Industry Networks and the Speed of Information Flow

by

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Abstract

We investigate whether an industry's position in the network of inter-industry trade affects the speed of information flow. We find that return predictability to central industries from their related (=customer and supplier) industries is substantially stronger than that to peripheral industries from their related industries. Long-short portfolios of central industries yield risk-adjusted returns of 7.0% to 7.9% per annum, which are 3.6% to 5.3% higher than those of peripheral industries. To explain this finding, we argue that investors who invest in central industries need to process more complicated information about related industries, making the prices of central industries slower to incorporate all the information. We find that sell-side analysts of central industries also face more complicated information about related industries, as their earnings forecast revisions of related industries predict their future revisions of central industries more strongly. In addition, we present evidence that our finding is not explained by existing anomalies.

1. Introduction

Financial economists have long recognized the importance of understanding how value-relevant information disseminates to stock markets and how market participants incorporate this information into stock prices. Classical asset pricing theories posit that value-relevant information diffuses immediately in a complete and frictionless market. However, considerable empirical evidence has been accumulated indicating that information can disseminate with sizable delay to financial markets.[1] The gradual information dissemination can be caused by many different sources, e.g., including asymmetric information, limited investors' cognitive resources, trading costs, institutional constraints, and other types of market frictions.

Our paper explores this fundamental research topic, i.e., information flow to stock markets, in the framework of networks.[2] We question whether a node's (industry or firm) position in the network affects the complexity of value-relevant information that investors process and thus influences the speed of information flow through the network. For example, the wholesale and fishery industries are central and peripheral, respectively, and the former is related (or connected) to more industries than the latter by definition. Suppose that the wholesale industry buys a non-negligible amount of canned fish from the fishery industry and a hurricane hits southern coastal fisheries and damages them. The stock price of the fishery industry would reflect this negative shock immediately. How would the stock price of the wholesale industry react to this shock and the price drop of the fishery industry? To price the wholesale industry, investors need to understand not only shocks to other related industries and their price movements but also how important canned fish is in the total revenue of the wholesale industry. Processing more complicated information (about related

[1] E.g., among others, Lo and MacKinlay (1990), Brennan et al. (1993), Badrinath et al. (1995), Chordia and Swaminathan (2000), Cohen and Frazzini (2008), Menzly and Ozbas (2010), and Cohen and Lou (2012).

[2] An emerging literature in finance and economics emphasizes the importance of direct and indirect connections through networks and investigates their economic and financial implications in different contexts, e.g., Acemoglu et al. (2012); Buraschi and Porchia (2012); Ahern (2013); Kelly et al. (2013); Ahern and Harford (2014); Aobdia et al. (2014); Anjos and Fracassi (2014); and Wu and Birge (2014).

industries) can slow down the information flow to the wholesale industry.

We utilize the network of inter-industry trade to answer our question. Extant studies have documented that the market is segmented along the boundaries of industries (e.g., Menzly and Ozbas (2010)). Furthermore, the industry-level supply chain provides clear economic links through which shocks and relevant information can propagate (Menzly and Ozbas (2010) and Chen et al. (2014)). We thus gauge the speed of information flow to different positions in the industry network by measuring the strength of lead-lag relations of returns among economically related (=customer and supplier) industries.

The specific research question that we want to answer is as follows: does the value-relevant information flow to central industries from their related industries more slowly than to peripheral industries from their related industries? The answer to this question is not obvious ex-ante since (at least) two conflicting economic factors can affect the speed of information flow to central industries.[3] The first economic factor can slow down the information flow to central industries. Since central industries, by definition, are connected to more related industries than peripheral industries,[4] investors (with bounded rationality[5]) are required to process more complicated information about related industries (Recall the example of the wholesale and fisher industries above).[6] Thus it takes them longer to incorporate all the information into the prices of central industries, producing more gradual information dissemination.[7] We call this the information complexity effect.[8] The slower information flow

[3]Examples of central industries are the finance (real estate and banking), automobile, construction, and wholesale trade industries.

[4]In our empirical analyses, we use eigenvector centralities. For more details, see Section 3.1.

[5]See, e.g., Simon (1955) and Jensen and Meckling (1992).

[6]This can be interpreted to mean that investors who invest in central industries have higher information collection or processing costs than those in peripheral industries.

[7]When new information arrives, investors with limited cognitive resources do not perform the rational expectations inference to recover the information from observed prices and thus they do not adjust their demand fully as in Grossman and Stiglitz (1980). Similarly to our logic, Cohen and Lou (2012) find that the prices of conglomerates are slower to reflect the same piece of information than those of standalone firms.

[8]Our information complexity effect is related to the literature of limited-information models and empirical tests of their predictions. A long line of extant work belongs to this literature. Examples of recent studies include Hong and Stein (1999), Hong et al. (2007a), Hong et al. (2007b), Cohen and Frazzini (2008), Menzly and Ozbas (2010), and Cohen and Lou (2012).

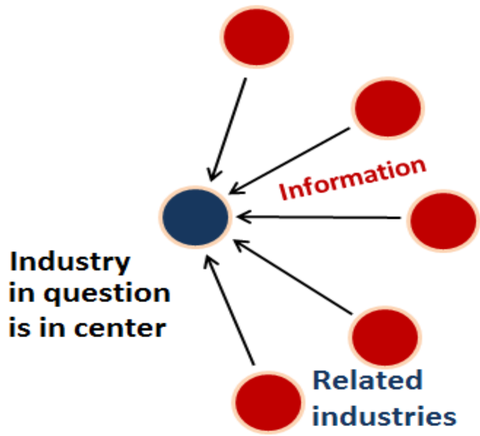

Figure 1. Directions of Information Flow and Return Predictability when the Industry in Question is Located at Different Locations. In the left (right) diagram, the industry in question is located in the center (periphery) of the industry network and related industries can be located anywhere in the network. In both diagrams, arrows indicate the directions of information flow and return predictability to the industry in question from its related industries. When the industry in question is located in the center (periphery), it is connected to more (less) related industries.

to central industries from their related industries implies that the return predictability to central industries from their related industries is stronger than that to peripheral industries from their related industries. Figure 1 demonstrates the directions of information flow and return predictability when the industry in question is located at two different locations: the center (left) and the periphery (right) of the network. Note that related industries can be located in any positions in the network. The second economic factor can accelerate the information flow to central industries. If investors understand the importance of central industries in shock propagation as shown in recent studies,[9] they may pay more attention or allocate more cognitive resources to central industries than to peripheral industries, making the information dissemination to central industries less gradual.[10] We call this the investors'

[9] Acemoglu et al. (2012) show that sectoral shocks from central industries, e.g., banking, automobile, and wholesale trade industries, are more likely to become macro-level fluctuations. Buraschi and Porchia (2012) and Ahern (2013) argue that central firms and industries are riskier due to their higher exposure to systematic risks.

[10] Among early theoretical studies, Holden and Subrahmanyam (1992) and Foster and Viswanathan (1993) show that the price reflects new information more rapidly as the number of informed investors increases. Among early empirical papers, using various proxies for investors' attention, Lo and MacKinlay (1990), Brennan et al. (1993), and Badrinath et al. (1995) document that the returns of stocks with high investors' attention lead those with low investors' attention.

attention effect.

In empirical analyses, we find that the information complexity effect substantially dominates the investors' attention effect in the center of industry network. More specifically, we first document robust evidence that return predictability to central industries from their related industries is significantly stronger than that to peripheral industries. We then quantify the economic magnitude of slower information flow to central industries from their related industries. For each month, we form quintile portfolios of central industries sorted on the return of related industries of central industries in the previous month, go long the quintile portfolio with the highest past return of related industries, and go short the quintile portfolio with the lowest past return of related industries. This self-financing trading strategy is rebalanced every month and involves the buying and selling of central industries. The self-financing trading strategies that invest exclusively in central industries provide significant and economically large risk-adjusted returns, ranging from 7.0% (VW) to 7.9% (EW) per annum, after controlling for the exposure to five known factors. In contrast, the same self-financing trading strategies that invest exclusively in peripheral industries produce risk-adjusted returns of 1.7% (VW) to 4.3% (EW) per annum.[11]

In the next set of tests, we conduct an in-depth investigation to better understand potential underlying economic mechanisms that drive the slower information flow to central industries from their related industries. Our hypothesis is that investors who invest in central industries need to process more complicated information about related industries. If these investors have limited information processing capabilities, it would take them longer to process all the information and to incorporate it into the prices of central industries fully. One testable prediction is that, when new informative signals about related industries arrive, investors who invest in central industries respond to them more slowly than those who invest in peripheral industries. We utilize the earnings forecast revisions of sell-side analysts

[11] 1.7% (VW) is statistically insignificant at any conventional levels.

to examine whether the speed of their responses to new information about related industries differs substantially in the center and periphery of the industry network. We uncover evidence that the sell-side analysts of central industries also need to process more complicated information about related industries, as their earnings forecast revisions of related industries predict their one-month-ahead and two-month-ahead revisions of central industries substantially more strongly than those of peripheral industries. In contrast, the earnings forecast revisions of related industries fail to predict the future revisions of peripheral industries. This evidence is consistent with our information complexity effect.

Our information complexity effect is distinct from the conglomerate effect documented by Cohen and Lou (2012). They find that the prices of conglomerates and standalone firms in the same industry react to the same piece of information differently. The conglomerate effect explains return predictability within an industry, while our information complexity effect explains the information flow across industries.[12] Investors who invest in standalone firms that belong to central industries can face more complicated information about related industries without having the conglomerate effect. In contrast, investors who invest in conglomerates that belong to peripheral industries can have less complicated information about related industries but experience the conglomerate effect. In empirical analyses, we present evidence that information flows significantly more slowly to standalone firms in central industries from their related industries, and the magnitude of return predictability to these standalone firms and that to all firms in central industries are similar, implying that our findings are not explained by the conglomerate effect.

In addition, we test whether other anomalies that previous studies have documented can explain our findings. We examine four representative anomalies: (1) the limits to arbitrage effect captured by idiosyncratic volatility, (2) the institutional ownership effect by Badrinath

[12]Another major difference is that in the conglomerate effect, the returns of standalone firms always lead those of conglomerates, while in our information complexity effect, the directions of information flow can change depending on which industries are the information sources.

et al. (1995) and Menzly and Ozbas (2010),[13] (3) the trading volume effect by Chordia and Swaminathan (2000), and (4) the illiquidity effect by Bali et al. (2014).[14] To control for each of these anomalies, we partition the stock universe into three sub-groups sorted on corresponding characteristic, e.g., idiosyncratic volatility. We document strong evidence that information still flows to central industries substantially more slowly within sub-groups, which indicates that our findings are not explained by these existing anomalies.

The remainder of this paper is organized as follow. Section 2 situates this paper in the extant literature. Section 3 presents the methodology to construct the US industry network and preliminary analyses. Section 4 tests whether the speed of information flow differs at different positions in the industry network. Section 4 also investigates potential underlying economic mechanisms that drive the difference in the speed of information flow across network positions. Section 5 concludes the paper. Throughout this paper, **return cross-predictability** signifies that the returns of customer and supplier industries predict the future returns of the industry in question.

2. Related Literatures

Our paper is related to a large and well-established literature in finance on how value-relevant information diffuses to stock markets and what frictions induce return predictability. One strand of this literature investigates the lead-lag relations of returns among stocks. For example, Lo and MacKinlay (1990), Brennan et al. (1993), Badrinath et al. (1995), Chordia and Swaminathan (2000), Hou (2007), and Cohen and Lou (2012) document evidence that one group of stocks always react to common information faster than another group of stocks. More recent empirical studies present evidence that return predictability along the supply

[13]In these studies, institutional ownership is used as a proxy for investors' inattention.

[14]We do not argue that we can disentangle our information complexity effect completely from underlying economic mechanisms that those existing studies argue. We aim to present evidence that our findings are not explained by the effects captured by the variables that those studies employed.

chain is a pervasive phenomenon caused by investors' inattention and resulting market segmentation. Cohen and Frazzini (2008) provide evidence of return predictability along the firm-level supply chain. Menzly and Ozbas (2010) and Chen et al. (2014) show that the return predictability along the supply chain exists even at industry-level and in different asset classes: stocks and corporate bonds, respectively. Our paper contributes to this literature by exploring the information flow to stock markets in the framework of networks and by identifying an unknown and unique friction inherent in the industry network, through which strong return predictability arises.

