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 stock prices. We then calculate *network informativeness*, measuring how easily information flows across sectors. We study relationships over the business cycle between network informativeness and other macroeconomic variables. We find that network informativeness is a leading indicator of real business cycles. Before a boom, information flows more easily driving stronger industrial production and real GDP. These dynamics reverse after information flow becomes more restricted. We link network informativeness to information production by stock analysts. Our measure is correlated 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 impact macroeconomic dynamics. Consider two sectors: if firms in Sector A heavily rely on stock price signals from Sector B when making investment decisions, then information flows efficiently across the economy. Our measure captures this cross-sector information reliance. If network informativeness is high, stock prices contain signals that firms effectively use for investment decisions. If network informativeness 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 $K_{j\ell}$ 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, leading to 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

[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".

leading relationship with the macroeconomic business cycle. Before a boom, information flows more easily driving 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 2 to 3 quarters. In other words, analysts produce information that helps to improve information flow, which leads to stronger economic growth.

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 itself is 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. However, 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 argument that financial market signals play a central role in economic coordination.

Finally, the study draws connections to 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.

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 Basic 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 change in firm earnings and sector-wide aggregate investment along with their expectations of future trends in earnings and sector-wide investment. 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:

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

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:

$$\Delta p_t^{ij} = \bar{\phi}^j + \phi_0^j \Delta x_t^{ij} + \phi_1^j \Delta x_{t+1}^{ij} + \bar{\phi}_0^j \Delta S_t^j + \bar{\phi}_1^j \Delta S_{t+1}^j + \phi_n^j \Delta n_t^{ij}, \tag{3}$$

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

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:

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

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. Note that there is only one 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 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:

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

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:

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

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 allows 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 the expectations influence actions that lead to 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:

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

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]

[2]If the investment function $g(\cdot)$ is nonlinear, the condition for uniqueness may require a bound on the

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 lead to 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.

2.2 Extension to the multi-sector case with firm heterogeneity

In the previous one-sector model, we assumed homogeneous firms, where noise variances were the same across all firms and sectors. Now, we introduce heterogeneous firms, allowing the variances of firm-specific and sector-wide shocks to differ. This modification leads to changes in the 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

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.

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 now accounts for the variability of firm-specific, sector-wide, and cross-sectoral noise, leading to different 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 investment based on their expectations.

Note that heteroscedasticity does not affect the existence of 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 create self-reinforcing dynamics that lead to 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 $\bar{\Delta I}_t^j$ represents 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 a measure of how much managers in each sector learn from asset prices within their own sector compared to asset prices from other sectors.

Note 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 $\bar{\gamma}_1^k = 0 \forall k$ 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 are significantly influenced by 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 in 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 a sector and between 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 $\bar{K}_j$ represent the average Kalman gain across all firms in sector j, which is 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 Kalman gain for sector j when considering 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 a sector and between 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

We define the network informativeness of a graph as a measure of how well information or resources can be transferred between nodes in a network.[3] Global network informativeness quantifies how efficiently information spreads across the entire network, capturing how well sectors in the economy communicate. 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. Likewise, local network informativeness focuses on how efficiently sectors communicate within local neighborhoods, measuring resilience when one sector is removed. If local network informativeness is high, information continues to flow smoothly despite the removal of a sector, reflecting the robustness of the network.

Formally, if d_{ij} represents the shortest path distance between node i and node j, global network informativeness E_{glob} is defined as:

$$E_{glob} = \frac{1}{n(n-1)} \sum_{i \neq j} \frac{1}{d_{ij}}, \tag{4}$$

where n is the number of nodes in the graph. A higher global network informativeness indicates a more interconnected and accessible network, where information flows smoothly between sectors.

