.2191	0.0836
σ_ε	inverse gamma	1.000	1.000	0.4683	0.0831

from above. As a consequence, the effect of shocks to the persistent component on the observable ω_t will be qualitatively different from the effect of shocks to the transitory component, as illustrated by the impulse response functions in Figures 5 and 6.

Lines 3–5 in Table 2 indicate that non-fundamental noise shocks to the publicly observable signal $\tilde{s}_t$ are more volatile than shocks to the persistent component ν_t, yet less volatile than shocks to the transitory component η_t. Note that a larger estimate of σ_ϵ relative to σ_ε implies that $\tilde{s}_t$ is a relatively more precise indicator of the unobservable persistent component than ω_t, which is "polluted" by shocks to the transitory component. As a result, a rational agent puts some faith in the public signal, which slows down the speed of learning and amplifies the effect of noise shocks on the bank's expectations about the state of the economy in period $t + 1$ and thus on its lending behavior.

4.6. Impulse Response Functions

It is straightforward to solve the simplified general equilibrium model and compute impulse response functions for the variables of interest. In what follows, we set $\alpha = 0.35$ and $R^w = \beta_w^{-1} = 1.01$, as in our partial equilibrium model, while 10% of the financial sector's net worth is consumed each period, i.e. $\delta = 0.1$. The volatility of shocks to the persistent component, shocks to the transitory component, and shocks to the public signal are taken from our parameter estimates in Table 2, i.e. $\sigma_e = 0.0670$, $\sigma_\epsilon = 1.2191$, and $\sigma_\varepsilon = 0.4683$. In the exogenous AR(1) processes for ν_t and η_t, we set $\rho_\nu = 0.7717$ and $\rho_\eta = 0.01$.

4.6.1. "Trend" shocks

Figure 10 plots the impulse responses to a positive one-standard-deviation innovation in the persistent component for the simplified general equilibrium model with two borrower types and *imperfect information* ("Kalman") against its counterpart with *full information* ("FIRE").[15] In period 1, ν_t and thus both ω_t and $\tilde{s}_t$

[15]Re-estimating the model with full information (i.e. $\sigma_\varepsilon = 0$) yields $\rho_\nu = 0.2874$, $\rho_\eta = 0.01$, $\sigma_e = 0.0727$, and $\sigma_\epsilon = 1.0242$.

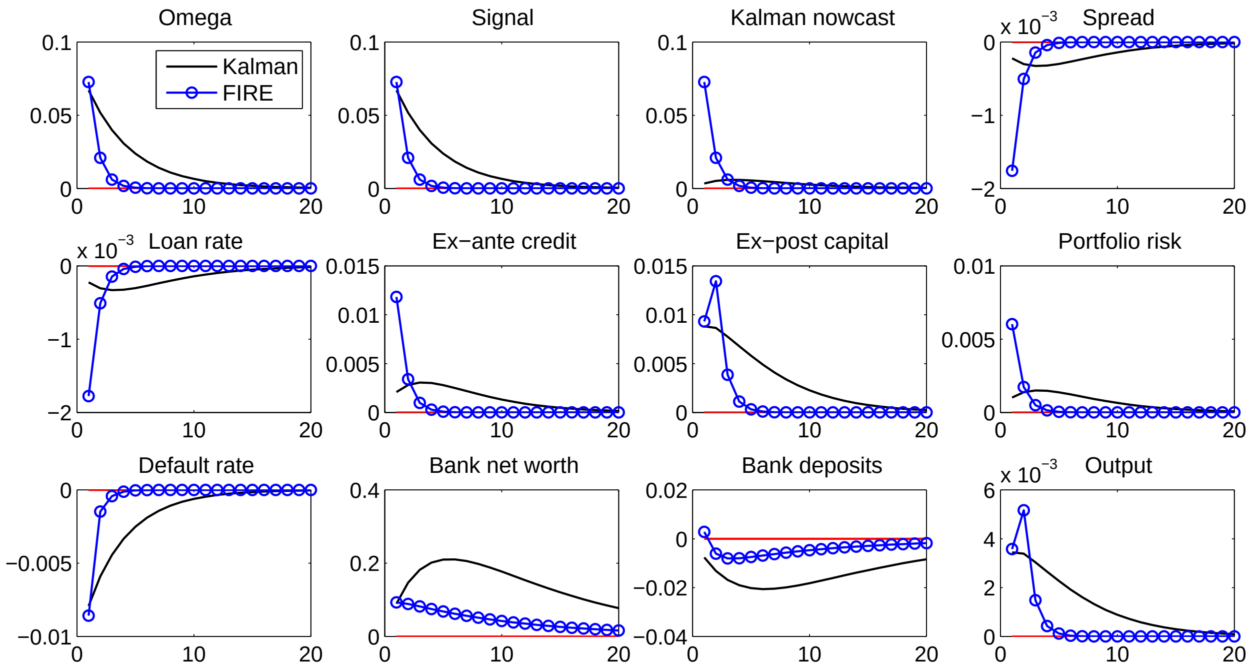

Figure 10: Impulse responses to a shock in the persistent component based on the simplified general equilibrium model in (23)–(35)

increase by the full amount of the "trend" shock e_t, while the increase in the Kalman filter nowcast of the persistent component depends on the information regime. With full information, $v_{t|t}$ rises one-for-one with the observables. With imperfect information, $v_{t|t}$ rises by a fraction of e_t, as economic agents assign most of the probability mass to states where the observed changes in ω_t and $\tilde{s}_t$ are driven by a shock in the transitory or noise component rather than by a "trend" shock.[16]

The increase in $v_{t|t}$ translates into an increase in the expected repayment probabilities for both risk types, $E_t Prob^i_{t+1}$, $i = 1, 2$, and thus a decrease in the respective credit spread. The size of these reductions and the corresponding increase in the demand for capital by both risk types and ex-ante aggregate credit again reflects the information regime. Note that shocks to the persistent component are *fundamental* in the sense that they affect the state ω_t, which determines the default probability of each firm type. Regardless of the information regime, the ex-post aggregate capital stock therefore increases on impact, as a smaller fraction of firms of both types defaults in response to a "trend" shock.