An emerging literature in finance and economics emphasizes the importance of the positions of industries in the US industry network in understanding the mechanisms of shock propagation and innovation transfer across industries. The seminal paper by Acemoglu et al. (2012) proposes a model in which idiosyncratic shocks from the central sectors of the economy can produce macro-economic fluctuations in outputs. Ahern (2013) investigates the relationship between industries' positions in the network and the cross-section of stock returns. He argues that companies in the center of the economy have higher market risk and thus their expected returns are higher as compensation for the risk. Aobdia et al. (2014) find evidence that the financial and accounting performance of central industries can be explained by systematic components to a larger extent than that of peripheral industries.[15] Our paper contributes to this burgeoning literature by presenting evidence that an industry's position in the network affects the complexity of information that investors process and thus the speed of information dissemination through the network. We believe that this is an important advance in understanding the asset pricing implications of complex networks and potential sources of anomalies in financial markets.

[15] Aobdia et al. (2014) also find evidence that the earnings of central industries can predict those of related industries more strongly. However, they fail to find evidence that the returns of central industries can predict those of related industries more strongly. This might seem contradictory to our findings. We emphasize that the opposite directions of lead-lag relations and information flow in these two papers lead to completely different economic effects and thus test outcomes. Appendix 6.2 provides more details on major differences between our paper and Aobdia et al. (2014).

3. Methodology, Data, and Preliminary Analyses

3.1. Methodology for the Industry Network

Constructing the Industry Network: To construct an industry network, we exploit the Detailed Input-Output (IO) Tables produced by the Bureau of Economic Analysis (BEA).[16] As of February 2014, twelve BEA reports are available. Among these BEA reports, eliminating the earliest four reports that span from January 1947 through December 1971,[17] we use eight BEA reports for our empirical analyses. Our entire sample period is January 1972 through December 2012. The BEA reports are published roughly every five years and they contain two tables: the MAKE and USE tables. The MAKE table records the dollar values of commodities that each industry produces and the USE table presents the dollar values of commodities that are consumed by each industry as inputs or by final user. In the BEA reports, a commodity means any good or service produced or provided by industries. The detailed BEA reports provide the MAKE and USE tables that record this information for roughly 400 to 500 industries and commodities,[18] whose exact numbers change across different BEA reports.

We interpret the MAKE and USE tables as matrices and perform several matrix algebraic operations.[19] If the (i, j) entry is negative, we move it and add its absolute value to the (j, i) entry, facilitating the interpretations of the MAKE and USE tables. Following Becker and Thomas (2010) and Ahern and Harford (2014), we construct a matrix that records industry-to-industry trades, which we call REVSHARE, by combining the MAKE and USE tables.[20]

[16] These IO-tables are available at *http://www.bea.gov/industry/index.htm#benchmark_io*.

[17] The earliest four BEA reports do not have accounts for the "compensation for employees" or "(total) value added" that reflects the labor costs in their USE tables. Thus the use of these BEA reports might distort industry networks by overestimating the labor-intensive industries compared to the capital-intensive industries.

[18] In our sample period, the BEA employs its own six-digit industry codes (IO-codes), which roughly correspond to six-digit SIC codes. The exact definitions of the IO-codes are provided in the BEA reports.

[19] The (i, j) entry of the MAKE table is the dollar value of commodity j produced by industry i and the (i, j) entry of the USE table corresponds to the dollar value of commodity i consumed by industry j.

[20] We first normalize the MAKE table along each column and multiply it by the USE table, producing the

Normalizing REVSHARE along each row produces a matrix, which we call CUST, recording the fraction of industry i's sales consumed by industry j. Therefore the (i, j) entry in CUST shows how important industry j is as a customer to industry i. Normalizing REVSHARE along each column produces a matrix, which we call SUPP, recording the fraction of industry j's purchases produced by industry i. Thus the (i, j) entry in SUPP shows how important industry i is as a supplier to industry j.

After creating these SUPP and CUST, we exclude the rows and columns that correspond to miscellaneous industry accounts, e.g., households, governments, special industries, and final users (including imports and exports), since the economic activities in these industries do not seem relevant to the theme of our paper. We then combine SUPP and CUST by averaging them into one square matrix, which we call COMB, and symmetrize the COMB by taking the maximum of (i, j) and (j, i) entries.[21] We relegate more detailed discussions on the construction of the industry network into Appendix 6.1.

Determining an Industry's Position in the Network: Interpreting the COMB as an adjacency matrix that defines the strength of links among nodes in a network,[22] we can determine the positions of all industries in the US industry network. For each BEA report, the eigenvector centrality is defined as follows: Setting $A_{i,i} = 0$ for all is,

$$c_i = \frac{1}{\lambda} \sum_j A_{i,j} c_j, \tag{1}$$

REVSHARE. As in Ahern (2013), to properly account for the labor costs in combining the MAKE and USE tables, we generate an artificial industry in the MAKE table, i.e., the account for the compensation for employees. In the same spirit, we generate sets of artificial industries, which vary across different BEA reports. For example, the artificial industries for the 1997 BEA report include the accounts for the compensation for employees, non-comparable imports, used and secondhand goods, rest of world adjustment to final users, indirect business tax and non-tax liability, and other value added. For other BEA reports, sets of artificial industries are similarly determined based on the accounts for adjustments in the USE tables.

[21] This symmetrization has two purposes. First, it facilitates the economic interpretation of COMB as its (i, j) entry defines the strength of connection between industries i and j. However, we can not determine the directions of connections (either customers or suppliers) in COMB. Second, the symmetrization also prevents the eigenvector centralities from being complex-valued.

[22] As in Ahern and Harford (2014), it is also possible to interpret SUPP and CUST as adjacency matrices of supplier and customer networks, respectively. However, in this case, the economic interpretations of network centralities may not be clear after symmetrizing the adjacency matrices.

where $A_{i,j}$ denotes the (i, j) entry of the adjacency matrix $\mathbf{A}$ and λ is a scaling constant (see Bonacich (1972)). Equation (1) is intuitively appealing because, to be more central in the network, an industry needs to be connected to more industries and/or connected strongly to other more central industries. Thus the eigenvector centrality captures not only the number of connections but also their strength in the industry network. In a matrix form, equation (1) is $\lambda\mathbf{c} = \mathbf{Ac}$, meaning that the principal eigenvector of $\mathbf{A}$ with the highest eigenvalue defines the eigenvector centralities of the industry network. Ahern (2013) argues that the eigenvector centrality is the most appropriate centrality measure for the network of inter-industry trade.

When assigning the eigenvector centralities to individual stocks, we use two different types of concordance tables provided by the BEA and US Census Bureau to map the BEA IO-codes into the standard SIC/NAICS codes.[23] Each BEA concordance table enables us to map the BEA IO-codes (unique in the corresponding BEA report) to the most recent SIC/NAICS codes available at its release date. The concordance tables by the Census Bureau enable us to convert SIC/NAICS codes in one BEA report to those in another BEA report.[24]

Dynamic versus Static Industry Networks: Assuming that the US industrial structure does not change over time substantially, Ahern and Harford (2014) and Aobdia et al. (2014) employ the 1997 BEA IO-tables located in the middle of their sample periods to construct the industry networks. Ahern and Harford (2014) present evidence that their findings in merger waves are robust to choosing a different BEA report. However, assuming that the industry network is static over time might not be valid for longer sample periods and/or in different applications.[25] For example, Carvalho and Gabaix (2013) provide evidence that the relative importance of US industries has changed substantially over their sample period:

[23]The concordance tables provided by the US Census Bureau are available at *http://www.census.gov/eos/www/naics/concordances/concordances.html*.

[24]We convert the 1997- and 2002-versions of NAICS codes to 1997-version of SIC codes since the NAICS codes in CRSP and COMPUSTAT are not well populated until 2004.

[25]The sample period of our paper is from January 1972 through December 2012, thus over 40 years.

1960 to 2008. They document that the US economy had experienced a decreasing share of manufacturing industries between 1975 and 1985 and the importance of financial industries has increased in recent years. They also argue that this change in the US industrial structure can explain the swings in the macroeconomic volatility such as the Great Moderation and its undoing.

Unlike the extant studies in which static networks are analyzed, we allow the industry network to change across different BEA reports. Our main tests of return cross-predictability involve Fama-MacBeth (FM) cross-sectional regressions both in firm- and industry-levels, and thus they do not suffer from the time-inconsistency of the definitions of IO-codes across different BEA reports.[26] When testing the comovement of operational performance proxied by ROAs and ΔROAs and testing revision predictability of sell-side analysts' earnings forecast, we perform firm-level pooled regressions. Industry-level pooled regressions can be unreliable due to the time-inconsistency in the definitions of IO-codes.

3.2. Other Data Sources and Variables

Other Data Sources: Empirical analyses in this paper are based on the intersection of the BEA IO-tables and two standard databases: daily and monthly financial data from the Center for Research in Security Prices (CRSP) and quarterly and annual accounting data available on the COMPUSTAT. The entire stock universe from NYSE/AMEX and NASDAQ is employed for the subsequent analyses after the following individual stock screenings. Since the trading characteristics of common stocks (with the CRSP share code of 10 or 11) might be different from those of other asset classes listed in exchanges, as in Chordia et al. (2000), we expunge assets that belong to the following categories from the sample universe: certificates, American depository receipts (ADRs), shares of beneficial interest, units, com-

[26] To reflect the changes in the US industrial structure properly, the BEA defines IO-codes for each BEA report and their definitions vary across different BEA reports.

panies incorporated outside the US, Americus Trust components, close-end funds, preferred stocks, and real estate investment trusts (REITs). Similar to Acharya and Pedersen (2005) and Korajczyk and Sadka (2008), stocks are required to have prices above $1.[27] Stocks are also required to have either historical SIC or NAICS codes since this information is utilized to combine the BEA IO-tables and the intersection of CRSP and COMPUSTAT.[28] After these screenings, we merge the stock universe with the BEA reports. Our sample universe has the average cross-sectional size of 1608 stocks per month. The institutional ownership data are obtained from Thomson Financial's 13F Holdings database, which are combined with CRSP through historical CUSIP codes. The analysts coverage and earnings forecast data come from the I/B/E/S database.

Variables: We here explain the variables frequently used in the subsequent analyses. Following Fama and French (1992) and Davis et al. (2000), we compute the book-to-market (BM) ratios at the end of every calendar year. We then merge them with monthly financial items, allowing a six-month delay to ensure that market participants are fully aware of firms' accounting information released to markets. BM ratios are cross-sectionally winsorized at the 0.5% and 99.5% levels each month. The size (SIZE) of a firm is defined as the natural logarithm of its market capitalization (=number of shares outstanding × price). The return on asset (ROA) is defined as the ratio of the income before extraordinary items (IBQ in quarterly COMPUSTAT) to total assets (ATQ in quarterly COMPUSTAT). To avoid the survivorship bias in returns that might be induced by delisting, we adjust the daily and monthly CRSP returns for delistings as suggested by Shumway (1997). The one-month treasury-bill rate from Ibbotson Associates is used as a proxy for the risk-free rate.

The following firm characteristics are included in monthly FM cross-sectional regressions: lagged SIZE and BM ratio by one month, momentum (MOM) over the past eleven months

[27] Choosing different cutoffs, e.g., $3 and $5, does not affect our main results.

[28] When merging the BEA IO-tables and the intersection of CRSP and COMPUSTAT, we use the primary SIC/NAICS codes available in COMPUSTAT. When this information is missing in COMPUSTAT, we use SIC/NAICS codes available in CRSP.

defined as a summation of monthly returns from month $t-2$ to $t-12$, and short-term return-reversal (REV) defined as a one-month lagged return. To control for the exposure to known risk factors in computing the risk-adjusted returns of self-financing trading strategies, we include the Fama-French three factors (downloaded from Ken French's homepage[29]), i.e., the market return in excess of the risk-free rate (MKTRF), small-minus-big (SMB), and high-minus-low (HML); the momentum factor, i.e., up-minus-down (UMD); and the Pastor and Stambaugh tradable liquidity (PS-LIQ) factor.

