Feedback Loops in Industry Trade Networks and the Term Structure of Momentum Profits

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ABSTRACT

Industries are economically linked through customer-supplier trade flows. We show theoretically and empirically that industry shocks propagating along this inter-sectoral trade network can feed back to the originating industry, causing an "echo" – intermediate-term autocorrelation in returns. Adopting techniques from graph theory, we find that the strength of the trade network feedback is a crucial determinant of the echo effect in industry returns. Returns of the echo strategy implemented within high-feedback strength industries exceed 1% monthly. Consistent with limited-information models, the relation between feedback strength and echo profits is strongest in industries with information diffusion frictions, such as low analyst coverage, along the feedback loop. Overall, our results identify inter-sectoral trade networks as important conduits of industry shocks and provide the first explanation for the echo effect.

JEL Classification: G12, G14, G17

Keywords: Industry trade networks, echo, stock returns, information diffusion, intersectoral input-output links, momentum, customer-supplier product market networks

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Understanding how information is incorporated into asset prices is a fundamental challenge in financial economics. Mounting empirical evidence suggests that, in contrast to implications of traditional theories of complete and frictionless markets, prices often impound information with a significant delay.[1] Recent research points to segmentation of industries as an important source of this slow diffusion of information. In particular, Menzly and Ozbas (2010), Ahern (2013), and Rapach, Strauss, Tu, and Zhou (2015) show that trade links between industries coupled with market segmentation lead to cross-industry return predictability at horizons as long as a year.

Inter-industry trade links are often aligned in such a way that the network offers a loop from an industry back to itself through its economic connections with other industries. As a result, a sectoral shock propagating along the network can echo back to the originating industry via its linkages with trade partners. The central hypothesis of this paper is that under the informational segmentation of the market and the resultant slow diffusion of information along the network of industries, this feedback effect induces intermediate-term autocorrelation in industry returns.

We find strong support for this hypothesis by showing that properties of the inter-industry network determine the term structure of momentum returns. Novy-Marx (2012) uncovers an "echo" in this term structure, a finding that momentum profits are driven by returns over the intermediate (past 7-12 months), rather than recent (past 2-6 months), horizon. The echo effect is puzzling because it is inconsistent with theoretical predictions that the power of past returns to predict performance should decay at higher lags.[2] Indeed, Novy-Marx notes that explanations consistent with echo "are not readily apparent and provide a significant challenge for future research" (p. 451). Similarly, Goyal and Wahal (2015) write, "For financial economists, the challenge to theory is enormous. No existing theory, whether behavioral or rational, predicts an

[1] See Lo and MacKinlay (1990), Brennan, Jegadeesh, and Swaminathan (1993), Badrinath, Kale, and Noe (1995), Sias and Starks (1997), Chordia and Swaminathan (2000), Hou and Moskowitz (2005), Hou (2007), Cohen and Frazzini (2008), Dellavigna and Pollet (2009), Hirshleifer, Lim, and Teoh (2009, 2011), Tetlock (2011), Cohen and Lou (2012), and Boguth, Carlson, Fisher, and Simutin (2016).

[2] Behavioral theories of momentum include Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999). Johnson (2002) and Sagi and Seasholes (2007) propose rational explanations.

echo in returns" (p. 1264). This paper is the first to offer a mechanism that generates the echo effect.

To see the intuition behind our hypothesis that feedback loops in industry trade networks generate the echo effect, consider an example of an unexpected favorable change in government policy that reduces the cost of production for firms in the *Mining* industry and so drives up their stock prices. In a competitive market, this news would result in cheaper inputs to the *Non-Metallic Minerals* industry, to which the *Mining* industry is a major supplier. If industries are informationally segmented, the prices of firms in the *Non-Metallic Minerals* industry would respond to this news with a delay (cf. Menzly and Ozbas, 2010). The lower cost of production of the *Non-Metallic Minerals* industry can be expected to boost demand for its services by its dependent customers, including firms in the *Construction* industry, whose valuation would benefit from lower cost of cement, mineral wool, and other non-metallic inputs into production. This would, in turn, increase the demand for the output of the dependent suppliers of the *Construction* firms, among which is the *Metals* industry, whose prices will be positively affected with an additional delay. The final ingredient of this example is the status of the *Metals* industry as a major customer of the *Mining* industry, which would benefit from increased demand for its products. This network structure suggests that a shock to the *Mining* industry will not be priced immediately in full. Rather, it will have a secondary effect that will be incorporated into prices with a delay after the shock has propagated along the customer-supplier trade network and has fed back to the *Mining* industry. We hypothesize that this secondary effect is the root cause of the echo-like pattern in the term structure of industry momentum.

Our hypothesis is motivated by the recent advances in theoretical and empirical research on the importance of product market networks in transmission of economic shocks. Shea (2002) demonstrates theoretically that shocks to an industry affect economically related industries with the same sign. In informationally segmented markets, where value-relevant information diffuses slowly, returns of economically connected entities should thus be positively serially correlated.[3] Cohen and Frazzini (2008) find that this is indeed the case for individual firms. In industry-level analysis, Menzly and Ozbas (2010), Ahern (2013), and Rapach, Strauss, Tu, and Zhou (2015) find strong evidence of positive cross-autocorrelation in returns. In particular, Ahern (2013) uncovers cross-predictability even among industries that are linked only indirectly, via other industries along the supply chain network. We extend this literature by proposing that shocks propagating along the industry trade network can feed back to the originating industry, causing the echo effect in industry returns.

