The Informational Centrality of Banks*

Nathan Foley-Fisher[1], Gary Gorton[2], and Stéphane Verani[1]

[1]Federal Reserve Board
[2]Yale School of Management and NBER

First version: January 2021; this version: June 2023

Abstract

The equity and debt prices of large nonbank firms contain information about the future state of the banking system. In this sense, banks are informationally central. The amount of this information varies over time and over equity and debt. During a financial crisis banks are, by definition of a crisis, at risk of failure. Debt prices became about 50 percent *more informative* than equity prices about the future state of the banking system during the financial crisis of 2007-2009. This was partly due to investors' fears that banks might not be able to refinance their debt.

JEL Codes: D82, E44, G14
Keywords: price informativeness, asset pricing, banking system, financial crises

*For providing valuable comments, we would like to thank, without implication, Elena Afanasyeva, Eduardo Davila, Borghan Narajabad, Anna Orlik, Dino Palazzo, Cecilia Parlatore, Coco Ramirez, and participants in the Federal Reserve Board Macro-Finance Workshop 2023. The views in this paper are solely the authors' and should not be interpreted as reflecting the views of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

1 Introduction

Banks sit at the center of the savings-investment process. But what does it mean that banks are at the "center" of the savings-investment process? To address this question, we ask whether the equity and debt prices of large nonbank firms contain information about the future state of the banking system ("the state of the banking system"). We look at normal times and during the financial crisis of 2007-2009. We find that the equity and debt prices of nonbank firms do indeed embed information about the state of the banking system. The amount of information embedded in prices varies over time, and over equity and debt.[1]

A large literature studies financial crises as information events in which short-term debt transits from being information-insensitive to information sensitive – a crisis. For a review of this literature see Dang, Gorton and Holmström (2020). A financial crisis is a systemic event, the solvency of the entire banking system is threatened. Ben Bernanke made this point in his testimony before the Financial Crisis Inquiry Commission Commission (2012). He said that during September and October of 2008 "...out of the 13 most important financial institutions in the United States, 12 were at

[1]There is a large literature establishing that firm outcomes depend on conditions in the banking sector, including bank financing constraints, competition, and profitability (Paravisini, 2008; Claessens and Laeven, 2005; Chava and Purnanandam, 2011). At the micro level, individual banks that tighten their loan supply have real effects on firm investment and employment decisions (Bassett, Chosak, Driscoll and Zakrajsek, 2014; Chodorow-Reich, 2014; Castro, Glancy, Ionescu and Marchal, 2022). An earlier strand of the same literature used aggregate bank data, including Owens and Schreft (1991) and Lown and Morgan (2002, 2006).

risk of failure within a period of a week or two" (p. 354). We show that during a financial crisis, there is a kind of information regime switch for *corporate assets* as well. We find that both equity and debt prices are always informative about the banking system. But during the financial crisis of 2007-2009 debt prices were about 50 percent *more informative* than equity prices about the future state of the banking system. We show that this was in part due to investors' fears that banks might not be able to refinance their debt.

We proceed by estimating price informativeness corresponding to the relative precision of the signal about future states contained in asset prices. In practice, a specific combination of R^2 statistics from linear regressions of changes in asset prices on changes in states exactly identifies relative price informativeness (Davila and Parlatore, 2022). In our setting we study whether a single nonbank firm's asset prices are informative about two unknown states: the firm state—measured as the firm's future earnings as in Davila and Parlatore (2022)—and the state of the banking system (defined below). Our calculations are analogous to an external observer updating her prior about the state of the banking system after observing changes in a nonbank firm's asset prices. We show that the observer can identify the information content about the state of the banking system. Under stylized conditions, the observer in our setting is a Bayesian learner applying a Kalman filter to extract information about two unknown linear

combinations of the firm and bank states—that is, both the states and their linear combination are unknown. Information about the state of the banking system can be analyzed by comparing two Kalman gains: The first obtained by imposing a constraint on the unknown linear combinations of the firm and bank states, and the second obtained from the unconstrained Kalman filter. When an asset price is uninformative about the banking system, the signal-to-noise ratios in the constrained and unconstrained Kalman filters are the same.

After calculating the information content of a firm's equity and debt prices about the state of the banking system, we can measure the *relative* information content about the bank state in a firm's equity price and in its debt price. In other words, are equity prices more informative about the state of the banking system compared to debt prices for the same firm? We contrast the relative information content of equity and debt prices during normal times and during the financial crisis 2007-2009, when the entire financial system was on the brink of collapse. We find that debt and equity are equally informative in normal times, while debt was *more informative* than equity during the financial crisis. This suggests that debt holders believed that there was a nontrivial chance that they would suffer losses and so they produced information about the future state of the banking system. This information becomes impounded into prices.

These calculations are done at the firm level in rolling windows of

15 quarters and then averaged across firms for each period of time t to obtain an aggregate time series of the information content of debt prices and equity prices about the future state of the banking system. We obtain asymptotically valid confidence intervals (CIs) for each point in this time series by subsampling. Subsampling the distribution of a sample mean at time t based on n firms requires calculating sample means for all the $\binom{n}{c}$ combinations of firm subsamples of size c at time t, where $c < n$. Subsampling yields a consistent estimate of the sampling distribution of the original sample mean under extremely weak assumptions (see Politis, Romano and Wolf (1999)). Note that subsampling is conceptually different from bootstrapping. Subsampling, by definition, draws samples from the true data generating process, whereas bootstrapping recomputes a statistic over artificial samples that are created from what the researcher assumes is the true data generating process. As we do not know a priori whether asset prices contain information about the future state of the banking system, we do not know the "true" model. Lastly, we can exploit the familiar duality between hypothesis testing and confidence intervals to formally test the hypothesis that the average firm's asset prices contain information about the state of the banking system.

We then investigate why the debt of large nonbank firms contains more information about the future state of the banking system than their own equity prices during the financial crisis. We analyze the relative information

content about the future bank state in equity and debt prices in a panel data setting. We calculate the fraction of each firm's total debt maturing over the next twelve months and show that in the cross section this measure of refinancing risk is significant during the crisis. That is, a nonbank's debt prices contain relatively more information about the state of the banking system than its equity prices when that firm's refinancing risk is higher. Benmelech, Frydman and Papanikolaou (2018) found that during the Great Depression, when public debt markets disappeared, firms with maturing debt at a location where local banks failed reduced their employment by 11 percent to 17 percent. Our findings suggest that firms feared this might happen during the 2007-2009 financial crisis.

Note that we are not addressing a question of market efficiency, which would test for information that the researcher a priori believed should be in asset prices. Rather, we are testing whether information about the future state of the banking system is reflected in nonbank firms' asset prices. We also study how priceinformativeness varies over time, in normal and crisis periods, and across equity and debt.

Related literature includes Ottonello and Song (2022). These authors show that changes in the net worth of intermediaries have real consequences for nonbank firms. They look at high-frequency changes in the market value of intermediaries in a narrow window around intermediaries' earnings announcements. They estimate that news of a one percent decline in the net

worth of intermediaries results in a 0.2—0.4 percent decline in the market value of nonbank firms. Our approach is much different. We show that changes in the future state of the banking system, *as reflected in the equity and debt prices of nonbank firms*, affect nonbank firms and we propose a mechanism through which that happens: refinancing risk.

Intermediary asset pricing is another framework that places financial intermediaries centrally in the economy (He and Krishnamurthy, 2013). But in this case the question is whether intermediaries are the marginal asset pricers, such that a representation of their current state can be taken as the stochastic discount factor. In the empirical studies of intermediary asset pricing, researchers define the current state of the banking system as the leverage of banks. Adrian, Etula and Muir (2014) and He, Kelly and Manela (2017) define leverage differently. We follow He et al. (2017) who define leverage as the equity capital ratio of primary dealers, that is counterparties of the Federal Reserve Bank of New York. These primary dealer banks would be the underwriters for firms' debt, making them the relevant set of financial intermediaries with respect to our sample of large nonbank firms.[2]

The paper proceeds as follows. In Section 2 we present a small model to explain and motivate the empirical approach. We describe how our

[2]The primary dealers that interact with the Federal Reserve Bank of New York are some of the largest banks in the world. See `https://www.newyorkfed.org/markets/primarydealers` for the list.

approach can be interpreted as a Kalman filter in Section 3. We provide an overview of our data in Section 4. We report our aggregate-level analysis in Section 5 and our firm-level analysis in Section 6. Section 7 concludes.

2 Model

In this section we provide a small parsimonious model to motivate the subsequent empirical work. The equity and debt market protocols in the model follow Chousakos, Gorton and Ordoñez (2023). The model is a tractable version of Grossman and Stiglitz (1980) in which the supply of the assets on the market is exogenously given. The intuition for this assumption is that liquidity traders are asymmetric: There can be an urgency to sell, but not the same urgency to buy.

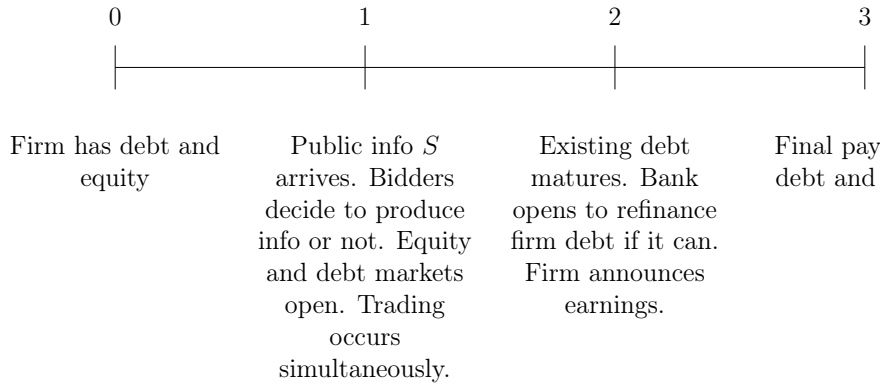
2.1 Setting

There are four dates: 0, 1, 2, and 3. There is a mass one of a continuum of ex-ante identical firms (and similarly for other agent types). At $t = 0$ a representative firm is already financed by debt, D_0, and equity, E_0. So, total assets are: $A_0 = D_0 + E_0$. The existing debt matures at $t = 2$ and, at that time, the firm would like to issue new debt, maturing at $t = 3$. To attempt to refinance its debt, the firm approaches a bank at $t = 2$. At $t = 3$ the debt (if the old debt has been refinanced) is repaid and the value

of the equity is paid out as a liquidating dividend.

At the start of $t = 1$, a *public signal*, S, about the future (i.e., $t = 2$) state of the banking system is realized. As detailed below, agents can learn the implications of this state variable at a cost. Then, at $t = 1$, an equity market and a debt market simultaneously open. In the $t = 1$ asset markets, there are liquidity traders who must sell their holdings of the firm's equity and debt. Bidders in these markets are risk neutral. There are twice as many bidders for the firm's debt and twice as many bidders for the firm's equity.[3] Two bidders are randomly matched to each seller. They submit sealed bids and the assets in each market go to the highest bidders. At $t = 2$, the firm announces its earnings and the firm goes to the bank for the underwriting of new debt.