The surprise increase in the productive capital stock translates directly into higher output, while the increased ex-post repayment of credit raises bank net worth on impact. The subsequent hump-shaped response

[16]Recall that the Kalman filter nowcast of the persistent component follows from equation (10) as a projection on the period-t realizations of the observable variables ω_t and $\tilde{s}_t$.

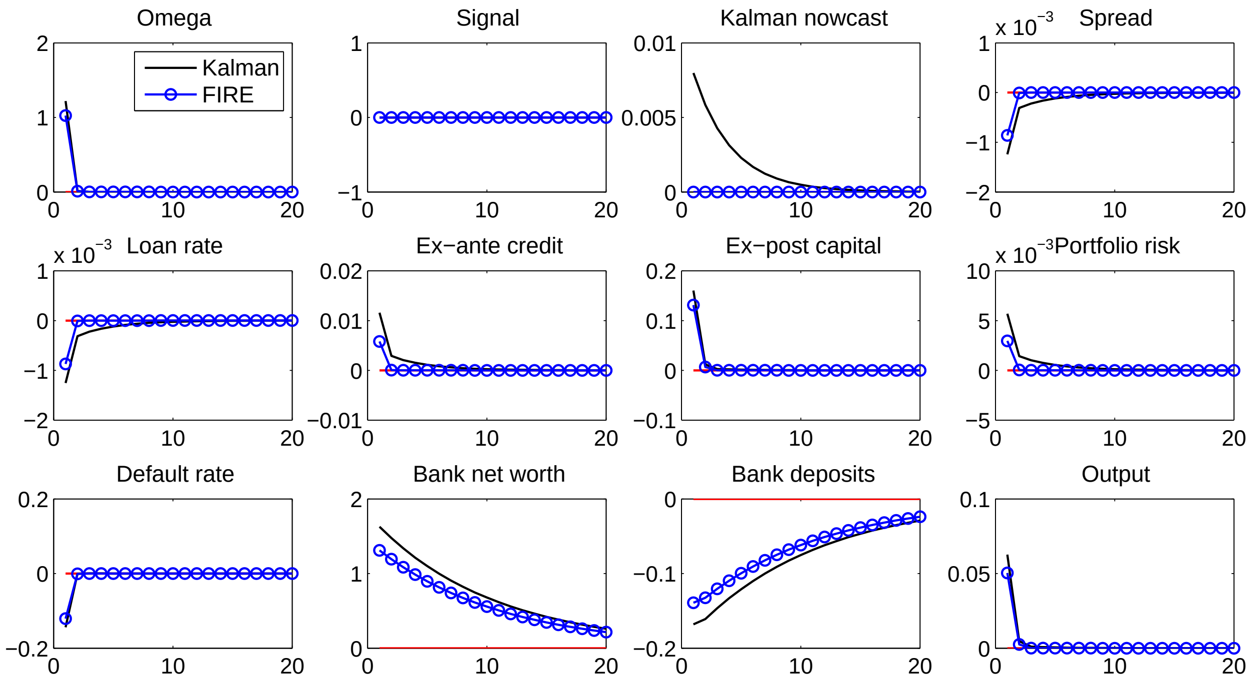

Figure 11: Impulse responses to a shock in the transitory component based on the simplified general equilibrium model in (23)–(35)

of *bank net worth* is reminiscent of the hump-shaped response of *entrepreneurial net worth* to fundamental shocks in Bernanke et al. (1999). As a consequence, banks can rely on a higher stock of net worth rather than on external funding in order to satisfy the increased demand for credit, and bank deposits fall short of their steady-state value. With full information, the adjustment is monotonic rather than hump-shaped.

4.6.2. "Cycle" shocks

Consider now the impulse responses to a positive one-standard-deviation shock in the transitory component with imperfect information ("Kalman") and with full information ("FIRE") in Figure 11. Given our assumption that $\rho_\eta = 0.01$ in (7), ω_t increases in period 1 by the full amount of the shock and virtually falls back to zero in period 2. In contrast, the unobservable persistent component ν_t and the observable signal $\tilde{s}_t$ remain equal to their steady-state values of zero throughout.

While ν_t and η_t are separately observable under full information, uncertainty about the origin of the observed increase in ω_t implies that the Kalman filter nowcast of the persistent component, $\nu_{t|t}$, increases, as agents attribute part of the increase in ω_t to the persistent component. As a result, the equilibrium credit spread decreases and the ex-ante aggregate demand for credit increases in the impact period under FIRE. When ν_t and η_t are *not* separately observable, the decrease in the credit spread and the increase in ex-ante