3.3. Preliminary Analyses

Before starting our main empirical analyses, we here perform some preliminary analyses. Panel A of Table 1 provides the summary statistics for eigenvector centralities obtained from the 1992 Detailed BEA IO-tables.[30] It shows that the distribution of eigenvector centralities is positively skewed. Based on the network centralities, Panel B of Table 1 presents the twenty most and least central industries in 1992. Examples of the most central industries include the wholesale trade, construction, finance, utility, and auto industries, while those of the least central industries contain the tobacco, hosiery, leather goods, and jewelery industries. These lists are largely consistent with our prior notion about which industries are likely to be central and with previous studies such as Ahern (2013) and Ahern and Harford (2014).[31]

Table 2 provides various average characteristics of centrality-sorted quintile portfolios: the market capitalization (MKTCAP) in billion dollars, BM ratio, return volatility (VOL), idiosyncratic return volatility (IVOL), share turnover (TURN), the number of analysts following on a given month (ANALFOLL), and the percentage of institutional holdings (IHP).

[29] *http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html*

[30] We choose a BEA report located in the middle of our sample period.

[31] The industry network that we constructed in this paper is different from the social accounting matrix (SAM) in Ahern (2013) in that ours models the US industries and their inter-connections as a network, while the SAM models the entire US economy as a network, thus including not only industries, but also government and household sectors.

For each month, VOL is defined as the standard deviation of daily returns. To compute IVOL each month, we run a time-series regression of monthly firm returns on the Fama-French three factors over the past 24 months, and we define the standard deviation of monthly residuals as IVOL. TURN is defined as the ratio of share trading volume to the number of shares outstanding for a given month. These characteristics are based on the constituent stocks of each quintile portfolio. The two rightmost columns in Table 2 are based on the following industry-level characteristics: the Herfindahl-Hirschman indices (HHIs) of customer and supplier industries for the industry in question. We call them the customer-HHI and supplier-HHI, respectively. The customer-HHI for industry i is defined as, excluding s_{ii},

$$\text{Customer-HHI}_i = \sum_{j \neq i} s_{ij}^2, \tag{2}$$

where s_{ij} is the fraction of industry i's sales that industry j consumes and $\sum_j s_{ij} = 1$. The supplier-HHI for industry j is defined in a similar way as, excluding p_{jj},

$$\text{Supplier-HHI}_j = \sum_{i \neq j} p_{ij}^2, \tag{3}$$

where p_{ij} is the fraction of industry j's purchases that industry i produces and $\sum_i p_{ij} = 1$. All portfolio characteristics are averaged over the sample period in which they are available. Table 2 indicates that the more central industries are, the higher BM ratios they have, the less volatile their idiosyncratic returns are, the less frequently traded they are, and the more analysts follow them. For MKTCAP, it is hard to find a clear monotonic pattern across centralities although the most central industries have the largest firms on average. For ANALFOLL, the highest quintile portfolio entertains about 0.5 more analysts following than the lowest quintile portfolio. This spread in the number of analysts following might be small economically. For Customer-HHIs, the most and least central industries tend to have more concentrated customer industries and the values of Customer-HHIs are generally considered by the Antitrust Division of the US Department of Justice as being moderately concentrated.[32] In contrast, for Supplier-HHIs, although a similar pattern exists, their magnitudes and the spread across quintile portfolios are substantially smaller than those of Customer-HHIs. The values of Supplier-HHIs in Table 2 are generally considered by the Antitrust Division of the US Department of Justice as being unconcentrated.

4. Empirical Results

We here conduct various tests to investigate the effect of an industry's position in the network on the speed of information flow. We first test whether central industries have stronger economic ties with their customer and supplier industries than peripheral industries in terms of operational performance. We next examine whether value-relevant information flows more slowly to central industries from their related industries than to peripheral industries. By constructing self-financing trading strategies, we then quantify the economic magnitude of the difference in return cross-predictability across different network positions.

4.1. Strength of Economic Ties

The comovement of operational performance of industries linked by a supplier-customer relation is a necessary condition for information dissemination along the supply chain and thus for return cross-predictability.[33] To test whether the position of the industry in question affects the strength of comovement of operational performance, we consider the following pooled regressions: for firm i in quarter q,

$$\mathrm{ROA}_{i,q} = \alpha_i + \gamma_Z^T Z_{i,q} + \sum_{l\in(C,M,P)} \lambda_l^{related} D_{i,l,q} \mathrm{ROA}_{i,q}^{related} + \varepsilon_{i,q}, \tag{4}$$

[32] $http://www.justice.gov/atr/public/guidelines/hhi.html$.

[33] In the limited-information models, one basic assumption for the existence of return cross-predictability is that the fundamentals of two assets in segmented markets are correlated. See Cohen and Frazzini (2008), Menzly and Ozbas (2010), and the discussion in the internet appendix of Menzly and Ozbas (2010).

$$\Delta\text{ROA}_{i,q} = \widetilde{\alpha}_i + \widetilde{\gamma}_Z^T Z_{i,q} + \sum_{l\in(C,M,P)} \widetilde{\lambda}_l^{related} D_{i,l,q} \Delta\text{ROA}_{i,q}^{related} + \widetilde{\varepsilon}_{i,q}, \tag{5}$$

where a column vector $Z_{i,q}$ contains control variables, e.g., lagged ROAs, lagged ΔROAs, and the market ROA.[34] The industry location subscript l is chosen from $(C, M, P) = (Center, Middle, Periphery)$ which correspond to centrality-sorted tercile portfolios. $D_{i,l,q}$ is an indicator variable defining the location of firm i in the industry network. For example, if the industry which firm i belongs to is located in the center of the industry network in quarter q, then $D_{i,C,q}$ is 1. Otherwise, it is 0. $\text{ROA}_{i,q}^{related}$ denotes the aggregate ROA of related (=customer and supplier) industries. To compute $\text{ROA}_{i,q}^{related}$, we employ the following three steps. For each industry, we first compute the industry-level ROA by averaging the ROAs of its constituent stocks. For each industry, we next calculate $\text{ROA}_{i,q}^{customer}$ ($\text{ROA}_{i,q}^{supplier}$) by weighting the industry-level ROAs of its customer (supplier) industries with the relative importance as a customer (supplier).[35] Then we average $\text{ROA}_{i,q}^{customer}$ and $\text{ROA}_{i,q}^{supplier}$ to obtain $\text{ROA}_{i,q}^{related}$. $\Delta\text{ROA}_{i,q}^{related}$ is the aggregate change in ROA of related industries from quarter $q-1$ to quarter q and we calculate $\Delta\text{ROA}_{i,q}^{related}$ in the same way as $\text{ROA}_{i,q}^{related}$. To control for any potential biases that might be induced by unobserved heterogeneity across firms, firm fixed effects (α_i and $\widetilde{\alpha}_i$) are included in regressions (4) and (5). To report t-statistics, robust standard errors are computed by double-clustering by firm and year-quarter.

Panels A and B in Table 3 present the slope coefficient estimates of regressions (4) and (5), respectively. In Column (1), we assign separate dummy variables to the center, middle, and periphery of the industry network. In Column (2), we assign dummy variables only to the center and middle of the industry network to formally test whether $\lambda_C^{related}$ and $\lambda_M^{related}$ are reliably different from $\lambda_P^{related}$. Panel A indicates that the ROA of a central industry comoves more strongly with the ROA of its related industries than that of a peripheral industry. The difference between $\widehat{\lambda}_C^{related}$ and $\widehat{\lambda}_P^{related}$ is 0.184 and statistically significant at the 5%

[34] The market ROA is constructed by value-weighting the ROAs of all eligible individual stocks.

[35] For industry k, the relative importance of industry j as a customer is s_{kj} in equation (2) and the relative importance of industry j as a supplier is p_{jk} in equation (3).

level (t-statistic=2.03). A middle industry also has the stronger comovement of operational performance with its related industries than a peripheral industry. The difference between $\widehat{\lambda}_M^{related}$ and $\widehat{\lambda}_P^{related}$ is 0.158 and marginally significant at the 10% level (t-statistic=1.67). The operational performance of a peripheral industry and its related industries comoves as well ($\widehat{\lambda}_P^{related}$=0.187 and t-statistic=2.03).

We repeat the same analyses with ΔROAs. Panel B indicates that the ΔROA of a central industry comoves significantly more strongly with the ΔROA of related industries than that of a peripheral industry. The difference between $\widehat{\widetilde{\lambda}}_C^{related}$ and $\widehat{\widetilde{\lambda}}_P^{related}$ is 0.299 and reliably different from zero at the 1% level (t-statistics=3.20). An industry in the middle of the network also has the stronger comovement of operational performance with its related industries than a peripheral industry. The difference between $\widehat{\widetilde{\lambda}}_M^{related}$ and $\widehat{\widetilde{\lambda}}_P^{related}$ is 0.156 and marginally significant at the 10% level (t-statistic=1.69). Overall, these regression results with ΔROAs are consistent with those with ROAs.[36]

Collectively, we find strong evidence that the operational performance of central industries comoves more strongly with that of their related industries. This finding suggests that central industries are economically more tied with their related industries than peripheral industries.

4.2. Speed of Information Flow

We here test whether value-relevant information flows more slowly to central industries from their related industries than to peripheral industries. We consider various special cases of the following monthly FM cross-sectional regression: for firm (or industry) i in month t,[37]

$$r_{i,t}^{e} = \alpha_t + \gamma_{Z,t}^{T} Z_{i,t} + \sum_{l \in (C,M,P)} \gamma_{l,t}^{related} D_{i,l,t-1} r_{i,t-1}^{related} + \varepsilon_{i,t}, \tag{6}$$

[36] Including the firm-fixed effects in regression (5) leaves the results in Panel B nearly intact.

[37] Our tests for return cross-predictability are conducted both in firm- and industry-levels.

where $r^e_{i,t}$ is the excess return of firm i, $Z_{i,t}$ contains the characteristics of interest, e.g., SIZE, BM, MOM, and REV, and the industry location subscript l is chosen from $(C, M, P) = (Center, Middle, Periphery)$ which correspond to centrality-sorted tercile portfolios. $D_{i,l,t-1}$ is an indicator variable defining the location of firm i in the industry network. For example, if the industry which firm i belongs to is located in the center of the industry network, $D_{i,C,t-1}$ is 1 in month $t-1$. Otherwise, it is 0. $r^{related}_{i,t-1}$ denotes the one-month lagged aggregate return of related (=customer and supplier) industries. To compute $r^{related}_{i,t}$, we employ the following three steps. For each industry, we first compute the industry-level return by averaging the returns of its constituent stocks. For each industry, we next calculate $r^{customer}_{i,t}$ ($r^{supplier}_{i,t}$) by weighting the industry-level returns of its customer (supplier) industries with the relative importance as a customer (supplier).[38] Then we average $r^{customer}_{i,t}$ and $r^{supplier}_{i,t}$ to obtain $r^{related}_{i,t}$. After running FM cross-sectional regressions, we take the time-series averages of slope coefficients. To make statistical inferences, we employ the heteroskedasticity and autocorrelation consistent (HAC) covariance matrix estimator proposed by Newey and West (1987), in which the number of lags is determined as suggested by Newey and West (1994).[39]

Panels A and B in Table 4 provide the slope coefficient estimates from regression (6) in firm- and industry-levels, respectively. In Column (1), we assign separate dummy variables to the center, middle, and periphery of the industry network. In Column (2), we assign dummy variables only to the center and middle of the industry network to formally test whether $\gamma^{related}_{C,t}$ and $\gamma^{related}_{M,t}$ are reliably different from $\gamma^{related}_{P,t}$. Column (1) in Panel A indicates that when the lagged return of related industries is used as the information source, $\widehat{\gamma}^{related}_l$s are monotonically aligned in network centralities, i.e., the highest ($\widehat{\gamma}^{related}_C$=0.182 with t-statistic=5.56) is in the center and the lowest ($\widehat{\gamma}^{related}_P$=0.095 with t-statistic=3.94) is in the periphery. Column (2) in Panel A confirms the finding by showing that the difference between

[38]For industry k, the relative importance of industry j as a customer is s_{kj} in equation (2) and the relative importance of industry j as a supplier is p_{jk} in equation (3).

[39]The number of lags is determined as $\lfloor 4(T/100)^{\frac{2}{9}} \rfloor$, where T is the number of time-series observations and the operator $\lfloor x \rfloor$ extracts the integer portion of a real number x.

$\widehat{\gamma}_C^{related}$ and $\widehat{\gamma}_P^{related}$ is 0.088 and statistically significant at the 5% level (t-statistic=2.36). In unreported tests, we find that controlling for industry-level momentum as in Moskowitz and Grinblatt (1999) does not alter these results.

