Information Networks over the Business Cycle*

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Abstract

We calculate a sectoral-level information flow matrix, quarterly, using a structural model of firm managers learning from equity prices. We then calculate *network informativeness*, measuring how easily information flows across sectors. We study relationships over the business cycle between network informativeness and macroeconomic variables. We find that network informativeness is a leading indicator of real business cycles. In time-series analysis, information flowing more easily occurs before stronger industrial production and real GDP. We link network informativeness to information production by equity analysts. Our measure correlates with the analyst recommendation cycle lagged by several quarters.

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1 Introduction

What is the relationship between macroeconomic outcomes and the flow of information through financial markets? In this paper, we examine how information propagates across sectors by constructing a sectoral information network based on stock prices. We introduce a new measure, *network informativeness*, which captures how effectively stock prices reflect and transmit economically-relevant signals that guide firms' investment decisions. Network informativeness generalizes the concept of price informativeness across an economic network. While price informativeness assesses how well stock prices reflect firm fundamentals, network informativeness extends this concept by incorporating cross-sectoral information flow, capturing coordination effects that influence macroeconomic dynamics. Consider two sectors: if firms in Sector A heavily rely on stock price signals from Sector B when making investment decisions, information flows efficiently across the economy. Our measure captures this cross-sector information reliance. When network informativeness is high, stock prices contain signals that firms effectively use for investment decisions. When it is low, price movements are noisy or segmented, limiting firms' ability to coordinate investments across sectors. We then study how our measure of network informativeness relates to the business cycle. We show that information production by equity analysts Granger causes our measure.

Our network-based measure is informed by a model in which managers use a Kalman filter to extract information from stock prices, updating their beliefs about their firm's future earnings and aggregate investment. Each firm manager makes investment decisions based on their expectations of their firm's expected future earnings, their expectations of their sector's future aggregate state, and their expectations about other sectors' future aggregate states.

By imposing restrictions on the manager's information production process, the model provides a lens to understand our empirical measures. Consider three different Kalman processes. First, the Kalman gain K_i represents the case where the manager

of firm i examines only firm-specific signals, with no influence from sector-wide or cross-sectoral signals. Second, the sector-specific Kalman gain K_{jj} captures the extent to which firm managers in sector j rely on information about firm-specific and sector-wide signals only within their own sector, with no cross-sectoral signals. A higher value of K_{jj} indicates that managers place more weight on signals from their own firm and sector. And third, the cross-sectoral Kalman gain $K_{j\ell}$ measures the importance of information coming from other sectors. A higher value of $K_{j\ell}$ means that managers in sector j place more weight on cross-sectoral information coming from the price signal of sector ℓ.

We show that averaging and comparing these Kalman gains across firms yields Kalman gain differences that measure how much managers learn from asset prices within their own sector compared to asset prices from other sectors. For example, the sector-specific Kalman gain difference between the sector-wide average of K_{jj} and K_i, $\Delta\bar{K}_{jj} \equiv \bar{K}_{jj} - \bar{K}_j$, measures the additional weight managers in sector j place on their own-sector signals beyond own-firm signals. Similarly, the Kalman gain difference between the sector-wide average of $K_{j\ell}$ and K_i, $\Delta\bar{K}_{j\ell} \equiv \bar{K}_{j\ell} - \bar{K}_j$, measures the additional weight managers place on signals from another sector ℓ.

We then construct a matrix to represent the flow of information by managers observing stock prices across the economy:

$$\begin{bmatrix} \Delta\bar{K}_{1,1} & \cdots & \Delta\bar{K}_{1,J} \\ \vdots & \ddots & \vdots \\ \Delta\bar{K}_{J,1} & \cdots & \Delta\bar{K}_{J,J} \end{bmatrix}$$

where each entry measures how much managers rely on sectoral signals averaged across firms in that sector. The diagonal entries measure own-sector signals and the off-diagonal entries measure other sector signals.

The matrix naturally forms a network of information flow, which can be studied using tools from network theory. In particular, we quantify how easily

information flows across the entire network, capturing how well sectors in the economy communicate.[1] Our measure is analogous to how easily water flows through a network of pipes or how much resistance restricts current is in an electronic circuit. A higher measure means that shorter paths exist between sectors, facilitating faster and more accurate flow of information, potentially producing better coordination of investment decisions.

We take this measurement framework to the data using CRSP-COMPUSTAT as a data source with a long time series of stock prices and firm earnings. We estimate the sectoral matrix of information flow quarterly and calculate a time series of how easily information flows through the network. Consistent with time series of stock price informativeness, our measure has a long-term upward trend (Bai, Philippon and Savov, 2016).

We then extract the business cycle component of how easily information flows through the network by removing the Hodrick-Prescott trend and we compare its cyclical variation with other macroeconomic variables. Our main finding is that our measure has a significant time-series relationship with the macroeconomic business cycle. Easier information flows tend to occur before stronger industrial production and real GDP. These dynamics reverse after information flow becomes more restricted.

We show that this interpretation is supported by evidence from a well-established measure of information production: analyst stock recommendations. Our measure of how easily information flows through the network is correlated with the analyst recommendation production cycle lagged by two to three quarters. In other words, a rise in analysts' information production tends to precede improved information flow and, subsequently, stronger economic growth.

[1] In other contexts, our measure is termed the "global efficiency" of a network. We avoid that term to prevent any potential confusion of our measure with the terms "price efficiency" or "allocative efficiency".

1.1 Related literature

Our study relates to two key strands of research: business cycle theory and financial market information dynamics. First, the paper connects to the real business cycle (RBC) literature, particularly the role of information frictions in economic fluctuations. Veldkamp (2006) argues that information acquisition costs vary over the business cycle, influencing economic decision-making. The findings in this paper suggest that network informativeness is itself cyclical, supporting Veldkamp's view that information frictions shape economic dynamics. Similarly, the study builds on Angeletos and La'O (2013), who emphasize signal quality and coordination, showing how better information flow improves economic coordination. This paper extends their framework by highlighting how network informativeness changes over time, adding a dynamic perspective to coordination frictions.

Beyond macroeconomic theory, the paper engages with the literature on information in financial markets and its real effects. Bond, Edmans and Goldstein (2012), as well as Goldstein (2023), review how information embedded in stock prices influences firm investment and broader economic activity. This study contributes to this line of research by introducing network informativeness as a new measure of how information moves across sectors, demonstrating its relationship with economic fluctuations. The results show that network informativeness is not just a reflection of economic activity but actively shapes investment behavior, reinforcing the view that financial market signals play a central role in economic coordination.

Finally, the study connects with models of self-fulfilling expectations and sentiment-driven cycles. The sentiment model of Angeletos and La'O (2013) shows how beliefs and imperfect information drive macroeconomic fluctuations, even in the absence of fundamental changes. This paper provides empirical support for this mechanism, showing that network informativeness rises during booms as firms coordinate expectations. By incorporating insights from monetary policy, credit cycles, and firm-level investment behavior, the study broadens the scope of the

literature on financial markets and macroeconomic coordination, offering a new perspective on how information networks contribute to business cycles.

The remainder of the paper proceeds as follows. Section 2 develops the theoretical model of sectoral coordination under information frictions. Section 3 derives a measure of information flow based on firm-level signal extraction. Section 4 formalizes the network informativeness measures. Sections 5 and 6 describe the data and estimation strategy. Sections 7 through 9 interpret the empirical results in light of the theoretical framework, and Section 10 concludes.

2 A model of endogenous multi-sector firm investment and coordination

To build intuition for the main result, we first describe a simplified version of the model with a single sector and homogeneous firms. We define the equilibrium of the model in which firms' expectations are consistent with actual outcomes. We prove existence of an equilibrium and derive the conditions under which the equilibrium is unique. We also describe the conditions under which multiple equilibria can arise due to self-reinforcing feedback loops between the sector-wide state and firm investment decisions.

We then generalize the model to multiple sectors and heterogeneous firms.

2.1 Ba'sic set-up: A one-sector economy with homogeneous firms

A manager of firm i in sector j makes an investment decision ΔI_t^{ij} in period t based on the realized changes in firm earnings and sector-wide aggregate investment, as well as their expectations of future trends in both. Stock prices act as a signal for both firm-specific fundamentals and broader macroeconomic conditions.

The state of the individual firm, denoted by x_t^{ij}, and the aggregate state of the

sector, denoted by S_t^j, follow the laws of motion:

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

$$\Delta S_{t+1}^j = \mu_{\Delta S}^j + \rho_S^j \Delta S_t^j + \alpha \sum_i \Delta I_t^{ij} + w_t^j, \tag{2}$$

where $u_t^{ij} \sim N(0, \sigma_u^2)$ and $w_t^j \sim N(0, \sigma_w^2)$. The term $\alpha \sum_i \Delta I_t^{ij}$ introduces the endogenous feedback effect, where the aggregate sectoral state depends on the investment decisions of all firms in the sector.

Each manager makes their investment decision based on the expected change in both firm-specific future earnings Δx_{t+1}^{ij} and the sectoral aggregate investment state ΔS_{t+1}^j:

$$\Delta I_t^{ij} = g(\mathbb{E}_t[\Delta x_{t+1}^{ij}], \mathbb{E}_t[\Delta S_{t+1}^j]), \tag{3}$$

where $g(\cdot)$ represents the firm's optimal policy rule. Managers use a Kalman filter to extract information from stock prices, updating their beliefs about future firm earnings and aggregate sectoral investment.

Assume the equilibrium one-period change in the stock price for firm i in sector j is given by:

$$\Delta p_t^{ij} = \bar{\phi}^j + \phi_0^j \Delta x_t^{ij} + \phi_1^j \Delta x_{t+1}^{ij} + \bar{\phi}_0^j \Delta S_t^j + \bar{\phi}_1^j \Delta S_{t+1}^j + \phi_n^j \Delta n_t^{ij}, \tag{4}$$

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

Substituting the laws of motion into equation (4), we can express the signal extraction problem in state-space form, where the noisy signal π_t about the combined state is:

$$\pi_t = \left(u_t^{ij} + \frac{\bar{\phi}_1^j}{\phi_1^j} w_t^j \right) + \frac{\phi_n^j}{\phi_1^j} (\Delta n_t - \mu_{\Delta n}),$$

an *unknown* linear combination of Gaussian innovations. Firm managers use this noisy signal to update their expectations of both the individual firm state x_t^{ij} and the sectoral aggregate S_t^j.

From the standard Kalman filter equations, it follows that the Kalman gain for this filtering problem is given by:

$$K = C^p H^T (H C^p H^T + C_o)^{-1} = \frac{\sigma_u^2 + \left(\frac{\bar{\phi}_1^j}{\phi_1^j}\right)^2 \sigma_w^2}{\sigma_u^2 + \left(\frac{\bar{\phi}_1^j}{\phi_1^j}\right)^2 \sigma_w^2 + \left(\frac{\phi_n^j}{\phi_1^j}\right)^2 \sigma_{\Delta n}^2}, \tag{5}$$

where $H = 1$ is the measurement sub-matrix, $C_o = \left(\frac{\phi_n}{\phi_1^j}\right)^2 \sigma_{\Delta n}^2$ is the measurement covariance sub-matrix, and $C^p = V\left(u_t^{ij} + \frac{\bar{\phi}_1^j}{\phi_1^j} w_t^j\right) = \sigma_u^2 + \left(\frac{\bar{\phi}_1^j}{\phi_1^j}\right)^2 \sigma_w^2$ is the covariance sub-matrix for the predicted states at time t. Equation (5) is the unique Kalman gain element because the Kalman filter is underdetermined: The stock price change is a noisy signal about the unknown combined state: $u_t^{ij} + \frac{\bar{\phi}_1^j}{\phi_1^j} w_t^j$.