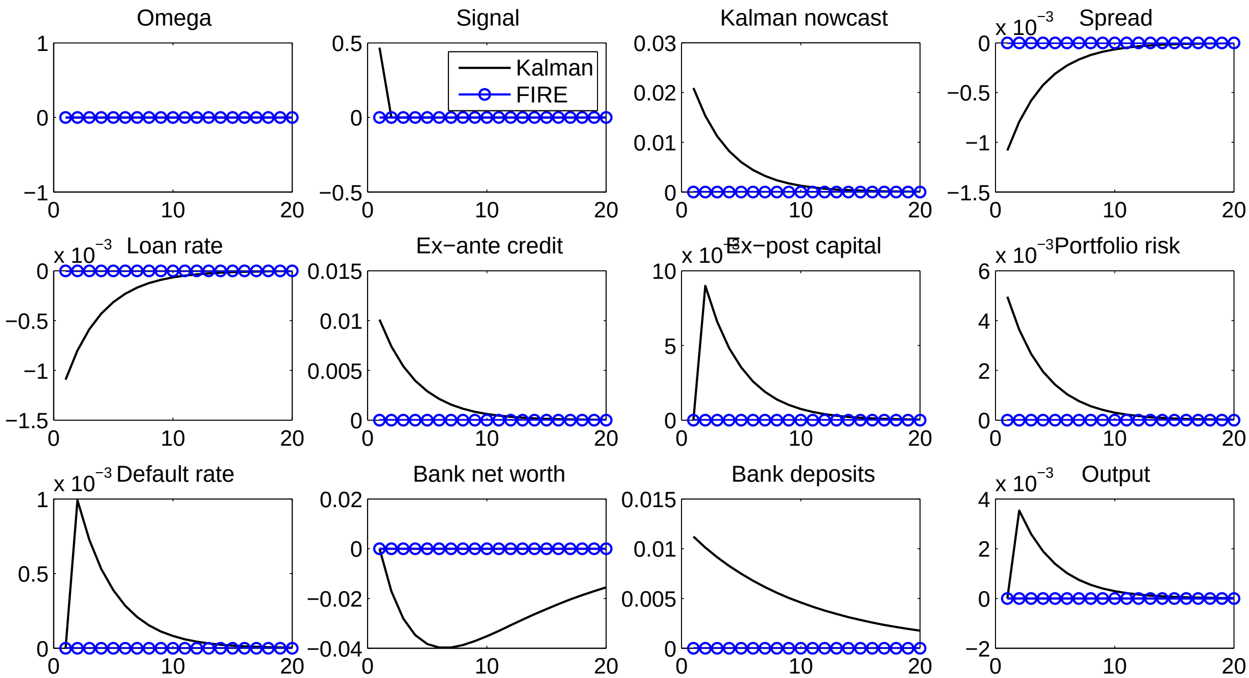

Figure 12: Impulse responses to a shock in the noise component based on the simplified general equilibrium model in (23)–(35)

aggregate credit persist even after the fundamental source of the disturbance has all but vanished in period 2, reflecting higher expected repayment probabilities for both risk types.

Due to the fundamental nature of the shock, reduced default of firms implies a higher ex-post aggregate stock of productive capital and a higher economy-wide output level. Regardless of the information regime, ex-post default decreases in the period of the shock, thus raising bank net worth on impact. After the initial increase, bank net worth monotonically converges to its steady-state value from above. Due to the ample supply of internal funds, the bank relies less on external funding in order to satisfy the increased demand for ex-ante credit. Hence, bank deposits decrease both with imperfect information and under FIRE.

4.6.3. Noise shocks

While the impulse responses in Figures 10 and 11 arise from shocks to the fundamental determinants of credit risk, pure noise shocks can also affect the bank's expectations and lending behavior in the presence of imperfect information. Figure 12 plots the impulse responses to a positive one-standard-deviation innovation in the public signal $\tilde{s}_t$ *without any change in fundamentals* with imperfect information ("Kalman") and full information ("FIRE").

Although the observable ω_t and its latent persistent component ν_t are *not* affected, the change in the signal induces rational agents to revise their Kalman filter nowcast of the "trend" component, $\nu_{t|t}$, upwards under imperfect information, whereas ν_t and η_t are separately observable under full information. While the "objective" repayment probability of either risk type is therefore unchanged, the equilibrium credit spread decreases on impact before monotonically converging back to its steady-state value from below, while the impulse response function of ex-ante aggregate credit follows a similar but inverted pattern under imperfect information. Note that the higher sensitivity of the relatively riskier firm type with respect to $E_t\omega_{t+1}$ in (21) implies that the bank lends disproportionately to the second risk type. As a consequence, the riskiness of the bank's loan portfolio, measured as the fraction of credit to the riskier type increases in response to a pure noise shock. While this holds true also in response to both fundamental shocks, as illustrated in Figures 10 and 11, we show below that noise shocks are an important driver of this "portfolio rebalancing".

In response to a non-fundamental noise shock, ex-post default, the aggregate stock of productive capital, and output are unaffected on impact. Only after the increase in ex-ante aggregate credit in period 1 translates into higher ex-post aggregate capital in period 2, both capital and output increase slightly under imperfect information, whereas nothing happens under FIRE. Note that the increase in ex-post aggregate capital is less pronounced than the expansion of ex-ante aggregate bank lending, leading to an increase in ex-post aggregate default in line with Figure 8. At the same time, the increase in the aggregate default *rate* plotted in Figure 12 reflects the shift in the bank's loan portfolio towards the riskier firm type.

This increase in the ex-post default rate cuts into the bank's net worth, which follows a U-shaped pattern and converges back to its steady-state value from below. The loss of internal funds induces the bank to draw on additional external funding in order to satisfy the increased demand for ex-ante aggregate credit. Hence, bank deposits increase under imperfect information. This is in contrast with the findings in Blanchard et al. (2013), where consumption *increases* in response to a pure noise shock. The reason is that, in our model, the signal extraction problem has to be solved by financial intermediaries rather than the household sector, implying a qualitatively different propagation of noise shocks.

4.7. Forecast Error Variance Decomposition

Table 3 reports the forecast error variance (FEV) contribution of the three shocks for selected variables from the simplified general equilibrium model with two risk types and imperfect information in (23)–(37). Consistent with our findings for the partial equilibrium investment model, the first two panels illustrate that noise shocks do *not* contribute to the FEV of ω_t, while shocks to the transitory component do *not* affect $\tilde{s}_t$.

Table 3: Forecast error variance decomposition of selected variables based on the model in (23)–(37)

	Omega			Signal			Kalman nowcast		
Quarter	Trend	Cycle	Noise	Trend	Cycle	Noise	Trend	Cycle	Noise
1	0.003	0.997	0.000	0.020	0.000	0.980	0.023	0.124	0.853
4	0.006	0.994	0.000	0.042	0.000	0.958	0.097	0.115	0.789
8	0.007	0.993	0.000	0.047	0.000	0.953	0.153	0.108	0.740
20	0.007	0.993	0.000	0.048	0.000	0.952	0.172	0.105	0.723
	Spread			Ex-ante credit			Ex-post default		
Quarter	Trend	Cycle	Noise	Trend	Cycle	Noise	Trend	Cycle	Noise
1	0.018	0.558	0.424	0.018	0.558	0.424	0.003	0.997	0.000
4	0.080	0.391	0.529	0.080	0.391	0.529	0.006	0.994	0.000
8	0.126	0.358	0.516	0.126	0.358	0.516	0.007	0.993	0.000
20	0.141	0.351	0.508	0.141	0.351	0.508	0.007	0.993	0.000

At the same time, both cycle and noise shocks contribute to the FEV of the Kalman filter nowcast of the persistent component, where the intuition follows from equation (10). Due to the large estimated variance of cycle shocks in Table 2, ω_t represents a comparatively noisy measure of the persistent component that is largely disregarded by economic agents, while a higher weight is placed on the relatively more precise signal $\tilde{s}_t$. As a result, non-fundamental noise shocks to the public signal enter the Kalman filter nowcast of ν_t with a large weight and contribute thus more to its FEV.