In Panel B, when running FM regressions in industry-level, we obtain similar results with the smaller magnitudes of $\widehat{\gamma}_l^{related}$s for all ls. For example, the industry-level and firm-level FM regressions produce the $\widehat{\gamma}_C^{related}$ of 0.140 and 0.182, respectively. However, the differences between $\widehat{\gamma}_C^{related}$ and $\widehat{\gamma}_P^{related}$ stay similar in industry- and firm-levels (0.076 and 0.088, respectively) and they are reliably different from zero at the 5% level. In summary, both firm- and industry-level FM regressions provide strong evidence that value-relevant information flows substantially more slowly to central industries from their customer and supplier industries than to peripheral industries.

4.3. Quantifying the Economic Magnitudes

Once finding that the returns of central industries are more predictable by their related industries, one may ask how much more attractive the trading strategy that invests exclusively in central industries can be to investors than the trading strategy that invests exclusively in peripheral industries. If central industries have higher exposure to systematic risk factors as documented by Ahern (2013) and Aobdia et al. (2014) and the higher profit of trading strategy that invests exclusively in central industries is mainly driven by this higher exposure, the difference in risk-adjusted returns between those two types of trading strategies might be economically negligible (after removing the portion explained by systematic risks). For self-financing trading strategies that invest in central (peripheral) industries, at the beginning of each month, we form quintile portfolios of central (peripheral) industries sorted on the average return of customer and supplier industries in the previous month. We then go long the quintile portfolio with the highest past return of related industries and go short the one with the lowest past return of related industries. These trading strategies are rebalanced every month and involve the buying and selling of central (peripheral) industries.

To determine central and peripheral industries, as before, we use centrality-sorted tercile portfolios. To compute risk-adjusted returns, we control for the exposure to the following five factors: the Fama-French three (MKTRF, SMB, HML), the momentum (UMD), and the Pastor-Stambaugh tradable liquidity (PS-LIQ) factors.[40] To avoid any potential forward-looking biases, we delay each BEA report until the end of the year in which it becomes publicly available. The different BEA reports became publicly available in 2013, 2007, 2002, 1997, 1994, 1991, 1984, and 1979, respectively.[41]

Excess and Risk-adjusted Returns: Panels A1 and B1 in Table 5 yield the annualized excess returns of value- and equal-weighted self-financing trading strategies, respectively. The rows labeled as "Central industries" ("Peripheral industries") correspond to the trading strategies that invest exclusively in central (peripheral) industries. For quintile portfolios that invest in central industries, in Panel A1, annualized excess returns and Sharpe ratios tend to decrease monotonically from the highest (in High (1)) to the lowest (in Low (5)) quintile portfolios. Excess returns range from 5.6% to 12.7% per annum and Sharpe ratios range from 0.299 to 0.686. Their annualized standard deviations are fairly stable across quintile portfolios. The long-short hedging portfolio (in High-Low) provides an annualized return of 7.1% with a Sharpe ratio of 0.544. For quintile portfolios that invest in peripheral industries, the long-short hedging portfolio produces an annualized return of 2.7% and a Sharpe ratio of 0.156, respectively, which are significantly lower than their counterparts that invest in central industries.

Controlling for the exposure to known risk factors, in Panel A2, the risk-adjusted return of the trading strategy that invests in central industries is 7.0% per annum and remains sta-

[40]The original liquidity factor proposed by Pastor and Stambaugh (2003) is non-tradable. PS-LIQ can be constructed based on factor-mimicking portfolios.

[41]When analyzing self-financing trading strategies, we do not use the 2007 BEA report since it was released at the end of 2013.

tistically significant at the 1% level (t-statistic=3.55). However, the risk-adjusted return of the trading strategy that invests in peripheral industries is 1.7% per annum and not reliably different from zero (t-statistic=0.53). The trading strategy that invests in peripheral industries has significant loadings on UMD and PS-LIQ. The difference in risk-adjusted returns between the trading strategies that invest in central industries and peripheral industries is 5.3% per annum. Thus, as an investment strategy, the trading strategy that invests in central industries seems more attractive than the other trading strategy (before transaction costs).

We repeat the same analyses with equal-weighted quintile portfolios and report the results in Panels B1 and B2. For the trading strategy that invests in central industries, its annualized excess return is 8.1% with a Sharpe ratio of 0.877. Its risk-adjusted return is 7.9% per annum and remains statistically significant at the 1% level (t-statistc=4.64). The risk-adjusted return of the trading strategy that invests in peripheral industries is 4.3% per annum and becomes significant at the 5% level (t-statistic=2.15). The difference in risk-adjusted returns between the trading strategies that invest in central industries and peripheral industries is 3.6% per annum and significant at the 5% level.[42]

In summary, we find evidence that self-financing trading strategies that exclusively invest in central industries produce significant and economically large risk-adjusted returns, ranging from 7.0% to 7.9% per annum. In contrast, the risk-adjusted returns of self-financing trading strategies that exclusively invest in peripheral industries range from 1.7% to 4.3% per annum. This evidence indicates that the economic magnitude of the slower information flow to central industries than to peripheral industries is large.

[42]We run seemingly unrelated regressions (SURs) of monthly returns of these two trading strategies on five risk factors and test whether their intercepts are statistically different.

4.4. Potential Economic Mechanism

In this section, we conduct an in-depth investigation to better understand what potential economic mechanisms drive the slower information flow to central industries from their related industries. By definition, central industries are connected to more related industries than peripheral industries. Investors with limited information processing capabilities who invest in central industries thus need to process more complicated information about their related industries. It takes these investors longer to incorporate all the information into the prices of central industries, inducing the slower information flow to central industries from related industries. We call it the information complexity effect and make the following testable prediction.

Prediction: *When new informative signals about related industries arrive, ceteris paribus, investors who invest in central industries respond to them more slowly than those who invest in peripheral industries.*

We utilize the earnings forecast revisions of sell-side analysts to test this prediction. If the sell-side analysts of central industries also face more complicated information about related industries as investors, then (1) their earnings forecast revisions of related industries would predict their future revisions of central industries more strongly than those of peripheral industries and (2) this stronger predictability of earnings forecast revisions to central industries would stay significant for longer time period than that to peripheral industries.

For firm i in month t, as in Cohen and Frazzini (2008), we define monthly analysts' earnings forecast revision as $\mathrm{AREV}_{i,t} = (\mathrm{UP}_{i,t} - \mathrm{DOWN}_{i,t})/\mathrm{NUMEST}_{i,t}$, where $\mathrm{NUMEST}_{i,t}$ is the number of estimates of firm i's earnings for the current fiscal quarter end, and $\mathrm{UP}_{i,t}$ ($\mathrm{DOWN}_{i,t}$) is the number of upward (downward) earnings forecast revisions.[43] We consider

[43]Using analysts' earnings forecast revisions for the current fiscal year end produces similar results.

the following pooled regressions for k-month lag ($k = 1, 2$):

$$\text{AREV}_{i,t} = \alpha_i + \beta_t + \gamma_Z^T Z_{i,t} + \sum_{l \in (C,M,P)} \psi_{l,k}^{related} D_{i,l,t-k} \text{AREV}_{i,t-k}^{related} + \varepsilon_{i,t,k}, \tag{7}$$

where α_i and β_t denote firm- and time-fixed effects, respectively, and $Z_{i,t}$ contains control variables: lagged AREV, the aggregate return of related industries of firm i lagged by one month, i.e., $r_{i,t-1}^{related}$, and the industry-level analysts' revision (AREVIND) lagged by one month.[44] Note that all control variables are lagged by only one month. $\text{AREV}_{i,t-k}^{related}$ is the aggregate analysts' revision of related industries of firm i lagged by k months and it is computed in the same way as $r_{i,t-1}^{related}$. The location dummy variable $D_{i,l,t-k}$ in month $t-k$ is defined in the same way as before. To report t-statistics, we compute robust standard errors by double-clustering by firm and year-month. To facilitate the economic interpretation of slope coefficient estimates, we standardize all variables by subtracting the means and dividing by the standard deviations of all observations.

Table 6 presents the results of panel regression (7) and evidence that the sell-side analysts of central industries also face more complicated information about related industries. From Columns (1) and (2), we find that analysts' earnings forecast revisions of related industries predict their one-month-ahead revisions of central industries substantially more strongly than those of peripheral industries. In Column (1), $\widehat{\psi}_{C,1}^{related}$ is 0.049 and highly significant at the 1% level (t-statistic=6.06), while $\widehat{\psi}_{P,1}^{related}$ is 0.009 and insignificant at any conventional level (t-statistic=1.34). When testing whether the difference between $\widehat{\psi}_{C,1}^{related}$ and $\widehat{\psi}_{P,1}^{related}$ differs from zero reliably, in Column (2), we find that the difference is 0.040, more than four-times larger than $\widehat{\psi}_{P,1}^{related}$, and highly significant at the 1% level (t-statistic=4.34). From Columns (3) and (4), we find that analysts' earnings forecast revisions of related industries can also predict two-month-ahead revisions of central industries substantially more strongly than those of

[44]Running monthly Fama-MacBeth regressions as in Cohen and Frazzini (2008) yields similar results to those in Table 6.

peripheral industries although the strength of predictability is reduced.[45] These results indicate that the sell-side analysts of central industries indeed respond to new information about related industries substantially more slowly than those of peripheral industries, while the sell-side analysts of peripheral industries digest new information about related industries immediately. This evidence is largely consistent with our information complexity effect.

We also examine potential impacts of staleness in analysts' earnings forecast revisions on our results. In unreported table, we uncover evidence that the contemporaneous correlation of $\text{AREV}_{i,t}$ and $\text{AREV}^{related}_{i,t}$ does not significantly differ in the center and periphery of the industry network, indicating that our findings in Table 6 are not driven by the staleness in analysts' earnings forecast revisions.[46]

4.5. Distinction from Existing Anomalies

We here examine whether our findings can be explained by anomalies that previous studies have documented. We do not attempt to disentangle our information complexity effect completely from underlying economic mechanisms that those anomalies are potentially based on. We aim to present evidence that our findings are not entirely explained by effects captured by particular variables used in previous studies. We consider the following five anomalies: (1) the conglomerate effect by Cohen and Lou (2012), (2) the limits to arbitrage effect captured by idiosyncratic volatility, (3) the institutional ownership effect by Badrinath et al. (1995) and Menzly and Ozbas (2010), (4) the trading volume effect by Chordia and Swaminathan (2000), and (5) the illiquidity effect by Bali et al. (2014).

Conglomerate Effect: Cohen and Lou (2012) find that conglomerates are slower to incorporate the same piece of information into their prices than standalone firms that op-

[45] These results of two-month-ahead revision predictability survive controlling for $\text{AREV}^{related}_{i,t-1}$ additionally.

[46] We find weak evidence that the contemporaneous correlation of $\text{AREV}_{i,t}$ and $\text{AREV}^{related}_{i,t}$ is stronger in the center than in the periphery of the industry network, indicating that the staleness in analysts' earnings forecast revisions can be more severe in the periphery.

erate in the same industry. If central industries have significantly more conglomerates than peripheral industries, ceteris paribus, the conglomerate effect might drive our findings. To disentangle our information complexity effect from the conglomerate effect, we choose standalone firms from the entire stock universe and then test whether value-relevant information still flows more slowly to standalone firms in central industries from their related industries. For each firm, we determine industry segments based on two-digit SIC codes and compute the HHI of segment sales. As in Cohen and Lou (2012), we define standalone firms as those that have HHIs greater than 0.64.[47]

Table 7 reports the testing results with standalone firms only. As in Table 4, Column (1) shows that the slope coefficients, i.e., $\widehat{\gamma}_l^{related}$s, of interaction terms between the lagged returns of related industries and location dummies are nicely aligned in network centralities. Column (2) confirms that the difference between $\widehat{\gamma}_C^{related}$ and $\widehat{\gamma}_P^{related}$ is 0.085 and significantly different from zero at the 5% level (t-statistic=2.13). With standalone firms which are free from the conglomerate effect by definition, we find that the magnitudes of $\widehat{\gamma}_C^{related}$ and $\widehat{\gamma}_P^{related}$ are slightly smaller than those with all firms (Table 4), implying that our findings are not explained by the conglomerate effect by Cohen and Lou (2012).