The Kalman filter updates are applied to the changes in the firm-specific state x_{t+1}^{ij} and the sector-wide state S_{t+1}^j. However, the investment function in equation (3) depends on the expectations of the *levels* of these states. Thus, to derive the expectations of the levels from the Kalman filter, we need to account for both the current levels and the expected changes.

The Kalman filter update for the changes in the firm-specific state is:

$$\mathbb{E}_t[\Delta x_{t+1}^{ij}] = \Delta \hat{x}_{t+1}^{ij} + K\left(\Delta p_t^{ij} - \Delta \hat{x}_{t+1}^{ij}\right), \tag{6}$$

where $\Delta \hat{x}_{t+1}^{ij}$ is the prior estimate of the change in the firm's state, Δp_t^{ij} is the observed change in stock price, and K is the Kalman gain.

Similarly, the Kalman filter update for the changes in the sector-wide state is:

$$\mathbb{E}_t[\Delta S_{t+1}^j] = \Delta \hat{S}_{t+1}^j + K\left(\Delta p_t^{ij} - \Delta \hat{S}_{t+1}^j\right). \tag{7}$$

Despite the presence of the unknown linear combination of innovations, $u_t^{ij} + \frac{\bar{\phi}_1^j}{\phi_1}{}^j w_t^j$, the Kalman filter updates shown in equations (6) and (7) allow the manager

to systematically integrate new information, thus refining their expectations and guiding their investment decisions in the context of endogenously determined sector-wide outcomes.

Remark Our one-sector model differs from the sentiment model of Angeletos and La'O (2013) by embedding an endogenous feedback loop between firm investment decisions and sectoral outcomes. Although Angeletos and La'O (2013) emphasize coordination frictions arising from exogenous private signals, firms in our model respond to public stock price signals that reflect both firm-specific earnings and aggregate investment, which are endogenously influenced by firm behavior. This feedback loop allows firm actions to directly affect the sectoral state, which in turn modifies the signals they rely on for decision-making. In contrast, investment coordination in Angeletos and La'O (2013) is driven by correlated private signals that do not alter the macroeconomic environment's fundamental structure. Our model is more closely aligned with the framework of Acharya, Benhabib and Huo (2021), who examine how firms' beliefs about future productivity can become self-fulfilling. However, economic outcomes in their model are shaped by firm-level actions driven by optimistic or pessimistic expectations and not direct signaling from financial markets. In our model, managers coordinate their investments based on the signals about both firm-specific fundamentals and aggregate sectoral investment decisions embedded in stock prices. This introduces a feedback loop between firm actions and stock prices leading to endogenous fluctuations and amplifying potential coordination failures.

In a self-fulfilling equilibrium, managers' expectations are consistent with actual outcomes, and those expectations influence actions that precede those outcomes.

Definition 1 *A **self-fulfilling equilibrium** is a set of expectations* $\mathbb{E}_t[\Delta x_{t+1}^{ij}]$ *and* $\mathbb{E}_t[\Delta S_{t+1}^{j}]$*, along with investment decisions* ΔI_t^{ij}*, such that:*

1. ***Expectations are consistent***: *The managers' expectations about firm-specific future states* Δx_{t+1}^{ij} *and sector-wide future states* ΔS_{t+1}^{j} *are consistent with the actual outcomes, i.e.,*

$$\mathbb{E}_t[\Delta x_{t+1}^{ij}] = \Delta \hat{x}_{t+1}^{ij} + K\left(\Delta p_t^{ij} - \Delta \hat{x}_{t+1}^{ij}\right),$$

$$\mathbb{E}_t[\Delta S_{t+1}^{j}] = \Delta \hat{S}_{t+1}^{j} + K\left(\Delta p_t^{ij} - \Delta \hat{S}_{t+1}^{j}\right),$$

where Δp_t^{ij} *is the observed price change and* K *is the Kalman gain.*

2. ***Actions are based on expectations***: *The investment decisions* ΔI_t^{ij} *are based on the expectations of future firm-specific and sector-wide states:*

$$\Delta I_t^{ij} = g(\mathbb{E}_t[\Delta x_{t+1}^{ij}], \mathbb{E}_t[\Delta S_{t+1}^{j}]).$$

3. ***Outcomes reflect actions***: *The actual outcomes for firm-specific and sector-wide states follow the laws of motion:*

$$\Delta x_{t+1}^{ij} = \mu_{\Delta x}^{j} + \rho^{j} \Delta x_t^{ij} + u_t^{ij},$$

$$\Delta S_{t+1}^{j} = \mu_{\Delta S}^{j} + \rho_S^{j} \Delta S_t^{j} + \alpha \sum_i I_t^{ij} + w_t^{j},$$

where $u_t^{ij} \sim N(0, \sigma_u^2)$ *and* $w_t^{j} \sim N(0, \sigma_w^2)$.

Assume the investment function $g(\cdot)$ is linear such that

$$\Delta I_t^{ij} = a\mathbb{E}_t[\Delta x_{t+1}^{ij}] + (1-a)\mathbb{E}_t[\Delta S_{t+1}^{j}],$$

where $a \in (0, 1)$. Assume further that the shock variances are finite and the state variables are bounded.

Proposition 2.1 *There exits a self-fulfilling equilibrium.*

Proof *The set of expectations* $(\mathbb{E}_t[\Delta x_{t+1}^{ij}], \mathbb{E}_t[\Delta S_{t+1}^{j}])$ *is compact and convex. Compactness arises from the bounded state variables, which are governed by the autoregressive structure and finite variances of the Gaussian noise. Convexity holds because expectations are formed as linear combinations of normally distributed random variables. The mapping from expectations to outcomes, given by the linear investment function and the Kalman filter update, is continuous. The Kalman filter updates depend smoothly on the observed price changes and the underlying state estimates, as the Kalman gain itself is a continuous function of the covariance matrix derived from the finite variance assumptions. Since the expectation space is non-empty, convex, and compact, and the mapping from expectations to outcomes is continuous, Brouwer's fixed point theorem guarantees the existence of a fixed point in the expectation space. This fixed point corresponds to a self-fulfilling equilibrium where the firms' expectations are consistent with the actual outcomes.* ∎

Proposition 2.2 *The self-fulfilling equilibrium is unique if* $1 - \alpha(1-a)\rho_S^j > 0$, *where:*

- α *captures the strength of the feedback between firm investment decisions and the sector-wide state* S_t^j.
- $1 - a$ *represents the weight mangers place on the sector-wide expectations.*
- ρ_S^j *is the persistence parameter of the sectoral state* S_t^j.

Proof *The self-fulfilling equilibrium requires consistency between expectations and actual outcomes. Substituting the expectations into the investment function and the law of motion for the sector-wide state, we get:*

$$\Delta I_t^{ij} = a\left(\Delta x_t^{ij} + K\Delta p_t^{ij} + (1-K)\Delta\hat{x}_{t+1}^{ij}\right) + (1-a)\left(\Delta S_t^j + K\Delta p_t^{ij} + (1-K)\Delta\hat{S}_{t+1}^j\right).$$

Aggregating across all firms, the law of motion for the sector-wide state becomes:

$$\Delta S_{t+1}^j = \mu_{\Delta S}^j + \rho_S^j \Delta S_t^j + \alpha \sum_i \Bigg(a \left(\Delta x_t^{ij} + K \Delta p_t^{ij} + (1-K) \Delta \hat{x}_{t+1}^{ij} \right) + (1-a) \left(\Delta S_t^j + K \Delta p_t^{ij} + (1-K) \Delta \hat{S}_{t+1}^j \right) \Bigg) + w_t^j.$$

For the equilibrium to be unique, we need to ensure that there is a single set of consistent expectations that firms use to make their investment decisions. This can be achieved if $1 - \alpha(1-a)\rho_S^j > 0$. ∎

This condition in Proposition 2.2 ensures that the sector-wide feedback is not too strong.[2] The term $\alpha(1-a)\rho_S^j$ represents the total influence of intra-sectoral feedback on the sector-wide state. If $\alpha(1-a)\rho_S^j$ is too large, multiple equilibria could arise due to self-reinforcing feedback loops between the sector-wide state and firm investment decisions. This is because firms make investment decisions based on expectations about their own firm-specific future state and the sector-wide future state. These expectations influence their investments, which in turn affect the sector-wide state S_t^j. This feedback can produce multiple equilibria:

- **Optimistic beliefs** Firms expect the sector to perform well, invest more, and thereby improve the sector's performance, validating their optimistic beliefs.
- **Pessimistic beliefs** Firms expect poor sectoral performance, invest less, and thus weaken the sector, validating their pessimistic beliefs.

[2] If the investment function $g(\cdot)$ is nonlinear, the condition for uniqueness may require a bound on the sensitivity of g with respect to expectations. Specifically, if we define the partial derivatives $g_x = \frac{\partial g}{\partial \mathbb{E}_t[\Delta x_{t+1}^{ij}]}$ and $g_S = \frac{\partial g}{\partial \mathbb{E}_t[\Delta S_{t+1}^j]}$, the stability condition ensuring uniqueness would be generalized to: $1 - \alpha g_S \rho_S^j > 0$, where g_S replaces the constant weight $(1-a)$. This condition requires that the responsiveness of investment to sector-wide expectations does not amplify feedback loops excessively. More generally, a contraction mapping argument would require that the combined feedback effect from expectations through investment back to the state variables remains below unity in magnitude. Without such a bound, nonlinearities in the response function can generate multiple fixed points, leading to potential multiplicity of self-fulfilling equilibria.

2.2 Extension to the multi-sector case with firm heterogeneity

In the one-sector model, we assumed homogeneous firms with identical noise variances across all firms and sectors. Now, we introduce heterogeneous firms, allowing the variances of firm-specific and sector-wide shocks to differ. This modification yields new derivations of the Kalman gains, investment decisions, and equilibrium uniqueness condition. Note that there is now a firm-specific Kalman gain.

Assume the economy consists of J sectors each with N_j firms with $j \in \{1, \ldots, J\}$. In the multi-sector heterogeneous firm model, the updated laws of motion for the firm-specific state x_t^{ij} and the sector-wide state S_t^j now incorporate heteroscedastic noise:

$$\Delta x_{t+1}^{ij} = \mu_{\Delta x}^j + \rho^j \Delta x_t^{ij} + u_t^{ij}, \quad u_t^{ij} \sim N(0, \sigma_{u^{ij}}^2),$$

$$\Delta S_{t+1}^j = \mu_{\Delta S}^j + \rho_S^j \Delta S_t^j + \alpha \sum_i \Delta I_t^{ij} + w_t^j, \quad w_t^j \sim N(0, \sigma_{w^j}^2),$$

$$\Delta S_{t+1}^k = \mu_{\Delta S}^k + \rho_S^k \Delta S_t^k + \alpha \sum_i \Delta I_t^{ik} + w_t^k, \quad w_t^k \sim N(0, \sigma_{w^k}^2) \quad \forall k \neq j.$$

Firm-specific and sector-specific variances are now heterogeneous, which impacts how firms update their expectations through the Kalman filter.