The timeline is as follows:



At $t = 2$ banks open and based on the state variable, S, the firm is

[3]There are four unit intervals of bidders, two for debt and two for equity. For simplicity, the bidders in the equity and debt markets are distinct. As the two markets open simultaneously, prices are formed at the same time and so information from one market does not inform traders in the other market. Cross-market information exchange could be added at the cost of more complexity.

affected. For example, the firm may not be able to issue new debt to replace the debt maturing at $t = 2$ if, say, there is a financial crisis. This is *refinancing risk*. The firm's interaction with the bank is summarized by the value of the firm at $t = 3$, which depends on the state of the banking system at $t = 2$.

The public signal about the state of the banking system at $t = 2$ that is realized at $t = 1$ is one of two realizations: C and N, i.e., Crisis and Normal, with probabilities γ_C and γ_N, summing to one, so $\Omega \in \{C,\ N\}$. The value of the firm at $t = 3$ depends on the realized state Ω, i.e., $V(\Omega)$. But, in addition, for each state the value of the firm can be $V_H(\Omega, x)$ or $V_L(\Omega, x)$, $\Omega \in \{C,\ N\}$, and where $V_H(\Omega, x) > V_L(\Omega, x)$ for each Ω. Further $V_L(N, x) > V_H(C, x)$. The variable x refers to the firm's final cash flows at $t = 3$ from the firm's project. These cash flows could also be a function of S and, in any case, are random, though to simplify notation that will be suppressed.

Uninformed agents know the state S, but do not know whether the firm is $V_L(\Omega)$ (a "low-type" firm,) or $V_H(\Omega)$ (a "high-type" firm), and implicitly they do not know x. They do know the probability the firm is H in each state, $\gamma_H(\Omega)$, or L, $\gamma_L(\Omega)$, in state Ω, where $\gamma_H(\Omega) + \gamma_L(\Omega) = 1$.

Table 1 describes how the state of the banking system realized at $t = 1$ will affect the value of the firm's $t = 3$ liabilities. Firms may not be able to refinance their debt at $t = 2$, so some of the debt in the table may be

zero. Agents cannot sell assets short.[4]

Table 1: Asset values in period $t = 2$ as a function of the state of the banking system (Ω).

State	Value of Debt $j = H$ or L	Value of Equity $j = H$ or L
$\Omega = C$	$D_2(C, j) = \min\{F, V_j(C)\}$	$E_2(C, j) = \max\{V_j(C) - F, 0\}$
$\Omega = N$	$D_2(N, j) = \min\{F, V_j(N)\}$	$E_2(N, j) = \max\{V_j(N) - F, 0\}$

2.2 Asset markets and information production

At $t = 1$, after the state of the banking system has been revealed and before asset markets open, debt and equity bidders choose whether to produce private information about the value of the firm liability that they are bidding on. Conditional on the realized state of the banking system the private information is about whether the firm value at $t = 3$ will be $V_H(\Omega)$ or $V_L(\Omega$. Based on that, informed agents know the corresponding asset value as shown in the table above. The cost of information production is κ_E and κ_D in the equity and debt markets respectively.

So, an informed agent knows $D_2(\Omega, j)$ or $E_2(\Omega, j)$, while an uninformed agent only knows the expected value of debt and equity in each state, $\gamma_H(\Omega)D_2(\Omega, H) + \gamma_L(\Omega)D_2(\Omega, L) \equiv \Delta_D(\Omega)$ and similarly for equity $\gamma_H(\Omega)E_2(\Omega, H) + \gamma_L(\Omega)E_2(\Omega, L) \equiv \Delta_E(\Omega)$. An uninformed bidder will

[4] D_0 is the expected value taken over all the uncertainty in the table.

always bid p_i where i is debt or equity (we shortly solve for p_i). At price p_i the asset is either overvalued or undervalued. If the firm state is L, the uninformed bidder overvalues the asset and wins the bid because an informed trader will never buy an overvalued asset. If the state is H, the uninformed bidder undervalues the asset, but the informed bidder bids $p_i + \epsilon$ and gets the undervalued asset.

When an uninformed bidder faces another uninformed bidder, he buys with probability $\frac{1}{2}$. When the uninformed bidder faces an informed bidder, he never buys an undervalued asset in equilibrium because the informed bidder will bid $p_i + \epsilon$ for an undervalued asset.

Let y be the fraction of uninformed bidders and assume for simplicity that an informed bidder knows whether the other bidder is informed or not. An informed buyer always bids the value of the asset when facing another informed bidder (who he knows is informed). Then the asset is allocated to one of the informed bidders with probability $\frac{1}{2}$. Only in this case is the true value of the asset revealed.

An informed bidder knows whether the firm is worth $V_H(\Omega)$ or $V_L(\Omega)$ and knows the associated asset value $D_2(\Omega, j)$ or $E_2(\Omega, j)$, The value of the equity from an informed bidder's point of view is:

$$\Pi_E^I = \left(y + \frac{1-y}{2} \right) (E(\Omega, H) - p_E)$$

and similarly for debt:

$$\Pi_D^I = \left(y + \frac{1-y}{2}\right)(D(\Omega, H) - p_D).$$

From an uninformed bidder's point of view, the values of the equity and debt are, respectively:

$$\begin{aligned} \Pi_E^U &= \left[\frac{y}{2}(E_L - p_E)\right] + \left[\left(1 - y + \frac{y}{2}\right)(E_H - p_E)\right], \\ \Pi_D^U &= \left[\frac{y}{2}(D_L - p_D)\right] + \left[\left(1 - y + \frac{y}{2}\right)(D_H - p_D)\right]. \end{aligned} \tag{1}$$

So, information about asset i is produced if: $\Pi_i^I - \Pi_i^U \geq \kappa_i$. Competition among the uninformed ensures that $\Pi_i^U = 0$. So, the price the uninformed bid, p_i, makes them indifferent between buying an undervalued asset and buying an overvalued asset.

The probability that the uninformed can buy an H-type firm out of all the available firms is (for each type of asset) is:

$$\omega\left(p_i|\Omega\right) = \frac{\frac{1}{2}\gamma_H(1-y)}{\frac{1}{2}\gamma_H\left(1-y\right) + \left(1-\gamma_H\right)\left(1-\frac{y}{2}\right)}$$

where $i = E$ or D has been suppressed and where the dependence of γ on Ω has also been suppressed. In the expression above, the uninformed can buy a H-type firm with probability $\frac{1}{2}$ only if facing another uninformed trader. The uninformed can also buy an L-type firm with complimentary

probability, $1 - \frac{1}{2}$.

So, the fraction of each asset type i that has its true value revealed is y_i^*, where y_i^* is the equilibrium value of y_i for i, which solves the following equation for each state S:

$$\omega^*(1-\omega^*)(i_H - i_L) = \kappa_i \text{ where } i = E,\ D, \tag{2}$$

Proposition 2.1 *The price the uninformed bid in equilibrium is:*

$$p_i^* = \omega_i^* i_H + (1-\omega_i^*) i_L, \text{ for } i = E, D \tag{3}$$

and where dependence on Ω *has been suppressed.*

Proof Competition across uninformed bidders make them bid so their gains are zero, otherwise there are incentives to marginally increase the bid p_i^* and discretely raise the probability of buying the average quality firm. The equilibrium price, p_i^*, balances the gains of buying a good firm and the losses of buying a bad one. So, the equilibrium is a pair $\{y_i^*,\ p_i^*\}$ such that the marginal trader is just indifferent between becoming informed or not, as per equation (3). There is a pricing equation for the debt and for the equity in each state of the banking system—equation (2) is obtained by substituting equation (3) into equation (1).

2.3 Price informativeness

The fraction y_i^* determines the amount of information in the economy for each asset i in each state (suppressed). In other words, in our parsimonious model, there is a clear mapping from the fundamental refinancing risk to information contained in prices.[5] For example, in the debt market:

$$\omega^*(1-\omega^*)(D_H - D_L) = \kappa_D \tag{4}$$

for each state, Normal (N) and Crisis (C), and where κ_D is the cost of producing information in the debt market.

Proposition 2.2 *(1) For each state (N and C) and for fixed γ_H if $(D_H - D_L)$ is small–i.e., strictly less than ϵ–, then y_D^* is low (little information is produced) and conversely for $(D_H - D_L)$ large (more information is produced).*

(2) For fixed $(D_H - D_L)$, if γ_H rises, then y_D^* rises and conversely for γ_H falling.

(3) (1) and (2) also characterize equity, E, with κ_E being the cost of producing information in equity markets.

Proof 1. Rewrite (3) as $\omega^* - (\omega^*)^2(D_H - D_L) = k_D$. As ω^* is between zero and one, the squared term is small. It is apparent from the

[5]For each state and each security, $y_i^*(\Omega)$, $i = D$ or E and $\Omega \in \{N, C\}$, is determined as the solution to equation (2), with ω given by the equation just above equation (2).

equation defining ω that is $(D_H - D_L)$ is relatively small, then to satisfy (3), y must go down. And conversely when $(D_H - D_L)$ is relatively large, y must go up.

2. The derivative of ω^* with respect to γ_H is positive, so for fixed $(D_H - D_L)$, when γ_H goes up, y_D^* must go up to reduce ω^*.

3. The same logic characterizes equity.

Proposition 2.3 *Define a Crisis as a situation where $(E_H - E_L)$ is small (and both levels are low) and γ_H is low. And for debt, $(D_H - D_L)$ is high, i.e., there is greater uncertainty about the future debt value for fixed γ_H. Then less information is produced in the equity market (compared to Normal times) and more information is produced in the debt market.*

Proof See Proposition 2.

Proposition 2.3 provides a roadmap for our empirical work to determine the price informativeness of equity and debt prices about the future state of the banking system. Each type of asset price is a linear function of the two random variables representing uncertainty about the state of the banking system, Ω, and (implicitly) uncertainty about the final project payoff, x. The state of the banking system and the state of the firm's cash flows are systematic risks and so enter the asset pricing equations.

For our purposes, the key point is that the equity and debt prices are functions of random variables, S and x, summarizing the firm and bank

state, respectively. We will take a linear approximation of each equity and debt price equation to get asset pricing equations for our empirical specifications:

$$p_E \approx a + bx_1 + cx_2 + dS_1 + eS_2 + \epsilon_E$$

$$p_D \approx a' + b'x_1 + c'x_2 + d'S_1 + e'S_2 + \epsilon_D$$

where the numerical subscripts indicate contemporaneous and future periods of time. These equations are what the econometrician sees. The econometrician does not observe the details of how prices are formed i.e., the interactions of the informed and the uninformed traders. The prices contain information (for the econometrician) about the future value of the firm and the future state of the banking system.

3 Measuring banks' information centrality

Our analysis builds on the insights of Davila and Parlatore (2022), who showed that a the coefficients estimates and R-squared of a linear regression of firm stock prices on a measure of firm fundamentals is sufficient to identify stock price informativeness about the evolution of the firm state. Their measure of relative price informativeness is the reduction in uncertainty about future firm states, relative to the remaining residual

uncertainty about future firm states, after conditioning on realized firm states and stock prices. Relative price informativeness takes values between 0 and 1, rendering it easy to interpret and compare across assets and time.[6] Like the theoretical model presented in section 2, the empirical measure used in this section is based on the notion of informativeness in Grossman and Stiglitz (1980). A difference relative to Davila and Parlatore (2022) is that we consider a framework in which firm security prices are informative about a linear combination of the idiosyncratic firm state and the state of the banking sector. Another difference is that we focus on the price informativeness of both firm stock and debt.