Turning to selected economic variables in the second line of Table 3, we find that the large contribution of noise shocks to the Kalman filter nowcast of the persistent component translates into a contribution of 42–53% in the FEV of the aggregate credit spread defined in equation (37). Note also that the contribution of shocks to the persistent component is monotonically increasing, while that of shocks to the transitory component is monotonically decreasing in the forecast horizon. The relative importance of the two fundamental shocks is largely determined by our estimates of σ_e and σ_ϵ.

Due to the assumption of a constant interest rate on deposits, the FEV of the credit spread is inherited by the interest rates on loans to either risk type, the corresponding equilibrium credit volumes, and thus the bank's portfolio risk. As a result, noise shocks feature a large contribution to the FEV of ex-ante aggregate credit, whereas they have little explanatory power for fluctuations in ex-post default, which is determined almost exclusively by shocks to the transitory component. This is due to the comparatively larger estimated variance of the latter, which implies that *ex-post* economic variables such as the capital stock and the default rate, for example, respond strongly to the fundamental cycle shocks on impact (see Figure 11).

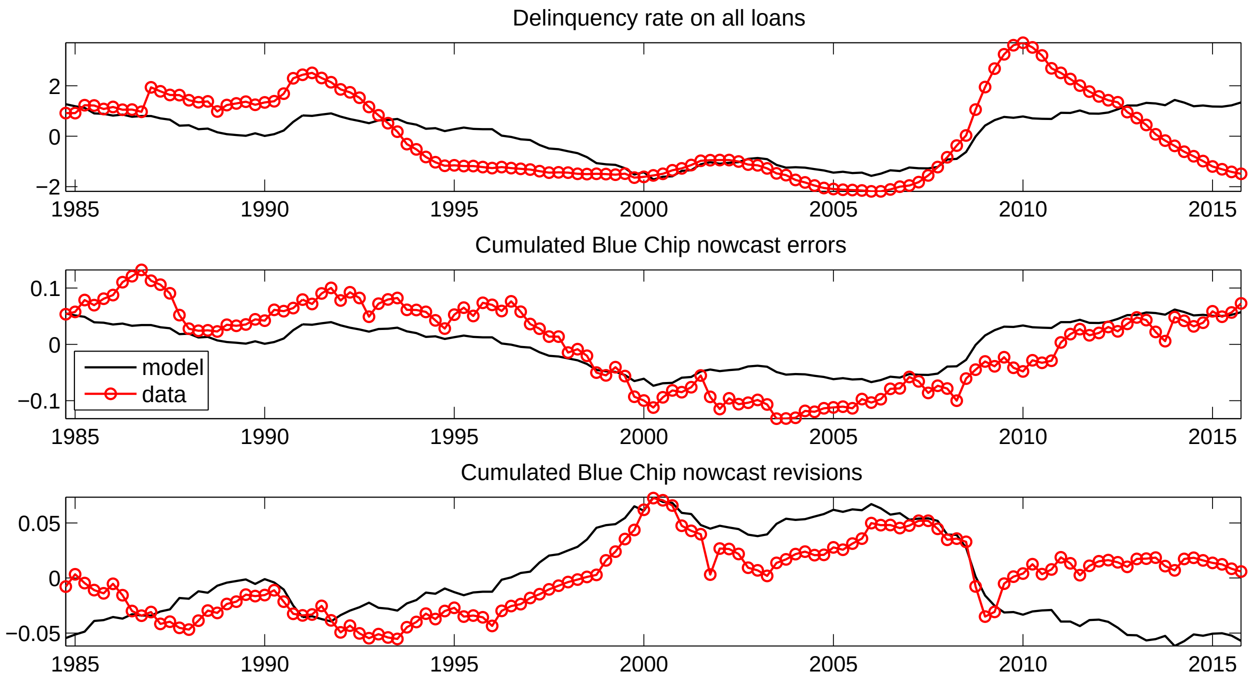

Figure 13: Historical fluctuations of variables not used when estimating the simplified general equilibrium model in (23)–(35)

4.8. *External Validity*

In order to check for external validity of the estimated simplified general equilibrium model, Figure 13 plots the delinquency rate on all loans for all U.S. commercial banks as well as the cumulated Blue Chip nowcast errors and revisions against their model counterparts, i.e. the average default rate on loans to both firm types, the cumulated Kalman filter nowcast errors, and the cumulated Kalman filter nowcast revisions. Note that none of these variables was used when estimating the model in (23)–(35).

Figure 13 illustrates that the general equilibrium model does a surprisingly good job in replicating the historical fluctuations of these additional variables during our sample period. In particular, it reproduces the downward trend in the delinquency rate between 1991 and 2007 as well as the subsequent steep increase during the financial crisis. It replicates the steady decrease and increase in cumulated nowcast errors before 2000 and after 2005, respectively. Finally, it reproduces the upward trend in cumulated nowcast revisions between 1991 and 2000 as well as the subsequent U-shape and the sudden drop in 2008.

The model fails to reproduce the decrease in delinquency rates and the relatively high level of cumulated Blue Chip nowcast revisions after 2010 — a period characterized by massive interference of policy makers in the financial sector and protracted non-standard monetary policy. Albeit, none of this is accommodated in our simple model.

5. Concluding Remarks

In this paper, we investigate whether imperfect information of financial intermediaries about the state of the economy can be a source of lending cycles. We start by analyzing a partial equilibrium neoclassical investment model, where a competitive bank must solve a signal extraction problem in order to distinguish between fundamental components that determine the underlying state of the economy and non-fundamental "noise" shocks. We find that credit booms can arise from informational frictions and that these credit booms are associated with higher ex-post default relative to a full-information and rational expectations benchmark.