The firm-specific Kalman gain for firm i in sector j, denoted K_{ij}, is now:

$$K_{ij} = \frac{\sigma_{u^{ij}}^2 + \left(\frac{\bar{\phi}_1^j}{\phi_1^j}\right)^2 \sigma_{w^j}^2 + \sum_{k \neq j} \left(\frac{\bar{\gamma}_1^k}{\phi_1^j}\right)^2 \sigma_{w^k}^2}{\sigma_{u^{ij}}^2 + \left(\frac{\bar{\phi}_1^j}{\phi_1^j}\right)^2 \sigma_{w^j}^2 + \sum_{k \neq j} \left(\frac{\bar{\gamma}_1^k}{\phi_1^j}\right)^2 \sigma_{w^k}^2 + \left(\frac{\phi_n^j}{\phi_1^j}\right)^2 \sigma_{\Delta n^{ij}}^2}.$$

This modified Kalman gain incorporates variability in noise at the firm, sector, and cross-sectoral levels, resulting in heterogeneous responses to stock price signals across firms and sectors. Firms with higher noise variances adjust their expectations more slowly, resulting in heterogeneous reactions to the information contained in stock prices.

Firm i's investment decision now depends on its unique Kalman gain K_{ij}:

$$\Delta I_t^{ij} = a\left(\Delta x_t^{ij} + K_{ij}\Delta p_t^{ij} + (1-K_{ij})\Delta\hat{x}_{t+1}^{ij}\right) + (1-a)\left(\Delta S_t^j + K_{ij}\Delta p_t^{ij} + (1-K_{ij})\Delta\hat{S}_{t+1}^j\right).$$

This introduces heterogeneity in how firms adjust their investment based on expectations. Intuitively, a higher Kalman gain on signals from another sector implies that firms in sector j place more weight on sector k's prices when forming expectations. This increases the likelihood that firms coordinate investments in response to common signals, amplifying intersectoral synchronization.

Note that heteroscedasticity does not affect the existence of an equilibrium, as the expectation space remains compact and convex, allowing the fixed-point theorem to hold. However, the proof of uniqueness requires a condition on the maximal feedback loop:

$$1 - \alpha \max_{ij}\left((1-a)\rho_S^j\right) > 0.$$

This condition ensures that heterogeneity in Kalman gains and noise variances does not induce self-reinforcing dynamics capable of producing multiple equilibria.

The law of motion for the sector-wide state becomes:

$$\Delta S_{t+1}^j = \mu_{\Delta S}^j + \rho_S^j \Delta S_t^j + \alpha N_j \bar{\Delta I}_t^j + w_t^j,$$

where $\bar{\Delta I}_t^j$ denotes the average investment decision across firms in sector j. After substituting the averaged firm investment decision, we recover sectoral dynamics with heterogeneity reflected through the averaged Kalman gains.

3 Information flow in the economy

We interpret the Kalman gain differences as measures of how much managers in each sector learn from asset prices within their own sector compared to asset prices from other sectors.

Consider the effect of the following three constraints imposed on the Kalman filter. If we set $\bar{\gamma}_1^k = 0$ for all sectors other than the i-th firm in sector j, then the restricted Kalman gain is:

$$K_{jj} = \frac{\sigma_u^2 + \left(\frac{\bar{\phi}_1^j}{\phi_1^j}\right)^2 \sigma_w^2}{\sigma_u^2 + \left(\frac{\bar{\phi}_1^j}{\phi_1^j}\right)^2 \sigma_w^2 + \left(\frac{\phi_n^j}{\phi_1^j}\right)^2 \sigma_{\Delta n}^2}.$$

If we set $\bar{\gamma}_1^k = 0$ for all sectors except sector ℓ and $\bar{\phi}_1^j = 0$, then the restricted Kalman gain is:

$$K_{j\ell} = \frac{\sigma_u^2 + \left(\frac{\bar{\gamma}_1^\ell}{\phi_1^j}\right)^2 \sigma_{w^\ell}^2}{\sigma_u^2 + \left(\frac{\bar{\gamma}_1^\ell}{\phi_1^j}\right)^2 \sigma_{w^\ell}^2 + \left(\frac{\phi_n^j}{\phi_1^j}\right)^2 \sigma_{\Delta n}^2}.$$

Likewise, if we set $\bar{\gamma}_1^k = 0$ for all k and $\bar{\phi}_1^j = 0$, then the restricted Kalman gain is:

$$K_i = \frac{\sigma_u^2}{\sigma_u^2 + \left(\frac{\phi_n^j}{\phi_1^j}\right)^2 \sigma_{\Delta n}^2}.$$

The Kalman gain K represents the weight that managers in sector j place on the information coming from the observed stock price signal when updating their expectations about the firm's future state. The Kalman gain depends on the relative importance of firm-specific noise, sectoral noise, and cross-sectoral noise. A higher Kalman gain implies that managers place greater weight on the stock price signal relative to their prior beliefs.

The sector-specific Kalman gain K_{jj} captures the extent to which managers in sector j rely on information about firm-specific and sector-wide shocks within their own sector. A higher value of K_{jj} indicates that managers place significant weight on sector-specific information, integrating both firm-specific noise σ_u^2 and sector-wide noise σ_w^2 when updating their beliefs.

The cross-sectoral Kalman gain $K_{j\ell}$ measures the importance of information

coming from other sectors, specifically from sector ℓ. A higher value of $K_{j\ell}$ means that managers in sector j place significant weight on cross-sectoral information, particularly from the price signal of sector ℓ, as reflected in the parameter $\bar{\gamma}_1^{\ell}$.

The restricted Kalman gain K_i reflects the case where only firm-specific noise is considered. When K_i is higher, managers rely predominantly on firm-specific noise σ_u^2 in making decisions, with no influence from sector-wide or cross-sectoral signals.

Define the differences between restricted Kalman gains:

$$\Delta K_{jj} = K_{jj} - K_i,$$

$$\Delta K_{j\ell} = K_{j\ell} - K_i.$$

The differences in constrained Kalman gains capture the additional information managers obtain from sectoral or cross-sectoral interactions. Larger ΔK_{jj} indicates reliance on sector-wide information, while larger $\Delta K_{j\ell}$ means greater dependence on cross-sectoral signals. Specifically, the Kalman gain differences ΔK_{jj} and $\Delta K_{j\ell}$ quantify the relative importance of sector-specific versus cross-sectoral information in shaping managers' expectations and investment decisions. When viewing the economy as a network of interconnected sectors, these Kalman gain differences measure how easily information flows both within and across sectors.

Now, average the Kalman gains across firms to measure information flows both within and across sectors, accounting for firm-level heterogeneity. Specifically, we define sector-specific Kalman gain differences, $\Delta\bar{K}_{jj}$, and cross-sectoral Kalman gain differences, $\Delta\bar{K}_{j\ell}$, which now reflect the heterogeneity among firms within each sector.

Let $\bar{K}_j$ denote the average Kalman gain across all firms in sector j, calculated as:

$$\bar{K}_j = \frac{1}{N_j} \sum_{i=1}^{N_j} K_i,$$

where K_i is the Kalman gain for firm i in sector j, and N_j is the number of firms

in sector j. This averaged Kalman gain accounts for the differing noise variances across firms.

The sector-specific Kalman gain difference, $\Delta\bar{K}_{jj}$, compares the average Kalman gain for sector j (which includes both firm-specific and sector-wide information) to the average firm-specific Kalman gain $\bar{K}_j$. This is expressed as:

$$\Delta\bar{K}_{jj} = \bar{K}_{jj} - \bar{K}_j,$$

where $\bar{K}_{jj}$ is the averaged Kalman gain for sector j, capturing sector-wide information flow within the sector. The term $\Delta\bar{K}_{jj}$ thus measures the additional weight managers place on sector-wide information beyond firm-specific noise.

Similarly, the cross-sectoral Kalman gain difference, $\Delta\bar{K}_{j\ell}$, compares the Kalman gain for sector j that incorporates information from sector ℓ to the average firm-specific Kalman gain $\bar{K}_i^j$. It is given by:

$$\Delta\bar{K}_{j\ell} = \bar{K}_{j\ell} - \bar{K}_j,$$

where $\bar{K}_{j\ell}$ represents the average Kalman gain for sector j when incorporating cross-sectoral information from sector ℓ. This measures the reliance on cross-sectoral information flows between sectors j and ℓ.

The averaged Kalman gain differences, $\Delta\bar{K}_{jj}$ and $\Delta\bar{K}_{j\ell}$, capture how information flows within and across sectors, respectively.

Definition 2 *The information matrix capturing the flow of information across sectors is defined as:*

$$\begin{bmatrix} \Delta\bar{K}_{11} & \dots & \Delta\bar{K}_{1J} \\ \vdots & \ddots & \vdots \\ \Delta\bar{K}_{J1} & \dots & \Delta\bar{K}_{JJ} \end{bmatrix},$$

where, each entry $\Delta\bar{K}_{jj}$ measures how much more managers in sector j rely on sector-specific information compared to firm-specific information, averaged across

firms in that sector. The off-diagonal entries $\Delta\bar{K}_{j\ell}$ reflect the extent to which managers in sector j rely on information from other sectors ℓ, also averaged across firms.

4 Measuring network informativeness

To construct the information network, we interpret the *Kalman gain differences* $\Delta\bar{K}_{j\ell}$ as measures of the intensity of information flow from sector ℓ to sector j. We define the weight of the directed edge capturing information flow from sector ℓ to sector j as:

$$w_{j\ell} = \Delta\bar{K}_{j\ell}.$$

We define the distance from sector j to sector ℓ as the inverse of the information flow:

$$d_{j\ell} = \frac{1}{w_{j\ell}},$$

whenever $\Delta\bar{K}_{j\ell} > 0$. If $\Delta\bar{K}_{j\ell} = 0$, we define $d_{j\ell} = \infty$, indicating that there is no direct informational link from sector ℓ to sector j. This transformation yields a directed, weighted network with well-defined path lengths, allowing us to apply standard graph-theoretic measures to assess the efficiency of information transmission across the economy. Note that $d_{j\ell}$ may differ from $d_{\ell j}$ when Kalman gain differences are asymmetric.

We distinguish between two levels of informativeness: a *global* measure that captures the average efficiency of information flow across the entire network, and a *local* measure that focuses on the connectivity among each node's immediate neighbors.[3] We define *network informativeness* as a global measure of how effectively information flows between sectors in the economy. A high level of network informativeness implies shorter paths between sectors, enabling more accurate and

[3]In graph or network theory, such measures are typically referred to as "efficiency" measures (Latora and Marchiori, 2001). We avoid that term to prevent confusion with concepts such as price or allocative efficiency in economics.

timely information exchange and supporting better coordination of investment decisions. The node-level counterpart, *local network informativeness*, captures the flow of information within each sector's immediate neighborhood. It also reflects the resilience of the network: if a sector is removed and local informativeness remains high, information continues to circulate among the remaining neighbors, indicating a robust local structure.