One key insight of Davila and Parlatore (2022) is that, under stylized assumptions, relative price informativeness corresponds to the Kalman gain of a Kalman filter applied to a linearized system with one noisy signal (price changes) about one unknown state (future earnings). In this section, we show how similar assumptions yield a measure of information about the state of the banking system from firm security prices using the difference between Kalman gains obtained from unconstrained and constrained Kalman filters. We only assume linear laws of motion with Gaussian noise to cast our problem as a Kalman filter and build intuition—

[6]Other measures of price informativeness, such as forecasting price efficiency (Bond, Edmans and Goldstein, 2012), are valid only after making assumptions about learning process(es) and the shapes of underlying distributions. In addition, those other measures of price informativeness typically depend on the volatility of states. The relative price informativeness measure suffers none of these shortcomings. Nevertheless, under certain conditions, there is a one-to-one mapping from relative price informativeness to those other notions of informativeness (Davila and Parlatore, 2022).

we do not need to make these assumptions to obtain the measure of relative price informativeness.

Start from the linearized debt and equity pricing equations derived in Section 2 and assume the following laws of motion for the state of the banking sector, S_t, and for the individual firm state, x_t:

$$\Delta x_{t+1} = \mu_{\Delta x} + \rho \Delta x_t + u_t \tag{5}$$

$$\Delta S_{t+1} = \mu_{\Delta S} + \rho_S \Delta S_t + w_t \ , \tag{6}$$

where $u_t \sim N(0, \sigma_u^2)$ and $w_t \sim N(0, \sigma_w^2)$.

Let the index $i \in \{\text{Debt}, \text{Equity}\}$ denote the asset type. We can then express the log-change in the equilibrium price of asset i as:

$$\Delta p_t^i = \bar{\phi}^i + \phi_0^i \Delta x_t + \phi_1^i \Delta x_{t+1} + \bar{\phi}_0^i \Delta S_t + \bar{\phi}_1^i \Delta S_{t+1} + \phi_n^i \Delta n_t^i \tag{7}$$

where the error term $\Delta n_t^i \sim N(\mu_{\Delta n^i}, \sigma_{\Delta n^i}^2)$.

After substituting the two laws of motion into the equilibrium asset price equations and rearranging, we obtain an expression for the linear combination of innovations in terms of Δp_t^i and the two state variables:

$$u_t + \frac{\bar{\phi}_1^i}{\phi_1^i} w_t = \frac{1}{\phi_1^i} \times \Big(\Delta p_t^i - \bar{\phi}^i + \phi_1^i \mu_{\Delta x} + \bar{\phi}_1^i \mu_{\Delta S} + \phi_n^i \mu_{\Delta n^i} - (\phi_0^i + \rho \phi_1^i) \Delta x_t - (\bar{\phi}_0^i + \rho_S \bar{\phi}_1^i) \Delta S_t - \phi_n^i \epsilon_t^{\Delta n^i} \Big)$$

Note that the ratio of parameters $\frac{\bar{\phi}_1^i}{\phi_1^i}$ is unknown. Therefore, $u_t + \frac{\bar{\phi}_1^i}{\phi_1^i} w_t$ for $i \in \{\text{Debt}, \text{Equity}\}$ are two unknown linear combinations of two unknown states, which we refer to as the *combined states*.

We can express the signal extraction problem in state space form by defining π_t^i as the noisy signal about the combined state, such that:

$$\pi_t^i = \left(u_t + \frac{\bar{\phi}_1^i}{\phi_1^i} w_t \right) + \frac{\phi_n^i}{\phi_1^i} (\Delta n_t^i - \mu_{\Delta n^i}),\ i \in \{\text{Debt}, \text{Equity}\},$$

which is a linear combination of Gaussian innovations. Without information about the true value of the linear combination of parameters, an investor uses price changes to learn about the combined state. We assume that the innovations to the two states, u_t and w_t, are orthogonal, which is a testable assumption in our empirical application.

We can use the state space form and standard Kalman filter arguments to measure how an external Bayesian observer learns about the unknown combined states from changes in asset prices. Our Kalman filtering problem has two noisy signals (equity and debt price changes) about two combined states ($u_t + \frac{\bar{\phi}_1^i}{\phi_1^i} w_t$ with $i \in \{\text{Debt}, \text{Equity}\}$). The Kalman gain of the Kalman filter is the optimal weight given to the changes in asset price measurements and the current-state estimate. Therefore, the Kalman gain is a 2×1 matrix where each element measures the informativeness of the i-th asset price

change about the i-th combined state.[7] For example, when the first element of the Kalman gain matrix corresponding to the debt price equation is close to 1, the external observer puts a relatively high weight on the information contained in the change in debt prices to revise his or her estimate of the debt-specific combined state $u_t + \frac{\bar{\phi}_1^{Debt}}{\phi_1^{Debt}} w_t$.

From the standard Kalman filter equations, it follows that the i-th element of the 2×1 Kalman gain matrix for this filtering problem is given by:

$$K_i = C_i^p H_i^T (H_i C_i^p H_i^T + C_{i,o})^{-1} = \frac{\sigma_u^2 + \left(\frac{\bar{\phi}_1^i}{\phi_1^i}\right)^2 \sigma_w^2}{\sigma_u^2 + \left(\frac{\bar{\phi}_1^i}{\phi_1^i}\right)^2 \sigma_w^2 + \left(\frac{\phi_n^i}{\phi_1^i}\right)^2 \sigma_{\Delta n^i}^2},$$

where $H_i = 1$ is the measurement sub-matrix, $C_{i,o} = \left(\frac{\phi_n^i}{\phi_1^i}\right)^2 \sigma_{\Delta n^i}^2$ is the measurement covariance sub-matrix, and $C_i^p = V\left(u_t + \frac{\bar{\phi}_1^i}{\phi_1^i} w_t\right) = \sigma_u^2 + \left(\frac{\bar{\phi}_1^i}{\phi_1^i}\right)^2 \sigma_w^2$ is the covariance sub-matrix for the predicted states at time t. Note that there is only one Kalman gain element per asset type because the Kalman filter is underdetermined: Each asset price change is a noisy signal about its respective unknown combined state: $u_t + \frac{\bar{\phi}_1^i}{\phi_1^i} w_t$ with $i \in \{\text{Debt}, \text{Equity}\}$.

We now show how to infer whether asset price changes contain

[7] In more technical terms, the i-th element of the Kalman gain matrix measures the precision of the i-th asset price signal about the i-th unknown combined state innovations relative to the precision of the prior and the signal precision of an external Bayesian observer who only learns about the i-th combined state from a firm i's asset price changes.

information about the state of the banking sector. We continue to use the Kalman filter and its properties for illustrative purposes only. Suppose the external Bayesian observer knows (or thinks) that the asset price changes do not contain information about the state of the banking sector. If this assumption is true, then a more efficient signal extraction can be obtained by imposing the following linear constraint in the original Kalman filter:

$$R_t \begin{pmatrix} u_t \\ \\ w_t \end{pmatrix} = r_t, \text{ where } R_t = \begin{pmatrix} 0 & 1 \end{pmatrix} \text{ and } r_t = 0. \tag{8}$$

The constraint can be added to the original Kalman filter by augmenting the vector measurement equations with one additional observation about the state vector (Doran, 1992). The state space representation of the *constrained* model can be written as:

$$\begin{pmatrix} \pi_t^{Debt} \\ \pi_t^{Equity} \\ \\ r_t \end{pmatrix} = \begin{pmatrix} 1 & \frac{\bar{\phi}_1^{Debt}}{\phi_1^{Debt}} \\ 1 & \frac{\bar{\phi^{Equity}}_1}{\phi_1^{Equity}} \\ 0 & 1 \end{pmatrix} \begin{pmatrix} u_t \\ \\ w_t \end{pmatrix} + \begin{pmatrix} \frac{\phi_n^{Debt}}{\phi_1^{Debt}}(\Delta n_t^{Debt} - \mu_{\Delta_n}^{Debt}) \\ \frac{\phi_n^{Equity}}{\phi_1^{Equity}}(\Delta n_t^{Equity} - \mu_{\Delta_n}^{Equity}) \\ 0 \end{pmatrix} \tag{9}$$

Imposing constraint (8) in the Kalman filter is equivalent to imposing the parametric constraint $\bar{\phi}_1^i = 0$ for all $i \in \{\text{Debt}, \text{Equity}\}$ in the structural equation (7). The only change relative to the unconstrained case is that $C_i^p = \sigma_u^2$ so that the i-th element of the 2×1 Kalman gain matrix for the

constrained problem is given by

$$\hat{K}_i = \frac{\sigma_u^2}{\sigma_u^2 + \left(\frac{\phi_n^i}{\phi_1^i}\right)^2 \sigma_{\Delta n^i}^2}, \quad i \in \{\text{Debt}, \text{Equity}\}.$$

Each element of the constrained 2×1 Kalman gain matrix is less than or equal to its counterpart in the unconstrained 2×1 Kalman gain matrix because each asset price signal is less informative about the state when the external observer erroneously assumes that the bank state is constant. To see this, define ΔK_i as the i-th element of a new 2×1 matrix obtained by subtracting the 2×1 constrained Kalman gain matrix from the 2×1 unconstrained Kalman gain matrix:

$$\Delta K_i = K_i - \hat{K}_i = \frac{\sigma_u^2 + \left(\frac{\bar{\phi}_1^i}{\phi_1^i}\right)^2 \sigma_w^2}{\sigma_u^2 + \left(\frac{\bar{\phi}_1^i}{\phi_1^i}\right)^2 \sigma_w^2 + \left(\frac{\phi_n^i}{\phi_1^i}\right)^2 \sigma_{\Delta n^i}^2} - \frac{\sigma_u^2}{\sigma_u^2 + \left(\frac{\phi_n^i}{\phi_1^i}\right)^2 \sigma_{\Delta n^i}^2},$$

with $i \in \{\text{Debt}, \text{Equity}\}$. It is clear that $\Delta K_i > 0$ when $\bar{\phi}_1^i \neq 0$, which occurs when asset prices are informative about the state of the banking sector.

The Kalman filtering problems described above provide intuition for the identification of relative price informativeness about the state of the banking sector. We now describe the empirical measures that we calculate in general terms and link them to the Kalman filtering problems.