Another relevant measure is *average local network informativeness*, which focuses on the network informativeness within the neighborhood of individual nodes. It assesses how well

[3] In graph or network theory, such measures are referred to as 'efficiency' measures (Latora and Marchiori, 2001). We avoid that term to prevent any potential confusion of our measure with the terms 'price efficiency' or 'allocative efficiency'.

the neighbors of a node can communicate when that node is removed. For each node i, the local network informativeness $E_{loc}(i)$ is defined as:

$$E_{loc}(i) = \frac{1}{|N(i)|(|N(i)|-1)} \sum_{j \neq k} \frac{1}{d_{jk}}, \tag{5}$$

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 formed by $N(i)$. The *average local network informativeness* E_{loc} is then calculated as:

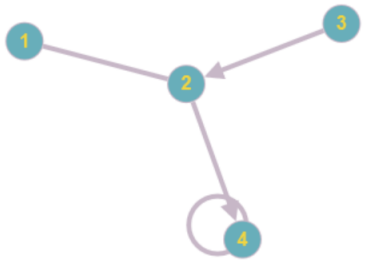
$$E_{loc} = \frac{1}{n} \sum_{i=1}^{n} E_{loc}(i). \tag{6}$$

This measure captures how robust the graph is to the loss of individual nodes, providing insights into the resilience of the network.

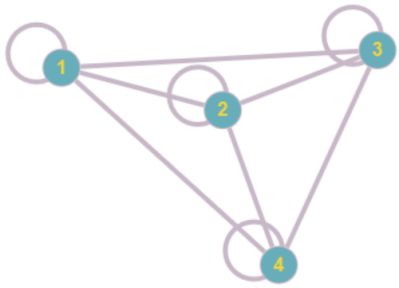
A simple example: The panels in Figure 1 show how the network informativeness measures vary in an example of an economy with four sectors identified by $k \in \{1, 2, 3, 4\}$. For simplicity, we consider binary values for the distance between the sectors. In the left-hand panel, the information network is relatively sparse, with a global network informativeness measure equal to 0.33 and an average local network informativeness measure equal to 0. In this case, the measures reflect relatively little information flow between the sectors in the economy. By contrast, the fully connected graph in the right-hand panel has global and average local network informativeness measures equal to 1. In this case, even if one sector is removed, information flows between sectors in the economy.

The average local network informativeness E of this multi-sector economy can be

Figure 1: Comparing measures of network informativeness in a simple economy. The panels show examples of an economy with four networked sectors identified by $i \in \{1, 2, 3, 4\}$.



(a) Information network with Global network informativeness (E_{glob}) = 0.33 Average local network informativeness (E_{loc}) = 0



(b) Information network with Global network informativeness (E_{glob}) = 1 Average local network informativeness (E_{loc}) = 1

expressed as:

$$E = \frac{1}{N(N-1)} \sum_{j \neq k} \Delta \bar{K}_j,$$

where N is the total number of sectors, and $\Delta \bar{K}_{jk}$ represents the Kalman gain difference for sector j, capturing how information from sector k influences sector j. A higher network informativeness means that managers across sectors can efficiently extract relevant information from other sectors, leading to better-informed and more synchronized investment decisions. We can also define a global network informativeness measure G, which captures the overall connectivity of the network in terms of how quickly and effectively information is exchanged between sectors. Global network informativeness G is defined as:

$$G = \frac{1}{N(N-1)} \sum_{i \neq j} \frac{1}{d_{ij}},$$

where d_{ij} denotes the shortest path length between sectors i and j, reflecting how well the entire network facilitates information sharing.

The Kalman gain differences measure how effectively each sector learns from others. Sectors with larger $\Delta\bar{K}_{jk}$ are more attuned to cross-sectoral signals, leading to higher network informativeness. This structure introduces a potential feedback loop: sectors with more network informativeness drive better overall network informativeness, while sectors with less network informativeness might become isolated, reducing their ability to contribute to the aggregate economy's performance. We can decompose each sector's contribution using the local network informativeness measure to assess the resilience and effectiveness of information flow within the network.

5 Data construction

We combine datasets from a range of sources, listed in the 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. We now discuss 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). First, we import monthly price data beginning in January 1960 from the Monthly Stock File (`MSF`) for 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 calculate the three-month change in the log equity 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.