In order to quantify the role of noise shocks in aggregate fluctuations, we embed the neoclassical investment model in a general equilibrium model with two risk types. The partial equilibrium model is closed by assuming that bank lending is funded by the bank's accumulated net worth and by external funds in the form of risk-free deposits by a risk-neutral foreign depositor at the world interest rate. We solve and estimate the model using Bayesian techniques and an equivalent full information representation of the general equilibrium model with imperfect information proposed by Blanchard et al. (2013). Calibrating the model's driving processes along the lines of our empirical estimates, we find that noise shocks contribute up to 50% to the forecast error variance of the spread between Moody's seasoned Baa corporate bond yield and the yield on 10-year treasury constant maturity at the 5-year horizon.

The current modeling framework allows us to isolate and quantify the effects of imperfect information in the banking sector on macroeconomic outcomes. An interesting extension would be to study the interaction of noisy information with financial frictions, such as balance sheet constraints of financial intermediaries. Our model is able to reproduce the historical fluctuations in average forecast errors and revisions based on the Blue Chip consensus forecast. Another relevant extension would therefore be to study the implications of financial intermediaries' expectations formation process at the individual level. These questions are beyond the scope of the current paper and left for future research.

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Appendix A. Kalman Filter

Solving equation (7) for the transitory component η_t and substituting into $\eta_t = \rho_\eta \eta_{t-1} + \epsilon_t$, we obtain

$$\omega_t = \nu_t + \rho_\eta (\omega_{t-1} - \nu_{t-1}) + \epsilon_t,$$
$$\tilde{s}_t = \nu_t + \varepsilon_t,$$
$$\nu_t = \rho_\nu \nu_{t-1} + e_t,$$

where the first two represent measurement equations, while the third represents the transition equation of ν_t. Defining the vector of states $\mathbf{s}_t \equiv [\nu_t, \nu_{t-1}]'$, we can write the above system in matrix notation as

$$\mathbf{y}_t = \mathbf{Z}\mathbf{s}_t + \mathbf{B}\mathbf{y}_{t-1} + \mathbf{u}_t,$$
$$\mathbf{s}_t = \mathbf{T}\mathbf{s}_{t-1} + \mathbf{v}_t,$$

where $\mathbf{y}_t \equiv \begin{bmatrix} \omega_t \\ \tilde{s}_t \end{bmatrix}$, $\mathbf{Z} \equiv \begin{bmatrix} 1 & -\rho_\eta \\ 1 & 0 \end{bmatrix}$, $\mathbf{B} \equiv \begin{bmatrix} \rho_\eta & 0 \\ 0 & 0 \end{bmatrix}$, $\mathbf{u}_t \equiv \begin{bmatrix} \epsilon_t \\ \varepsilon_t \end{bmatrix}$, $\mathbf{T} \equiv \begin{bmatrix} \rho_\nu & 0 \\ 1 & 0 \end{bmatrix}$, and $\mathbf{v}_t \equiv \begin{bmatrix} e_t \\ 0 \end{bmatrix}$.

From the above system of equations, it is straightforward to derive Kalman filter *updating* expressions for the state vector and its variance conditional on information available at time t, $\mathbf{s}_{t|t}$ respectively $\Sigma_{t|t}$:

$$\begin{aligned} \mathbf{s}_{t|t} &= \mathbf{s}_{t|t-1} + \Sigma_{t|t-1}\mathbf{Z}' \left(\mathbf{Z}\Sigma_{t|t-1}\mathbf{Z}' + \mathbf{H}\right)^{-1} \left(\mathbf{y}_t - \mathbf{y}_{t|t-1}\right), \\ \Sigma_{t|t} &= \Sigma_{t|t-1} - \Sigma_{t|t-1}\mathbf{Z}' \left(\mathbf{Z}\Sigma_{t|t-1}\mathbf{Z}' + \mathbf{H}\right)^{-1} \mathbf{Z}\Sigma_{t|t-1}, \end{aligned} \tag{A.1}$$

where the corresponding Kalman filter *forecasting* expressions are given by

$$\begin{aligned} \mathbf{s}_{t+1|t} &= \mathbf{T}\mathbf{s}_{t|t}, \\ \Sigma_{t+1|t} &= \mathbf{T}\Sigma_{t|t}\mathbf{T}' + \mathbf{Q}, \\ \mathbf{y}_{t+1|t} &= \mathbf{Z}\mathbf{s}_{t+1|t} + \mathbf{B}\mathbf{y}_t, \end{aligned} \tag{A.2}$$

and the covariance matrices of the disturbance term vectors $\mathbf{u}_t$ and $\mathbf{v}_t$, respectively, are given by

$$\mathbf{H} = \begin{pmatrix} \sigma_\epsilon^2 & 0 \\ 0 & \sigma_\varepsilon^2 \end{pmatrix}, \quad \mathbf{Q} = \begin{pmatrix} \sigma_e^2 & 0 \\ 0 & 0 \end{pmatrix}.$$

Note that the Kalman filter gain, $\mathbf{K} \equiv \Sigma_{t|t-1}\mathbf{Z}' \left(\mathbf{Z}\Sigma_{t|t-1}\mathbf{Z}' + \mathbf{H}\right)^{-1}$, is increasing in σ_e while it is decreasing in σ_ϵ and σ_ε, i.e., the extent to which the bank optimally updates its *nowcast* of $\mathbf{s}_{t|t}$ depends on the so-called "signal-to-noise ratio".

Appendix B. Log-Linearized General Equilibrium Model with Two Risk Types

Assuming that $R_t^d = R^w \ \forall t$, it is straightforward to log-linearize the equilibrium conditions in equations (23)–(37) around the non-stochastic steady state:

$$\hat{R}_t^d = 0, \tag{B.1}$$

$$\hat{R}_t^1 = \hat{R}_t^d - E_t\widehat{Prob}_{t+1}^1, \tag{B.2}$$

$$\hat{R}_t^2 = \hat{R}_t^d - E_t\widehat{Prob}_{t+1}^2, \tag{B.3}$$

$$E_t\widehat{Prob}_{t+1}^1 + \hat{L}_t^1 = -\frac{1}{1-\alpha}\hat{R}_t^1, \tag{B.4}$$

$$E_t\widehat{Prob}_{t+1}^2 + \hat{L}_t^2 = -\frac{1}{1-\alpha}\hat{R}_t^2, \tag{B.5}$$