3.1 Identification

We will run *two* pairs of regressions for each asset type. For ease of exposition, we temporarily drop the asset type index i. Consider first the pair of regression equations:

$$\Delta p_t = \bar{\beta} + \beta_0 \Delta x_t + \beta_1 \Delta x_{t+1} + \beta_2 \Delta S_t + \beta_3 \Delta S_{t+1} + e_t \qquad \text{(R1)}$$

$$\Delta p_t = \bar{\gamma} + \gamma_0 \Delta x_t + \gamma_1 \Delta S_t + e_t^{\gamma} \qquad \text{(R2)}$$

with the corresponding R^2 statistics given by:

$$R^2_{\Delta,\Delta'} = 1 - \frac{var(e_t)}{var(\Delta p_t)} \text{ and } R^2_{\Delta} = \frac{var(\gamma_0 \Delta x_t + \gamma_1 \Delta S_t)}{var(\Delta p_t)}$$

Substituting the two laws of motion into the structural equation yields:

$$\begin{aligned} \Delta p_t \;\; = \;\; & \bar{\phi} + \phi_1 \mu_{\Delta x} + \bar{\phi}_1 \mu_{\Delta S} + \phi_n \mu_{\Delta n} + (\phi_0 + \phi_1 \rho)\, \Delta x_t + \\ & \left(\bar{\phi}_0 + \bar{\phi}_1 \rho_S\right) \Delta S_t + \phi_1 u_t + \bar{\phi}_1 w_t + \epsilon_t^{\Delta n}. \end{aligned} \qquad (10)$$

Comparing equation (10) to regression equation R2 shows that: $\bar{\gamma} = \bar{\phi} + \phi_1 \mu_{\Delta x} + \bar{\phi}_1 \mu_{\Delta B} + \phi_n \mu_{\Delta n}$, $\gamma_0 = \phi_0 + \phi_1 \rho$, $\gamma_1 = \bar{\phi}_0 + \phi_1 \rho_B$, and $e_t^{\gamma} = \phi_1 u_t + \bar{\phi}_1 w_t + \epsilon_t^{\Delta n}$. Likewise, comparing regression equation R1 to the structural equation shows that: $\bar{\beta} = \bar{\phi} + \phi_n \mu_{\Delta n}$, $\beta_0 = \phi_0$, $\beta_1 = \phi_1$, $\beta_2 = \bar{\phi}_0$, $\beta_3 = \bar{\phi}_1$, and $e_t = \epsilon_t^{\Delta n}$. Exploiting the variance decomposition of equation (10) and

rearranging:

$$\frac{R^2_{\Delta,\Delta'} - R^2_{\Delta}}{1 - R^2_{\Delta}} = \frac{\sigma_u^2 + \left(\frac{\bar{\phi}_1}{\phi_1}\right)^2 \sigma_w^2}{\sigma_u^2 + \left(\frac{\bar{\phi}_1}{\phi_1}\right)^2 \sigma_w^2 + \left(\frac{\phi_n}{\phi_1}\right)^2 \sigma_n^2} = K \quad .$$

In words, the difference $R^2_{\Delta,\Delta'} - R^2_{\Delta}$ normalized by $1 - R^2_{\Delta}$ is identical to the Kalman gain from the unconstrained filtering problem. This combination of R^2 statistics identifies relative price informativeness, as in Davila and Parlatore (2022). Intuitively, the numerator is the percentage reduction in uncertainty about future combined state after observing the asset price and the realized value of the combined state. The denominator is the residual uncertainty about the future combined state after conditioning on the realized combined state.

Consider now a second pair of regression equations corresponding to the hypothesis under which a nonbank firm's asset price does not contain information about the state of the banking sector:

$$\Delta p_t = \bar{\alpha} + \alpha_0 \Delta x_t + \alpha_1 \Delta x_{t+1} + \bar{e}_t \tag{R3}$$

$$\Delta p_t = \bar{\delta} + \delta_0 \Delta x_t + \bar{e}_t^{\delta} \tag{R4}$$

with the corresponding R^2 statistics given by

$$R^2_{\Delta x,\Delta x'} = 1 - \frac{var(\bar{e}_t)}{var(\Delta p_t)} \text{ and } R^2_{\Delta x} = \frac{var(\delta_0 \Delta x_t)}{var(\Delta p_t)} \quad .$$

Using a similar argument, we obtain:

$$\frac{R^2_{\Delta x,\Delta x'} - R^2_{\Delta x}}{1 - R^2_{\Delta x}} = \frac{\sigma_u^2}{\sigma_u^2 + \left(\frac{\phi_n}{\phi_1}\right)^2 \sigma^2_{\Delta n}} = \hat{K} \quad .$$

This combination of R^2 statistics identifies relative price informativeness under the hypothesis that prices are not informative about the bank state– under this hypothesis, the combined state is simply the firm state. This measure is identical to the Kalman gain from the constrained filtering problem i.e., imposing constraint (8). The Kalman gain in this case is the reduction in uncertainty about the future firm state relative to the remaining residual uncertainty about the future firm state after conditioning on the realized firm state.

The difference between the two Kalman gains is a statistic—a combination of R^2 statistics from four regressions—that we use to test whether asset prices are informative about the banking sector. The *Kalman gain difference*, ΔK, can be written as:

$$\Delta K = \frac{R^2_{\Delta,\Delta'} - R^2_{\Delta}}{1 - R^2_{\Delta}} - \frac{R^2_{\Delta x,\Delta x'} - R^2_{\Delta x}}{1 - R^2_{\Delta x}}. \tag{11}$$

The statistic ΔK is close in spirit to a Wald statistic in the context of two nested linear regression models. That is, ΔK measures the distance between the (random) value of the Kalman gain in the unconstrained model

and the (random) value of the Kalman gain in the constrained model. Under the null hypothesis that asset prices are not informative about the future state of the banking sector, equivalent to satisfying constraint (8), then ΔK is not statistically different from 0.

In the remainder of this section, we show how we estimate ΔK from data and construct asymptotically valid hypothesis tests about banks' information centrality.

3.2 Estimation

We estimate time- and firm-specific measures of ΔK using rolling windows of data for each firm's debt and equity prices. We continue to suppress the index i for asset type. Let $\Delta K_{j,q}$ be the j-th firm's estimate of ΔK, calculated as the combination of R^2 statistics given in equation (11) and obtained by estimating the regression equations (R1)-(R4) on a rolling window $q \in \{1, \ldots, T\}$, where $j \in \{1, \ldots, J\}$. In our application, we use a 15-quarter rolling window. If we knew the distribution of $\Delta K_{j,q}$, we could test whether $\bar{\phi}_1 \neq 0$ for firm j in quarter q by testing if $\Delta K_{j,q}$ is statistically different from 0. However, a firm-level test is not feasible, as we only have one observation per firm in a rolling window.

Nevertheless, it is possible to obtain a consistent estimate of the distribution of the sample mean of $\Delta K_{j,q}$ across nonbank firms within a quarter q under weak assumptions. To proceed, we treat each firm-

level estimate $\Delta K_{j,q}$ as independently and identically distributed random variables drawn from a common yet unknown distribution. We can then use this estimate of the distribution to construct asymptotically valid hypothesis tests.

3.3 Statistical inference

We obtain an asymptotically valid hypothesis test for the sample mean of $\Delta K_{j,q}$ in each quarter q using the subsampling method (Politis et al., 1999). In each quarter q, we treat $\{\Delta K_{1,q}, \ldots, \Delta K_{J,q}\}$ as a sample of J independently and identically distributed random variables taking values in sample space Ω. This approach is justified as we estimate each $\Delta K_{j,q}$ independently. The probability law generating the sample $\{\Delta K_{1,q}, \ldots, \Delta K_{J,q}\}$ is P, which is unknown. Note that P could depend on q, which we omit from the notation for simplicity. We wish to estimate the true sampling distribution of the sample mean of $\Delta K_{j,q}$ in a given quarter q, denoted by $\hat{\theta}_{J,q}$, to make inference about $\theta(P)$, which, once again, could depend on q.

Denote by $\mathcal{J}_J(P)$ the sampling distribution of the normalized statistic $\sqrt{J}(\hat{\theta}_{J,q} - \theta(P))$ based on a sample of size J from P. The corresponding cumulative distribution function is given by:

$$\mathcal{J}_J(x, P) = Prob_P\{\sqrt{J}(\hat{\theta}_{J,q} - \theta(P)) \leq x\}.$$

The basic idea of subsampling is to approximate the sampling distribution of the mean of $\Delta K_{j,q}$ in a quarter q based on the means computed over all the possible smaller firm subsets of size $c < J$ of $\Delta K_{j,q}$ from the same quarter. Politis et al. (1999) shows that subsampling behaves well under extremely weak assumptions because each subset of size c taken without replacement from the original sample of size n is a sample of size c from the true model. The only additional assumption needed to construct asymptotically valid confidence intervals for $\theta(P)$ is Assumption 1 below:

Assumption 1 *There exists a limiting law $\mathcal{J}(P)$ such that $\mathcal{J}_J(P)$ converges weakly to $\mathcal{J}(P)$ as $J \to \infty$.*

The subsampling method consists of approximating the sampling distribution of $\sqrt{J}(\hat{\theta}_{J,q} - \theta(P))$ with the empirical distribution generated by its subsample counterpart. Let $Y_1, \ldots, Y_{N_J}$ be equal to the $N_J = \binom{J}{c}$ subset of size c of the quarter q sample $\{\Delta K_{1,q}, \ldots, \Delta K_{J,q}\}$. Each subset Y_k depends on c and J, which we omit from the notation for simplicity. Let $\hat{\theta}_{J,c,t,k}$ be the average of $\Delta K_{j,q}$ calculated over the subset Y_k. The approximation to $\mathcal{J}_J(x, P)$ is defined by

$$L_{J,c}(x) = N_J^{-1} \sum_{k=1}^{N_J} 1\{\sqrt{c}(\hat{\theta}_{J,c,q,k} - \hat{\theta}_{J,q}) \leq x\}.$$

Note that our limiting concept is that the number of firms in a quarter q becomes large.

Theorem A.1 in Appendix A from Politis et al. (1999) shows that we can derive asymptotically valid confidence intervals for $\hat{\theta}_{J,q}$ using $L_{J,c}(x)$ because it is a consistent estimator of $\mathcal{J}(x, P)$. Then, we can draw asymptotically valid inference about the true $\theta(P)$ by exploiting the usual duality between the construction of confidence intervals for the sample mean $\hat{\theta}_{J,q}$ and the construction of hypothesis tests about $\hat{\theta}_{J,q}$.

In our application, we wish to test the null hypothesis that each quarter's $\theta(P)$ is 0. That is, the null hypothesis in each quarter is that the average nonbank firm's asset prices do not contain information about the future state of the banking sector. This test is equivalent to testing whether constraint (8) in the Kalman filtering problem holds on average. If the value of the estimated $\theta(P)$ for quarter q falls outside the quarterly confidence interval, we reject the null hypothesis on that date.

3.4 Measurement

Thus far, we have shown how to obtain an asymptotically valid test of banks' information centrality using nonbank firms' asset prices. Our statistical test answers the question: Do asset price changes contain information about the future state of the banking sector? Moving beyond this hypothesis test, we turn to the issue of *measuring* the level of bank information in nonbank firms' asset prices. We are particularly interested in measuring variation in price informativeness across asset types and over

time. In other words, when is debt more informative than equity about the state of the banking system?

Measuring the level of bank information content in nonbank firms' asset prices requires obtaining a consistent estimate of both K and $\hat{K}$. (Note again that our hypothesis test only requires a consistent estimate of ΔK.) The ordinary least square estimate of $\hat{K}_{j,q}$ is consistent if $Cov(u_t, w_t) = 0$ holds. Under this additional assumption, the residuals in the constrained pair of regression equations R2 and R4 are orthogonal to the regressors. Although it is not obvious whether this assumption holds *a priori*, it is straightforward to test it and we discuss the details in Appendix C. In the rest of this section, we assume that $Cov(u_t, w_t) = 0$ holds.