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. Our measure of the state of individual firms is operating income after depreciation (OIADPQ), deflated using the personal consumption expenditure price index (PCEPI) from FRED. As this measure can be negative, we calculate the quarterly growth rate as:

$$\Delta x_t = \begin{cases} \frac{x_t}{x_{t-1}} - 1 & \text{if } x_{t-1} > 0 \\ \frac{x_t}{|x_{t-1}|} + 1 & \text{if } x_{t-1} < 0 \\ NA & \text{if } x_{t-1} = 0 \end{cases} \tag{7}$$

We merge these data with the lagged quarterly change in equity prices using the CRSP/COMPUSTAT Merged (CCM) data crosswalk 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 only keep observations where the observation date is between the beginning and end of the period for which the CCM link is valid.

As the measure of 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 don't use North America Industrial Classification System (NAICS) codes because they are only available beginning in 2000.

5.1.1 Descriptive statistics

Table 1 shows the distribution of total assets across firms for each year in our sample. 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 2 reports the median number of firms for each two-digit SIC sector in our sample. In subsequent analysis of network informativeness, we focus on the larger sectors indicated in **bold font**.

5.2 I/B/E/S analyst recommendations data

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)).

As our measure of information production by analysts, we calculate the total number of recommendations issued by all analysts in a given quarter as reported in the North

Table 1: 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.

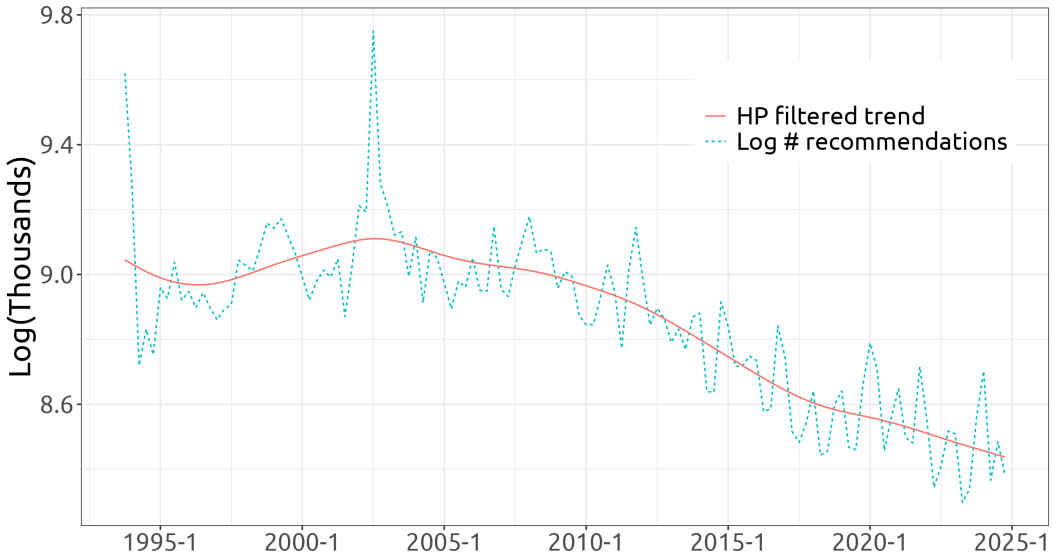
		Total assets ($bn)							Total assets ($bn)				
Year	# Firms	Min	p25	Median	p75	Max	Year	# Firms	Min	p25	Median	p75	Max
1962	190	15.22	21.49	27.77	34.04	40.31	1993	1,599	0	0.06	0.33	1.95	383.5
1963	207	15.64	21.44	27.23	33.02	38.81	1994	1,646	0	0.06	0.33	1.94	406.78
1964	218	16.25	22.42	28.58	34.75	40.91	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 2: 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			

American Summary & Detail Estimates from Refinitiv. Figure 2 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 2: Analyst recommendations. Source: IBES.



5.3 Other macroeconomic data

Table 3 reports the sources for all the other macroeconomic data that we use in our analysis. All the data are downloaded from FRED.

6 Estimation of network informativeness cycles

This section presents the empirical findings on the relationship between network informativeness and macroeconomic variables, shedding light on how information flows evolve over the

Table 3: 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

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 act as a leading or lagging indicator of economic activity, helping to identify the role of financial markets in shaping macroeconomic fluctuations.