$$L_{ss}\hat{L}_t = L_{ss}^1\hat{L}_t^1 + L_{ss}^2\hat{L}_t^2, \tag{B.6}$$

$$\hat{K}_t^1 = \widehat{Prob}_t^1 + \hat{L}_{t-1}^1, \tag{B.7}$$

$$\hat{K}_t^2 = \widehat{Prob}_t^2 + \hat{L}_{t-1}^2, \tag{B.8}$$

$$K_{ss}\hat{K}_t = K_{ss}^1\hat{K}_t^1 + K_{ss}^2\hat{K}_t^2, \tag{B.9}$$

$$Y_{ss}\hat{Y}_t = \alpha\left(Y_{ss}^1\hat{K}_t^1 + Y_{ss}^2\hat{K}_t^2\right), \tag{B.10}$$

$$Y_{ss}\hat{Y}_t = C_{ss}\hat{C}_t + N_{ss}\hat{N}_t + R_{ss}^d D_{ss}\left(R_{t-1}^d + D_{t-1}\right), \tag{B.11}$$

$$L_{ss}\hat{L}_t = D_{ss}\hat{D}_t + N_{ss}\hat{N}_t, \tag{B.12}$$

$$N_{ss}\hat{N}_t = (1-\delta)\left[R_{ss}^1K_{ss}^1\left(R_{t-1}^1 + K_t^1\right) + R_{ss}^2K_{ss}^2\left(R_{t-1}^2 + K_t^2\right) - R_{ss}^d D_{ss}\left(R_{t-1}^d + D_{t-1}\right)\right], \tag{B.13}$$

$$R_{ss}\left(L_{ss}^1\hat{L}_t^1 + L_{ss}^2\hat{L}_t^2\right) = R_{ss}^1L_{ss}^1\left(\hat{R}_t^1 + \hat{L}_t^1\right) + R_{ss}^2L_{ss}^2\left(\hat{R}_t^2 + \hat{L}_t^2\right) - R_{ss}\left(L_{ss}^1 + L_{ss}^2\right)\hat{R}_t, \tag{B.14}$$

$$\widehat{spread}_t = \hat{R}_t - \hat{R}_t^d. \tag{B.15}$$

where X_{ss} denotes the steady-state value of variable X and $\hat{X}_t$ the percentage deviation of X in period t from its steady-state value, i.e. $\hat{X}_t \equiv (X_t - X_{ss})/X_{ss}$.

Appendix C. Reduced-Form VAR Representation of the Model

Assume — without loss of generality — that the economy is populated by borrowers of one risk type. The purpose of this assumption is to render the algebra more transparent, while it can be relaxed to two or more risk types without affecting our result qualitatively. With just one risk type, the lending rate R_t and the lending volume L_t are determined by the following log-linearized equations:

$$R_t = -E_t Prob_{t+1},$$
$$E_t Prob_{t+1} + L_t = -\frac{1}{1-\alpha} R_t.$$

Substituting for the lending rate, we obtain

$$L_t = \frac{\alpha}{1-\alpha} E_t Prob_{t+1},$$

which can be rewritten as

$$L_t = \frac{\alpha}{1-\alpha} \zeta \rho_\nu \nu_{t|t}, \tag{C.1}$$

where ζ denotes the sensitivity of the lending rate with respect to the observable state of the economy, ω_t.

In order to arrive at a reduced-form equation for ω_t, consider

$$\begin{aligned} & \omega_t - \rho_\nu \omega_{t-1} = \nu_t + \epsilon_t - \rho_\nu \left(\nu_{t-1} + \epsilon_{t-1}\right), \\ \Leftrightarrow \quad & \omega_t - \rho_\nu \omega_{t-1} = e_t + \epsilon_t - \rho_\nu \epsilon_{t-1}, \\ \Leftrightarrow \quad & \omega_t - \rho_\nu \omega_{t-1} = e_t + \epsilon_t - \rho_\nu \omega_{t-1} + \rho_\nu \nu_{t-1}. \end{aligned}$$

Rearranging and taking expectations as of period $t-1$ yields

$$E_{t-1}\omega_t = \rho_\nu \nu_{t-1|t-1}.$$

Using (C.1), we can rewrite the above expression as

$$\omega_t = A^\omega L_{t-1} + \epsilon_t^\omega, \tag{C.2}$$

where $A^{\omega} \equiv \frac{1-\alpha}{\alpha\zeta}$.

In order to arrive at a reduced-form representation of L_t, recall that the optimal nowcast implied by the Kalman filter in equation (10) equals

$$\nu_{t|t} = (1 - \kappa_1 - \kappa_2)\,\rho_\nu \nu_{t-1|t-1} + \kappa_1 \omega_t + \kappa_2 \tilde{s}_t, \tag{C.3}$$

where $\kappa_1 \equiv \frac{\sigma_\nu^2 \sigma_\varepsilon^2}{\sigma_\nu^2\sigma_\epsilon^2 + \sigma_\nu^2\sigma_\varepsilon^2 + \sigma_\epsilon^2\sigma_\varepsilon^2}$, $\kappa_2 \equiv \frac{\sigma_\nu^2 \sigma_\epsilon^2}{\sigma_\nu^2\sigma_\epsilon^2 + \sigma_\nu^2\sigma_\varepsilon^2 + \sigma_\epsilon^2\sigma_\varepsilon^2}$, and σ_ν^2 implicitly solves $\sigma_\nu^2 = \rho_\nu^2 \left(\frac{1}{\sigma_\epsilon^2} + \frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_\nu^2}\right)^{-1} + \sigma_e^2$.

Combining (C.1) and (C.3), we obtain

$$L_t = \frac{\alpha\zeta}{1-\alpha}\rho_\nu \left[(1 - \kappa_1 - \kappa_2)\,\rho_\nu \nu_{t-1|t-1} + \kappa_1 \omega_t + \kappa_2 \tilde{s}_t\right].$$

Substituting for ω_t and $\tilde{s}_t$, rearranging, and taking expectations as of period $t-1$ yields

$$E_{t-1} L_t = \frac{\alpha\zeta}{1-\alpha}\rho_\nu^2 \nu_{t-1|t-1},$$

which can be rewritten as

$$L_t = B^L L_{t-1} + \epsilon_t^L, \tag{C.4}$$

where $B^L \equiv \rho_\nu$. Accordingly, (C.2) and (C.4) yield a reduced-form VAR representation in the state of the economy ω_t and the ex-ante credit volume L_t.