To solidify the intuition behind the idea that the structure of inter-sectoral trade networks affects intermediate-term autocorrelation in industry returns, we show theoretically that in an informationally segmented market, slow diffusion of information along the network of industries induces industry echo. We then begin our empirical analysis by providing robust evidence of the echo effect in the U.S. industry returns. We find that forming momentum portfolios on intermediate-horizon past returns generates a three-factor alpha of 0.78% monthly, while the corresponding value is only 0.19% when forming portfolios on recent-horizon returns. While Novy-Marx (2012) has shown the existence of echo in the Fama-French 49 industry portfolios, our evidence is important in light of the recent findings of Goyal and Wahal (2015) and Gong, Liu, and Liu (2015). These authors dispute Novy-Marx's conclusion that momentum in *stock* returns is in fact an echo. Among other concerns, they point out several potential biases in his specifications. We find that the echo effect in *industry* returns remains strong even after controlling for these biases.[4]

Once we establish the existence of industry echo, we turn to testing our main hypothesis that it is driven by the structure of the industry trade network. To this end, we construct an empirical inter-sectoral trade network using the Input-Output accounts

[3] Of course, some positive shocks to an industry may affect economically related industries negatively. Thus, the overall impact of feedback loops in industry trade networks on the echo in industry returns is likely larger than we estimate.

[4] While the results of Goyal and Wahal (2015) and Gong, Liu, and Liu (2015) cast doubt on the claim that stock-level momentum is entirely an echo, their result that intermediate-horizon returns predict momentum profits as well as recent-horizon returns still poses a significant challenge for leading theories. Our findings help to resolve this challenge.

data from the Bureau of Economic Analysis. We adopt techniques from graph theory to measure the extent to which the supply and demand for commodities and services by each industry influence those of other industries in the network. Using these measures, we calculate the key variable of our analysis, the strength of the feedback loop that connects an industry to itself via the trade network. This variable, termed feedback strength (FS), is high for industries whose network loops back to themselves contain strong connections between nodes. For a hypothetical industry that is isolated from the rest of the network, FS is zero.

For an industry with low FS, we expect a shock propagating along the network to significantly weaken by the time it feeds back to the industry and hence not manifest in a discernible echo. By contrast, for a high-FS industry, we expect the shock to retain its strength as it moves from node to node in the feedback loop, and so generate the echo effect. Consistent with this hypothesis, we show in panel regressions that intermediate-horizon return autocorrelations increase with FS.

To quantify the economic magnitude of this result, we examine the profitability of the echo strategy in portfolios of industries ranked by FS. We show that an echo strategy implemented on high-FS industries outperforms the one applied using low-FS industries by 0.64% (0.97% vs 0.33%) per month. By contrast, we find insignificant differences between performance of the high- and low-FS groups when we study momentum strategies based on industry returns over the recent, rather than intermediate, past horizon. The difference in echo profits from industries with high and low FS measure reaches 0.88% monthly (1.09% vs 0.21%) in response to variations in the FS calculation.

We next show that the relation between FS and echo profits depends on the extent of informational segmentation of industries. Limited-information models suggest that slow diffusion of information and the resultant cross-predictability between economically related assets should be more pronounced when markets are more segmented, such as when there are fewer informed investors (Hong and Stein, 1999). The implication of these models for our study is that FS should relate to echo profits only when investor specialization and market segmentation inhibit information diffusion. Our empirical results support this prediction. In particular, we find that when fewer analysts cover multiple industries that are linked along the feedback loop, information diffuses slower, resulting in higher echo profits of high-FS industries.

This paper contributes to and bridges two lines of literature. First, it adds to the voluminous work on momentum pioneered by Jegadeesh and Titman (1993). Following their seminal analysis of momentum in U.S. stock returns, researchers have documented this regularity in different countries, asset classes, and sample periods.[5] Our contribution to this strand of literature lies in establishing that industry echo is an important factor in the term structure of momentum profits, even after controlling for specification biases pointed out by Goyal and Wahal (2015). We show that there is still significant merit to the debate on the existence of echo at the industry level and propose a mechanism that generates this effect.

Second, this paper extends the growing literature on the importance of product market networks. In addition to the aforementioned studies analyzing the impact of trade connections on industry returns, mounting evidence suggests that these networks have broad impact in a variety of economic settings. For example, Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) show that topology of the network affects how microeconomic shocks to an industry transform into aggregate fluctuations. Ahern (2013), Aobdia, Caskey, and Ozel (2014), and Herskovic (2015) show that networks structure determines an industry's exposure to systematic risks and hence its expected returns, and Kelly, Lustig, and Van Nieuwerburgh (2013) provide a network-based explanation of firm volatility. Recent research also uncovers the role of trade networks for corporate decisions and outcomes. For example, Hertzel, Li, Officer, and Rodgers (2008) show that distress and bankruptcy filings negatively affect suppliers and customers of filing firms, while Ahern and Harford (2014) find that industry networks affect incidence of mergers. Our contribution to this branch of literature lies in applying insights from

[5]In particular, momentum exists in industry portfolios (Moskowitz and Grinblatt, 1999), foreign equity markets (Fama and French, 1998), international indices (Asness, Liew, and Stevens, 1997, Asness, Moskowitz, and Pedersen, 2013), commodities (Erb and Harvey, 2006, Gorton, Hayashi, and Rouwenhorst, 2012), currencies (LeBaron, 1999, Lustig, Roussanov, and Verdelhan, 2011), and corporate bonds (Jostova, Nikolova, Philipov, and Stahel, 2013).

graph theory to measure the strength with which a shock feeds back to the originating industry and relating this measure to the term structure of momentum profits.

1. Theoretical Framework

We present a theoretical framework to support our main argument that informational segmentation of the market and the resultant slow diffusion of information along the network of industries induce intermediate-term autocorrelation in industry returns. This motivating framework builds on the model of Hong, Torous, and Valkanov (2007), where the limited information-processing capacity of investors leads to a predictive relation between returns of certain industries and returns of the stock market. Menzly and Ozbas (2010) suggest this limited information-processing capacity as the reason behind industry specialization and informational segmentation of the market, which in turn induces cross-predictability between related industries. We use the same setup and extend this prior work by showing that when an industry is connected to itself via an inter-industry supply chain, its returns will be autocorrelated and can exhibit an echo: a higher autocorrelation at larger lags.