Formally, let d_{ij} denote the shortest path distance between nodes i and j. Then global network informativeness E_{glob} is defined as:

$$E_{\text{glob}} = \frac{1}{n(n-1)} \sum_{i \neq j} \frac{1}{d_{ij}}, \tag{8}$$

where n is the number of nodes in the graph. A higher value of E_{glob} reflects a more interconnected and accessible network, where information flows more efficiently across the entire system.

Local network informativeness for node i, denoted $E_{\text{loc}}(i)$, is defined as:

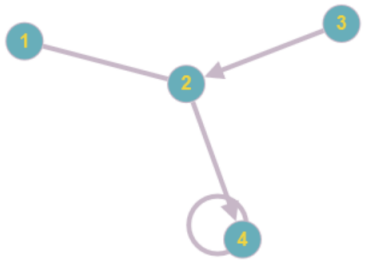
$$E_{\text{loc}}(i) = \frac{1}{|N(i)|(|N(i)|-1)} \sum_{j \neq k} \frac{1}{d_{jk}}, \tag{9}$$

where $N(i)$ is the set of neighbors of node i, and d_{jk} is the shortest path distance between neighbors j and k in the subgraph induced by $N(i)$, excluding node i. This measure captures the degree to which node i's neighbors remain connected in its absence.

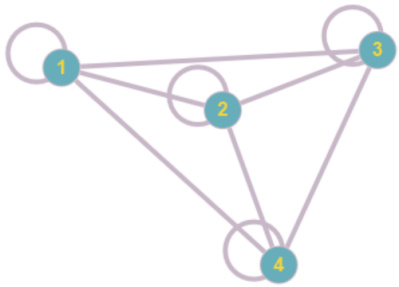
A simple example: Figure 1 illustrates how global and local network informativeness respond to different network configurations in a stylized economy with four sectors, $i \in \{1, 2, 3, 4\}$. For simplicity, we assume binary links and set the distance between connected nodes to 1.

In panel (a), the network is sparse, with limited direct connections between sectors. Global network informativeness is low ($E_{\text{glob}} = 0.33$), reflecting longer average distances. Local network informativeness is also minimal: removing any

Figure 1: Global and local network informativeness in a simple economy. Each panel shows a stylized network with four sectors, illustrating how connectivity influences global and local network informativeness.



(a) Sparse network with $E_{\text{glob}} = 0.33$ and $E_{\text{loc}}(i) = 0$ for all i



(b) Fully connected network with $E_{\text{glob}} = 1$ and $E_{\text{loc}}(i) = 1$ for all i

sector isolates its neighbors, demonstrating fragile neighborhood connectivity.

In contrast, panel (b) shows a fully connected network. Here, global informativeness reaches its maximum value of 1, since all sectors are directly linked. Local informativeness is also maximized: the removal of any node does not disrupt communication among the remaining sectors. This structure facilitates robust information exchange at both the global and local levels.

While the stylized examples build intuition, our empirical measures of network informativeness are derived from the Kalman gain structure presented earlier. Specifically, we compute a sector's local network informativeness based on how effectively it learns from the price signals of nearby sectors. Sectors with larger Kalman gain differences $\Delta\bar{K}_{jk}$ are more responsive to cross-sectoral information, resulting in higher local informativeness. This structure implies a feedback loop: sectors embedded in more informative neighborhoods become more synchronized with the broader economy, while those in weakly connected areas may become informationally isolated.

These stylized network configurations illustrate how the structure of connections influences informativeness metrics. In our empirical implementation, we weight network edges using Kalman gain differences to quantify both global and local informational integration across sectors. This approach provides a granular perspective on each sector's informational role and its resilience within the broader economic network.

5 Data construction

We combine datasets from a range of sources, as detailed in online appendix B. Data on stock market prices and firm earnings information come from CRSP-COMPUSTAT. Data on information produced by analysts are provided by Refinitiv. The other macroeconomic time series we employ are available through FRED. Below we describe each of these datasets in detail.

5.1 Stock prices and earnings

We obtain stock market price data from the Center for Research in Security Prices (CRSP). We begin by importing monthly price data beginning in January 1960 from the Monthly Stock File (`MSF`), restricted to ordinary common shares (`SHRCD = 10 or 11`). We restrict our sample to securities listed on the NYSE, AMEX or the NASDAQ (`EXCHCD = 1, 2, or 3`). We use monthly equity prices adjusted for equity splits and deflated using the personal consumption expenditure price index (`PCEPI`) monthly series from FRED, which begins in 1959. We compute the three-month change in log equity prices and lag the data by three months to ensure that the information was public during the trading period before merging with COMPUSTAT data.

We import quarterly earnings data from the COMPUSTAT Fundamentals Quarterly Data in the standard, consolidated, industrial format for domestic firms (`INDFMT = 'INDL'` and `DATAFMT = 'STD'` and `CONSOL = 'C'` and `POPSRC = 'D'`) beginning in January 1960. We use operating income after depreciation (OIADPQ),

deflated by the personal consumption expenditure price index (PCEPI) from FRED, as our measure of individual firm state. Because OIADPQ can be negative, we calculate the quarterly growth rate using the following piecewise transformation:

$$\Delta x_t = \begin{cases} \frac{x_t}{x_{t-1}} - 1 & \text{if } x_{t-1} > 0 \\ \frac{x_t}{|x_{t-1}|} + 1 & \text{if } x_{t-1} < 0 \\ NA & \text{if } x_{t-1} = 0 \end{cases} \tag{10}$$

We merge these data with the lagged quarterly equity price changes using the CRSP/COMPUSTAT Merged (CCM) link table provided by Wharton Research Data Services (WRDS). We link CRSP and COMPUSTAT by importing `GVKEY` and `PERMNO` identifiers from the CCM database, keeping the following linktypes: `'LU,'` `'LC,'` or `'LS,'` and for which the issue marker is primary (`LINKPRIM = 'P'` or `'C'`). We retain only observations with dates falling within the valid date range specified in the CCM link table.

To measure the state of each sector, we construct the asset-weighted (`ATQ`) average of individual firm states (Δx_t) for each two-digit historical standard industrial classification (SIC) code as prescribed by e.g., `https://files.stlouisfed.org/files/htdocs/conferences/btn2016/docs/papers/hines.pdf`. We do not use North America Industrial Classification System (NAICS) codes, as they are only available beginning in 2000. Appendix C reports descriptive statistics for total assets across firms, by year, as well as the number of firms in each sector.

5.2 Other macroeconomic data

Table 1 lists the sources of all other macroeconomic variables used in our analysis. All the data are downloaded from FRED. We describe our measure of total analyst recommendations in Section 9.

Table 1: Sources of other macroeconomic data.

Series	FRED code	Original source
Real GDP	GDPC1	U.S. Bureau of Economic Analysis
Unemployment rate	UNRATE	U.S. Bureau of Labor Statistics
Industrial production	INDPRO	Federal Reserve Board of Governors
Housing starts	HOUST	U.S. Department of Housing and Urban Development

6 Estimation of network informativeness cycles

This section presents empirical findings on the relationship between network informativeness and macroeconomic variables, shedding light on how information flows evolve over the business cycle. To quantify these relationships, we estimate the cyclical component of network informativeness and analyze its correlation with real GDP, industrial production, analyst recommendations, and housing starts. Using cross-correlation tests, we assess whether changes in network informativeness serve as indicators of economic activity, helping to identify the role of financial markets in shaping macroeconomic fluctuations.

To empirically evaluate the predictions of our theoretical framework, we construct time-varying measures of network informativeness that directly correspond to objects derived from the model in Section 2. In the model, firms form expectations about their own fundamentals and sectoral aggregates by filtering noisy price signals, with the Kalman gain determining the weight placed on information from different sources. Heterogeneity in these gains–across firms and sectors–captures how much information flows within and between sectors, and drives the degree of investment coordination. We estimate these Kalman gain differences, ΔK_{jk}, using firm-level data on stock prices and fundamentals, and use them to construct a sectoral information network. From this network, we derive a measure of global informativeness, E_{glob}, which captures the average efficiency of cross-sectoral information flow, and local informativeness measures, $E_{loc}(i)$, that

reflect each sector's informational position within the network. These measures provide a direct empirical analog to the informational coordination mechanisms in the model and allow us to test its central implication: that fluctuations in the precision and diffusion of information–measured through network informativeness– are systematically associated with real macroeconomic dynamics.

In each quarter t, we define $\widehat{\Delta K_{jk}}$ as the arithmetic average of firm-level ΔK_{jk} values across all firms in sector j. By treating each industry sector as a node in a graph, we can use $\widehat{\Delta K_{jk}}$ as a weighted connection from sector k to sector j, where the weight reflects the extent to which equity prices in sector j incorporate information about sector k. This approach allows us to visualize and analyze inter-sectoral relationships, highlighting how fluctuations in one sector's stock prices may influence or be influenced by its own sector and, by extension, other sectors of the economy. Higher values of $\widehat{\Delta K_{jk}}$ indicate stronger connections, suggesting that stock prices in those sectors provide more information about another sector's future conditions. Conversely, lower values imply weaker connections, signifying that stock prices in those sectors are less informative regarding future conditions in other sectors.

This sectoral network provides a time-varying estimate of information flow across the economy. We measure how efficiently information spreads across the entire network, capturing how well sectors in the economy communicate, by calculating global network informativeness in each quarter. Higher global network informativeness means that shorter paths exist between sectors, facilitating faster and more accurate exchange of information, leading to better coordination of investment decisions. We then extract the cyclical component of global network informativeness by using a standard Hodrick-Prescott (HP) filter with $\lambda = 1600$.

To better understand network informativeness in the business cycle, Figure 2a presents the cyclical components of key macroeconomic variables after detrending with the Hodrick-Prescott filter. These variables include real GDP, industrial production, housing starts, the federal funds rate, the number of analyst

recommendations, and our measure of global network informativeness. Comparing these time series allows us to identify patterns and relationships that emerge over the business cycle.