In each quarter t, we define $\widehat{\Delta K_{jk}}$ as the arithmetic average of all the firm-level ΔK_{jk} values for firms within sector j, respectively. By treating each industry sector as a node in a graph, we can use $\widehat{\Delta K_{jk}}$ as the weighted connection between sectors, where the weight reflects the extent to which equity prices in sector j incorporate information about the k-th sector's state. 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 network of sectors is an estimate of the flow of information across the economy and

over time in each quarter. 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 filter with $\lambda = 1600$.

To better understand network informativeness in the business cycle, Figure 3 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 4 reports the contemporaneous Pearson correlations between network informativeness and the other business cycle variables. Notably, network informativeness does not exhibit a significant contemporaneous correlation with real GDP. This suggests that its relationship with economic activity is not immediate but may instead operate with a time lag.

While contemporaneous correlations suggest limited direct alignment with GDP, cross-correlation tests reveal that network informativeness consistently leads economic activity by 2 to 3 quarters. Figure 5 presents cross-correlation estimates, where positive lags indicate that network informativeness leads another variable, while negative lags indicate that it lags behind. More specifically, each chart shows estimates of $corr[x(t + LAG), y(t)]$. Thus x leads y if LAG is positive and x lags y if LAG is negative. A key finding is that

Figure 3: Business cycles variables. Each chart shows the business cycle (removing the HP trend) of a macroeconomic variable and cycle of our measure of global network informativeness and number of analyst recommendations. Source: Authors' calculations based on data from CRSP.

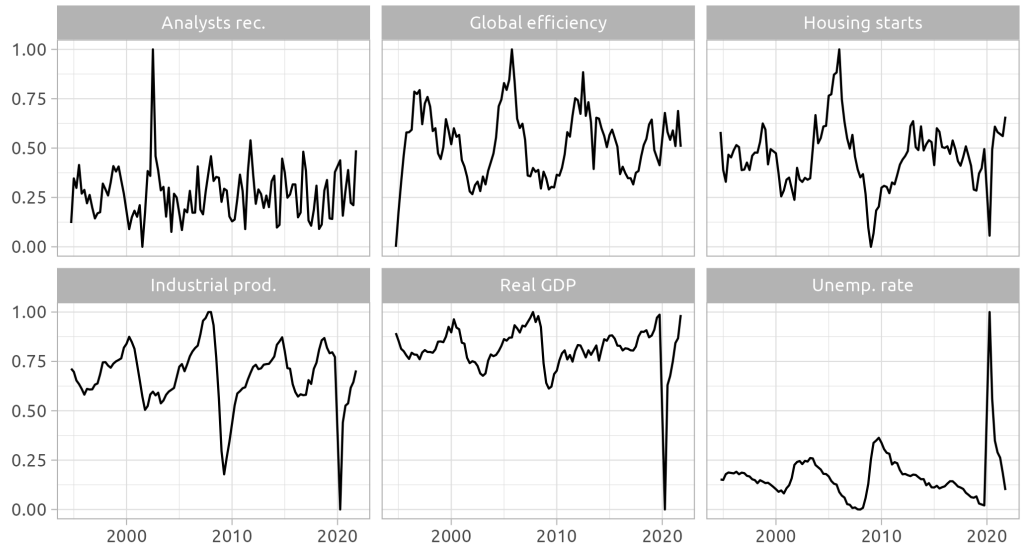
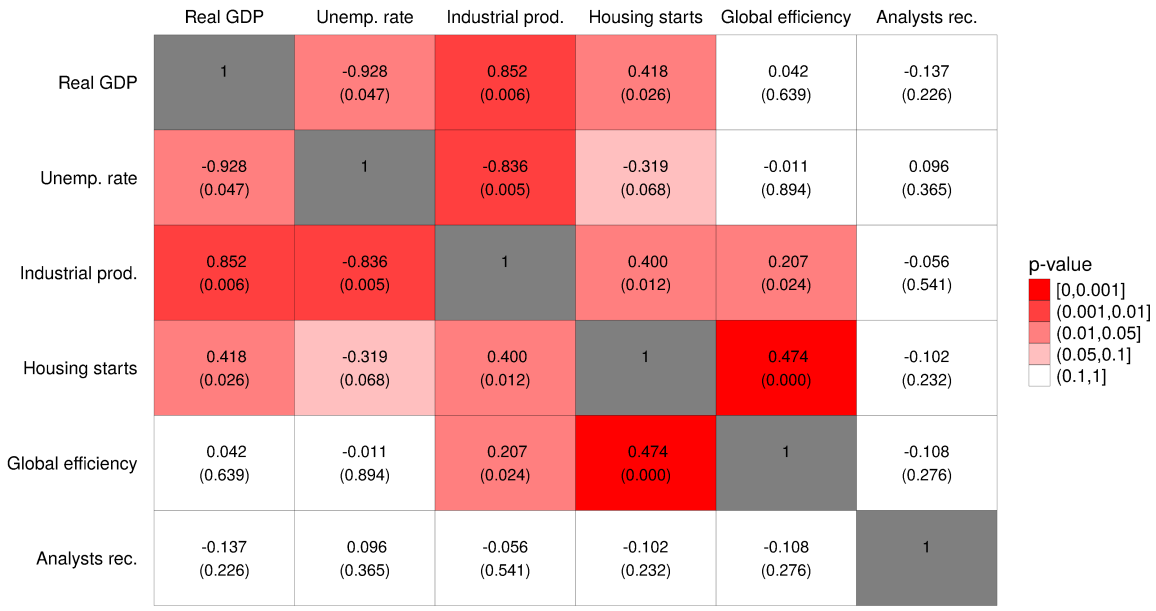