1.1. Setup

Consider an economy with four dates, $t = 0, 1, 2, 3$ and two industry portfolios, $k = X, Y$, with terminal values D_k, which represent liquidating dividends paid by each industry at $t = 3$. Each terminal value consists of three components $D_{k,O}$, $D_{k,P}$ and $D_{k,F}$, which are normally distributed with mean 0 and variances $\sigma^2_{k,O}$, $\sigma^2_{k,P}$ and $\sigma^2_{k,F}$, respectively. $D_{k,O}$ is the component of the terminal value of industry k that is associated with its *Own* operations irrespective of the operations of the other industry. In other words, it is the terminal value of the industry k if it operated as a stand-alone entity with no exposure to the shocks affecting the other industry. By contrast, $D_{k,P}$ is the component of the terminal value that depends only on the operation of industry k's supply chain *Partner*, independent of the operation of industry k itself. Finally, $D_{k,F}$ captures the feedback component, reflecting the indirect effect of industry k's operations on its terminal value through its influence on the operation of the other industry. We assume that $D_{X,O}$ and $D_{Y,O}$ are independent, meaning that if the two industries were to operate in isolation from each other, their terminal values would be uncorrelated. The trade partnership between the two industries induces a positive correlation between their terminal values through the $D_{k,P}$ terms. We impose this correlation by assuming the following linear functional forms between the *Own* terms and the *Partner* terms: $D_{X,P} = k_{Y \to X} D_{Y,O}$ and $D_{Y,P} = k_{X \to Y} D_{X,O}$, where $k_{Y \to X} > 0$ captures how dependent the operations of industry X are on the operations of industry Y, while $k_{X \to Y} > 0$ represents this relation in the opposite direction. Based on this formulation, the feedback component of the terminal value of industry X is

$$D_{X,F} = k_{X \to Y} \times k_{Y \to X} \times D_{X,O}. \tag{1}$$

Consistent with the evidence in Cohen and Frazzini (2008), we assume that investors fail to fully take into account the customer-supplier linkages between industries when forming expectations about future cash flows of industry portfolios. Specifically, we assume that industry X investors underestimate $k_{X \to Y}$ by a deterministic value η. Hence, $\eta = k_{X \to Y}$ means that industry X investors completely ignore the effect of industry X on industry Y, while $\eta = 0$ implies that these investors are aware of the full extent to which operations of industry X affect industry Y. To keep our model assumptions minimal, we assume that industry Y investors form an unbiased estimate of $k_{X \to Y}$. Hence, given a perfect estimation of $D_{X,O}$, the exact value of $D_{Y,P}$ is known to investors in industry Y.

Following Hong and Stein (1999), investors in our model have CARA preferences, implying that the equilibrium price of industry k at time t is

$$P_{k,t} = E_{k,t}[D_k] - b_{k,t} Q_k, \tag{2}$$

where $E_{k,t}[D_k]$ is the conditional expectation of the terminal value of industry k given the information available to industry k investors at time t, and Q_k is the (fixed) supply of industry k. We assume that at $t = 0$, investors are symmetrically uninformed about the terminal values of both industries. At $t = 1$, investors receive signals about the

Own component of the terminal value of their corresponding industry. That is, industry X investors receive signal $S_X = D_{X,O} + \epsilon_{X,O}$ about the cash flow of industry X, where $\epsilon_{X,O} \sim N(0, \sigma^2_{\epsilon_{X,O}})$ is independent of $D_{X,O}$ and $D_{Y,O}$. We assume that investors participate only in their corresponding industries, which implies that the two industries are informationally segmented.[6] As a result, S_X is observed only by investors in industry X. Similarly, industry Y investors receive the signal $S_Y = D_{Y,O} + \epsilon_{Y,O}$. At $t = 2$, investors receive signals about the part of their terminal value that depends on operations of their partner industry. That is, industry k investors receive signal $S_k = D_{k,P} + \epsilon_{k,P}$. This is our slow diffusion of information assumption, by which the information about operations of an industry is received by investors of other industries with a delay. Finally, the terminal values of the two industries become known to both groups of investors at $t = 3$.

1.2. The Term Structure of Momentum

We define $R_{k,t} = P_{k,t} - P_{k,t-1}$ as the return of industry k at time t. Based on the equilibrium industry prices in Eq. (2), we can derive the return autocovariance for each industry at lags 1 and 2. This establishes the following proposition:

Proposition 1. *For each industry, the autocovariance at lag 1 is equal to zero: $cov(R_{k,1}, R_{k,2}) = cov(R_{k,2}, R_{k,3}) = 0$. At lag 2, the autocovariance for industry X is*

$$cov(R_{X,1}, R_{X,3}) = \eta k_{Y\to X} \left(1 + (k_{X\to Y} - \eta) \cdot k_{Y\to X}\right) \frac{\sigma^4_{X,O}}{\sigma^2_{X,O} + \sigma^2_{\epsilon_{X,O}}}. \tag{3}$$

Expression (3) is positive when $0 < \eta < k_{X\to Y} + \frac{1}{k_{Y\to X}}$, i.e., when industry X investors underestimate the feedback effect up to a level at which the effect of feedback completely offsets the effect of operations of industry X on its terminal value. When $\eta = 0$, investors form a perfect estimate of the net effect of industry X operations on its terminal value. As a result, the information about the feedback effect is fully impounded into the price of industry X at time 1. By contrast, when $\eta = k_{X\to Y} + \frac{1}{k_{Y\to X}}$, investors

[6] Market segmentation can be due to investors' limited information processing capacity or fixed costs of participating in each market. For an extensive discussion of the informational segmentation of the markets and its causes and implications, see Hong, Torous, and Valkanov (2007) and Menzly and Ozbas (2010).

attribute a zero net effect of the shock to industry X operations on its terminal value, resulting in time 1 return of 0.