From the above discussion, conducting inference on the amount of information contained in asset prices about the state of the banking system is limited by the presence of the unknown and idiosyncratic linear combination parameters $\frac{\bar{\phi}_1^i}{\phi_1^i}$ with $i \in \{\text{Debt}, \text{Equity}\}$. This feature means that our estimate of ΔK is a lower bound estimate of the average information about the state of the banking sector. To see this, note that the estimate of $\Delta K_{j,q}$ partially identifies the information content about the state of the banking system in a nonbank firm j's asset price (Manski, 2009; Tamer, 2010). More formally, under our stylized linear Gaussian

assumptions:

$$0 \leq \Delta K \leq \frac{\sigma_u^2 + \left(\frac{\bar{\phi}_1}{\phi_1}\right)^2 \sigma_w^2}{\sigma_u^2 + \left(\frac{\bar{\phi}_1}{\phi_1}\right)^2 \sigma_w^2 + \left(\frac{\phi_n}{\phi_1}\right)^2 \sigma_n^2} - \frac{\sigma_u^2}{\sigma_u^2 + \left(\frac{\bar{\phi}_1}{\phi_1}\right)^2 \sigma_w^2 + \left(\frac{\phi_n}{\phi_1}\right)^2 \sigma_n^2}$$
$$= \frac{\sigma_w^2}{\sigma_w^2 + \left(\frac{\phi_1}{\bar{\phi}_1}\right)^2 \sigma_u^2 + \left(\frac{\phi_n}{\bar{\phi}_1}\right)^2 \sigma_n^2} \leq 1.$$

This inequality means that the price informativeness about the state of the banking system is bounded from below by our estimate of ΔK and bounded from above by 1. This is intuitive because changes in ΔK conditional on $\bar{\phi}_1 \neq 0$ could be driven by changes in either the measurement or noise process. Or, put differently, ΔK is the most an external observer can learn about the state of the banking sector by analyzing changes in asset prices. Therefore, the sample mean of $\Delta K_{j,q}$ in quarter q is a conservative estimate. When the sample mean of $\Delta K_{i,q}$ is statistically different from 0 and asset prices do contain information about the state of the banking system, its value is a lower bound estimate of the true price informativeness. The sample mean of ΔK measures the fraction of an external observer's precision about the state of the banking sector that is conveyed, on average, by observing asset prices. For example, an average ΔK of 0.3 means that, on average, at least 30 percent of investors' ex-post precision about the innovation to the state of the banking sector comes from conditioning on non-financial firm asset prices.

4 Data

Our empirical analysis uses data on equity prices, debt prices, the state of individual nonbank firms, firm-level debt refinancing, and the state of the banking system. We construct our data closely following Davila and Parlatore (2022). In this section, we describe our entire process in detail.

For equity prices, we begin with the merged CRSP-COMPUSTAT database and the COMPUSTAT bank fundamentals data provided by Wharton Research Data Services (WRDS). We use monthly stock prices adjusted for stock splits and deflated using the personal consumption expenditure price index (PCEPI) from FRED.[8] We winsorize these prices at the 2.5^{th} and 97.5^{th} percentiles. We calculate the three month change in the log stock prices and then lag the data by three months before merging with COMPUSTAT data to ensure that the data were public during the period of trading.

For debt prices, we begin with the daily ICE-IDC database, which is the leading provider of evaluated prices for the widest range of corporate fixed income securities. We identify a firm by its equity ticker, which restricts us to large issuers of corporate debt. We find 5,956 individual bonds for 792 individual firms. We can match 97 percent of these firms to CRSP

[8]We restrict the sample to securities listed on the NYSE, AMEX, or NASDAQ for standard, consolidated, domestic firms reporting the industrial format. We link the datasets using the linktypes 'LU', 'LC', or 'LS' and with issue marker 'P' or 'C'.

by ticker.[9] We then calculate a weighted-average bond price for each firm, where the weights are the amounts of each bond outstanding. We deflate these prices using the PCEPI from FRED and winsorize them at the 2.5^{th} and 97.5^{th} percentiles. We calculate the three month change in the log bond prices and then lag the data by three months before merging with COMPUSTAT data to ensure that the data were public during the period of trading.

4.1 State of nonbank firms

As our measure of the state of the firm we use quarterly earnings before interest and tax (EBIT) deflated using the PCEPI and winsorized as for equity prices. As earnings can be negative, we calculate the growth rate in earnings as:

$$\Delta x_t = \begin{cases} \frac{x_t}{x_{t-1}} - 1 & \text{if } x_{t-1} > 0 \\ \frac{x_t}{|x_{t-1}|} + 1 & \text{if } x_{t-1} < 0 \\ NA & \text{if } x_{t-1} = 0 \end{cases} \tag{12}$$

We merge these data with the lagged quarterly change in equity prices using the CCM data crosswalk provided by WRDS.

[9] Although we match ICE-IDC to CRSP by ticker, our firm-level analysis is done using firms identified by GVKEY from COMPUSTAT, as described later, to avoid concerns about significant changes in firm structure over time.

Our analysis uses firm-level debt refinancing that we construct using Moody's Credit Watch data, which provides detailed information about individual debt actions including when a bond is called or paid down early. We use the firm organization structure from Moody's to aggregate information about actions on individual bonds issued by all subsidiaries up to the parent company identified by its ticker.[10] For each bond, we construct a daily time series of the amount outstanding, paying close attention to calls and paydowns. We then aggregate for each firm the total amount scheduled to mature in the coming twelve months and divide by the total amount outstanding.

We restrict our sample to public nonbank firms that we could match in CRSP and IDC. These firms finance their operations by issuing publicly listed equity and public corporate debt. We match by ticker. We identify nonbank firms as those whose two-digit SIC code is not 60-62. There are roughly 250 firms at the end of our sample. Table 2 shows the distributions of their total asset size ($bn) at the end of each year in our sample. Evidently, these are all large firms. Table 3 shows the count of firms by credit ratings at the end of each year in our sample.

[10]Moody's also provides the CIK identifier. The final merge of Moody's data with CRSP-ICE-IDC is done using the GVKEY identifier, which we obtain using the CIK-GVKEY crosswalk from WRDS.

Table 2: Firm total assets ($bn) at end of year.

Year	N	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
2005	74	0.01	14.26	26.06	61.11	48.62	968.41
2006	80	0.01	12.83	26.88	50.43	49.53	588.97
2007	85	2.01	16.50	32.84	67.27	52.35	1126.70
2008	85	2.18	15.47	29.42	48.29	51.05	303.25
2009	90	2.18	17.04	33.32	59.24	58.20	824.29
2010	94	2.46	16.01	37.56	67.39	60.23	781.42
2011	99	2.43	15.90	35.95	68.68	61.65	809.95
2012	114	2.65	16.07	33.84	59.97	63.95	680.72
2013	134	0.39	13.57	31.63	59.02	64.62	645.45
2014	149	1.76	10.75	28.62	49.43	55.76	509.98
2015	187	0.98	7.74	21.56	42.47	46.69	534.75
2016	214	0.73	6.84	18.31	43.61	44.67	592.50
2017	220	0.74	6.66	17.07	44.08	46.25	675.02
2018	244	0.70	6.48	13.94	38.40	40.26	631.21
2019	262	0.69	6.50	14.66	43.44	41.09	740.54

4.2 State of the banking system

Our measure of the state of the banking system is the equity capital ratio of financial intermediaries from He et al. (2017), henceforth HKM.[11] An important qualification is that He et al. (2017) calculate the equity capital ratio using only Primary Dealer counterparties of the New York Federal Reserve, rather than all commercial banks. As such, it represents a specific–albeit central–part of the financial system. The equity capital ratio is a measure of financial system leverage, whose effect on the real economy has been studied in an extensive literature.[12] We calculate its growth rate

[11]Downloaded in January 2022 from `https://voices.uchicago.edu/zhiguohe/`.

[12]See, for example, Bernanke, Lown and Friedman (1991); Hancock and Wilcox (1998); Van den Heuvel (2008); Meh and Moran (2010).

Table 3: Moody's credit ratings for firms at the end of each year.

Year	Aaa	Aa	A	Baa	Ba	B	Caa
2005	7	10	38	16	1	0	0
2006	7	12	40	18	0	0	0
2007	8	13	40	21	0	0	0
2008	7	14	34	18	0	0	0
2009	7	13	37	22	0	1	0
2010	7	15	43	28	0	1	0
2011	7	15	45	26	2	0	0
2012	7	16	51	36	1	0	0
2013	7	15	53	51	3	3	0
2014	6	15	54	63	4	3	0
2015	7	17	60	80	7	7	0
2016	8	19	56	87	16	15	0
2017	8	18	56	94	19	19	0
2018	9	17	56	100	26	28	0
2019	9	18	51	105	29	22	1

$\Delta b_t = \frac{b_t}{b_{t-1}} - 1$. As an alternative measure of the state of the banking system, we consider the asset-weighted average net interest margin for all available banks in Appendix D.1.

In the next section, we present our main results about the price informativeness of nonbank firms' asset prices for the future state of the banking system.

5 Informativeness of debt and equity prices

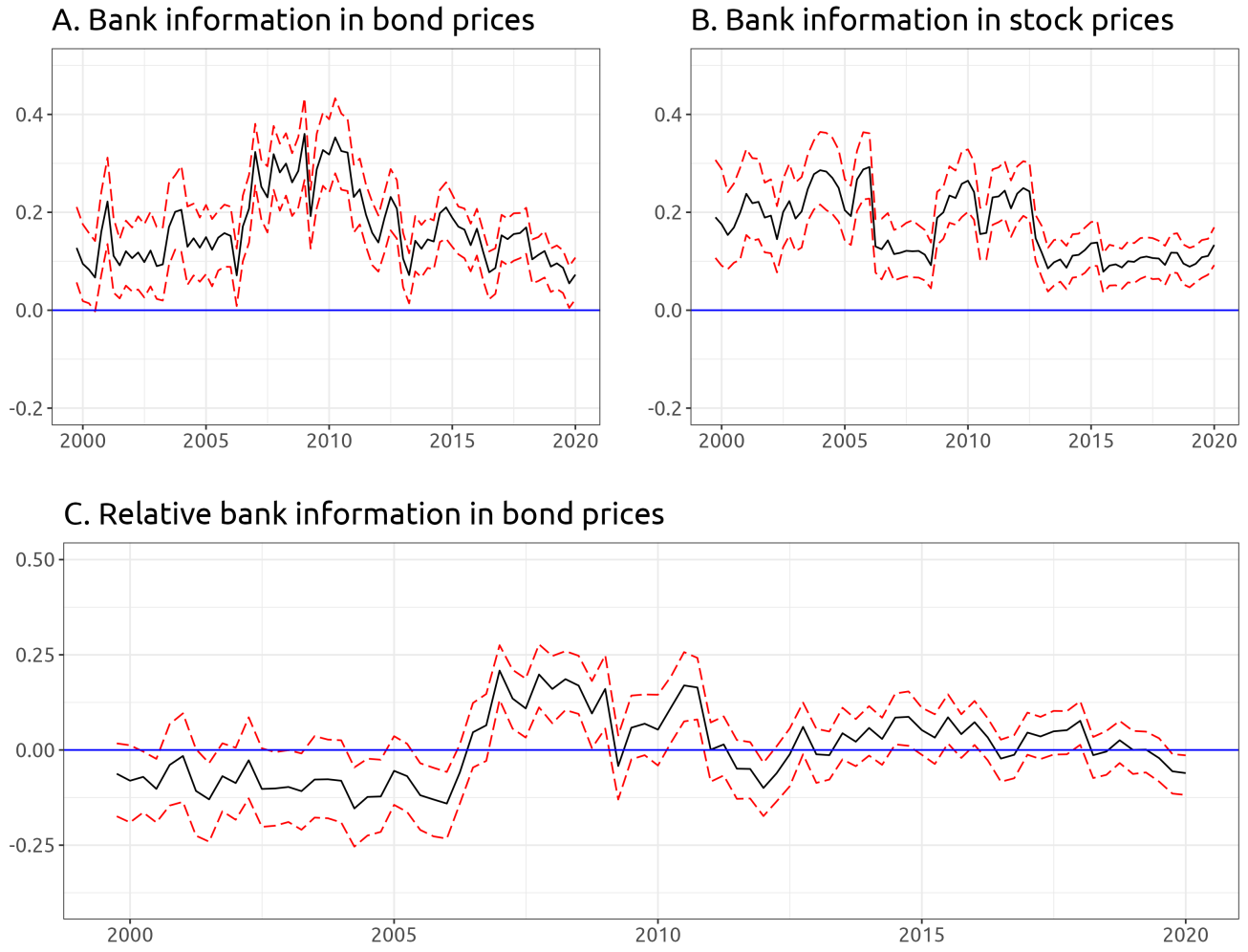
Figure 1 summarizes our main findings. In each quarter q from 1999Q3 to 2020Q4, we estimate $\Delta K_{q,i}$ for each firm $i \in \{1, \ldots, n_q\}$ in our matched