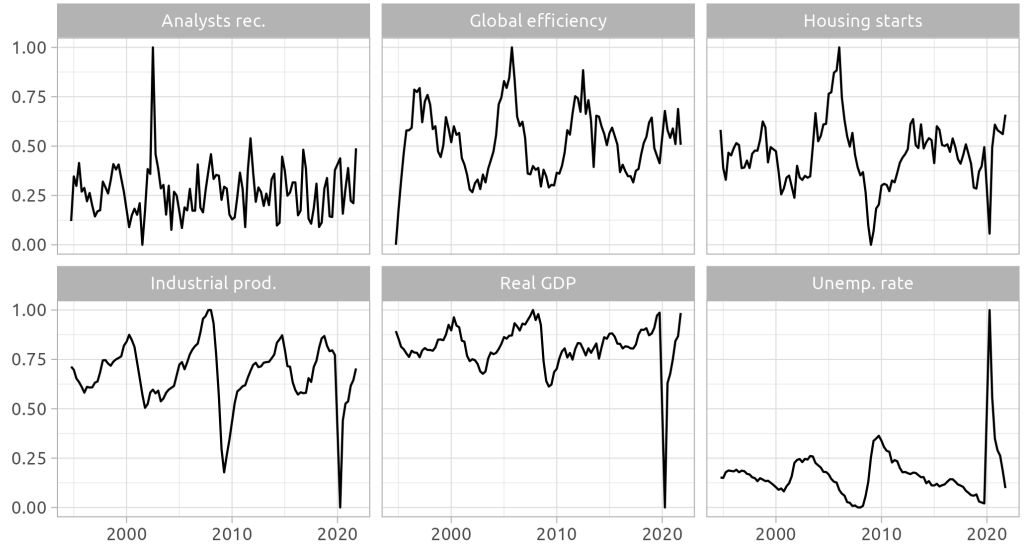
To quantify these relationships, Figure 2b reports the contemporaneous Pearson correlations between network informativeness and the other business cycle variables. Notably, global network informativeness does not exhibit a statistically significant contemporaneous correlation with real GDP. This suggests that the relationship with economic activity operates with a lag, rather than contemporaneously.

While contemporaneous correlations suggest limited direct alignment with GDP, cross-correlation tests reveal that network informativeness consistently rises two to three quarters before economic activity increases. Figure 3 presents cross-correlation estimates, where positive lags indicate that network informativeness tends to precede another variable, while negative lags indicate that it tends to occur afterwards. More specifically, each chart displays estimates of $corr[x(t + LAG), y(t)]$, where x occurs before y if LAG is positive and x occurs after y if LAG is negative. A key finding is that network informativeness rises approximately two to three quarters before real GDP. This suggests that changes in information flow across sectors tend to precede shifts in overall real economic activity, reinforcing the idea that financial market signals contain information about future macroeconomic conditions.

Taken together, these findings suggest that network informativeness is not merely a passive reflection of economic conditions but rather an active component of the business cycle. Increases in network informativeness appear to enhance investment coordination, thereby facilitating stronger economic activity in subsequent quarters. However, as we explore in the next section, this dynamic can also contribute to self-reinforcing cycles that may amplify economic fluctuations.

Figure 2: Key macroeconomic variables. Source: Authors' calculations based on data from CRSP-COMPUSTAT and FRED.

(a) Business cycles. Each panel shows the business-cycle component (HP-detrended) of a macroeconomic variable, alongside the cycles of global network informativeness and analyst recommendations.

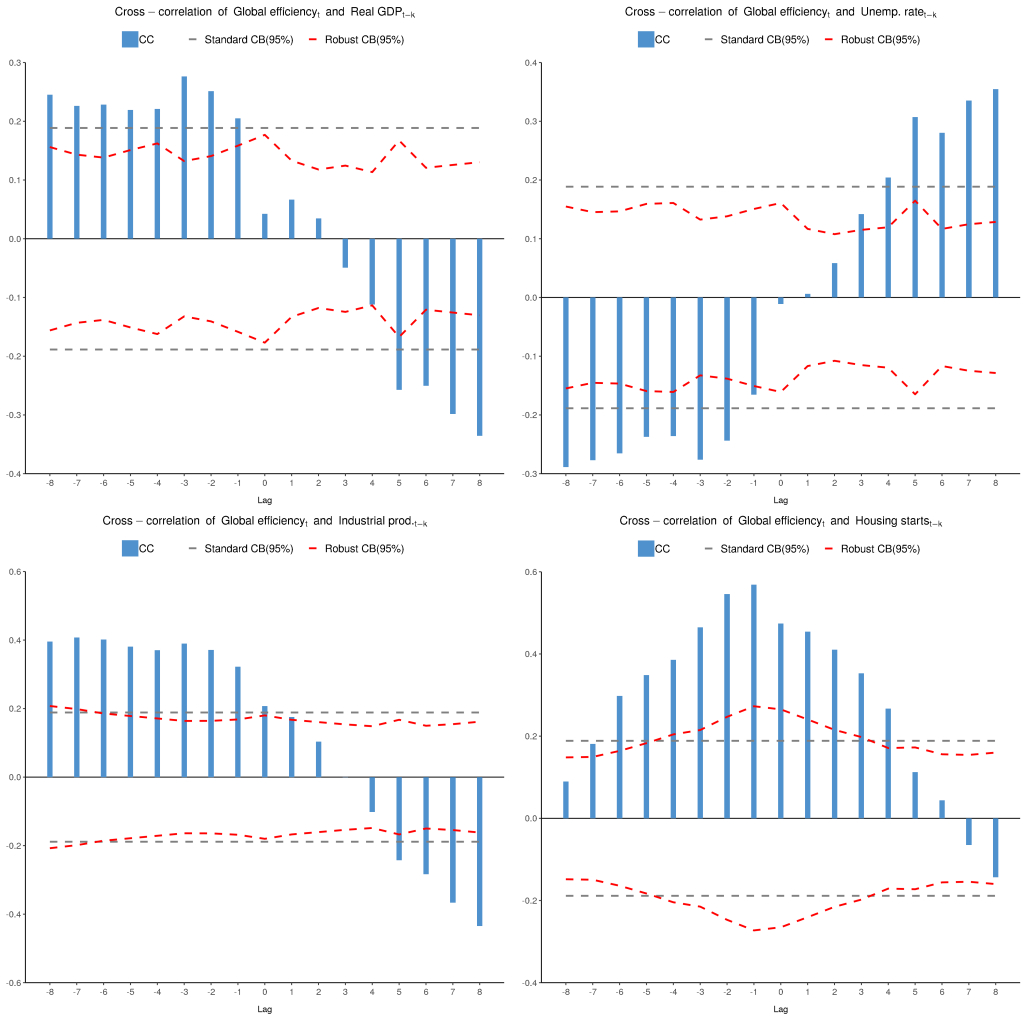


(b) Pearson contemporaneous correlations with robust p-values. Robust p-values obtained using the method of Dalla, Giraitis and Phillips (2022).

	Real GDP	Unemp. rate	Industrial prod.	Housing starts	Global efficiency	Analysts rec.
Real GDP	1	-0.928 (0.047)	0.852 (0.006)	0.418 (0.026)	0.042 (0.639)	-0.137 (0.226)
Unemp. rate	-0.928 (0.047)	1	-0.836 (0.005)	-0.319 (0.068)	-0.011 (0.894)	0.096 (0.365)
Industrial prod.	0.852 (0.006)	-0.836 (0.005)	1	0.400 (0.012)	0.207 (0.024)	-0.056 (0.541)
Housing starts	0.418 (0.026)	-0.319 (0.068)	0.400 (0.012)	1	0.474 (0.000)	-0.102 (0.232)
Global efficiency	0.042 (0.639)	-0.011 (0.894)	0.207 (0.024)	0.474 (0.000)	1	-0.108 (0.276)
Analysts rec.	-0.137 (0.226)	0.096 (0.365)	-0.056 (0.541)	-0.102 (0.232)	-0.108 (0.276)	1

p-value
[0,0.001]
(0.001,0.01]
(0.01,0.05]
(0.05,0.1]
(0.1,1]

Figure 3: Cross-correlation test for the network informativeness cycle and real business cycle variables. Each panel reports test statistics (blue bars) for the significance of cross-correlation in bivariate time series using the method of Dalla, Giraitis and Phillips (2022) that allows for heteroscedasticity and dependence in each series and mutual dependence across series. The blue dashed line indicates the standard 95 percent confidence band for the null hypothesis of no cross-correlation at individual lags. The red dashed line indicates the robust 95 percent confidence band for the same null hypothesis. Source: Authors' calculations based on data from CRSP-COMPUSTAT and FRED.



7 Interpretation of the results using the model

The data show that increases in network informativeness tend to precede expansions in industrial production and real GDP by up to eight quarters, while declines in activity often follow elevated informativeness with a delay of six to eight quarters—patterns consistent with the boom-and-bust dynamics of the self-fulfilling investment coordination model.

During the boom phase, stronger industrial production occurs before increased investment activity and higher information production. As firms observe rising output and stronger market conditions, they align their expectations more closely, improving network informativeness through enhanced coordination. This alignment reinforces investment activity in the short term, as market participants interpret elevated network informativeness as a positive signal of stable future conditions.

The bust phase arises when network informativeness peaks and expectations become excessively synchronized. The observed negative cross-correlation suggests that elevated network informativeness, reflecting increased information precision, may ultimately contribute to over-coordination. Firms, relying on similar informational signals, may collectively delay or reduce investment, anticipating diminishing returns. This synchronized caution is followed by a contraction of industrial production several quarters later, as the effects of reduced investment propagate through the economy.

Additional support for the proposed mechanism comes from examining correlations with housing starts and the monetary policy cycle. While the model does not explicitly include monetary policy or housing dynamics, we interpret these results through the lens of our coordination framework, without claiming structural identification. We find a strong contemporaneous correlation between housing starts and network informativeness, which reinforces the interpretation of a self-fulfilling investment coordination cycle. Housing starts, often a forward-looking indicator of real estate investment activity, closely track shifts in market

expectations and financial conditions. The positive correlation suggests that rising network informativeness coincides with increased housing activity, reflecting aligned expectations and synchronized investment decisions across sectors.

During periods of rising network informativeness, synchronized expectations may reduce perceived uncertainty, encouraging investment not just in housing but across the broader economy. However, this alignment can also generate procyclical optimism, whereby rising network informativeness amplifies investment coordination beyond what fundamentals warrant. When network informativeness peaks, the risk of over-coordination increases, which may contribute to the delayed downturn observed in production activity.

A related pattern emerges when examining the monetary policy cycle. The federal funds rate cycle is significantly negatively correlated with network informativeness four to eight quarters in advance, and positively correlated with it two to six quarters afterward. This pattern suggests that tighter monetary policy today predicts lower future network informativeness in the future due to constrained investment. Conversely, past periods of lower interest rates are associated with higher network informativeness, as easier credit fosters investment and information production.