Our model highlights the role of supply chain feedbacks in determining the term structure of momentum. Under the informational segmentation of the market, the supply chain feedback can induce positive return autocorrelation at higher lags, and zero at shorter lags.

The model also suggests two testable predictions based on proposition 1. First, it is straightforward to show that when η is within the above-mentioned boundary, $cov(R_{X,1}, R_{X,3})$ increases in $k_{Y \to X}$ and $k_{Y \to X}$. This implies a positive relation between the strength of the supply chain feedback and the long-term autocovariance. We provide empirical support for this prediction by showing that the echo effect is more pronounced among industries with stronger feedback loops. Our second prediction concerns the role of investors' underestimation of the effect of supply chain linkages when forming expectations about the terminal value of their industry portfolio. When investors are less likely to take into account the effect of these linkages, the impact of the supply chain feedback should be stronger. In line with this prediction, our empirical analysis shows that the relation between feedback strength and echo profits is particularly pronounced when fewer analysts cover multiple industries on the feedback loop.

2. Data

We construct the inter-sectoral trade network using data from the Bureau of Economic Analysis (BEA) Input-Output (IO) accounts. For a set of industries, these accounts report the dollar value of each commodity and service produced and used by each industry in the *Make* and *Use* matrices, respectively. Starting in 1972, the BEA updated this dataset only every five years but at a granular level of over 400 industries. Since 1997, it has additionally provided these accounts annually but for a courser set of 66 industries.

To analyze industry momentum, it is important that we deal with a fixed set of industries over time. The BEA occasionally modifies industry definitions, and we need to ensure that intermediate-horizon, recent-horizon, and holding period returns, as well as our measures of feedback strength all refer to the same industry. Following the procedures described in detail in the Appendix, we aggregate the BEA data into a balanced panel of 49 industries defined consistently over our sample period and listed in Table 1. Each year, we then combine the *Make* and *Use* matrices to obtain the IO matrix s, each (i, j) element of which contains that year's U.S. dollar sales of commodities and services from industry i to industry j.

The resultant IO matrix can be viewed as a graph that consists of nodes, which represent industries, and directed links, which represent trade connections. Figure 1 shows the graph based on the 2013 data. The weight of the arrows captures the relative importance of an industry for its trading partners. To obtain these weights, we normalize the elements of the IO matrix by the total level of incoming or outgoing transactions. In particular, we gauge the importance to industry i of having industry j as a customer by dividing sales of i to j by the total sales of industry i. Similarly, we quantify the importance to industry i of having j as a supplier by scaling sales of j to i by the total sales of all industries to i:

$$w_{ij}^C = \frac{s_{ij}}{\sum_{k=1}^{49} s_{ik}} \text{ and } w_{ij}^S = \frac{s_{ji}}{\sum_{k=1}^{49} s_{ki}}. \tag{4}$$

This definition follows Menzly and Ozbas (2010) who form customer and supplier portfolios using similarly computed weights, and Ahern and Harford (2014) who use these weights when forming customer and supplier matrices. High w_{ij}^C suggests that industry i depends heavily on having j as its customer, and so is likely to be affected by an economic shock to industry j. High w_{ij}^S indicates that industry j supplies a large portion of i's production inputs, and hence an economic shock to j can have a strong effect on i. Building on Menzly and Ozbas (2010), who show that shocks can be transmitted through the supply chain in either direction, we calculate the overall influence of industry i on industry j by averaging these two measures:

$$\tilde{w}_{ij} = \frac{w_{ij}^S + w_{ij}^C}{2}. \tag{5}$$

We use this directional measure of influence to capture the strength of economic connections between industries and to trace how industry shocks propagate along the inter-sectoral trade network. As the BEA does not provide the network data for every year between 1973 and 1996, we follow the literature and use the most recently available data to calculate the influence measures.[7] As a result, we have a continuous time series of the network structure, and hence the measures of influence for the 49 industries.

We obtain the data on returns and firm market capitalizations from the Center for Research in Security Prices. We use common stocks listed in NYSE, Amex, or Nasdaq to compute value-weighted returns of the 49 industries. Our industry network data spans the 1972-2013 period, and consequently the returns of the momentum portfolios we study run from 1973 to 2014. Finally, we use I/B/E/S detail history files to construct measures of analyst coverage for industries. Following Zhang (2006), for the tests using analyst coverage data, we restrict our analysis to post-1984 data to avoid potential issues that may arise due to lack of reliable analyst data.

3. Echo in Industry Returns

In this section, we establish a robust echo effect in the term structure of industry returns. While Novy-Marx's (2012) focus is on echo in the cross-section of individual stocks, he also shows that it exists in other assets, including the industry portfolios defined on Ken French's website. Revisiting the industry-level evidence before we begin our trade network-related analysis is important not only because our industry definitions are different but also in light of the recent findings of Goyal and Wahal (2015) and Gong, Liu, and Liu (2015), who dispute Novy-Marx's conclusion that momentum in stock returns is in fact an echo.