Limits to Arbitrage Effect: To test whether our findings can be explained by the limits to arbitrage captured by idiosyncratic volatility, we partition the entire stock universe into three sub-groups sorted on IVOL and then run FM cross-sectional regressions in equation (6) within each sub-group. Table 8 presents the results of FM cross-sectional regressions for three sub-groups. Within sub-groups that have high and medium levels of IVOL, the slope coefficients, i.e., $\widehat{\gamma}_l^{related}$s, are nicely aligned in network centralities. For these sub-groups, the differences between $\widehat{\gamma}_C^{related}$ and $\widehat{\gamma}_P^{related}$ differ from zero significantly at the 5% level, indicating that information still flows significantly more slowly to central industries from

[47] Cohen and Lou (2012) define standalone firms as those that operate in one industry and whose segment sales account for more than 80% of the total sales. Altering the cutoff for standalone firms and using one-digit SIC codes to determine industry segments do not change the results in Table 7.

related industries even after controlling for IVOL levels. When analyzing the sub-group that has low IVOL level, we find that the difference between $\widehat{\gamma}_C^{related}$ and $\widehat{\gamma}_P^{related}$ is not reliably different from zero, although $\widehat{\gamma}_l^{related}$ still increases monotonically in network centralities. Across three sub-groups, regardless of network positions, return cross-predictability becomes stronger monotonically as the level of IVOL increases, implying that the more binding limits to arbitrage are, the slower the information flow is.

Institutional Ownership Effect: Theories in the limited-information models predict that the higher level of investors' inattention makes information dissemination more gradual (see, e.g., Merton (1987); Hong and Stein (1999); Hirshleifer and Teoh (2003); Hong et al. (2007b)). Among empirical studies, e.g., Badrinath et al. (1995) and Menzly and Ozbas (2010) employ institutional ownership as a proxy for investors' inattention. To disentangle our information complexity effect from the institutional ownership effect, we partition the entire stock universe into three sub-groups sorted on the percentage ownership of institutional investors, i.e., IHP. We then test whether information still flows significantly more slowly to central industries from related industries within each sub-group.

Panel A in Table 9 reports the results of FM cross-sectional regressions when we control for the institutional ownership effect. Within all sub-groups, $\widehat{\gamma}_l^{related}$s increase monotonically in network centralities and the differences between $\widehat{\gamma}_C^{related}$ and $\widehat{\gamma}_P^{related}$ are significantly different from zero at the 5% level. Within the sub-groups of high and medium IHP levels, $\widehat{\gamma}_P^{related}$s are insignificant at the 5% level (t-statistics are 0.83 and 1.85, respectively). This implies that the weakest return cross-predictability to peripheral industries disappears first as IHP level increases from Column (6) to Column (1). Overall, these results strongly suggest that our information complexity effect is not explained by the institutional ownership effect.

Turnover Effect: Chordia and Swaminathan (2000) document that the returns of firms with high trading volume lead those with low trading volume. To test whether our findings can be explained by this turnover effect to a certain extent, we partition the NYSE/AMEX stock universe into three sub-groups sorted on share turnover, i.e., TURN. Panel B in Table 9 reports the results of FM cross-sectional regressions. Within sub-groups that have medium and low TURN levels, the differences between $\widehat{\gamma}_C^{related}$ and $\widehat{\gamma}_P^{related}$ stay significant at the 5% level (t-statistics are 2.11 and 2.09, respectively). For the sub-group that has high TURN level, this difference becomes insignificant although $\widehat{\gamma}_l^{related}$s are increasingly monotonic in network centralities.

Illiquidity Effect: Bali et al. (2014) document evidence that illiquidity contributes to the short-term stock market under-reaction (up to six months) and thus price discovery can be delayed following liquidity shocks. To test whether our findings can be explained by this illiquidity effect, we partition the NYSE/AMEX stock universe into three sub-groups sorted on Amihud illiquidity (ILLIQ). Panel C in Table 9 reports the results of FM cross-sectional regressions. Within sub-groups that have high and medium levels of ILLIQ, the differences between $\widehat{\gamma}_C^{related}$ and $\widehat{\gamma}_P^{related}$ stay significant at the 5% level (t-statistics are 2.07 and 2.14, respectively). For the sub-group that has low ILLIQ level, this difference is marginally significant at the 10% level (t-statistic=1.68). Overall, the evidence suggests that our findings are not explained by the illiquidity effect by Bali et al. (2014).

Cumulative Returns: We also investigate whether the returns of self-financing trading strategies that invest in central and peripheral industries (studied in Section 4.3) experience significant reversals over a longer horizon than one month. Table 10 provides the cumulative returns of value- and equal-weighted self-financing trading strategies up to 12 months. These cumulative returns are obtained by summing up monthly excess returns of long-short hedging portfolios. Columns (1) to (4) show that none of trading strategies that invest in central and peripheral industries experience significant return-reversals over 12 months after portfolio formation. This evidence implies that a certain form of investors' over-reaction to central industries is unlikely to drive our findings.

In summary, all the evidence in this section supports that our findings are distinct from existing anomalies that previous studies have documented in the literature and makes our information complexity effect more compelling as a potential explanation for our findings.

4.6. Change in Institutional Co-ownership

Institutional investors are likely to be more efficient in processing value-relevant information obtained from related industries or to have lower information collection costs than retail investors. In addition, self-financing trading strategies that invest in central industries might be fairly attractive to institutional investors in several respects. For example, Table 5 shows that the risk-adjusted returns of trading strategies with top centrality are significantly higher than those of the other two trading strategies. It is thus possible that institutional investors might exploit the stronger return cross-predictability from related industries to central industries for their investment.

We here test whether institutional investors increase (decrease) their positions more in central industries when they increase (decrease) the positions in related industries. We consider the following panel regression: for firm i in quarter q,

$$\Delta\text{IHP}_{i,q} = \alpha_i + \beta_q + \sum_{l\in(C,M,P)} \theta_l^{related} D_{i,l,q} \Delta\text{IHP}_{i,q}^{related} + \varepsilon_{i,q}, \tag{8}$$

where $\Delta\text{IHP}_{i,q}$ denotes the change in the percentage ownership of institutional investors in firm i from quarter $q-1$ to quarter q and $\Delta\text{IHP}_{i,q}^{related}$ is the aggregate change in the percentage ownership of institutional investors in related industries of firm i from quarter $q-1$ to quarter q.[48] We compute $\Delta\text{IHP}_{i,q}^{related}$ in the same way as $\text{ROA}_{i,q}^{related}$ and $\Delta\text{ROA}_{i,q}^{related}$. To control for any potential biases that might be induced by unobserved heterogeneity across firms and for systematic fund inflows and outflows of institutional investors, firm (α_i) and year-quarter (β_q) fixed effects are included in regression (8), respectively. To report t-statistics, robust

[48]We winsorize the percentage ownership of each firm by institutional investors into 100% when it is over 100%. Winsorizing or eliminating these observations produces similar results.

standard errors are computed by double-clustering by firm and year-quarter.

Table 11 presents the results of panel regression (8) and shows that all $\widehat{\theta}_l^{related}$s have similar values to each other (in Column (1)) and their differences are not significant (in Column (2)). For example, $\widehat{\theta}_C^{related}$ is not reliably different from $\widehat{\theta}_P^{related}$ with a low t-statistic of 0.19. The finding that $\widehat{\theta}_l^{related}$s are all significant with high t-statistics indicates that institutional investors exploit the value-relevant information disseminated from customer and supplier industries when they rebalance their portfolio positions. However, the insignificant differences among $\widehat{\theta}_l^{related}$s do not support that institutional investors invest (disinvest) more in central industries than in peripheral industries when they invest (disinvest) in related industries. This implies that even sophisticated and potentially more informed institutional investors as a whole do not exploit the difference in return cross-predictability across network positions.

Overall, the finding in this section is consistent with the small spread (=0.5 analysts) in the number of analysts following across centrality-sorted quintile portfolios presented in Table 2. These two findings imply that investors as a whole do not pay significantly more attention nor allocate by far more cognitive resources to central industries although they need to process more complicated information about related industries.

5. Conclusions

We interpret the US industries and their inter-industry trades as a network over 40 years and identify an unknown and unique anomaly inherent in the US industry network. We find robust and strong evidence that value-relevant information flows substantially more slowly to central industries from their economically related (=customer and supplier) industries than to peripheral industries. Long-short portfolios formed on the past returns of related industries of central industries yield significant and economically large risk-adjusted returns of 7.0% to 7.9% per annum.

To better understand a potential economic mechanism that drives our findings, we conduct an in-depth investigation into the differential information complexity that investors at different network positions face. The information complexity effect is that investors who invest in central industries need to process more complicated information about economically related industries, and thus it take them longer to process all the information and to incorporate it into the prices of central industries fully. To support the information complexity effect, we document strong evidence that the sell-side analysts of central industries respond to new information about related industries substantially more slowly than those of peripheral industries. We also present evidence that our information complexity effect is not explained by various anomalies that previous studies have documented.

6. Appendices

This section covers the detailed materials not provided in the main text of this paper: (1) the construction of the industry network from the BEA reports and (2) the reconciliation of our findings with Aobdia et al. (2014).

6.1. Details on Constructing the Industry Network

For each pair of the MAKE and USE tables, we aggregate the IO-codes with the same SIC/NAICS codes since they will be assigned to the same stocks when we merge the BEA report and the standard databases: CRSP and COMPUSTAT. The lists of aggregated IO-codes are different across different BEA reports. We also expunge the IO-codes that do not have SIC/NAICS codes in the BEA concordance tables.

Following Ahern (2013), we generate sets of artificial industries to take the adjustment accounts in the USE table into consideration. After adding the rows and columns for these artificial industries to the MAKE table, we combine the MAKE and USE tables, producing the REVSHARE matrix. The list of artificial industries is as follows: (1) non-comparable imports, (2) used and second-hand goods, (3) rest of the world adjustment to final users, (4) compensation for employees, (5) taxes on production and imports less subsidies, (6) gross operating surplus, (7) indirect business tax and non-tax liability, (8) other or total value added, (9) commodity credit corporation, and (10) profit-type income. Subsets of these accounts show up in different BEA reports and these artificial industries are not included when we compute the eigenvector centralities of the industry network.

6.2. Reconciliation with the Existing Evidence

Aobdia et al. (2014) fail to find evidence that the returns of central industries predict the future returns of related industries more strongly, which might look contradictory to our

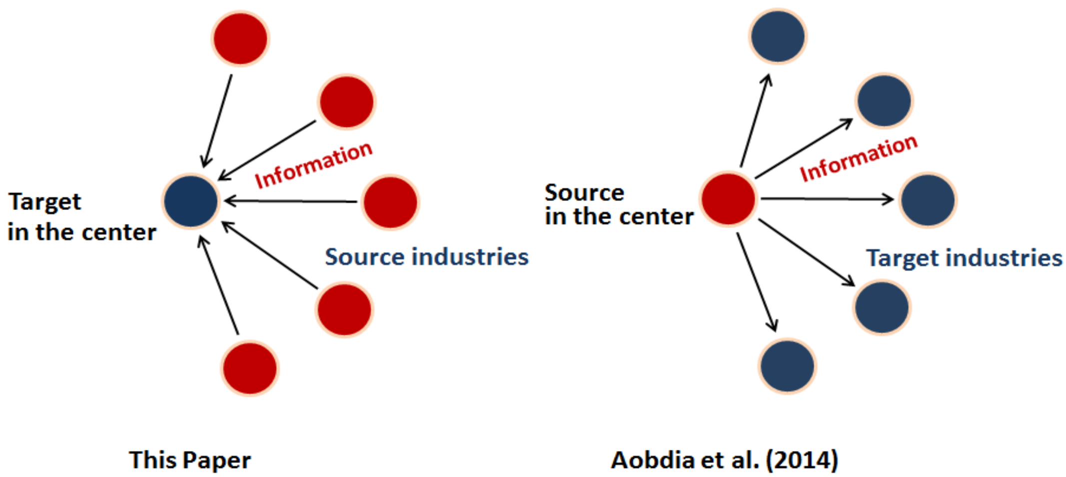

Figure 2. Opposite Directions of Information Flow and Return Cross-Predictability in Our Paper and Aobdia et al. (2014). In the left (right) diagram, the target (source) industry is located in the center of the industry network and source (target) industries can be located anywhere in the network. In both diagrams, arrows indicate the directions of information flow and thus return cross-predictability from source to target industries.

main findings at the first glance. In this section, we reconcile the seemingly opposite findings in these two papers.