sample using quarterly observations from $t = q$ to $t = q + 14$. We choose a 15-quarter rolling window width because it is a good compromise between retaining high-frequency variation in information flow and a large enough sample for ordinary least square estimation.

The solid black line in panels A and B of Figure 1 is the average of $\Delta K_{i,q}$ taken across firms in quarter q i.e., $\Delta K_q = \frac{1}{n_q} \sum_{i=1}^{n_q} \Delta K_{i,q}$. The 99 percent confidence interval (CI) of ΔK_q obtained with subsampling is represented by the upper and lower dashed red lines. Panels A and B plot the banking sector information content in nonbank firms' debt and equity prices, respectively. Whenever the ΔK_q CI lies above 0, nonbank firms' debt or equity contain statistically significant information about the state of the banking sector, on average. Note that, because the information content is partially identified (section 3.4) our estimates are a lower bound for the information content about the state of the banking system. For example, panel A in Figure 1 shows that during the financial crisis 2007-2009, at least 30 percent of investors' ex-post precision about the innovation to the state of the banking sector came from conditioning on nonbank firms' debt prices.

Table 4 reports summary statistics for the time series reported in Panels A and B of Figure 1. The upper and lower parts of the table shows statistics for debt and equity, respectively. The summary statistics suggest that, in normal times, the information content of debt and equity about

Figure 1: Information in asset prices about the future state of the banking system. The figure shows the time series of the sample mean of $\Delta K_{i,q}$ for debt (Panel A), equity (Panel B), and the difference between debt and equity (Panel C). The state of the banking system is measured as the equity capital ratio of financial intermediaries (He et al., 2017). The red dashed lines in each figure show the 99 percent subsampling confidence intervals. Source: Authors' calculations based on data from CRSP, COMPUSTAT, and ICE-IDC.



the future state of the banking system is about the same. By contrast, during the 2007-09 financial crisis, the information content of debt was about 50 percent higher than that of equity.

Table 4: Summary statistics of the information in asset prices about the future state of the banking system. The table shows summary statistics across nonbank firms and time for debt and equity of $\Delta K_{i,q}$, representing the information content in prices about the future state of the banking system, measured as the equity capital ratio of financial intermediaries (He et al., 2017). The period of the crisis is defined as 2007Q3-2009Q4. Source: Authors' calculations based on data from CRSP, COMPUSTAT, and ICE-IDC.

	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Debt							
full sample	10,653	0.161	0.176	−0.525	0.032	0.252	0.978
crisis sample	954	0.256	0.209	−0.361	0.088	0.403	0.968
no crisis sample	9,699	0.152	0.169	−0.525	0.028	0.235	0.978
Equity							
full sample	10,653	0.149	0.179	−0.480	0.021	0.233	0.985
crisis sample	954	0.170	0.175	−0.272	0.032	0.267	0.985
no crisis sample	9,699	0.147	0.179	−0.480	0.020	0.229	0.957

Panel C of Figure 1 expands the analysis of the information content of debt *relative to* equity about the state of the banking sector. The black line is $\Delta K_q^{debt} - \Delta K_q^{equity}$ with the 99 percent CI obtained by subsampling represented by the dashed red lines. Whenever the CI is above zero, debt contains more information than equity on average, and *vice versa* when the CI is below zero. The main takeaway from the difference between the two measures is that debt and equity contain roughly the same information about the banking sector in normal times. However, during the financial

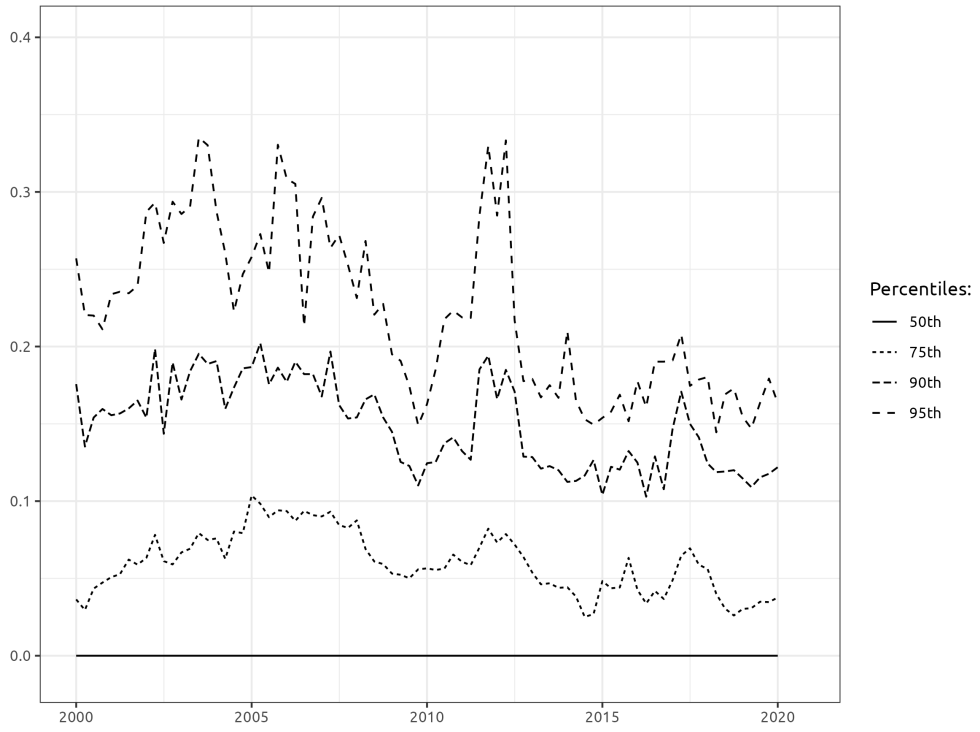
crisis of 2007-2009, nonbank firms' debt prices contained significantly more information about the state of the banking sector.

6 Why was debt more informative?

We investigate the drivers of variation in the relative information content of debt prices during the financial crisis 2007-2009 using firm-level regressions. Informed by our theoretical model in section 2, our analysis focuses on refinancing risk. For each firm in our matched sample we use data from Moody's to create a quarterly time series of how much of that firm's corporate debt will mature in the next 12 months expressed as a fraction of that firm's total amount of debt outstanding. When calculating the total amount outstanding we are careful to account for debt that is called by the firm using detailed rating changes information.

Figure 2 plots the distribution across all firms' debt refinancing ratio in each quarter. The median fraction of debt maturing within 12 months is essentially zero over the sample period. Most of the variation comes from firms in the upper part of the distribution. There is a gradual widening of the distribution in the year leading up to the financial crisis 2007-2009 followed by a substantial contraction during the crisis.

Figure 2: Distribution of the ratio of debt maturing within 12 months to total debt outstanding across nonbank firms



We implement our test with the following regression specification:

$$\begin{aligned}\text{KG\_ddiff}_{i,q} =& \beta_0 + \beta_1 \text{crisis}_q + \beta_2 \text{Debt\_12m\_roll}_{i,q} \\ &+ \beta_3 \text{crisis}_q \times \text{Debt\_12m\_roll}_{i,q} + \epsilon_{i,q} \quad .\end{aligned}$$

Our dependent variable $\text{KG\_ddiff}_{i,q} = \Delta K_{i,q}^{debt} - \Delta K_{i,q}^{equity}$ is the informativeness of firm i's debt prices about the future state of the banking sector relative to the informativeness of the same firm's equity prices in quarter q. The binary variable crisis_q takes the value 1 if the quarter q falls in the range 2007Q3-2009Q4 and 0 otherwise. The variable $\text{Debt\_12m\_roll}_{i,q}$ is

the ratio of the par value of firm i's corporate debt maturing in the next 12 months to the same firm's total par value of corporate debt outstanding in quarter q (shown in Figure 2). Table 5 contains summary statistics of the regression variables.

Table 5: Summary statistics of regression variables.

	N	Mean	St. Dev.	Min	Max
$\text{KG\_ddiff}_{i,q}$					
full sample	10,653	0.012	0.225	−0.979	1.101
crisis sample	954	0.086	0.261	−0.751	0.985
no crisis sample	9,699	0.005	0.220	−0.979	1.101
$\text{Debt\_12m\_roll}_{i,q}$	7,331	0.052	0.097	0	1
crisis_q	10,653	0.090	0.286	0	1

Table 6 summarizes the regression results. We report bootstrapped standard errors that are clustered at the firm level. In Column 2, the coefficient on the interaction term between $\text{Debt\_12m\_roll}_{i,q}$ and crisis_q suggests that a one standard deviation (50 percent) increase in our debt refinancing measure during the 2007-2009 financial crisis implies that investors' ex-post precision about the innovation to the state of the banking sector was 1 percentage point greater when conditioning on debt prices relative to equity prices. As a benchmark for economic significance, note that the *unconditional* increase in the difference in informativeness during the 2007-2009 financial crisis was 6 percentage points (Column 1).

Columns 4 and 5 include firm fixed effects to analyze the within-firm effect. We find similar results indicating that the relevant variation is within firms over time, rather than across firms.

What about equity? It pays to produce information when the uncertainty about future payments is greatest.[13] During the Financial Crisis it may well have been the case that investors believed that the prospects for equity values were dire. In that case, it may have been that it was not profitable to produce information. Equity holders knew the situation was dire without producing information. But debt holders wanted to know how bad the crisis would be for their specific firm as it might affect not just the payout, but also the payout timing or recovery values that are outside the scope of our model, which entails producing information about the future state of the banking sector.[14]

7 Conclusion

Banks are at the center of the savings-investment process. Banks are special. One reason is that they produce short-term debt. But another reason is that firms rely on banks for loans and to underwrite their debt. Firms have relationships with banks. Consequently, firms care about the

[13]While this is quite intuitive, it cannot be proven analytically in our model. With the same asset price formation protocol, Chousakos et al. (2023) provide a numerical example showing this.