In particular, Goyal and Wahal (2015) point out that three specification issues can bias Novy-Marx's results in favor of finding the stock-level echo. First, intermediate-horizon returns ("IR") are computed using six months of data, $t-12$ to $t-7$, whereas recent-horizon returns ("RR") are based on five months, $t-6$ to $t-2$. This difference

[7] Considering the inherent persistence in the inter-sectoral trades, we do not expect this assumption to produce a systematic bias in the results. In Figure 2 and additional untabulated analyses, we verify that our findings are robust throughout the sample period.

in period lengths mechanically increases the coefficient on IR in regressions explaining month t return. Second, the inclusion of month $t-12$ in the calculation of IR induces a bias in favor of finding echo because of the annual seasonality effect documented by Heston and Sadka (2008). Third, including month $t-2$ in the RR computation leads to a similar bias due to negative second-order autocorrelation in monthly stock returns (Jegadeesh, 1990, Subrahmanyam, 2005). The last issue is not a concern in our industry-level analysis because, unlike stocks, industries do not exhibit significant negative first- or second-order return autocorrelation (Moskowitz and Grinblatt, 1999). To address the first two issues, throughout the paper we calculate IR and RR over same-length periods, $t-11$ to $t-7$ and $t-6$ to $t-2$, respectively. We now use portfolio sorts, spanning tests, and panel regressions to evaluate how returns over these periods relate to industry returns in month t.

3.1. Portfolio Sorts

We sort industries into quintiles by their IR or RR returns. To form the intermediate-horizon momentum portfolio, MOM_{IR}, we buy the quintile of industries with the highest IR returns and sell the quintile with the lowest IR return, holding the resultant position during month t. We similarly construct the recent-horizon momentum portfolio, MOM_{RR}. As in Novy-Marx (2012), while stocks within an industry are value-weighted, industries in the momentum portfolios are equally weighted.

Table 2 summarizes raw and factor-adjusted returns of the two momentum portfolios, and of their difference, $\text{MOM}_{\text{IR}} - \text{MOM}_{\text{RR}}$. We find that the echo effect in industry returns remains robust even after controlling for the biases pointed out by Goyal and Wahal (2015). In particular, the IR-based momentum generates between 0.67% (t=4.55) and 0.78% (t=5.22) monthly, depending on factor adjustment. By contrast, and consistent with the results of Moskowitz and Grinblatt (1999) and Novy-Marx (2012), there is little evidence of RR-based momentum in industry returns. The difference between the profits of the two momentum strategies is economically large and statistically significant, ranging between 0.53% (t=2.42) and 0.60% (t=2.72).

3.2. Industry Momentum Spanning Tests

Having established in portfolio sorts that intermediate-horizon returns are a more powerful predictor of industry returns than recent-horizon returns, we now use spanning tests to assess the benefits of these two strategies as components of an investment portfolio. To determine whether the RR-based strategy (the test asset) is spanned by the IR-based strategy (the benchmark asset), we regress RR momentum portfolio returns on IR momentum returns (cf. Kan and Zhou, 2012). We also consider the reverse specification, and further test if a momentum strategy based on industry returns over the period $t-11$ to $t-2$ is spanned by either RR- or IR-based strategy. For robustness, we also add the three Fama and French (1993) factors to the set of benchmark assets.[8]

The large and significant intercepts in regressions (1) and (2) of Table 3 indicate that the IR portfolio contributes significantly to the investment opportunity set of an investor who is already holding the RR-based portfolio. By contrast, specifications (3) and (4) show that the reverse is not the case: the RR-based momentum strategy is spanned by the IR-based strategy.

The results of the spanning tests in regressions (5) through (9), where the test asset is the momentum portfolio based on industry returns from $t-11$ to $t-2$, provide further evidence that the intermediate past horizon is the relevant period for predicting future industry returns. In particular, while specification (5) shows that this portfolio generates an average monthly return of 0.51% (t=2.63), it is spanned by the IR-based strategy, as evidenced by the insignificant intercept in regressions (6) and (7). By contrast, specifications (8) and (9) show that the RR-based strategy does not span the returns of the momentum portfolio. Overall, the results in Table 3 suggest that the echo component in industry returns is strong and spans both the short-horizon and long-horizon industry momentum strategies.

[8]Note that when benchmark assets and test assets are zero-cost investments, the necessary and sufficient condition to reject the null hypothesis that the test strategy is spanned by the benchmark strategy is that the intercept is significantly different from zero.

3.3. Panel Regressions

For our third set of tests of the industry echo phenomenon, we run panel regressions of industry returns in month t on the RR and IR returns. We also include month $t-1$ return to account for the known positive autocorrelation in industry returns (Moskowitz and Grinblatt, 1999). Following Petersen (2009), we include industry fixed effects and cluster standard errors by time. We use raw returns as well as alphas from the CAPM, the Fama and French (1993) three-factor model, and the Carhart (1997) four-factor model as dependent variables. Alphas are computed as sums of the intercept and residuals from in-sample regressions of industry excess returns on the factors.

Table 4 summarizes the results of panel regressions. Consistent with Moskowitz and Grinblatt (1999), we observe a significant positive one-month autocorrelation in industry returns. More importantly for our purposes, the coefficients on intermediate-horizon returns are positive and statistically significant in all specifications, while recent-horizon performance is unrelated to month t industry returns, further highlighting the importance of echo in industry portfolios.

Taken together, the findings of this section set the stage for the main research question of this paper: Why does the term structure of industry momentum contain a significant echo component? We now turn to addressing this question.

4. Feedback Loops in Trade Networks and Echo Profits

In this section, we introduce the key variable of our analysis, the strength of the feedback loop connecting an industry to itself via the inter-sectoral trade network. After discussing the determinants of this measure of feedback strength (FS), we show that it is a crucial determinant of the echo effect in the term structure of momentum profits.

4.1. Measuring Feedback Strength

To determine the strength of the feedback loop of an industry, we use Dijkstra's (1959) algorithm, which identifies the strongest path from any departure node to any destination node in a directed graph. This algorithm takes as inputs the set of nodes and the distance (weights) from each node to any other node it is directly connected to. It outputs the shortest distance from each node to any other node in the graph, whether they are directly connected or not. To apply this algorithm, we use the inverse of the direct influence measure, $(\tilde{w}_{ij})^{-1}$, as the input representing the direct distance from industry i to industry j in the network. The algorithm then outputs the strongest level of direct or indirect connection offered by the network from each industry to any other industry in the network.