8 Variation in local network informativeness

Building on the node-level measure introduced in Section 4, this section focuses on the dispersion in local network informativeness across sectors. For each sector i and quarter t, we compute local network informativeness, $E_{\text{loc}}(i,t)$, defined as the average inverse shortest-path distance among sector i's neighbors in the subgraph that excludes sector i itself.[4]

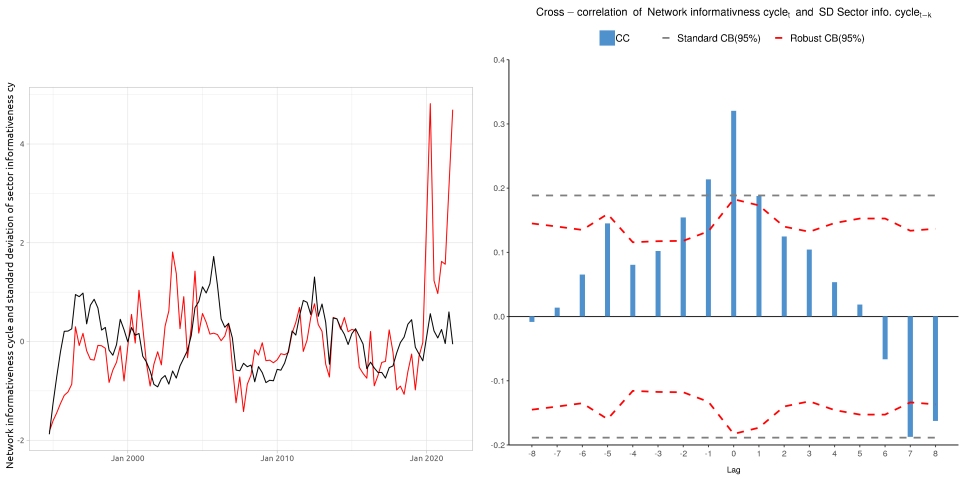
We apply the Hodrick-Prescott (HP) filter to extract the cyclical component of each $E_{\text{loc}}(i,t)$, then compute the cross-sectional standard deviation across sectors

[4] $E_{\text{loc}}(i,t)$ is often termed 'local efficiency' in network theory. We adopt the term "informativeness" to reflect the information-theoretic interpretation and to avoid confusion with economic notions of efficiency.

in each quarter. This dispersion measure, denoted σ_t^{local}, captures the degree of fragmentation or heterogeneity in local informativeness across the network. We study its comovement with the aggregate network informativeness cycle, GE_t.

Figure 4 illustrates the time series of GE_t and σ_t^{local}, along with their cross-correlation. To assess the dynamic relationship between these measures, we estimate a bivariate vector autoregression (VAR) model with GE_t and σ_t^{local} as endogenous variables, using quarterly data. We determine the optimal lag length using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan-Quinn Criterion (HQ), and Final Prediction Error (FPE). All criteria select a single lag; we therefore estimate a VAR(1) with a constant.

Figure 4: Network informativeness cycle and the contemporaneous standard deviation of sector informativeness. The left-hand panel shows the time series of global network informativeness and the standard deviation of local network informativeness. The right-hand panel shows the test statistics (blue bars) for the significance of cross-correlation in bivariate time series using the method of Dalla, Giraitis and Phillips (2022) that allows for heteroscedasticity and dependence in each series and mutual dependence across series. The blue dashed line indicates the standard 95 percent confidence band for the null hypothesis of no cross-correlation at individual lags. The red dashed line indicates the robust 95 percent confidence band for the same null hypothesis. Source: Authors' calculations based on data from CRSP-COMPUSTAT.



To assess both temporal and contemporaneous relationships, we conduct Granger causality and instantaneous causality tests. Table 2 reports the corresponding F-

statistics. We find no evidence of Granger causality in either direction, suggesting that lagged values of local dispersion and global network informativeness do not predict each other over time. However, the instantaneous causality tests reject the null hypothesis in both directions, indicating that shocks to local and global informativeness are contemporaneously correlated. This implies that both variables respond simultaneously to common shocks—such as macroeconomic developments—rather than sequentially via dynamic propagation mechanisms.

Table 2: Causality tests between local dispersion and network informativeness. Source: Authors' calculations based on data from CRSP-COMPUSTAT.

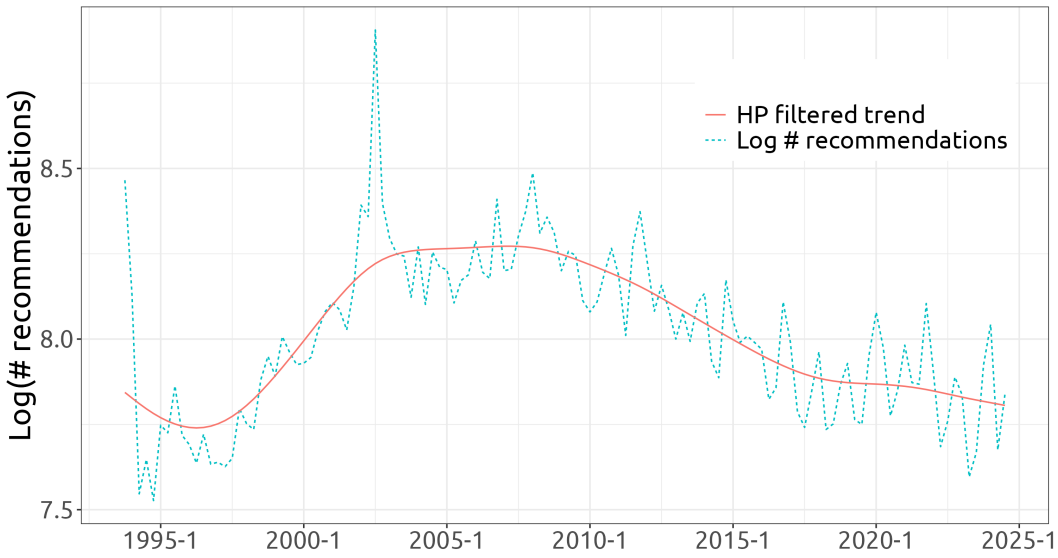
Direction	Test	Statistic
Local → Global	Granger causality	1.055
Local → Global	Instantaneous causality	13.216***
Global → Local	Granger causality	0.318
Global → Local	Instantaneous causality	13.216***

9 Network informativeness and information production

We investigate if the production of information by stock analysts tends to move ahead of the network informativeness cycle. We measure information production by analysts by calculating the total number of recommendations issued by all analysts in a given quarter as reported in the North American Summary & Detail Estimates from Refinitiv. Institutional Brokers' Estimate System (I/B/E/S) analyst recommendations data is a collection of buy, hold, or sell stock recommendations compiled from financial analysts. These data are collected from a wide range of analysts at different brokerage firms, contributing their individual stock recommendations. The data are purchased by portfolio managers making investment decisions and there is a extensive academic literature studying the information content of analysts' reports (see for example Bondt and Thaler (1990), Jegadeesh and Kim (2006), and Casey (2013)).

Figure 5 shows the log of the number of recommendations (blue dashed line), HP filtered to identify the trend (red solid line). The spike at the beginning of the series is likely due to data initialization and the spike in 2002Q3 is probably due to the passage of the Sarbanes-Oxley Act.

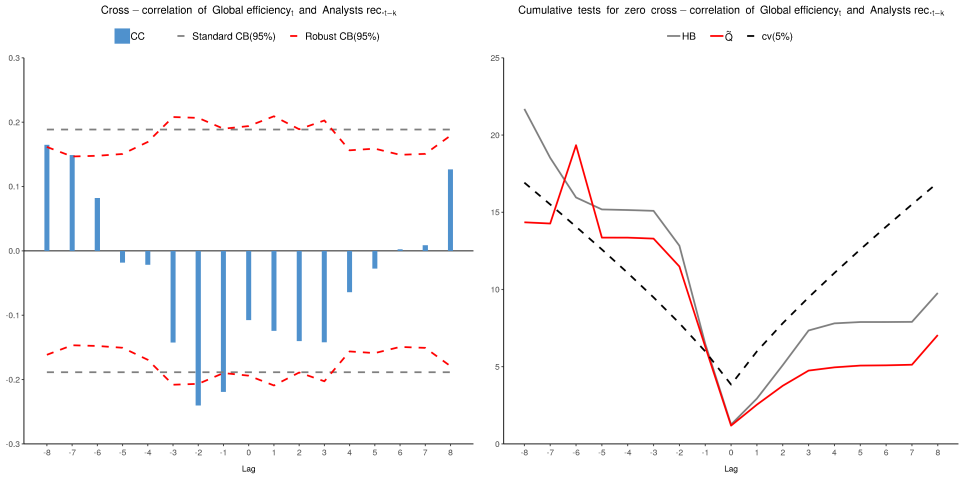
Figure 5: Analyst recommendations. The sample is all firms in CRSP with recommendations in IBES. Source: Authors' calculations based on data from IBES and CRSP-COMPUSTAT.



We examine the relationship between network informativeness and information production by financial analysts. Figure 6 reports the cross-correlation estimates between global network informativeness and the number of analyst recommendations. A delayed response characterizes the relationship between analyst recommendations and network informativeness. Falling analyst recommendations over the past half-year are associated with rising network informativeness in the current quarter. The cumulative cross-correlation function (CCCF) is significant at -2 and -3 quarters, indicating that historical values of the recommendation cycle are significantly correlated with network informativeness cycle when shifted back by two to three

quarters. The significant negative cross-correlation at lags of -1 and -2 quarters suggests that increases in analyst recommendations–representing greater information production–precede rising network informativeness.

Figure 6: Cross-correlation test for network informativeness cycle and number of analyst recommendation cycle.
Computes the test statistics for examining the significance of cross-correlation in bivariate time series using the method of Dalla, Giraitis and Phillips (2022) that allows for heteroscedasticity and dependence in each series and mutual dependence across series. The charts test H_0 of no cross-correlation at individual lags. The robust test rejects H_0 for any of the cross-correlation (CC, the blue vertical bars) outside the red dashed lines. The bottom charts test H_0 of no cross-correlation at cumulative lags. The robust test rejects H_0 when the red solid line lies above the black dashed line. The left- and right-hand side panels show the 5 and 1 percent significance level results. Source: Authors' calculations based on data from CRSP-COMPUSTAT.

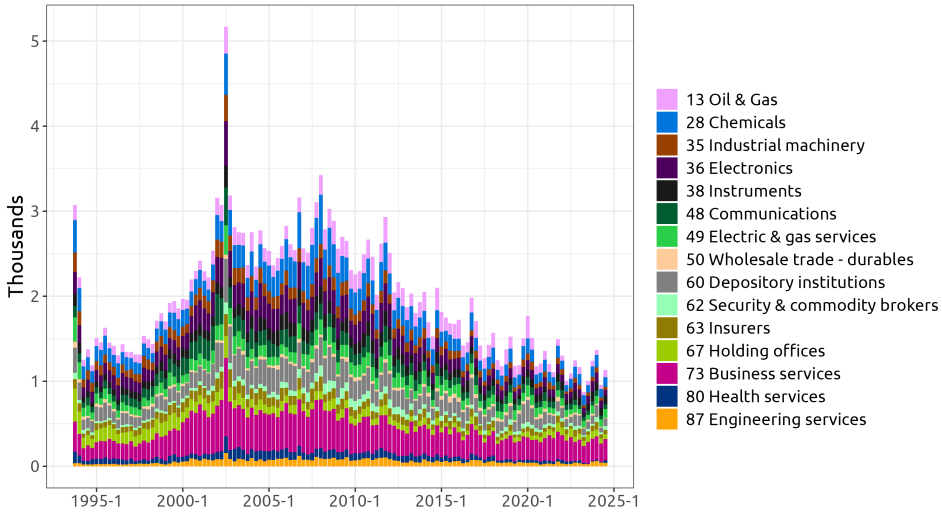


This pattern implies that analyst activity plays a crucial role in shaping the flow of information through financial markets, with fluctuations in recommendation activity influencing the informativeness of stock prices across sectors. This pattern also aligns with the investment coordination model, where increased information availability enhances market coordination and network informativeness. However, the effects on sector-level network informativeness take two to three quarters to materialize, reflecting the time required for information to be embedded in stock prices and investment behavior.