[14]This is a topic for further research.

Table 6: Debt refinancing determines the amount of information about the future state of the banking system conveyed in debt prices relative to equity prices. The dependent variable is $\text{KG\_ddiff}_{i,q} = \Delta K^{debt}_{i,q} - \Delta K^{equity}_{i,q}$, as defined in the text. The first explanatory variable is crisis_q, which takes the value 1 if the quarter q falls in the range 2007Q3-2009Q4 and 0 otherwise. The second explanatory variable ($\text{Debt\_12m\_roll}_{i,q}$) is the ratio of the par value of firm i's corporate debt maturing in the next 12 months to the same firm's total par value of corporate debt outstanding in quarter q (shown in Figure 2). Table 5 contains summary statistics of the regression variables. We report bootstrapped standard errors clustered at the firm level with 2,999 replications. Note: *p<0.1; **p<0.05; ***p<0.01

Dep. var.: $\text{KG\_ddiff}_{i,q}$	(1)	(2)	(3)	(4)
crisis_q	0.055**	0.060***	0.058**	0.062***
	(0.022)	(0.021)	(0.023)	(0.021)
$\text{Debt\_12m\_roll}_{i,q}$		0.022		0.023
		(0.056)		(0.069)
$\text{Debt\_12m\_roll}_{i,q} \times \text{crisis}_q$		0.203**		0.259***
		(0.090)		(0.098)
Constant	0.001	0.009		
	(0.008)	(0.007)		
Firm FE	N	N	Y	Y
Observations	7,331	7,331	7,331	7,331
Adjusted R^2	0.013	0.011	0.157	0.158

future state of the banking system. We showed that firms' debt and equity prices reflect information about the future state of the banking system.

Financial crises have been viewed as information events in which information-insensitive short-term bank debt becomes sensitive. We showed that corporate debt also displays an important change in information sensitivity during a financial crisis. Corporate debt becomes 50 percent more informative than equity during the 2007-2009 financial crisis. The reason is partly due to refinancing risk: firms are concerned that they will not be able to borrow to refinance existing debt during the crisis.

References

Adrian, Tobias, Arturo Estrella, and Hyun Song Shin, "Risk-taking channel of monetary policy," *Financial Management*, 2019, *48* (3), 725–738.

_ , Erkko Etula, and Tyler Muir, "Financial Intermediaries and the Cross-Section of Asset Returns," *Journal of Finance*, 2014, *LXIX*, 2557–2596.

Bassett, William F., Mary Beth Chosak, John Driscoll, and Egon Zakrajsek, "Changes in Bank Lending Standards and the Macroeconomy," *Journal of Monetary Economics*, 2014, *62* (C), 23–40.

Benmelech, Efraim, Carola Frydman, and Dimitris Papanikolaou, "Financial Frictions and Employment during the Great Depression," *Journal of Financial Economics*, 2018, *133*, 541–563.

Bernanke, Ben S, Cara S Lown, and Benjamin M Friedman, "The credit crunch," *Brookings Papers on Economic Activity*, 1991, *1991* (2), 205–247.

Bond, Philip, Alex Edmans, and Itay Goldstein, "The Real Effects of Financial Markets," *Annual Review of Financial Economics*, 2012, *4* (1), 339–360.

Castro, Andrew, David Glancy, Felicia Ionescu, and Greg Marchal, "What Happens When Banks Tighten C&I Loan Supply?," *FEDS Notes*, 2022.

Chava, Sudheer and Amiyatosh Purnanandam, "The Effect of Banking Crisis on Bank-Dependent Borrowers," *Journal of Financial Economics*, 2011, *99* (1), 116–135.

Chodorow-Reich, Gabriel, "The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008-09 Financial Crisis," *Quarterly Journal of Economics*, 2014, *129* (1).

Chousakos, Kyriakos, Gary Gorton, and Guillermo Ordoñez, "Information Dynamics and Macro Fluctuations," *American Economic Journal: Macro, forthcoming*, 2023.

Claessens, Stijn and Luc Laeven, "Financial Dependence, Banking Sector Competition, and Economic Growth," *Journal of the European Economic Association*, 2005, *3* (1), 179–207.

Commission, Financial Crisis Inquiry, *The Financial Crisis Inquiry Report of the National Commission on the Causes of the Financial and Economic Crisis*, U.S. Government Printing Office, 2012.

Dang, Tri Vi, Gary Gorton, and Bengt Holmström, "The Information View of Financial Crises," *Annual Review of Financial Economics*, 2020, *12*, 39–65.

Davila, Eduardo and Cecilia Parlatore, "Identifying Price Informativeness," Working Paper, Yale University 2022.

den Heuvel, Skander J Van, "The welfare cost of bank capital requirements," *Journal of Monetary Economics*, 2008, *55* (2), 298–320.

Doran, Howard E, "Constraining Kalman filter and smoothing estimates to satisfy time-varying restrictions," *The Review of Economics and Statistics*, 1992, pp. 568–572.

Grossman, Sanford and Joseph Stiglitz, "On the impossibility of Informationally Efficient Markets," *American Economic Review*, 1980, *70* (3), 393 – 408.

Hancock, Diana and James A Wilcox, "The "credit crunch" and the availability of credit to small business," *Journal of Banking & Finance*, 1998, *22* (6), 983–1014.

He, Zhiguo and Arvind Krishnamurthy, "Intermediary Asset Pricing," *American Economic Review*, 2013, *103* (2), 732–770.

_ , Brian Kelly, and Asaf Manela, "Intermediary Asset Pricing: New Evidence from Many Asset Classes," *126*, 2017, pp. 1–35.

Lown, Cara and Donald Morgan, "The Credit Cycle and the Business Cycle: New Findings Using the Loan Officer Opinion Survey," *Journal of Money, Credit and Banking*, 02 2006, *38*, 1575–1597.

Lown, Cara S. and Donald Morgan, "Credit effects in the monetary mechanism," *NY Fed Economic Policy Review*, 2002, *8* (May), 217–235.

Manski, Charles F, *Identification for prediction and decision*, Harvard University Press, 2009.

Meh, Césaire A. and Kevin Moran, "The role of bank capital in the propagation of shocks," *Journal of Economic Dynamics and Control*, 2010, *34* (3), 555–576.

Ottonello, Pablo and Wenting Song, "Financial Intermediaries and the Macroeconomy: Evidenc from a High-Frequency Identification," Working Paper 29638, National Bureau of Economic Research January 2022.

Owens, Raymond and Stacey Schreft, "Survey Evidence of Tighter Credit Conditions: What Does It Mean?," *Federal Reserve Bank of Richmond Economic Review*, 1991.

Paravisini, Daniel, "Local Bank Financial Constraints and Firm Access to External Finance," *The Journal of Finance*, 2008, *63* (5), 2161–2193.

Politis, Dimitris, Joseph Romano, and Michael Wolf, *Subsampling*, Springer-Verlag, 1999.

Tamer, Elie, "Partial identification in econometrics," *Annu. Rev. Econ.*, 2010, *2* (1), 167–195.

Appendix for online publication

A Asymptotically valid hypothesis tests of price informativeness

In each rolling window $q \in \{1, \ldots, T\}$, denote by $\Delta K_{j,q}$ the j-th firm's asset (debt or equity) price informativeness of about the future state of the banking sector in rolling window q, where $j \in \{1, \ldots, m\}$. As in the main text, we drop the asset type index i for readability. In each q, we treat $\{\Delta K_{1,q}, \ldots, \Delta K_{m,q}\}$ as a sample of m independently and identically distributed random variables taking values in the sample space Ω–recall that each $\Delta K_{j,q}$ is estimated independently. The probability law generating the sample $\{\Delta K_{1,q}, \ldots, \Delta K_{m,q}\}$ is P, which is unknown. It is understood that P could depend on q, which we omit from the notation for simplicity. We wish to estimate the true sampling distribution of the sample mean of $\Delta K_{j,q}$ in a given rolling window q, denoted by $\hat{\theta}_{m,q}$, to make inference about $\theta(P)$, which, once again, could depend on q.

Denote by $J_m(P)$ the sampling distribution of the normalized statistic $\sqrt{m}(\hat{\theta}_{m,q} - \theta(P))$ based on a sample of size m from P. The corresponding cumulative distribution function is given by:

$$J_m(x, P) = Prob_P\{\sqrt{m}(\hat{\theta}_{m,q} - \theta(P)) \leq x\}.$$

As explained by Politis et al. (1999), the only assumption needed to construct asymptotically valid confidence intervals for $\theta(P)$ is Assumption 2 below:

Assumption 2 *There exists a limiting law $J(P)$ such that $J_m(P)$ converges weakly to $J(P)$ as $m \to \infty$.*

Let $Y_1, \ldots, Y_{N_m}$ be equal to the $N_m = \binom{m}{c}$ subset of size c of the time q sample $\{\Delta K_{1,q}, \ldots, \Delta K_{m,q}\}$. Each subset Y_k depends on c and m, which we omit from the notation for simplicity. Let $\hat{\theta}_{m,c,q,k}$ be the average calculated over the subset Y_k. The approximation to $J_n(x, P)$ is defined by

$$L_{m,c}(x) = N_m^{-1} \sum_{k=1}^{N_m} 1\{\sqrt{c}(\hat{\theta}_{m,c,q,k} - \hat{\theta}_{m,q}) \leq x\}.$$

Our limiting concept is that the number of firms in a rolling window q becomes large. The following theorem of subsampling (Theorem 2.2.1 from Politis et al. (1999)) follows:

Theorem A.1 *Assume Assumption 1 and assume that $c/m \to 0$ and $c \to \infty$ as $m \to \infty$.*

i. If x is a continuity point of $J(\cdot, P)$, then $L_{m,c}(x) \to J(x, P)$ in probability

ii. If $J(\cdot, P)$ is continuous, then $\sup_x |L_{m,c}(x) - J_m(x, P)| \to 0$ in probability.

iii. Let

$$a_{m,c}(1-\alpha) = \inf\{x : L_{m,c}(x) \geq 1-\alpha\}.$$

Correspondingly, define

$$a(1-\alpha, P) = \inf\{x : J(x, P) \geq 1-\alpha\}.$$

If $J(\cdot, P)$ *is continuous at* $a(1-\alpha, P)$*, then*

$$Prob_P\{\sqrt{n}(\hat{\theta}_{m,q} - \theta(P)) \leq a_{m,c}(1-\alpha)\} \to 1-\alpha \text{ as } m \to \infty.$$

Therefore, the asymptotic coverage probability under P *of the confidence interval* $[\hat{\theta}_{m,q} - \sqrt{m}^{-1} a_{m,c}(1-\alpha), \infty)$ *is the nominal level* $1-\alpha$.

iv. Assume $\sqrt{c}(\hat{\theta}_{m,q} - \theta(P) \to 0$ *almost surely and, for every* $d > 0$*,*

$$\sum_m \exp\{-d(m/c)\} < \infty.$$

Then, the convergence in i. and ii. holds with probability one.