Our goal is to determine the strongest connection of each industry to itself rather than to another industry. To calculate this measure of feedback strength, we define a "shadow self" for each node. This shadow self inherits all inbound links of the node, but none its outbound links. We then use Dijkstra's algorithm to find the strongest path from each node to its shadow self. The strength of this feedback path, FS, is high for industries whose network loops back to themselves contain strong connections between nodes. For a hypothetical industry that is isolated from the rest of the network, FS is zero. We measure FS for every industry at each point in time in our sample. Table 1 summarizes the mean and other statistics of FS for each industry. Time series averages of FS range from a low of 0.004 for the *Social assistance* industry to a high of 0.135 for the *Petroleum and coal products* firms.

4.2. Determinants of Feedback Strength

The strength of the feedback loop of an industry is a function of the structure of the inter-sectoral trade network, which in turn is affected by industry characteristics. To understand the determinants of the FS measure better, and to ensure that it captures information distinct from that in industry-level variables used in prior studies, we run panel regressions of FS on industry characteristics. We include time fixed effects, cluster standard errors by industry, and summarize the results of this analysis in Table 5.

In regression (1), we ask how centrality of an industry in a network is related to FS. Ahern (2013) shows that centrality is an important determinant of systematic risk of an industry. An industry that is more central can be expected to have stronger connections with other industries and hence a higher FS. We measure centrality following Ahern (2013), and uncover that this is indeed the case.[9]

Specifications (2) through (4) show that the size of an industry, measured by either the count of firms, average firm size, or market share of the industry, relates positively to FS. This result is consistent with the intuition that larger industries are likely to have more inbound and outbound connections with others and hence can be expected to have higher FS. Out of the three industry size variables, only the firm count enters significantly in a multivariate specification (7).

Regressions (5) and (6) show that while the age of firms in an industry is unrelated to FS, the Hirfindahl index based on market capitalizations of firms in an industry relates to it negatively, although this relation is not robust in a multivariate setting. Indeed, only the centrality measure and the number of firms in the industry enter as robust determinants in this setting, as specification (7) shows. In fact, regressions (7) and (8) indicate that these two variables alone explain as much variation in FS as they do in combination with the other considered variables. In robustness tests, we are therefore careful to establish that these two industry characteristics do not drive our findings on the importance of feedback strength in determining echo profits.

4.3. Feedback Strength and Echo Strategy Profits

The central hypothesis of this paper is that under the informational segmentation of the market and the resultant slow diffusion of information along the network of industries, the feedback effect induces intermediate-term autocorrelation in industry returns. We hence expect the echo effect to increase with industry FS, and now test this prediction in portfolio sorts and panel regressions.

4.3.1. Portfolio Sorts

At the end of every month $t-1$, we sort industries into terciles by FS. Within each tercile, we then sort industries into quintiles by their intermediate-horizon returns ($t-11$

[9] The average cross-sectional correlation between centrality and FS is significant at 0.34.

through $t - 7$). The difference in month t returns of the winner and loser quintile portfolios defines the time series of the echo strategy profits.

For each FS tercile, Table 6 reports average excess returns and alphas from the CAPM, three- and four-factor models. We also show the difference in performance of high- and low-FS industries. Consistent with our hypothesis, we find that the profitability of the industry echo strategy increases significantly with FS. In particular, in low-FS industries, where we expect shocks to significantly attenuate along the feedback loop, the echo effect is economically weak (0.33% monthly) and statistically insignificant (t=1.41). By contrast, the echo effect is three times larger in high-FS industries, reaching nearly 1% monthly (t=4.10). We find similar results when studying factor-adjusted returns. For example, the three-factor alphas increase monotonically with FS, reaching 0.43%, 0.60%, and 1.02% for low-, medium-, and high-FS industries, respectively. The difference in echo profits of the high- and low-FS groups is economically large (0.60%) and statistically significant (t=2.20).

The focus of our theoretical and empirical analysis is on the echo effect in industry returns. Nonetheless, it is interesting to consider how industry FS impacts short-term momentum. To this end, we repeat the above analysis using recent-horizon rather than intermediate-horizon returns and summarize the results in the right set of columns of Table 6. Consistent with the idea that feedback strength is responsible for the intermediate-horizon, rather than the recent-horizon component of the term structure of momentum profits, we observe no statistically significant relation between profitability of the RR-based momentum strategy and industry feedback strength.

4.3.2. Persistence of the Feedback Strength-Echo Profits Relation Over Time

The results of portfolio sorts suggest that FS is a crucial determinant of echo strategy profits. We now evaluate whether this relation persists over time, and compare the performance of the unconditional echo strategy with the performance of echo strategies that condition on FS. To this end, we plot the time series of cumulative returns to the echo strategy without conditioning on FS, as well as echo returns of high- and low-FS industries. Figure 2 shows that the echo strategy based on investing in high-FS industries robustly outperforms the other echo portfolios over the entire sample period.

4.3.3. Panel Regressions

To evaluate robustness of the impact of FS in inter-sectoral networks on the echo effect in industry returns, we run panel regressions of industry returns in month t on past industry returns, feedback strength, and their products. As we did in Table 4, we include industry fixed effects and cluster standard errors by time. We consider both raw returns and alphas from the Fama and French (1993) three-factor model.

Table 7 summarizes the results of this analysis. Regressions (1) and (4) re-establish intermediate-horizon returns as an important predictor of industry returns. Regressions (2) and (5) include the term interacting FS and intermediate-horizon returns as a regressor. The coefficient on this variable is significantly positive, emphasizing that industries in which information propagates slowly along the feedback loops generate particularly large echo strategy returns. By contrast, specifications (3) and (6) show that the feedback strength and recent-horizon returns do not interact in a way that significantly affects future returns.