9.1 Analyst information production by sector

In this section, we analyze the relationship between information production and network informativeness across sectors. Figure 7 shows the time-series variation in the number of recommendations produced by analysts for the fifteen sectors in our network.[5] We study the time-series relationships between the cyclical component of information production and local network informativeness $E_{\text{loc}}(i,t)$, defined in Section 4 as the average inverse shortest-path distance among sector i's neighbors within the subgraph excluding the sector itself during quarter t. We find analyst information production about certain sectors—particularly business services and communications—Granger cause local network informativeness in many other sectors, while local network informativeness Granger causes analyst information production in sectors such as oil & gas and utilities services.

Figure 7: Number of analyst recommendations by sector. The sample is all firms in CRSP with recommendations in IBES. Source: Authors' calculations based on data from IBES and CRSP-COMPUSTAT.



[5]The sample use in the figure is all firms in CRSP that match (by CUSIP) with analysts' recommendations reported in IBES.

For each sector-pair $(i,\ j)$, we estimate a bivariate vector autoregression (VAR) between $E_{\text{loc}}(i,t)$ and $\text{rec_cyc}_{j,t}$, defined as the HP-filtered cyclical component of the number of recommendations for firms in sector j during quarter t. The optimal lag length is selected using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan-Quinn Criterion (HQ), and Final Prediction Error (FPE). All VARs are estimated with a constant term.

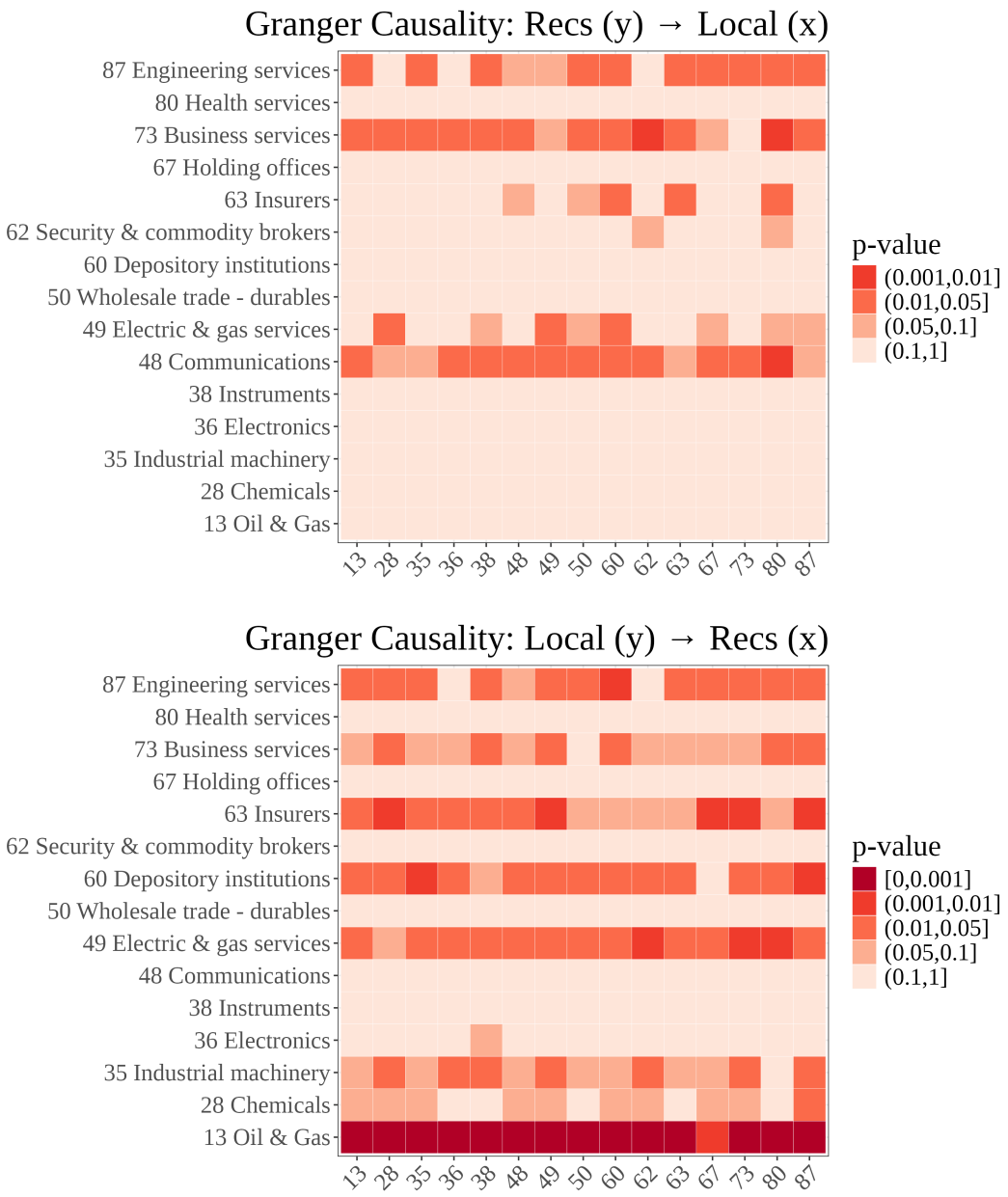
Figure 8 reports the p-values from Granger causality tests for all sector pairs in graphical matrices. The upper panel shows the results from testing whether the number of recommendations in each sector listed on the y-axis Granger causes local informativeness in each sector listed on the x-axis. Darker shading indicates more statistical significance, with analyst recommendations for firms in business services and communications Granger causing local informativeness in a wide range of other sectors in the economy.

The lower panel in Figure 8 shows the results from testing whether local informativeness in each sector listed on the y-axis Granger causes the number of recommendations in each sector listed on the x-axis. As in the upper panel, darker shading indicates more statistical significance. We find that local network informativeness in the oil & gas sector, the electric & gas services sector Granger cause analyst recommendations for firms in most other sectors in the economy.

10 Concluding remarks

This paper introduces a novel measure of network informativeness, capturing how efficiently information flows across sectors through financial markets. By constructing a sectoral information flow matrix, we demonstrate that network informativeness rises approximately two to three quarters before GDP growth. Our findings indicate that financial market signals are not merely passive reflections of economic activity but actively shape investment coordination, reinforcing the central role of information diffusion in business cycle dynamics.

Figure 8: Analyst information production and local informativeness by sector. The sample is all firms in CRSP with recommendations in IBES. Source: Authors' calculations based on data from IBES and CRSP-COMPUSTAT.



Beyond its empirical contributions, this study provides new insights into the mechanisms of investment coordination and self-fulfilling cycles. We show that while increased network informativeness enhances coordination during economic expansions, excessive synchronization can contribute to downturns. These results underscore the critical roles of financial analysts and policymakers in shaping and coordinating the flow of information, with implications for policymakers aiming to stabilize economic fluctuations.

Future research could extend our approach by exploring heterogeneous effects across industries, incorporating firm-level investment responses, or examining global information networks beyond U.S. markets. Additionally, alternative filtering techniques and causal inference methods could further validate the economic effects of network informativeness. By deepening our understanding of how financial information propagates through the economy, this research opens new avenues for studying the interplay between financial markets, information diffusion, and macroeconomic stability.

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Appendix for online publication only

A Sectoral analysis

Figures 9 and 10 show the average network informativeness cycle (the black line), which is defined as the average network informativeness series minus the HP-filtered trend. Each colored bar in the chart is a sectoral measure of the deviation of the local network informativeness cycle from the average network informativeness cycle and measures each sector's individual contribution to the cyclical measure of overall network informativeness. Figure 9 shows the contributions of all fifteen sectors, while Figure 10 shows the contributions of only four subsectors related to the financial sector.

The figures suggest that contributions to network informativeness vary over time and across sectors. This variation may help identify causal mechanisms underlying information production and its relationship to network informativeness.

Figure 9: Deviation of each local network informativeness cycle from the average network informativeness cycle. The average network informativeness cycle is the average network informativeness series minus the HP filter cycle of the average network informativeness (the black line). The local network informativeness cycle is the local network informativeness series minus the HP filter cycle of the average network informativeness. You can also net out the HP filter trend of the industry series but because they co-move highly, it amounts to roughly the same thing (same trend). Each colored bar is a sectoral measure of the deviation of the local network informativeness cycle from the average network informativeness cycle. Source: Authors' calculations based on data from CRSP-COMPUSTAT.