Theorem A.1 shows that we can derive asymptotically valid confidence intervals for the average debt or equity price informativeness of about the future state of the banking sector in rolling window q using $L_{m,c}(x)$ because

it is a consistent estimator of $J(x, P)$. By exploiting the usual duality between the construction of confidence interval for the sample mean $\hat{\theta}_{m,q}$ and the construction of hypothesis test about $\hat{\theta}_{m,q}$, subsampling allow us to draw asymptotically valid inference about the true $\theta(P)$. In our application, we wish to test the null hypotheses that the daily $\theta(P)$ equals zero. That is, under the null, the average nonbank firm's asset prices do not contain information about the future state of the banking sector. If the value zero is outside the daily confidence interval, we reject null hypotheses on that date.

B Bootstrapping and subsampling

The subsampling method is not as well known as the bootstrap method in economics and finance, which warrants a cursory comparison—see Politis et al. (1999) for textbook-length treatment. The most relevant bootstrap method for our application is the block bootstrap. In a given rolling window q, the block bootstrap draws entire firm-level time series with replacement to form a bootstrap sample of size n and evaluate the statistic of interest on the set of bootstrap samples to estimate its sampling distribution. A key issue with the block bootstrap is establishing consistency for the distribution of a sample mean. In our application, this requires establishing that the distribution of the average $\Delta K_{i,q}$ is locally smooth as a function of the unknown model. Therefore, we would either need to assume such smoothness or verify such smoothness by making assumptions about the (unknown) true model. Neither of these options is desirable in our application. A considerable advantage of subsampling is that we do not need to make such assumptions or carry out this type of verification to draw asymptotically valid inference. All that is required is that our (normalized) statistic has a limit distribution under the true model.

C Consistency of the ΔK estimate

It is straightforward to investigate the validity of assuming that $Cov(u_t, w_t) = 0$ holds by regressing firm state innovations on the bank state innovations with and without firm fixed effects. The results are summarized in Table 7. The lack of statistical significance between the firm state innovations (DeltaEarnings$_{i,t}$) and the bank state innovations (DeltaHKM$_t$ and DeltaNIM$_t$) confirm that the two state innovations are uncorrelated.

Table 7: Correlation between firm state and bank state innovations. Columns 1 and 3 report Driscoll-Kraay standard errors and Columns 2 and 4 report firm-level clustered standard errors.

Dep. var: DeltaEarnings$_{i,t}$	(1)	(2)	(3)	(4)
DeltaHKM$_t$	0.74	0.64		
	(0.52)	(0.62)		
DeltaNIM$_t$			0.78	0.72
			(0.72)	(0.91)
Firm FE	N	Y	N	Y
Standard errors				
Driscoll-Kraay	Y	N	Y	N
Cluster by firm	N	Y	N	Y
R^2	0	0.04	0	0.04
Observations	309,645	309,645	312,492	312,492

D Notes on merging data

List of identifiers by dataset:

- IDC identifiers are *CUSIP* and *ticker*.
- CRSP identifiers are *permno* and *ticker*.
- COMPUSTAT identifiers are *gvkey* and *ticker*.
- Moody's debt data identifiers are *OrgID*, *ticker*, *CIK*, and *CUSIP*.

Summary of merging process:

- We use CCM (accessed through WRDS) to match CRSP and COMPUSTAT
  - This is a well-known and often-used match between *permno* and *gvkey* that is date dependent.
- We use ticker-date to match IDC-CRSP
  - There are 767 unique ticker matches.
  - Of the universe of ticker-dates in IDC, 90 percent are matched in CRSP.
- The only identifier from our analysis of CRSP-IDC is *gvkey*.
- We use several cross-walks to merge with Moody's debt data.
  1. WRDS provides a crosswalk from *gvkey* to *CIK*.
     - This is a unique match that yields 35,000 firms.
  2. SEC provides a crosswalk from *CIK* to *ticker*.
     - There are many related tickers (preferred stock, reinsurer, units...)
  3. We constructed a new merged crosswalk *ticker-CIK-gvkey* that yields 427 unique matches.
  4. We then merged this new cross-walk to include many Moody's *OrgID* identifiers that represent subsidiaries of the 427 entities identified by *ticker-CIK-gvkey*.

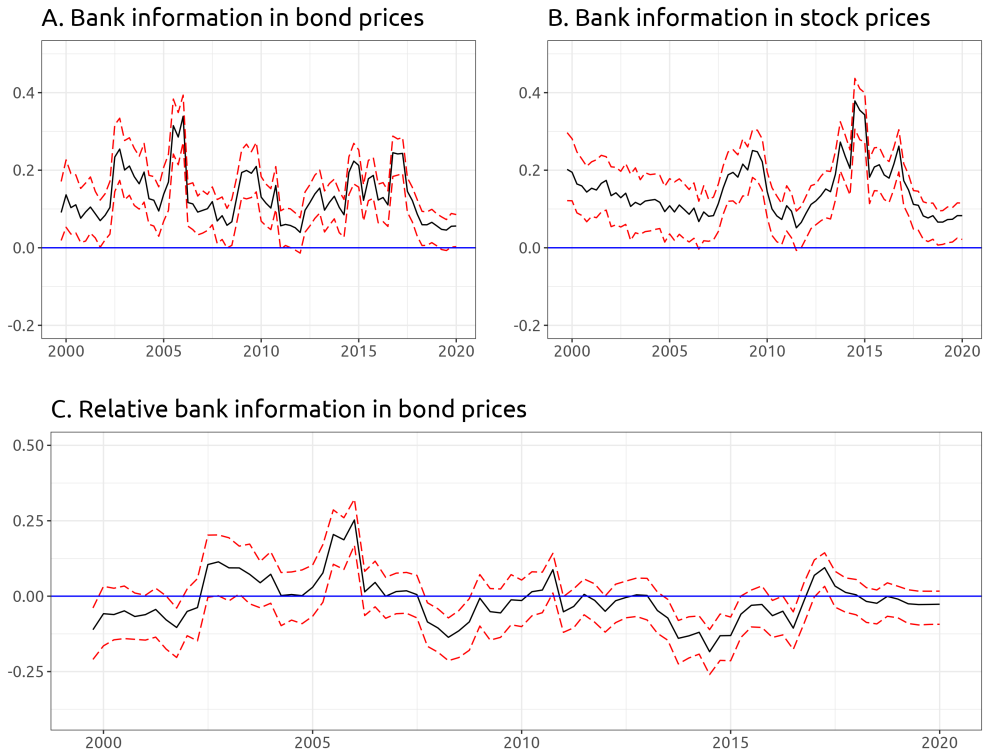
D.1 Alternative state of the banking system

From the COMPUSTAT bank fundamentals quarterly data, we construct our second state variable for the state of the banking system as the asset-weighted average net interest margin (NIM) for all available banks.[15] NIM is the difference between the interest income earned and the interest paid by a bank scaled by its assets. This measure reflects the state of the banking sector as it is generally viewed as a barometer of the effectiveness—or profitability—of a bank's investment decisions. It captures the flow of profit from the stock of assets and liabilities on the bank's balance sheet. When aggregated, the measure is a common proxy for efficiency of the banking sector as a whole. Lastly, the role of NIM in banks' credit decisions means it can be a channel for policy to affect real economic activity (Adrian, Estrella and Shin, 2019). In contrast to our main measure of the state of the banking sector, which is a stock measure calculated using the stock of assets and liabilities on the balance sheet, NIM is a flow measure. Nevertheless, there is a relationship between our two state variables because a bank's equity depends on the (discounted) flows of profit, including flows from NIM.

Figure 3 summarizes our main findings. The solid black line in the top panels of figure 3 is the average of $\Delta K_{i,q}^{NIM}$ taken across firms in quarter q–

[15] We use all available banks because He et al. (2017) do not report the GVKEY identifiers of the primary dealer counterparties used to construct their data. We exclude observations where NIM was recorded as being greater than 100.

Figure 3: NIM as the state of the banking sector



i.e., $\Delta K_q^{NIM} = \frac{1}{n_q} \sum_{i=1}^{n_q} \Delta K_{i,q}^{NIM}$. The 99 percent confidence interval (CIs) of ΔK_q^{NIM} obtained with subsampling is represented by the upper and lower dashed red lines. The top left and right charts plot the banking sector information content in nonbank firms' debt and equity prices, respectively. Whenever zero is outside the CI, nonbank firm debt or equity contain statistically significant information about the state of the banking sector, on average.

The bottom chart in figure 3 investigates the relative information content of debt and equity about the state of the banking sector over

the sample period. The black line is $\Delta K_q^{NIM,debt} - \Delta K_q^{NIM,equity}$ with the 99 percent subsampling CI represented by the dashed red lines. Whenever the CI is above zero, debt contains more information than equity on average, and *vice versa* when the CI is below zero. The results are roughly similar to those we obtained using HKM as the bank state variable.

We implement our test with the following regression specification:

$$\begin{aligned}\text{KG\_ddiff}_{i,q}^{NIM} =& \beta_0 + \beta_1 \text{crisis}_q + \beta_2 \text{Debt\_12m\_roll}_{i,q} \\ &+ \beta_3 \text{crisis}_q \times \text{Debt\_12m\_roll}_{i,q} + \epsilon_{i,q},\end{aligned}$$

Our dependent variable $\text{KG\_ddiff}_{i,q}^{NIM} = \Delta K_{i,q}^{NIM,debt} - \Delta K_{i,q}^{NIM,equity}$ is the informativeness of firm i's debt prices about the future state of the banking sector relative to the informativeness of its equity prices in quarter q. The binary variable crisis_q takes the value 1 if the quarter t falls in the time range 2007Q3-2009Q4 and 0 otherwise. The variable $\text{Debt\_12m\_roll}_{i,q}$ measures how much of firm i's corporate debt is maturing in the next 12 months. We use two different measures. One measure is simply the ratio of firm i's corporate debt maturing in the next 12 months to this firm total debt outstanding in quarter q. The second measure is an indicator variable that takes the value 1 if the share of firm i's debt maturing in the next 12 months is above the median share of all firms in that quarter.

The results shown in Table 8 using NIM as the bank state variable are

similar as the ones obtained using the HKM ratio as the bakn state variable. Columns 1 and 2 report the pooled cross-section, while columns 3 and 4 focus on within-firm variation. We report clustered bootstrapped standard errors with clustering at the firm level.

Table 8: Debt information about banks—pooled regressions We report bootstrapped standard errors clustered at the firm level with 2,999 replications. Note: *p<0.1; **p<0.05; ***p<0.01

Dep. var.: KG_ddiff$_{i,q}^{NIM}$	(1)	(2)	(3)	(4)
crisis$_q$	-0.072^{***}	-0.046^{**}	-0.079^{***}	-0.046^{**}
	(0.023)	(0.019)	(0.022)	(0.019)
Debt_12m_roll$_{i,q}$ (dummy) $\times$crisis$_q$	0.081^{**}		0.089^{***}	
	(0.032)		(0.030)	
Debt_12m_roll$_{i,q}$ (ratio) $\times$crisis$_q$		0.206^{**}		0.174
		(0.101)		(0.111)
Debt_12m_roll$_{i,q}$ (dummy)	-0.015^{*}		-0.008	
	(0.008)		(0.009)	
Debt_12m_roll$_{i,q}$ (ratio)		-0.067^{*}		-0.042
		(0.040)		(0.047)
Constant	0.003	0.0003		
	(0.006)	(0.005)		
Firm FE	N	N	Y	Y
Observations	6,583	6,583	6,583	6,583
Adjusted R^2	0.005	0.003	0.067	0.065