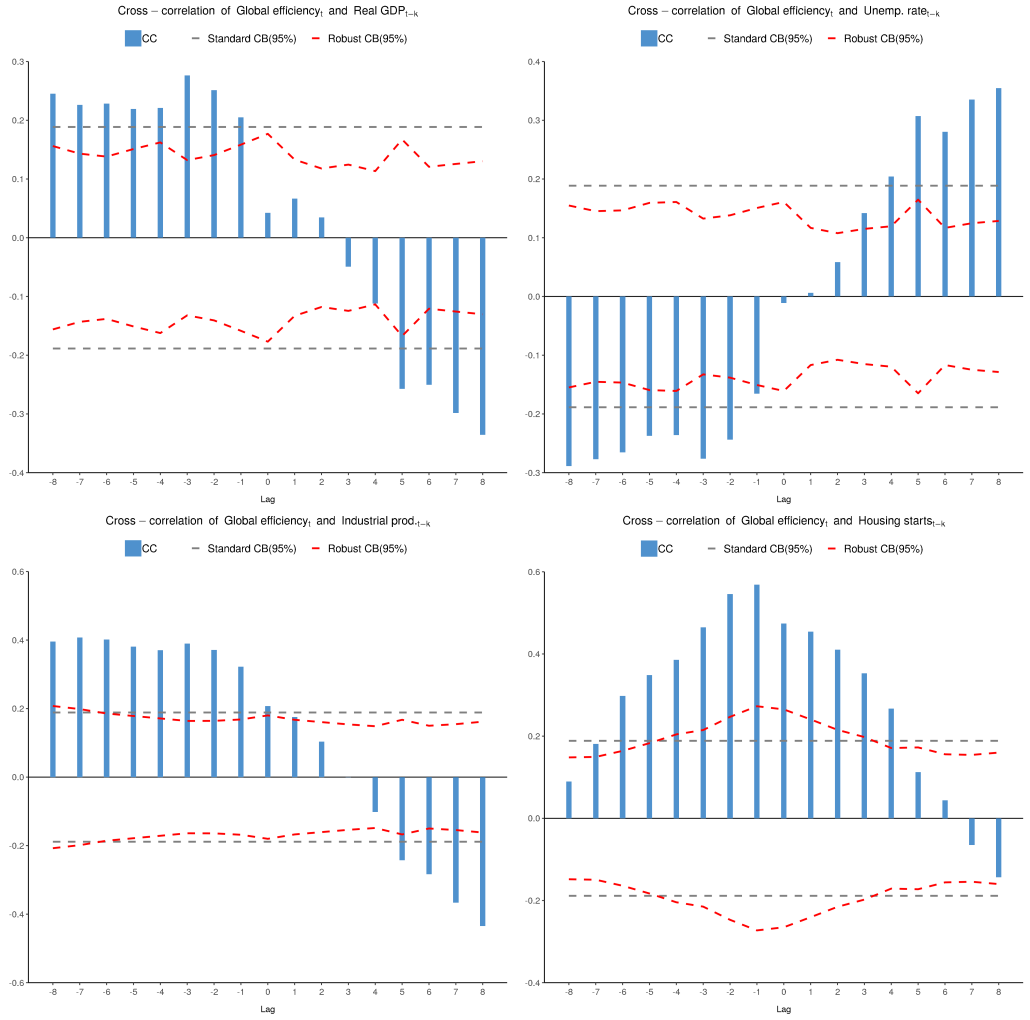
Figure 4: Pearson contemporaneous correlations with robust p-values Robust p-value obtained using the method of Dalla, Giraitis and Phillips (2022)