4.4. A Conditional Echo Strategy

Our focus thus far has been on examining the profitability of the echo and short-horizon momentum strategies in industries with different FS. Our hypothesis that feedback loops in industry trade networks generate the observed echo effect also has implications for the time series properties the echo strategy. In particular, if echo is due to the feedback of shocks to industries that are being traded as part of the strategy, we expect that the echo strategy to be most profitable during periods when the traded industries have strong measures of FS. To evaluate this conjecture, we build on the approach of Lou and Polk (2013) and analyze returns of an echo strategy that conditions on the formation-period magnitude of the winner portfolio FS.

At the end of each month, we rank industries by their cumulative intermediate- and recent-horizon returns over the formation period, and identify industries that belong to the winner portfolio. Over the same formation period, we calculate the market capitalization-weighted average of the feedback strengths of the industries that belong to the winner portfolio. We then evaluate momentum returns in months when winner portfolio formation-period FS falls in the top quartile or the top decile of its time-series distribution. This approach is in-sample but it allows us to further assess the importance of FS for echo strategy profits.

Table 8 reports average excess returns of the RR- and IR-based conditional momentum strategies. We examine settings in which the winner-minus-loser portfolio is constructed by ranking industries into terciles or deciles on their formation-period returns. Consistent with the argument above, we find that the profitability of the echo strategy that conditions on formation-period FS of winners (up to 1.82% monthly) is dramatically higher relative to the base-case in Table 6 (0.64%). The statistical significance of returns of the conditional echo strategy is somewhat weaker (t-statistics between 1.55 and 2.24) than in the base case, which is expected given the considerably fewer monthly observations that are chosen for the implementation of the strategy. Overall, this evidence suggests that the profitability of the echo strategy can be significantly enhanced not only by investing in high-FS industries but also by conditioning on the magnitude of FS during portfolio formation.

5. Feedback Strength and Echo: The Role Limited Information

Menzly and Ozbas (2010) examine the impact of informed investors on cross-predictability of returns of directly connected industries. They present evidence supporting the hypothesis that in the presence of many informed investors, information is incorporated into the prices faster, leaving little room for cross-predictability. Their finding has important implications for our results. We argue that the echo effect in the term structure of industry momentum is driven by slow diffusion of information. Hence, a natural prediction is that the roles of the trade network and of the feedback loops within it should be more important when fewer market participants process information. To test this conjecture, we examine the relation between feedback strength and echo strategy profits conditional on the extent of analyst coverage along the feedback loops.

A simple count of the number of analysts covering stocks in different industries along the feedback loops may seem like a sensible first proxy. However, it is possible that each analyst covers only a single industry and has limited understanding of how shocks to connected industries may affect the firm in the covered industry. What is important to facilitate information diffusion along the trade network is to have informed investors like analysts who cover firms in connected industries along the feedback loop. For example, if an analyst covers both the *Metals* and the *Mining* industries, they would be able to discern how shocks to the former industry affects the latter, and hence information will diffuse faster along the feedback loop, resulting in a weaker echo effect. Following this logic, we construct a measure of analyst coverage for each industry i at each point in time by first identifying industries that belong to its strongest feedback loop. For each pair of linked industries on this loop, we count the number of analysts covering firms in both industries. We then normalize the number of analysts for each industry pair by the total number of firms in the outbound industry,[10] and calculate the geometric average of this normalized pairwise analyst coverage over the identified feedback loop. At each given point in time, we consider a firm as being covered by an analyst if they provided at least one earnings-per-share estimate during the previous six months.

Table 9 repeats the panel regression analysis of Table 7, but adds analyst coverage and its interaction with other variables as regressors. The availability of analyst coverage data restricts our sample to the period from 1984 to 2014. Regression (1) shows that FS is an important determinant of echo strategy profits even in this shorter sample, as the coefficient on the FS $\times$ IR term remains significant. As in Table 7, FS does not significantly relate to profits from short-term RR-based momentum, as specification (2) shows.

Regression (3) offers support the conjecture we propose above: the relation between FS and echo profits significantly depends on the extent of analyst coverage along the feedback loop. The coefficient on the term interacting analyst coverage, FS, and IR is

[10] In a feedback loop that includes the *Metals*$\rightarrow$*Mining* link, the former is the outbound industry.

significantly negative, indicating that the link between FS and echo strategy returns amplifies when fewer analysts cover firms along the loop. This result provides strong support for the key hypothesis of our paper, that in informationally segmented markets, where value-relevant information diffuses slowly along the network of industries, a sectoral shock propagating along the network can feed back to the originating industry, generating the echo effect.

6. Robustness Checks

In this section, we perform two tests to ensure robustness of the relation between feedback strength and echo strategy profits.

6.1. Augmented Feedback Strength Measure

To measure feedback strength, we rely on the Dijkstra's (1959) algorithm, which identifies the strongest path from each industry to itself via the trade network. A drawback of this algorithm is that it could label industry A as having a weak feedback loop, and hence a weak echo effect, even if this industry is highly dependent on industry B with a strong loop. This is in contrast with the intuition that A will be affected by any shock to B and by the echo of that shock once it has propagated along B's strong feedback loop. Thus, the echo in returns of industry B may give rise to the echo in returns of industry A despite the latter's own weak feedback loop.

To address this concern that low-FS industries can still experience echo through a major trading partner with a strong feedback loop, we augment the FS measure by assigning a higher FS value not only to industries that have a strong feedback loop, but also to those influenced by such industries. To this end, we use an iterative procedure based on the PageRank algorithm. Developed by Google, it is used to rank nodes (e.g., webpages) in a directed graph (e.g., internet) based on a certain measure (e.g., importance). The intuition behind this algorithm is that nodes gain importance not only through their own inherent initial content, but also through their inbound links from other important nodes. We implement this algorithm such that the strength of the feedback loop replaces the importance measure in the algorithm, and $\tilde{w}_{ij}$ from Eq. (5) replaces the directional links between nodes in the network.