Appendix D. Robustness of Results

In what follows, we show that the results in Section 4 are robust to replacing the difference between Moody's seasoned Baa corporate bond yield and the yield on 10-year treasury constant maturity by Gilchrist and Zakrakšek's (2012) *excess bond premium* (EBP) as an empirical proxy for $spread_t$ in the model.

Table D.1: Bayesian priors and maximum likelihood posterior estimates of the parameters in equations (7) and (8)

Parameter	Prior type	Prior mean	Prior s.d.	Posterior mode	Posterior s.d.
ρ_ν	beta	0.600	0.200	0.7281	0.0391
ρ_η	beta	0.600	0.200	0.0100	0.0005
σ_e	inverse gamma	0.500	1.000	0.0711	0.0063
σ_ϵ	inverse gamma	1.000	1.000	1.2287	0.0826
σ_ε	inverse gamma	1.000	1.000	0.4281	0.0740

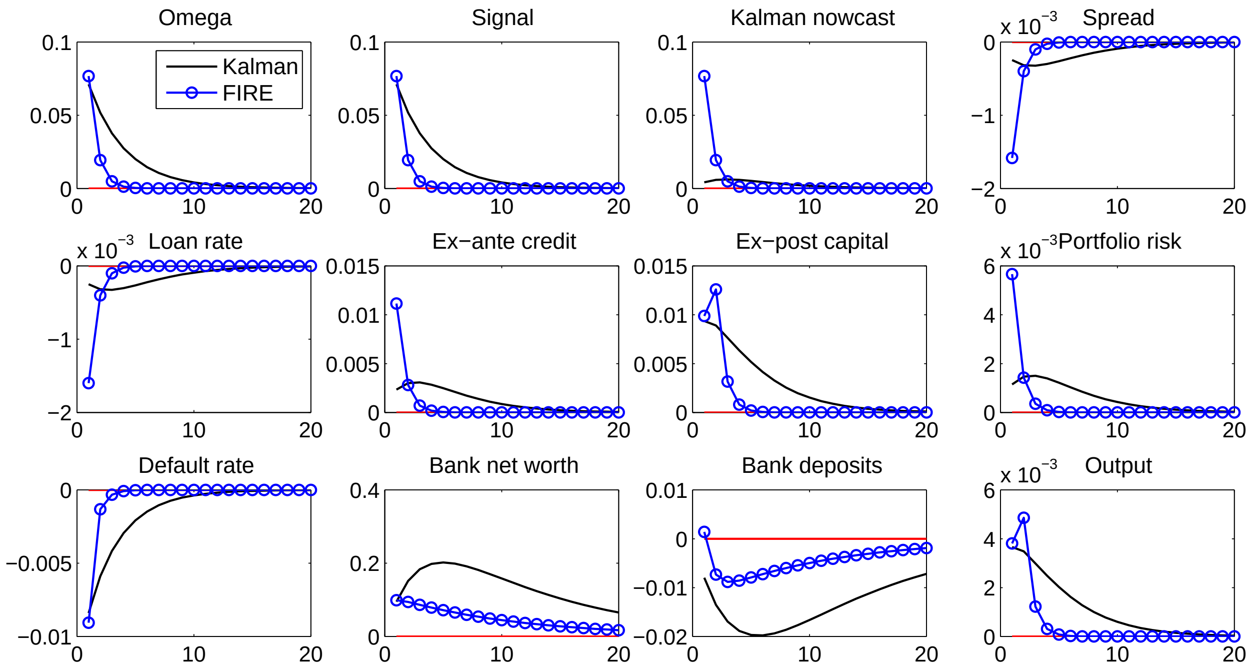

Figure D.1: Impulse responses to a shock in the transitory component based on the simplified general equilibrium model in (23)–(35)

Table D.1 reports the type and mean of the Bayesian priors, which are identical to those in Table 2, as well as the posterior mode of the parameters in (7) and (8) and illustrates that the parameter estimates are very similar to those obtained for the Baa–10YT spread.

Figures D.1–D.3 plot the impulse responses to a positive one-standard-deviation in the persistent component, the transitory component, and the public signal, respectively, for the simplified general equilibrium model with two borrower types and *imperfect information* ("Kalman") against its counterpart with *full information* ("FIRE").[17] A comparison with Figures 10–12 reveals that the impulse response functions are qualitatively identical and quantitatively very similar for either empirical proxy for $spread_t$.

As a consequence, one would expect that the model estimated on real GDP growth and the EBP also has similar implications for the forecast error variance (FEV) decomposition. Indeed, the contribution of each structural shock to the FEV in Table D.2 is virtually identical to the respective values in Table 3. Whether we use the Baa spread or the EBP as an empirical proxy for $spread_t$, the simplified model with two risk types in (23)–(35) implies that noise shocks contribute more than 50% to the FEV of the credit spread, ex-ante credit volumes, and the riskiness of the bank's portfolio.

[17]Re-estimating the model with full information for the EBP yields $\rho_v = 0.2519$, $\rho_\eta = 0.01$, $\sigma_e = 0.0767$, and $\sigma_\epsilon = 1.0501$.