network informativeness appears to lead real GDP by approximately two to three quarters. This suggests that changes in information flow across sectors precede shifts in overall real economic activity, reinforcing the idea that financial market signals contain information about future macroeconomic conditions.

Figure 5: Cross-correlation test for the network informativeness cycle and real business cycle variables

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-corelation (CC, the blue vertical bars) outside the red dashed lines.



We also 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. The results reveal that declines in analyst recommendations tend to precede increases in network informativeness by two to three quarters. This pattern suggests that analyst activity plays a crucial role in shaping how information flows through financial markets, with fluctuations in recommendation activity influencing the informativeness of stock prices across sectors.

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. By improving the coordination of investment decisions, increases in network informativeness appear to facilitate 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.

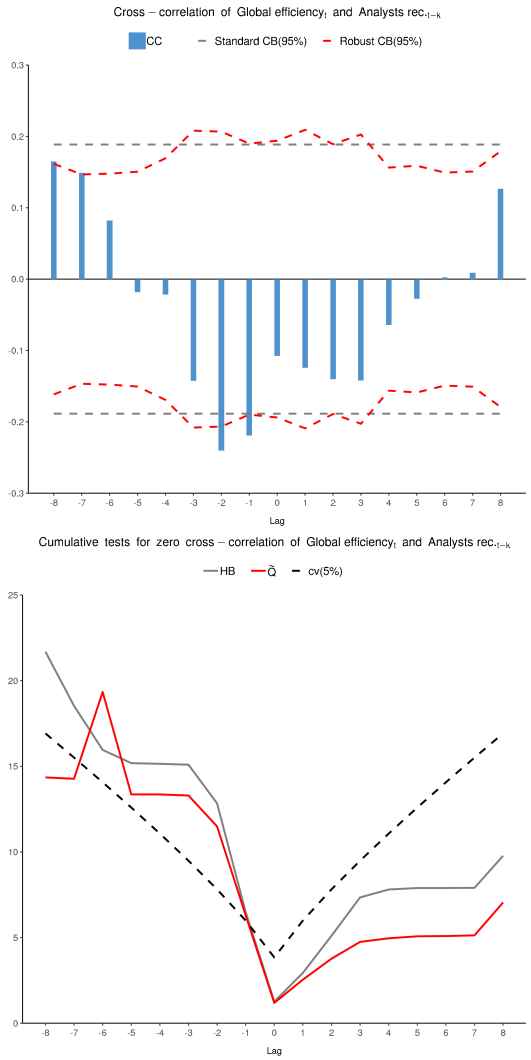
6.1 Interpretation of the results using the model

The observed pattern of positive cross-correlation at lags -1 through -8 quarters and negative cross-correlation at leads 6, 7, and 8 quarters between the network informativeness cycle and the industrial production and real GDP cycle suggests a boom-and-bust dynamic consistent with the self-fulfilling investment coordination model.

During the boom phase, stronger industrial production (positive lags) drives 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 further reinforces investment activity in the short term, as market participants interpret higher network

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 inidividual lags. The robust test rejects H_0 for any of the cross-corelation (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. **Interpretation:** Falling analyst recommendations over the past half-year are associated with rising global 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 the network informativeness cycle when shifted back by 2 to 3 quarters.



informativeness as a positive signal of stable future conditions.