First of all, the focuses of the two papers differ substantially. We investigate whether an industry's position in the network affects the complexity of value-relevant information that investors process and thus the speed of information dissemination to the industry in question from related industries. We identify an unknown and unique market friction inherent in the US industry network through which strong return cross-predictability can arise. In contrast, Aobdia et al. (2014) emphasize that the financial and accounting performance of central industries is explained to a larger extent by systematic components such as risk factors and macro variables than that of peripheral industries. They do not investigate the relationship between an industry's position in the network and the complexity of value-relevant information that investors face nor the effects of the information complexity on the speed of information flow at different network positions. Accordingly, their research design and empirical tests differ from ours significantly. Figure 2 contrasts the opposite directions of information flow, the lead-lag relations of returns, and thus return cross-predictability in the two papers.

Second, in their study, when a shock propagates from source to target industries, the targets can diversify it away since they have alternative suppliers and/or customers (see the right diagram in Figure 2). When we replicate their empirical tests, we uncover weak evidence that an industry's position in the network affects the speed of information flow and also find that the economic magnitudes of their return predictability are five to ten times smaller than those of ours. The diversification effect may explain their substantially weaker results to a certain extent.

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Table 1.

Summary Statistics for the Industry Network Centrality (in 1992)

This table provides the summary statistics for the industry network centralities (Panel A) and the lists of the twenty most and twenty least central industries (Panel B) in the 1992 BEA report. 465 disaggregate industries are analyzed in the 1992 Detailed Input-Output Tables from the Bureau of Economic Analysis (BEA). The reported centralities are the eigenvector centralities based on their inter-industry trades.

Panel A: Summary Statistics for Centralities

Statistics & percentiles	Eigenvector centrality of the industry network
Mean	0.038
Standard deviation	0.027
Minimum	0.010
5th percentile	0.018
10th percentile	0.021
25th percentile	0.025
Median	0.033
75th percentile	0.040
90th percentile	0.056
95 percentile	0.068
Maximum	0.347
Number of observations	465

Panel B: Lists of the Twenty Most and Twenty Least Central Industries

Twenty most central industries	Twenty least central industries
Wholesale trade	Petroleum, natural gas, solid mineral exploration
Eating and drinking places	Racing, including track operation
Construction industries	Cigars
Real estate agents, managers, and operators	Boot and shoe cut stock and findings
Commercial construction industries	Women's hosiery, except socks
Trucking and courier services, except air	Hosiery
Blast furnaces and steel mills	Tobacco stemming and redrying
Electric services (utilities)	Manufactured ice
Miscellaneous plastics products	Chewing and smoking tobacco and snuff
Motor vehicles and passenger car bodies	Schiffli machine embroideries
Banking	Professional sports clubs and promoters
Petroleum refining	Women's handbags and purses
Retail trade, except eating and drinking	Burial caskets
Industrial inorganic and organic chemicals	Leather gloves and mittens
Paper and paperboard mills	Personal leather goods
Paperboard containers and boxes	Special product sawmills
Motor vehicle parts and accessories	Jewelers' materials and lapidary work
Telephone, telgraph communications, and communications	X-ray apparatus and tubes
Hospitals	Leather goods
Bread, cake, and related products	Costume jewelry
Automotive repair shops and services	Nonferrous metal ores, except copper

Table 2.

Characteristics of Centrality-sorted Quintile Portfolios

This table provides the averages of various characteristics of centrality-sorted quintile portfolios over January 1972 through December 2012. Eight detailed Input-Output tables from the Bureau of Economic Analysis (BEA) are merged with CRSP and COMPUSTAT data through SIC/NAICS codes. For each BEA report, eigenvector centralities are computed and assigned to individual stocks based on their industry memberships. Within each quintile portfolio, the following characteristics are computed by equal-weighting constituent stocks: the market capitalization (MKTCAP) in billion dollars, book-to-market (BM) ratio, return volatility (VOL), idiosyncratic return volatility (IVOL), share turnover (TURN), the number of analysts following on a given month (ANALFOLL), and the percentage of institutional holdings (IHP). Customer-HHI and Supplier-HHI (two rightmost columns) are the Herfindahl-Hirschman indices (HHIs) for sales and purchases per industry, respectively, which are aggregated across industries. Characteristics of quintile portfolios are averaged over the sample period.

Panel: Average Characteristics of Centrality-sorted Quintile Portfolios

Centrality rank	MKTCAP (Bill$)	BM ratio	VOL	IVOL	TURN	ANAL-FOLL	IHP (%)	Customer-HHI	Supplier-HHI
High (1)	2.563	1.094	0.026	0.085	0.078	3.10	42.1	0.292	0.117
(2)	1.986	0.934	0.026	0.087	0.084	2.88	44.5	0.157	0.099
(3)	1.979	0.938	0.026	0.089	0.082	2.93	45.1	0.170	0.092
(4)	2.104	0.866	0.028	0.094	0.085	2.74	44.0	0.203	0.102
Low (5)	2.070	0.895	0.028	0.096	0.084	2.58	43.2	0.259	0.127

Table 3.

Strength of Economic Ties and Network Positions

We consider special cases of the following pooled regressions: for firm i in quarter q,

$$\begin{aligned}\text{ROA}_{i,q} &= \alpha_i + \gamma_Z^T Z_{i,q} + \sum_{l\in(C,M,P)} \lambda_l^{related} D_{i,l,q}\text{ROA}_{i,q}^{related} + \varepsilon_{i,q},\\ \Delta\text{ROA}_{i,q} &= \widetilde{\alpha}_i + \widetilde{\gamma}_Z^T Z_{i,q} + \sum_{l\in(C,M,P)} \widetilde{\lambda}_l^{related} D_{i,l,q}\Delta\text{ROA}_{i,q}^{related} + \widetilde{\varepsilon}_{i,q},\end{aligned}$$

where $Z_{i,q}$ contains control variables, e.g., lagged ROAs and ΔROAs, and l is chosen from $(C, M, P) = (Center, Middle, Periphery)$. $D_{i,l,q}$ is an indicator variable defining the location of firm i in quarter q. For example, if the industry which firm i belongs to is central, $D_{i,C,q}$ is 1 otherwise 0. $\text{ROA}_{i,q}^{related}$ is the aggregate ROA of customer and supplier industries of firm i. To report t-statistics in parentheses (bold if significant at the 5% level), robust standard errors are computed by double-clustering by firm and year-quarter. Panels A and B provide the slope coefficient estimates of pooled regressions with ROAs and ΔROAs, respectively.

Panel A: Quarterly ROA

	(1) ROA(q)	(2) ROA(q)
ROA(q-1)	**0.099**	**0.099**
	(4.71)	**(4.70)**
ROA(q-2)	**0.053**	**0.053**
	(5.25)	**(5.23)**
ROA(Market)	**0.636**	**0.636**
	(5.93)	**(5.93)**
ROA(Related) × Dummy(Center)	**0.371**	
	(7.56)	
ROA(Related) × Dummy(Middle)	**0.345**	
	(5.18)	
ROA(Related) × Dummy(Periphery)	**0.187**	
	(2.03)	
ROA(Related) × Dummy(Center)		**0.184**
		(2.03)
ROA(Related) × Dummy(Middle)		0.158
		(1.67)
ROA(Related)		**0.187**
		(2.04)
Dummy(Center)	-0.001	-0.001
	(-0.98)	(-1.14)
Dummy(Middle)	0.000	0.000
	(-0.23)	(-0.27)
Constant	**-0.009**	**-0.009**
	(-3.76)	**(-3.78)**
Firm-fixed Effects	Yes	Yes
Clustered S.E.	Firm/Year-Quarter	Firm/Year-Quarter

Table 3.
Strength of Economic Ties and Network Positions (Continued)

Panel B: Quarterly ΔROA

	(1) ΔROA(q)	(2) ΔROA(q)
ΔROA(q-1)	**-0.428**	**-0.429**
	(-7.61)	**(-7.58)**
ΔROA(q-2)	**-0.154**	**-0.156**
	(-4.41)	**(-4.40)**
ΔROA(Related) × Dummy(Center)	**0.556**	
	(4.83)	
ΔROA(Related) × Dummy(Middle)	**0.413**	
	(3.92)	
ΔROA(Related) × Dummy(Periphery)	**0.255**	
	(2.13)	
ΔROA(Related) × Dummy(Center)		**0.299**
		(3.20)
ΔROA(Related) × Dummy(Middle)		0.156
		(1.69)
ΔROA(Related)		**0.257**
		(2.15)
Dummy(Center)	0.000	0.000
	(1.16)	(1.03)
Dummy(Middle)	0.000	0.000
	(1.04)	(0.97)
Constant	**-0.001**	**-0.001**
	(-2.13)	**(-2.08)**
Firm-fixed Effects	No	No
Clustered S.E.	Firm/Year-Quarter	Firm/Year-Quarter

Table 4.

Speed of Information Flow and Network Positions

We consider special cases of the following FM cross-sectional regression: for firm i in month t,

$$r^e_{i,t} = \alpha_t + \gamma^T_{Z,t} Z_{i,t} + \sum_{l \in (C,M,P)} \gamma^{related}_{l,t} D_{i,l,t-1} r^{related}_{i,t-1} + \varepsilon_{i,t},$$

where $r^e_{i,t}$ is the excess return of firm i which belongs to the industry in question, $Z_{i,t}$ contains characteristics of interest: SIZE, BM, MOM, and REV, and l is chosen from $(C, M, P) = (Center, Middle, Periphery)$. $D_{i,l,t-1}$ is an indicator variable defining the location of firm i in the industry network in month $t-1$. For example, if the industry which firm i belongs to is central, $D_{i,C,t-1}$ is 1 otherwise 0. $r^{related}_{i,t-1}$ is the lagged aggregate return of customer and supplier industries of firm i by one month. Panels A and B conduct the firm-level and industry-level FM cross-sectional regressions, respectively. To report t-statistics in parentheses (bold if significant at the 5% level), the Newey-West HAC covariance matrix estimators are employed.

Panel A: Firm-level

	(1) RET	(2) RET
SIZE	-0.001	-0.001
	(-1.43)	(-1.43)
BM	**0.002**	**0.002**
	(2.99)	**(2.99)**
MOM	**0.006**	**0.006**
	(3.06)	**(3.06)**
REV	**-0.050**	**-0.050**
	(-10.45)	**(-10.45)**
RET(Related) × Dummy(Center)	**0.182**	
	(5.56)	
RET(Related) × Dummy(Middle)	**0.156**	
	(5.73)	
RET(Related) × Dummy(Periphery)	**0.095**	
	(3.94)	
RET(Related) × Dummy(Center)		**0.088**
		(2.36)
RET(Related) × Dummy(Middle)		0.062
		(1.84)
RET(Related)		**0.095**
		(3.94)
Dummy(Center)	**0.020**	**0.020**
	(2.39)	**(2.39)**
Dummy(Middle)	**0.020**	**0.020**
	(2.33)	**(2.33)**
Dummy(Periphery)	**0.019**	**0.019**
	(2.31)	**(2.31)**

Table 4.
Speed of Information Flow and Network Positions (Continued)

Panel B: Industry-level

	(1) RET	(2) RET
SIZE	0.000	0.000
	(-0.71)	(-0.71)
BM	**0.002**	**0.002**
	(2.18)	**(2.18)**
MOM	**0.008**	**0.008**
	(3.27)	**(3.27)**
REV	**-0.035**	**-0.035**
	(-5.39)	**(-5.39)**
RET(Related) × Dummy(Center)	**0.140**	
	(4.75)	
RET(Related) × Dummy(Middle)	**0.115**	
	(4.50)	
RET(Related) × Dummy(Periphery)	**0.064**	
	(2.58)	
RET(Related) × Dummy(Center)		**0.076**
		(2.09)
RET(Related) × Dummy(Middle)		0.051
		(1.44)
RET (Related)		**0.064**
		(2.58)
Dummy(Center)	0.012	0.012
	(1.27)	(1.27)
Dummy(Middle)	0.014	0.014
	(1.51)	(1.51)
Dummy(Periphery)	0.014	0.014
	(1.52)	(1.52)

Table 5.

Self-financing Trading Strategies based on Central and Peripheral Industries

Panels A1 (B1) and A2 (B2) provide the value-weighted (equal-weighted) excess and risk-adjusted returns of self-financing trading strategies that invest exclusively in central or peripheral industries, respectively. For example, to implement a trading strategy that invests exclusively in central industries, quintile portfolios are formed based on the average one-month lagged return of customer and supplier industries and a long-short hedging portfolio (labeled as "High-Low") is constructed by going long the highest quintile (labeled as "High (1)") and going short the lowest quintile (labeled as "Low (5)") portfolios. Quintile portfolios are rebalanced every month. Returns and their standard deviations are annualized in Panels A1 and B1. Monthly risk-adjusted returns (alphas) are obtained after controlling for the exposure to Fama-French three (MKTRF, SMB, HML), momentum (UMD), and Pastor and Stambaugh tradable liquidity (PS-LIQ) factors. In Panels A2 and B2, t-statistics are presented in parentheses (bold if significant at the 5% level).