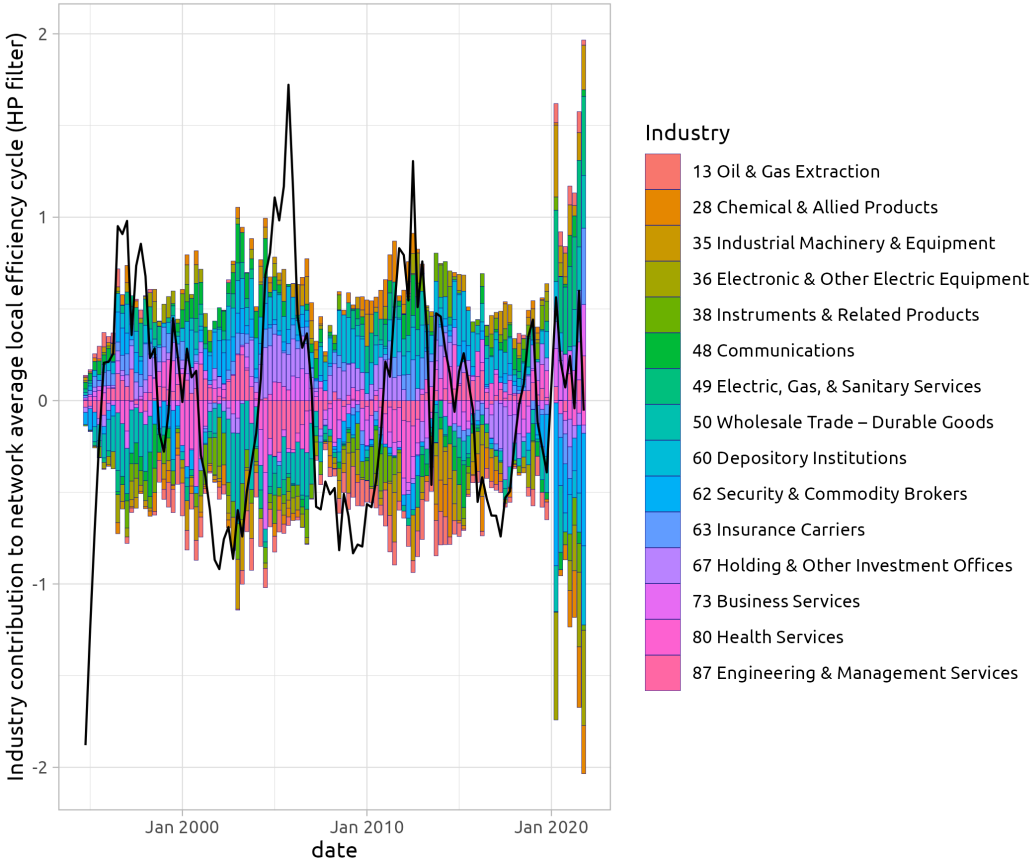
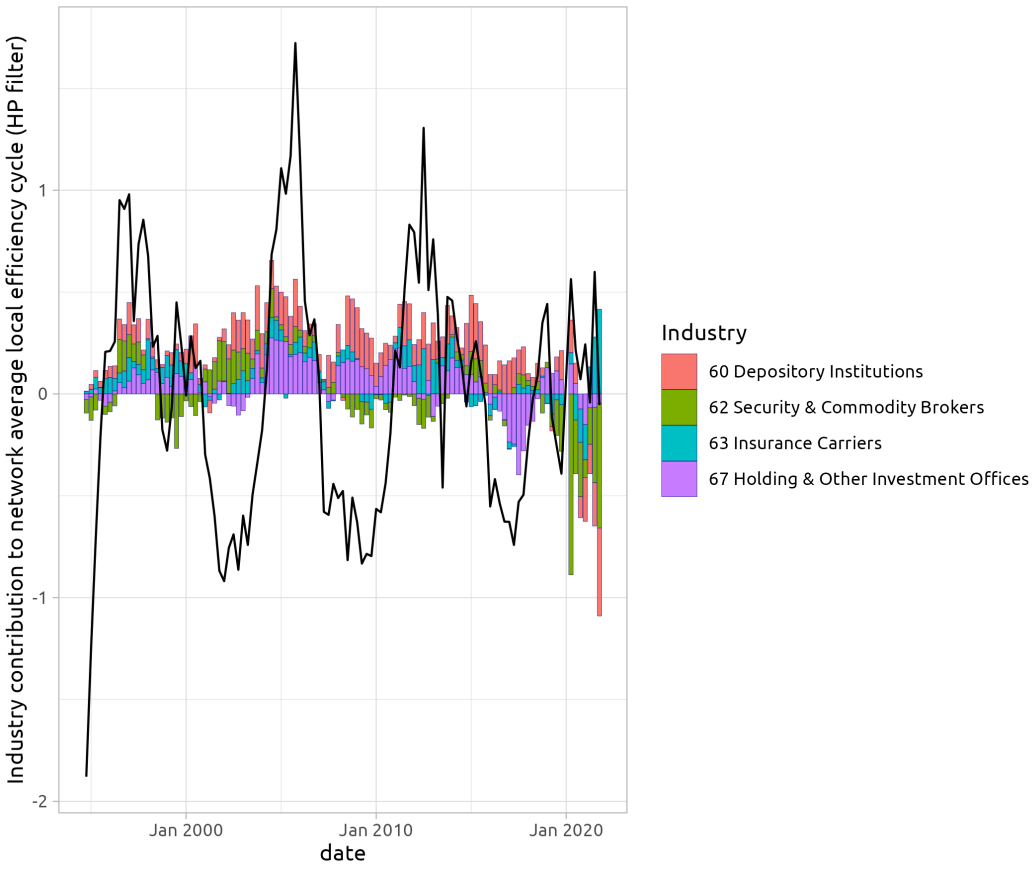


Figure 10: Deviation of the each local network informativeness cycle from the average network informativeness cycle–banking only. Source: Authors' calculations based on data from IBES and CRSP-COMPUSTAT.



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C Descriptive statistics

Table 3 reports the distribution of total assets across firms, by year, using fourth-quarter observations. The statistics are based on data reported in the fourth quarter of each year, deflated using the personal consumption expenditure price index (`PCEPI`) from FRED. Our data on total assets begin in 1962.

Table 3: Annual firm size distributions. Statistics are based on data reported in the fourth quarter of each year, deflated using the personal consumption expenditure price index (`PCEPI`). Source: Authors' calculations based on data from CRSP-COMPUSTAT and FRED.

		Total assets ($bn)							Total assets ($bn)				
Year	# Firms	Min	p25	Median	p75	Max	Year	# Firms	Min	p25	Median	p75	Max
1962	190	15.22	21.49	27.77	34.04	40.31	1993	1,599	0	0.06	0.33	1.95	383.5
1963	207	15.64	21.44	27.23	33.02	38.81	1994	1,646	0	0.06	0.33	1.94	406.78
1964	218	16.25	22.42	28.58	34.75	40.91	1995	1,721	0	0.06	0.35	2.01	463.47
1965	250	17.1	23.65	30.21	36.76	43.32	1996	1,825	0	0.06	0.37	1.95	502.1
1966	365	17.8	24.59	31.38	38.16	44.95	1997	1,847	0	0.07	0.39	2.17	553.99
1967	379	19.6	26.87	34.14	41.4	48.67	1998	1,873	0	0.08	0.47	2.5	937.81
1968	416	21.75	37.46	53.18	79.91	106.63	1999	1,979	0	0.1	0.47	2.39	985.3
1969	447	0.52	18.22	50.44	57.86	119.6	2000	2,351	0	0.1	0.41	1.99	1,209.87
1970	473	0.27	1.17	3.35	7.54	127.96	2001	2,321	0	0.1	0.42	2.01	1,395.18
1971	487	0.01	0.41	1.4	5.02	140.01	2002	2,261	0	0.09	0.45	2.14	1,425.46
1972	589	0.01	0.4	1.43	5.25	158.97	2003	2,291	0	0.11	0.48	2.38	1,608.08
1973	588	0.01	0.41	1.52	5.75	188.92	2004	2,460	0	0.11	0.48	2.16	1,836.74
1974	591	0.01	0.41	1.6	5.57	221.69	2005	2,559	0	0.11	0.51	2.11	1,797.21
1975	598	0.01	0.35	1.35	5.17	208.92	2006	2,638	0	0.11	0.53	2.16	2,216.01
1976	599	0.01	0.31	1.26	5.02	220.94	2007	2,710	0	0.11	0.52	2.15	2,486.40
1977	586	0.01	0.35	1.29	5.35	248.66	2008	2,494	0	0.11	0.56	2.31	2,468.90
1978	591	0.01	0.36	1.46	5.66	264.49	2009	2,333	0	0.13	0.62	2.48	2,472.01
1979	590	0	0.36	1.63	5.79	289.53	2010	2,261	0	0.15	0.63	2.78	2,481.60
1980	609	0.01	0.35	1.54	5.82	282.91	2011	2,171	0	0.16	0.67	2.97	2,421.39
1981	863	0	0.14	0.66	4.49	273.51	2012	2,143	0	0.17	0.72	3.17	2,480.85
1982	919	0	0.07	0.46	3.36	284.5	2013	2,205	0	0.15	0.73	3.29	2,505.54
1983	1,006	0	0.06	0.38	3.12	284.33	2014	2,358	0	0.14	0.69	3.36	2,649.43
1984	1,057	0	0.06	0.38	3.21	306.81	2015	2,356	0	0.14	0.68	3.29	2,413.09
1985	1,116	0	0.05	0.35	3.08	341.39	2016	2,282	0	0.12	0.72	3.2	2,514.33
1986	1,207	0	0.05	0.31	2.71	379.71	2017	2,290	0	0.12	0.72	3.42	2,512.97
1987	1,314	0	0.04	0.29	2.6	379.39	2018	2,336	0	0.13	0.71	3.2	2,553.56
1988	1,294	0	0.04	0.3	2.84	371.31	2019	2,378	0	0.13	0.75	3.36	2,576.41
1989	1,295	0	0.04	0.29	2.67	396.89	2020	2,515	0	0.15	0.73	3.2	3,203.78
1990	1,293	0	0.04	0.31	2.8	356.04	2021	2,874	0	0.15	0.65	2.81	3,335.89
1991	1,365	0	0.04	0.29	2.63	346.78	2022	2,868	0	0.1	0.56	2.74	3,095.99
1992	1,443	0	0.05	0.31	2.45	332.99	2023	2,759	0	0.08	0.55	2.92	3,186.95

Table 4 reports the median number of firms in each two-digit Standard Industrial Classification (SIC) sector over the sample period. In subsequent analysis of network informativeness, we focus on the larger sectors indicated in **bold font**.

Table 4: Firms per sector. This table shows the median number of firms for each two-digit sector code (SIC). Source: Authors' calculations based on data from CRSP-COMPUSTAT and FRED.

Sector Code	Sector Name	Count (median)	Sector Code	Sector Name	Count (median)
1	Agricultural Production - Crops	1	49	**Electric, Gas, & Sanitary Services**	71
2	Agricultural Production - Livestock	1	50	**Wholesale Trade - Durable Goods**	27
7	Agricultural Services	1	51	Wholesale Trade - Nondurable Goods	19
9	Fishing, Hunting, & Trapping	1	52	Building Materials & Gardening Supplies	2
10	Metal, Mining	14	53	General Merchandise Stores	2
12	Coal Mining	5	54	Food Stores	8
13	**Oil & Gas Extraction**	70	55	Automative Dealers & Service Stations	3
14	Nonmetallic Minerals, Except Fuels	2	56	Apparel & Accessory Stores	4
15	General Building Contractors	9	57	Furniture & Homefurnishings Stores	5
16	Heavy Construction, Except Building	5	58	Eating & Drinking Places	20
17	Special Trade Contractors	4	59	Miscellaneous Retail	18
20	Food & Kindred Products	25	60	**Depository Institutions**	23
21	Tobacco Products	4	61	Nondepository Institutions	23
22	Textile Mill Products	5	62	**Security & Commodity Brokers**	30
23	Apparel & Other Textile Products	9	63	**Insurance Carriers**	51
24	Lumber & Wood Products	5	64	Insurance Agents, Brokers, & Service	5
25	Furniture & Fixtures	4	65	Real Estate	12
26	Paper & Allied Products	14	66	Auxiliary Financial Services	4
27	Printing & Publishing	17	67	**Holding & Other Investment Offices**	56
28	**Chemical & Allied Products**	92	70	Hotels & Other Lodging Places	9
29	Petroleum & Coal Products	10	72	Personal Services	4
30	Rubber & Miscellaneous Plastics Products	10	73	**Business Services**	139.5
31	Leather & Leather Products	4	75	Auto Repair, Services, & Parking	2
32	Stone, Clay, & Glass Products	6	76	Miscellaneous Repair Services	1
33	Primary Metal Industries	16	78	Motion Pictures	8
34	Fabricated Metal Products	15	79	Amusement & Recreation Services	13
35	**Industrial Machinery & Equipment**	55	80	**Health Services**	39
36	**Electronic & Other Electric Equipment**	87	81	Legal Services	1
37	Transportation Equipment	28	82	Educational Services	7
38	**Instruments & Related Products**	78	83	Social Services	3
39	Miscellaneous Manufacturing Industries	9	86	Membership Organizations	1
40	Railroad Transportation	4	87	**Engineering & Management Services**	56
41	Local & Interurban Passenger Transit	1	89	Services, Not Elsewhere Classified	3
42	Trucking & Warehousing	8	94	Administration of Human Resources	1
44	Water Transportation	5	95	Environmental Quality & Housing	1
45	Transportation by Air	11	96	Administration of Economic Programs	1
46	Pipelines, Except Natural Gas	1	97	National Security & International Affairs	1
47	Transportation Services	4	99	Non-Classifiable Establishments	402
48	**Communications**	45			