However, the bust phase arises when network informativeness peaks and expectations become overly synchronized. The negative cross-correlation at leads suggests that heightened network informativeness today-reflecting increased information precision-may eventually contribute to over-coordination. Firms, relying on similar informational signals, may collectively delay or reduce investment, anticipating diminishing returns. This synchronized caution in turn results in a contraction of industrial production several quarters later, as the effects of reduced investment ripple through the economy.

6.1.1 Network informativeness and information production

There is a delayed response in 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 2 to 3 quarters. The significant negative cross-correlation at -1 and -2 quarters suggests that an increase in analyst recommendations, representing higher information production, precedes rising network informativeness after a delay.

This pattern 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 this information to be embedded in stock prices, investment behavior, and ultimately, network informativeness.

6.1.2 Network informativeness, housing starts, and monetary policy

We find additional support for the proposed mechanism looking at the correlation with housing starts and the monetary policy cycle. 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 same alignment may also lead to procyclical optimism, where rising network informativeness amplifies investment coordination beyond fundamentals. As network informativeness peaks, the risk of over-coordination increases, leading to the observed delayed downturn in production activity.

A related pattern emerges when examining the monetary policy cycle. The Fed funds rate cycle exhibits a negative and significant correlation at leads 4 through 8 quarters and a positive correlation at lags 2 through 6 quarters with network informativeness. This suggests that tighter monetary policy today predicts weaker network informativeness in the future due to constrained investment, while past lower rates are associated with higher network informativeness as easier credit fosters increased investment and information production.

7 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 leads GDP growth by two to three quarters. Our findings suggest that financial market signals are not merely passive reflections of economic activity but actively shape investment coordination, reinforcing the role of information diffusion in driving business cycle dynamics.

Beyond its empirical contributions, this study provides new insights into the mechanisms of investment coordination and self-fulfilling cycles. We show that increased network informativeness enhances coordination during economic expansions, but excessive synchronization can contribute to downturns. These results underscore the importance of financial analysts and policymakers in influencing 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 [in progress]

Figures 7 and 8 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 7 shows the contributions of all fifteen sectors, while Figure 8 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 be helpful in teasing out a causal test of the information production process underpinning the measure(s) of network informativeness.

Figure 7: 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.