Panel A1: Excess Returns (Value-weighted)

		High (1)	(2)	(3)	(4)	Low (5)	High-Low
Central	Mean excess return	0.127	0.091	0.073	0.078	0.056	0.071
industries	Standard deviation	0.185	0.186	0.187	0.182	0.189	0.131
	Sharpe ratio	0.686	0.489	0.391	0.426	0.299	0.544
Peripheral	Mean excess return	0.122	0.110	0.077	0.081	0.095	0.027
industries	Standard deviation	0.195	0.200	0.178	0.207	0.214	0.173
	Sharpe ratio	0.627	0.549	0.432	0.390	0.447	0.156

Panel A2: Risk-adjusted Returns (Value-weighted)

Trading Strategy based on	Alpha	MKTRF	SMB	HML	UMD	PS-LIQ	Adj-R^2
Central	**0.006**	0.007	-0.040	-0.022	0.043	0.008	-0.007
industries	**(3.55)**	(0.17)	(-0.76)	(-0.40)	(1.27)	(0.30)	
Peripheral	0.001	-0.081	-0.153	0.034	**0.162**	**0.103**	0.037
industries	(0.53)	(-1.30)	(-1.77)	(0.38)	**(2.93)**	**(2.32)**	

Panel B1: Excess Returns (Equal-weighted)

		High (1)	(2)	(3)	(4)	Low (5)	High-Low
Central	Mean excess return	0.141	0.110	0.093	0.079	0.060	0.081
industries	Standard deviation	0.184	0.184	0.183	0.181	0.186	0.092
	Sharpe ratio	0.770	0.596	0.510	0.435	0.325	0.877
Peripheral	Mean excess return	0.131	0.104	0.090	0.089	0.086	0.045
industries	Standard deviation	0.180	0.184	0.177	0.185	0.207	0.117
	Sharpe ratio	0.727	0.567	0.508	0.481	0.414	0.384

Panel B2: Risk-adjusted Returns (Equal-weighted)

Trading Strategy based on	Alpha	MKTRF	SMB	HML	UMD	PS-LIQ	Adj-R^2
Central	**0.007**	0.031	-0.034	0.013	0.012	-0.024	-0.008
industries	**(4.64)**	(0.92)	(-0.72)	(0.26)	(0.40)	(-0.99)	
Peripheral	**0.004**	**-0.113**	-0.087	0.039	**0.088**	0.013	0.045
industries	**(2.15)**	**(-2.70)**	(-1.50)	(0.63)	**(2.36)**	(0.44)	

Table 6.

Cross-predictability of Analysts' Earnings Forecast Revisions

We consider the following pooled regression: for firm i in month t and k-month lag ($k = 1, 2$),

$$\text{AREV}_{i,t} = \alpha_i + \beta_t + \gamma_Z^T Z_{i,t} + \sum_{l \in (C,M,P)} \psi_{l,k}^{related} D_{i,l,t-k} \text{AREV}_{i,t-k}^{related} + \varepsilon_{i,t,k},$$

where $\text{AREV}_{i,t}$ is the analysts' revision of earnings forecast of firm i in month t. We define the analysts' revision as $\text{AREV}_{i,t} = (\text{UP}_{i,t} - \text{DOWN}_{i,t})/\text{NUMEST}_{i,t}$, where $\text{NUMEST}_{i,t}$ is the number of estimates of firm i's earnings for the current fiscal quarter end, and $\text{UP}_{i,t}$ ($\text{DOWN}_{i,t}$) is the number of upward (downward) earnings forecast revisions. $Z_{i,t}$ contains control variables: lagged AREV, the aggregate return of related industries of firm i lagged by one month, and the industry-level analysts' revision (AREVIND) lagged by one month. l is chosen from $(C, M, P) = (Center, Middle, Periphery)$. $D_{i,l,t-k}$ is an indicator variable defining the location of firm i in month $t-k$. For example, if the industry which firm i belongs to is central, $D_{i,C,t-k}$ is 1 otherwise 0. $\text{AREV}_{i,t-k}^{related}$ is the aggregate analysts' revision of the related industries of firm i in month $t-k$. To report t-statistics in parentheses (bold if significant at the 5% level), robust standard errors are computed by double-clustering by firm and year-month.

Panel: Revisions of Analysts' Earnings Forecast

	(1) AREV(t) $k = 1$	(2) AREV(t) $k = 1$	(3) AREV(t) $k = 2$	(4) AREV(t) $k = 2$
AREV(t-1)	**0.063**	**0.063**	**0.063**	**0.063**
	(12.67)	**(12.67)**	**(12.88)**	**(12.88)**
RET(Related,t-1)	**0.044**	**0.044**	**0.048**	**0.048**
	(3.84)	**(3.84)**	**(3.99)**	**(3.99)**
AREVIND(t-1)	**0.042**	**0.042**	**0.044**	**0.044**
	(10.51)	**(10.51)**	**(10.83)**	**(10.83)**
AREV(Related) × Dummy(Center)	**0.049**		**0.032**	
	(6.06)		**(4.83)**	
AREV(Related) × Dummy(Middle)	**0.033**		**0.020**	
	(5.17)		**(3.40)**	
AREV(Related) × Dummy(Periphery)	0.009		0.006	
	(1.34)		(0.77)	
AREV(Related) × Dummy(Center)		**0.040**		**0.026**
		(4.34)		**(2.80)**
AREV(Related) × Dummy(Middle)		**0.024**		0.014
		(3.24)		(1.69)
AREV(Related)		0.009		0.006
		(1.34)		(0.77)
Dummy(Center)	-0.002	-0.002	-0.003	-0.003
	(-0.12)	(-0.12)	(-0.18)	(-0.18)
Dummy(Middle)	-0.003	-0.003	-0.003	-0.003
	(-0.19)	(-0.19)	(-0.21)	(-0.21)
Constant	**0.092**	**0.092**	-0.043	-0.043
	(3.94)	**(3.94)**	(-1.46)	(-1.46)
Firm/Time-fixed Effects	Yes	Yes	Yes	Yes
Clustered S.E.	Firm/ Year-Month	Firm/ Year-Month	Firm/ Year-Month	Firm/ Year-Month

Table 7.

Testing Existing Anomalies: the Conglomerate Effect

Using standalone firms, we consider special cases of the following FM cross-sectional regression: for firm i in month t,

$$r^e_{i,t} = \alpha_t + \gamma^T_{Z,t} Z_{i,t} + \sum_{l \in (C,M,P)} \gamma^{related}_{l,t} D_{i,l,t-1} r^{related}_{i,t-1} + \varepsilon_{i,t},$$

where $r^e_{i,t}$ is the excess return of firm i which belongs to the industry in question, $Z_{i,t}$ contains characteristics of interest: SIZE, BM, MOM, and REV, and l is chosen from $(C, M, P) = (Center, Middle, Periphery)$. $D_{i,l,t-1}$ is an indicator variable defining the location of firm i in the industry network in month $t-1$. For example, if the industry which firm i belongs to is central, $D_{i,C,t-1}$ is 1 otherwise 0. $r^{related}_{i,t-1}$ is the lagged aggregate return of customer and supplier industries of firm i by one month. To report t-statistics in parentheses (bold if significant at the 5% level), the Newey-West HAC covariance matrix estimators are employed.

Panel: Standalone Firms

	(1) RET	(2) RET
SIZE	**-0.001**	**-0.001**
	(-2.43)	**(-2.43)**
BM	**0.002**	**0.002**
	(2.75)	**(2.75)**
MOM	**0.005**	**0.005**
	(2.57)	**(2.57)**
REV	**-0.043**	**-0.043**
	(-10.53)	**(-10.53)**
RET(Related) × Dummy(Center)	**0.162**	
	(4.05)	
RET(Related) × Dummy(Middle)	**0.104**	
	(2.78)	
RET(Related) × Dummy(Periphery)	**0.078**	
	(2.43)	
RET(Related) × Dummy(Center)		**0.085**
		(2.13)
RET(Related) × Dummy(Middle)		**0.026**
		(0.58)
RET(Related)		**0.078**
		(2.43)
Dummy(Center)	**0.033**	**0.033**
	(3.28)	**(3.28)**
Dummy(Middle)	**0.034**	**0.034**
	(3.35)	**(3.35)**
Dummy(Periphery)	**0.034**	**0.034**
	(3.47)	**(3.47)**

Table 8.

Testing Existing Anomalies: Limits to Arbitrage

We partition the entire stock universe into three sub-groups sorted on firm-level idiosyncratic volatility. For example, columns titled H-IVOL mean that the sub-group with high level of idiosyncratic volatility are analyzed. Within each sub-group, we consider special cases of the following FM cross-sectional regression: for firm i in month t,

$$r^e_{i,t} = \alpha_t + \gamma^T_{Z,t} Z_{i,t} + \sum_{l \in (C,M,P)} \gamma^{related}_{l,t} D_{i,l,t-1} r^{related}_{i,t-1} + \varepsilon_{i,t},$$

where $r^e_{i,t}$ is the excess return of firm i which belongs to the industry in question, $Z_{i,t}$ contains characteristics of interest: SIZE, BM, MOM, and REV, and l is chosen from $(C, M, P) = (Center, Middle, Periphery)$. $D_{i,l,t-1}$ is an indicator variable defining the location of firm i in the industry network in month $t-1$. For example, if the industry which firm i belongs to is central, $D_{i,C,t-1}$ is 1 otherwise 0. $r^{related}_{i,t-1}$ is the lagged aggregate return of customer and supplier industries of firm i by one month. To report t-statistics in parentheses (bold if significant at the 5% level), the Newey-West HAC covariance matrix estimators are employed.

Panel: Subsets sorted on Idiosyncratic Volatility

	(1) RET H-IVOL	(2) RET H-IVOL	(3) RET M-IVOL	(4) RET M-IVOL	(5) RET L-IVOL	(6) RET L-IVOL
SIZE	**-0.001**	**-0.001**	**-0.001**	**-0.001**	**-0.001**	**-0.001**
	(-3.09)	**(-3.09)**	**(-2.36)**	**(-2.36)**	**(-2.32)**	**(-2.32)**
BM	**0.002**	**0.002**	**0.001**	**0.001**	**0.001**	0.001
	(3.22)	**(3.22)**	**(2.02)**	**(2.02)**	**(1.73)**	(1.73)
MOM	**0.005**	**0.005**	**0.010**	**0.010**	**0.008**	**0.008**
	(2.78)	**(2.78)**	**(4.28)**	**(4.28)**	**(3.07)**	**(3.07)**
REV	**-0.050**	**-0.050**	**-0.054**	**-0.054**	**-0.058**	**-0.058**
	(-8.61)	**(-8.61)**	**(-10.49)**	**(-10.49)**	**(-11.65)**	**(-11.65)**
RET(Related) × Dummy(Center)	**0.301**		**0.170**		**0.125**	
	(4.70)		**(5.37)**		**(4.14)**	
RET(Related) × Dummy(Middle)	**0.161**		**0.162**		**0.122**	
	(3.15)		**(4.25)**		**(4.64)**	
RET(Related) × Dummy(Periphery)	**0.151**		0.055		**0.079**	
	(3.25)		(1.87)		**(3.28)**	
RET(Related) × Dummy(Center)		**0.149**		**0.115**		0.046
		(2.00)		**(2.87)**		(1.35)
RET(Related) × Dummy(Middle)		0.009		**0.107**		0.043
		(0.14)		**(2.55)**		(1.29)
RET(Related)		**0.151**		0.055		**0.079**
		(3.25)		(1.87)		**(3.28)**
Dummy(Center)	**0.035**	**0.035**	**0.024**	**0.024**	**0.020**	**0.020**
	(4.08)	**(4.08)**	**(3.07)**	**(3.07)**	**(3.41)**	**(3.41)**
Dummy(Middle)	**0.034**	**0.034**	**0.025**	**0.025**	**0.022**	**0.022**
	(3.55)	**(3.55)**	**(3.31)**	**(3.31)**	**(3.47)**	**(3.47)**
Dummy(Periphery)	**0.029**	**0.029**	**0.026**	**0.026**	**0.025**	**0.025**
	(3.43)	**(3.43)**	**(3.37)**	**(3.37)**	**(4.06)**	**(4.06)**

Table 9.