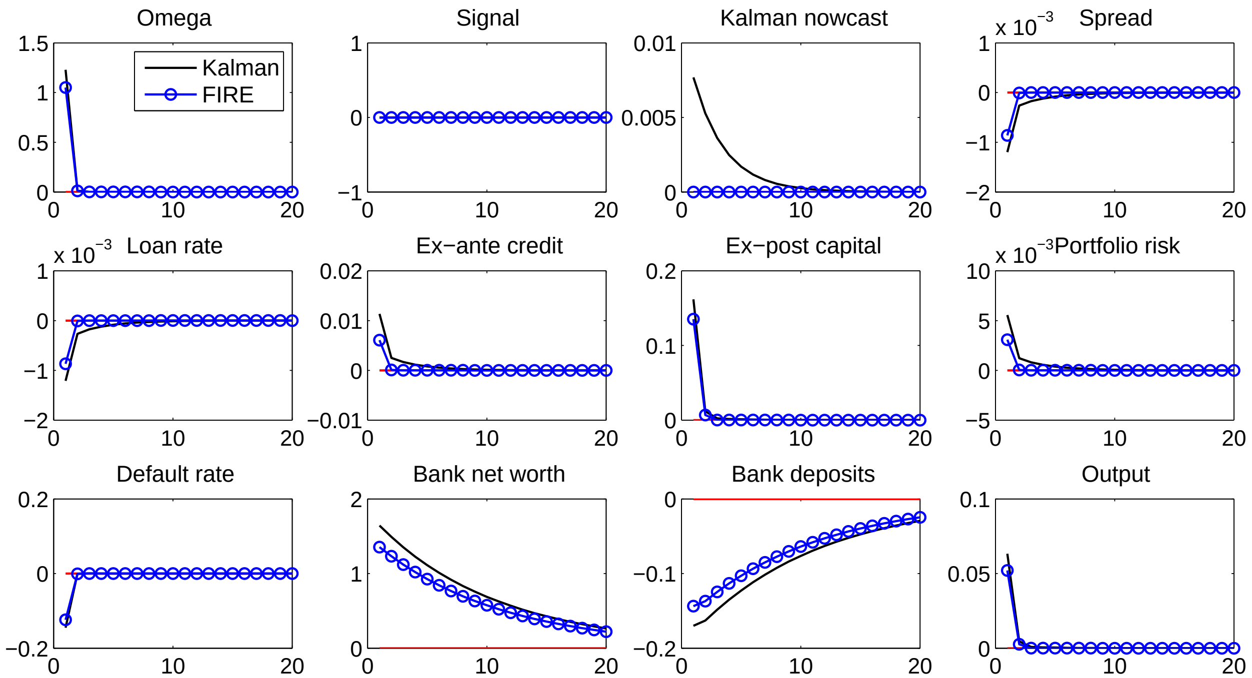

Figure D.2: Impulse responses to a shock in the transitory component based on the simplified general equilibrium model in (23)–(35)

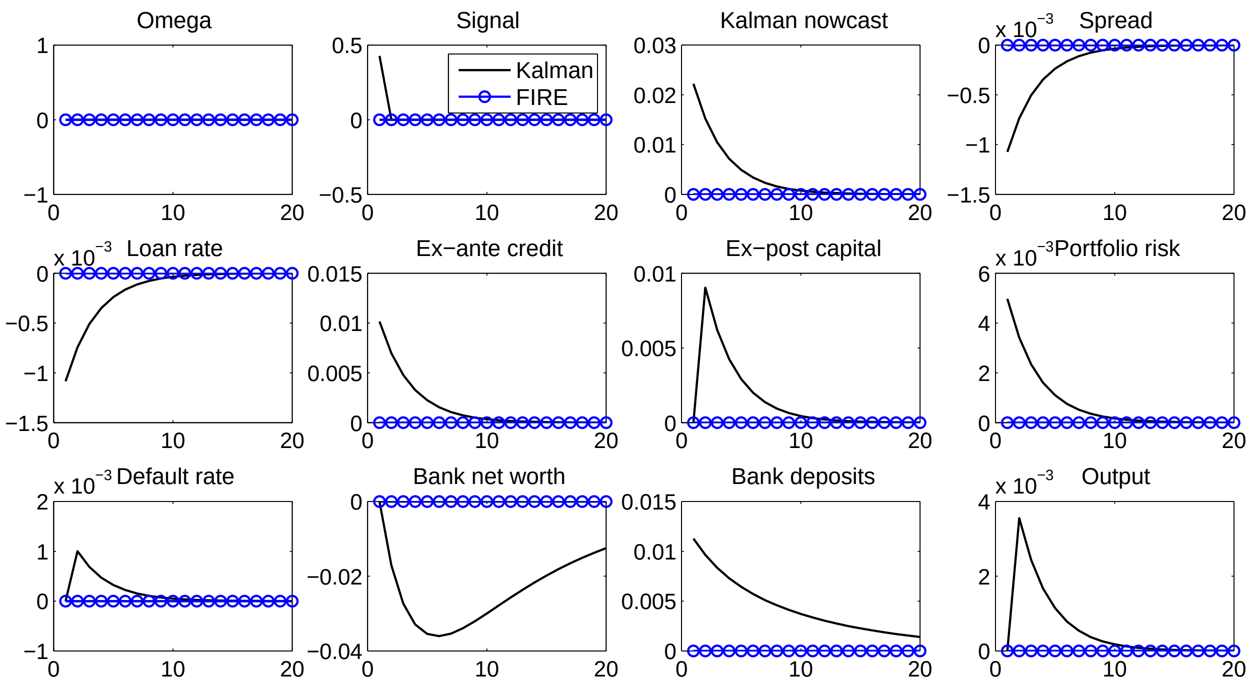

Figure D.3: Impulse responses to a shock in the noise component based on the simplified general equilibrium model in (23)–(35)

Table D.2: Forecast error variance decomposition of selected variables based on the model in (23)–(37)

	Omega			Signal			Kalman nowcast		
Quarter	Trend	Cycle	Noise	Trend	Cycle	Noise	Trend	Cycle	Noise
1	0.003	0.997	0.000	0.027	0.000	0.973	0.030	0.104	0.866
4	0.007	0.993	0.000	0.051	0.000	0.949	0.111	0.095	0.794
8	0.007	0.993	0.000	0.055	0.000	0.945	0.155	0.090	0.754
20	0.007	0.993	0.000	0.055	0.000	0.945	0.164	0.089	0.746
	Spread			Ex-ante credit			Ex-post default		
Quarter	Trend	Cycle	Noise	Trend	Cycle	Noise	Trend	Cycle	Noise
1	0.023	0.542	0.435	0.023	0.542	0.435	0.003	0.997	0.000
4	0.090	0.390	0.520	0.090	0.390	0.520	0.006	0.994	0.000
8	0.125	0.366	0.509	0.125	0.366	0.509	0.007	0.993	0.000
20	0.131	0.363	0.506	0.131	0.363	0.506	0.007	0.993	0.000