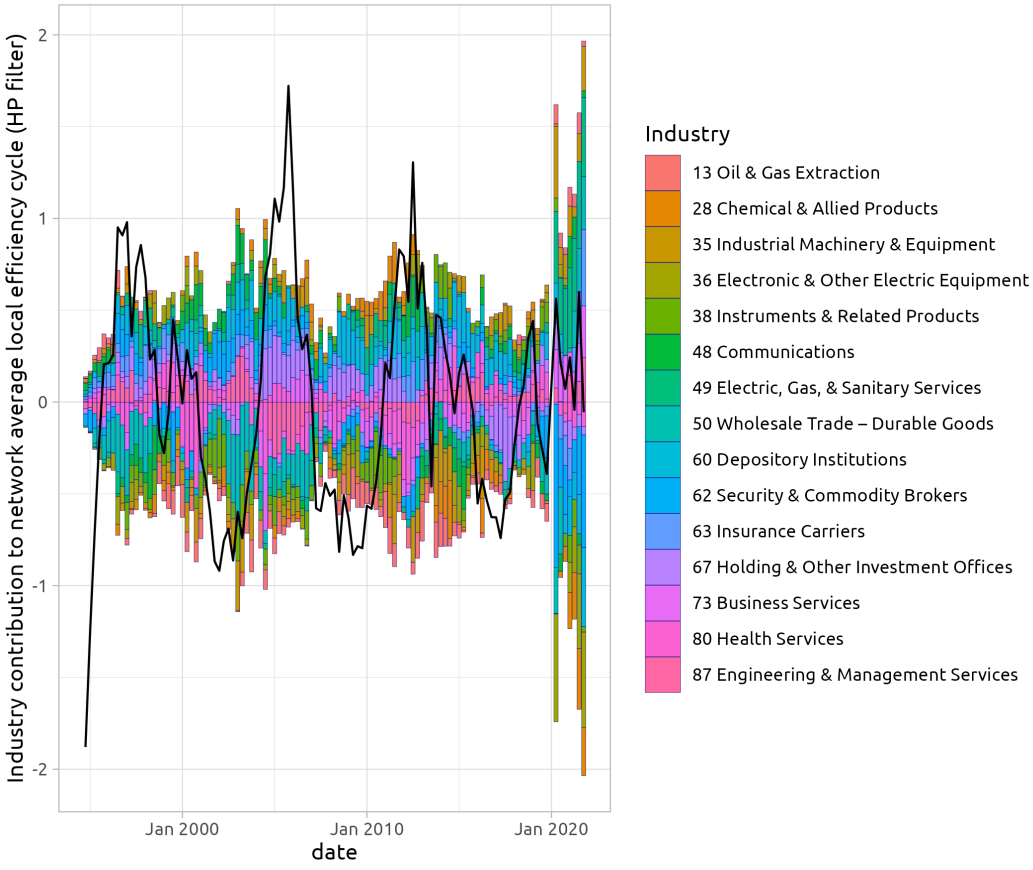
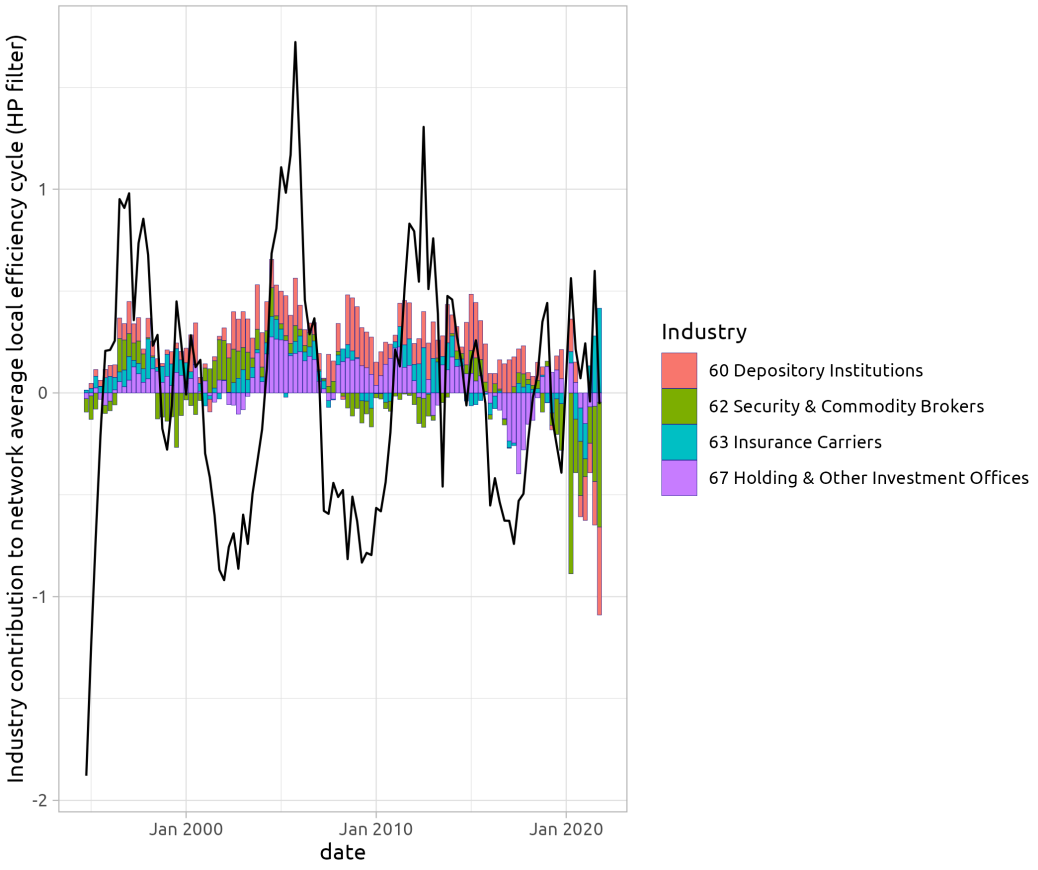


Figure 8: Deviation of the each local network informativeness cycle from the average network informativeness cycle–banking only.



B Data citations

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Online appendix references