Testing Existing Anomalies: the Institutional Ownership, Turnover, and Illiquidity Effects

We partition the entire stock universe into three sub-groups sorted on the percentage ownership of institutional investors (IHP), share turnover (TURN), or Amihud illiquidity (ILLIQ). For example, in Panel A (Panel B), columns titled H-IHP (H-TURN) mean that the sub-group with high level of IHP (TURN) are analyzed. Within each sub-group, we consider special cases of the following FM cross-sectional regression: for firm i in month t,

$$r_{i,t}^{e} = \alpha_t + \gamma_{Z,t}^{T} Z_{i,t} + \sum_{l \in (C,M,P)} \gamma_{l,t}^{related} D_{i,l,t-1} r_{i,t-1}^{related} + \varepsilon_{i,t},$$

where $r_{i,t}^{e}$ is the excess return of firm i which belongs to the industry in question, $Z_{i,t}$ contains characteristics of interest: SIZE, BM, MOM, and REV, and l is chosen from $(C, M, P) = (Center, Middle, Periphery)$. $D_{i,l,t-1}$ is an indicator variable defining the location of firm i in the industry network in month $t-1$. For example, if the industry which firm i belongs to is central, $D_{i,C,t-1}$ is 1 otherwise 0. $r_{i,t-1}^{related}$ is the lagged aggregate return of customer and supplier industries of firm i by one month. To report t-statistics in parentheses (bold if significant at the 5% level), the Newey-West HAC covariance matrix estimators are employed.

Panel A: Subsets sorted on IHP

	(1) RET H-IHP	(2) RET H-IHP	(3) RET M-IHP	(4) RET M-IHP	(5) RET L-IHP	(6) RET L-IHP
SIZE	**0.001**	**0.001**	0.000	0.000	**-0.001**	**-0.001**
	(2.68)	**(2.68)**	(-0.66)	(-0.66)	**(-3.08)**	**(-3.08)**
BM	0.000	0.000	**0.002**	**0.002**	**0.002**	**0.002**
	(0.39)	(0.39)	**(2.94)**	**(2.94)**	**(3.35)**	**(3.35)**
MOM	**0.005**	**0.005**	0.003	0.003	**0.006**	**0.006**
	(1.98)	**(1.98)**	(1.08)	(1.08)	**(2.95)**	**(2.95)**
REV	**-0.037**	**-0.037**	**-0.046**	**-0.046**	**-0.038**	**-0.038**
	(-7.37)	**(-7.37)**	**(-10.30)**	**(-10.30)**	**(-7.17)**	**(-7.17)**
RET(Related) × Dummy(Center)	**0.152**		**0.219**		**0.223**	
	(3.17)		**(4.85)**		**(4.78)**	
RET(Related) × Dummy(Middle)	**0.118**		**0.164**		**0.161**	
	(2.87)		**(3.40)**		**(3.50)**	
RET(Related) × Dummy(Periphery)	0.029		0.069		**0.136**	
	(0.83)		(1.85)		**(3.34)**	
RET(Related) × Dummy(Center)		**0.123**		**0.149**		**0.088**
		(2.24)		**(3.16)**		**(2.29)**
RET(Related) × Dummy(Middle)		0.088		0.095		0.025
		(1.64)		(1.80)		(0.42)
RET(Related)		0.029		0.069		**0.136**
		(0.83)		(1.85)		**(3.34)**
Dummy(Center)	-0.018	-0.018	0.017	0.017	**0.032**	**0.032**
	(-1.75)	(-1.75)	(1.70)	(1.70)	**(3.62)**	**(3.62)**
Dummy(Middle)	**-0.020**	**-0.020**	0.019	0.019	**0.035**	**0.035**
	(-2.08)	**(-2.08)**	(1.73)	(1.73)	**(4.02)**	**(4.02)**
Dummy(Periphery)	-0.019	-0.019	0.017	0.017	**0.034**	**0.034**
	(-1.86)	(-1.86)	(1.72)	(1.72)	**(3.84)**	**(3.84)**

Table 9.
Testing Existing Anomalies: the Institutional Ownership, Turnover, and Illiquidity Effects (Continued)

Panel B: Subsets sorted on TURN

	(1) RET H-TURN	(2) RET H-TURN	(3) RET M-TURN	(4) RET M-TURN	(5) RET L-TURN	(6) RET L-TURN
SIZE	**-0.001**	**-0.001**	**-0.001**	**-0.001**	0.000	0.000
	(-2.82)	**(-2.82)**	**(-1.99)**	**(-1.99)**	(-0.49)	(-0.49)
BM	0.002	0.002	**0.002**	**0.002**	**0.002**	**0.002**
	(1.65)	(1.65)	**(2.58)**	**(2.58)**	**(3.54)**	**(3.54)**
MOM	**0.005**	**0.005**	**0.006**	**0.006**	**0.009**	**0.009**
	(2.26)	**(2.26)**	**(2.94)**	**(2.94)**	**(4.57)**	**(4.57)**
REV	**-0.029**	**-0.029**	**-0.067**	**-0.067**	**-0.084**	**-0.084**
	(-5.76)	**(-5.76)**	**(-10.96)**	**(-10.96)**	**(-14.48)**	**(-14.48)**
RET(Related) × Dummy(Center)	**0.156**		**0.198**		**0.211**	
	(3.06)		**(5.37)**		**(6.29)**	
RET(Related) × Dummy(Middle)	**0.140**		**0.163**		**0.181**	
	(3.11)		**(4.89)**		**(5.11)**	
RET(Related) × Dummy(Periphery)	**0.078**		**0.098**		**0.111**	
	(2.04)		**(3.44)**		**(3.23)**	
RET(Related) × Dummy(Center)		0.078		**0.101**		**0.100**
		(1.43)		**(2.11)**		**(2.09)**
RET(Related) × Dummy(Middle)		0.062		0.066		0.069
		(1.20)		(1.50)		(1.52)
RET(Related)		**0.078**		**0.098**		**0.111**
		(2.04)		**(3.44)**		**(3.23)**
Dummy(Center)	**0.036**	**0.036**	**0.028**	**0.028**	0.011	0.011
	(3.15)	**(3.15)**	**(2.77)**	**(2.77)**	(1.25)	(1.25)
Dummy(Middle)	**0.032**	**0.032**	**0.027**	**0.027**	0.016	0.016
	(2.89)	**(2.89)**	**(2.62)**	**(2.62)**	(1.65)	(1.65)
Dummy(Periphery)	**0.035**	**0.035**	**0.027**	**0.027**	0.012	0.012
	(3.07)	**(3.07)**	**(2.74)**	**(2.74)**	(1.35)	(1.35)

Table 9.
Testing Existing Anomalies: the Institutional Ownership, Turnover, and Illiquidity Effects (Continued)

Panel C: Subsets sorted on Amihud Illiquidity

	(1) RET H-ILLIQ	(2) RET H-ILLIQ	(3) RET M-ILLIQ	(4) RET M-ILLIQ	(5) RET L-ILLIQ	(6) RET L-ILLIQ
SIZE	-0.001	-0.001	**-0.002**	**-0.002**	-0.001	-0.001
	(-1.95)	(-1.95)	**(-2.58)**	**(-2.58)**	(-1.22)	(-1.22)
BM	**0.002**	**0.002**	0.001	0.001	**0.002**	**0.002**
	(3.74)	**(3.74)**	(1.11)	(1.11)	**(2.24)**	**(2.24)**
MOM	**0.005**	**0.005**	**0.008**	**0.008**	0.004	0.004
	(2.37)	**(2.37)**	**(3.50)**	**(3.50)**	(1.59)	(1.59)
REV	**-0.065**	**-0.065**	**-0.031**	**-0.031**	**-0.027**	**-0.027**
	(-8.93)	**(-8.93)**	**(-5.01)**	**(-5.01)**	**(-4.56)**	**(-4.56)**
RET(Related) × Dummy(Center)	**0.220**		**0.172**		**0.107**	
	(5.73)		**(4.08)**		**(2.86)**	
RET(Related) × Dummy(Middle)	**0.133**		**0.127**		**0.100**	
	(3.41)		**(3.73)**		**(2.86)**	
RET(Related) × Dummy(Periphery)	**0.114**		0.060		0.029	
	(3.06)		(1.63)		(0.98)	
RET(Related) × Dummy(Center)		**0.105**		**0.112**		0.078
		(2.07)		**(2.14)**		(1.68)
RET(Related) × Dummy(Middle)		0.018		0.067		0.072
		(0.33)		(1.46)		(1.64)
RET(Related)		**0.114**		0.060		0.029
		(3.06)		(1.63)		(0.98)
Dummy(Center)	**0.029**	**0.029**	**0.044**	**0.044**	0.021	0.021
	(2.69)	**(2.69)**	**(3.04)**	**(3.04)**	(1.77)	(1.77)
Dummy(Middle)	**0.026**	**0.026**	**0.042**	**0.042**	0.020	0.020
	(2.39)	**(2.39)**	**(2.81)**	**(2.81)**	(1.71)	(1.71)
Dummy(Periphery)	**0.025**	**0.025**	**0.043**	**0.043**	0.022	0.022
	(2.35)	**(2.35)**	**(2.93)**	**(2.93)**	(1.86)	(1.86)

Table 10.

Cumulative Returns of Self-financing Trading Strategies

This table provides the cumulative returns of self-financing trading strategies that invest exclusively in central or peripheral industries. Columns (1) and (2) present the value-weighted cumulative returns of long-short hedging portfolios. Columns (3) and (4) provide the equal-weighted cumulative returns of long-short hedging portfolios.

Panel: Value- and Equal-weighted Cumulative Returns

Number of months	VW cumulative returns		EW cumulative returns	
	Central industries (1)	Peripheral industries (2)	Central industries (3)	Peripheral industries (4)
1	0.006	0.002	0.007	0.004
2	0.012	0.004	0.014	0.008
3	0.018	0.007	0.021	0.011
4	0.024	0.008	0.027	0.015
5	0.030	0.011	0.034	0.018
6	0.036	0.013	0.040	0.022
7	0.042	0.016	0.047	0.026
8	0.047	0.018	0.053	0.030
9	0.053	0.020	0.060	0.034
10	0.058	0.022	0.067	0.038
11	0.064	0.025	0.074	0.042
12	0.070	0.027	0.081	0.046

Table 11.

Changes in Institutional Co-ownership

We consider special cases of the following pooled regression: for firm i in quarter q,

$$\Delta\text{IHP}_{i,q} = \alpha_i + \beta_q + \sum_{l \in (C,M,P)} \theta_l^{related} D_{i,l,q} \Delta\text{IHP}_{i,q}^{related} + \varepsilon_{i,q},$$

where $\Delta\text{IHP}_{i,q}$ is the change in the percentage ownership of institutional investors in firm i from quarter $q-1$ to quarter q. l is chosen from $(C, M, P) = (Center, Middle, Periphery)$. $D_{i,l,q}$ is an indicator variable defining the location of firm i in quarter q. For example, if the industry which firm i belongs to is central, $D_{i,C,q}$ is 1 otherwise 0. $\Delta\text{IHP}_{i,q}^{related}$ denotes the aggregate change in the percentage ownership of institutional investors in the customer and supplier industries of firm i from quarter $q-1$ to quarter q. To report t-statistics in parentheses (bold if significant at the 5% level), robust standard errors are computed by double-clustering by firm and year-quarter.

Panel: Changes in Institutional Co-ownership

	(1) ΔIHP	(2) ΔIHP
ΔIHP(Related) × Dummy(Center)	**0.203**	
	(6.18)	
ΔIHP(Related) × Dummy(Middle)	**0.195**	
	(6.06)	
ΔIHP(Related) × Dummy(Periphery)	**0.200**	
	(5.66)	
ΔIHP(Related) × Dummy(Center)		0.004
		(0.19)
ΔIHP(Related) × Dummy(Middle)		-0.004
		(-0.21)
ΔIHP(Related)		**0.205**
		(6.02)
Dummy(Center)	0.056	0.068
	(1.29)	(1.58)
Dummy(Middle)	0.055	0.064
	(1.43)	(1.68)
Constant	-0.073	-0.075
	(-0.83)	(-0.86)
Firm/Time-fixed Effects	Yes	Yes
Clustered S.E.	Firm/Year-Quarter	Firm/Year-Quarter