Similar to the benchmark test in the paper, we rank industries based on this augmented measure, and within each group we form portfolios based on industry returns over the intermediate past horizon or the recent horizon as before. Table 10 shows that, similar to the benchmark results, profits of the IR-based strategy increase with the augmented FS measure. The difference in echo strategy profits of terciles with high and low measures widens relative to the base-case results of Table 6, reaching 0.94% monthly (t=3.20).

6.2. Controlling for Industry Centrality and Number of Firms

The analysis in Table 5 shows that the centrality of an industry in the inter-sectoral trade network and the number of firms in it are important determinants of the feedback strength, explaining approximately a quarter of the variation in the measure. To establish that the relation between FS and echo profits that we document is not driven by these two industry characteristics, we repeat the panel regression analysis of Table 7, but include industry centrality and log of firm count, and their interactions with the intermediate-horizon return as independent variables.

We summarize the results of this analysis in Table 11. For convenience, regression (1) re-establishes the result of Table 7 that FS is an important determinant of echo strategy profits. Specifications (2) and (3) add industry centrality, and its interactions with IR or RR as controls. Centrality does not appear to relate to echo strategy returns, and including it as an independent variable does not meaningfully impact the magnitude of the coefficient on the FS $\times$ IR term, nor its significance. We similarly find in regressions (4) and (5) that this coefficient is not sensitive to including the log of the number of firms in the industry, or its interactions with IR or IR as regressors. Overall, the results in Table 11 show that the relation between feedback strength and echo strategy profits that we establish in this paper is not driven by industry centrality or the number of firms in the industry.

7. Conclusion

Recent literature uncovers that intermediate horizon past performance, rather than recent past performance, drives momentum in stock returns. This echo-like pattern poses a significant and unresolved challenge to both rational and behavioral models of momentum, neither of which predict intermediate-term autocorrelation in returns. In this paper, we offer the first explanation of this echo effect.

Our analysis builds on the growing literature that shows that value-relevant information diffuses along the customer-supplier trade network with a significant delay. As a result, returns of connected industries are positively serially correlated. Our insight is that inter-sectoral trade links are often aligned in such a way that the network offers a loop from an industry back to itself through its economic connections with other industries. Consequently, a sectoral shock propagating along the trade network can echo back to the originating industry. We show theoretically and empirically that under the informational segmentation of the market and the resultant slow diffusion of information along the network of industries, this feedback effect induces intermediate-term autocorrelation in industry returns.

Adopting techniques from graph theory, we measure the strength of the feedback loop that connects an industry to itself. We show that this feedback strength is a crucial determinant of the profitability of the echo effect in industry returns. Profits of the echo strategy are three times larger within high-feedback strength industries than they are within industries with low measures. Consistent with limited-information models, we show that as the number of analysts covering firms in multiple industries along the feedback loop declines, the relation between feedback strength and echo profits becomes more pronounced. Taken together, our results suggest that industry trade networks plays an important role in facilitating the diffusion of value-relevant information and thereby in determining the term structure of momentum profits.

Appendix

Construction of the supply chain network

In this appendix, we describe the construction of the trade network of the 49 industries that we analyze in the paper. Our goal is to use this network to measure the extent of dependence of an industry, as a customer or a supplier, on another industry. We begin by obtaining the data on inter-industry trade flows from the Input-Output (IO) Accounts of the Bureau of Economic Analysis (BEA). The dataset provides the dollar value of each commodity produced or used as an intermediate input by each industry in the *Make* and *Use* tables, respectively. The commodities include both services and manufacturing goods. To ensure that the values of inter-sectoral trades are not contaminated by variations in transportation costs and trade margins, we follow the literature and use the IO tables in which transaction of commodities are at "producers' prices". We do not differentiate between "primary" and "secondary" classifications of commodities made or used by industries because a shock to that industry will affect connected industries irrespective of the commodity type. We hence use the *Use* and *Make* tables that are labeled as "before redefinition".

To identify the set of industries and their trades that would constitute the network, we use two sets of IO tables. The first set includes annually updated information on 66 industries and spans the 1997-2013 period. The second set contains information for a broader set of industries (typically more than 400) and is available only for years ending in 2 and 7, with the last vintage corresponding to 2007. Following the BEA, we refer to the former industry classification set as the summary level classification, and to the latter one as the detail level classification. Given its annual availability, we use the summary level data for the 1997-2013 period. Prior to that, we use the detail level files. In years between 1973 and 1996 when the IO tables are not published, we follow the literature and use the most recently available data.

We start the construction of the inter-sectoral trade network by determining the broadest set of industries for which the data are consistently available for the entire sample period. To this end, we map the pre-1997 detail level industries to the post-1997 summary level industry groups. Ideally, we want each pre-1997 industry to map into only one post-1997 industry. Several data limitations complicate this mapping process. First, for the post-1997 accounts, BEA uses NAICS codes to identify the industries, whereas the pre-1997 industries are identified using SIC codes. The SIC-NAICS cross-walk files sometimes map a single SIC code to several NAICS codes, and consequently some pre-1997 industries could be mapped to more than one post-1997 industry group. Second, many of the pre-1997 industries are given more than one SIC codes, among which are codes that are assigned to more than one summary level industry, again leading to a one-to-many mapping. Finally, although the vast majority of the pre-1997 detail level industries are narrower than the post-1997 summary level industries, this is not always the case. For example, the industry defined as the *Retail trade* in pre-1997 detail level classification is equivalent to the aggregate of four industries in the post-1997 summary level industries, namely *Motor vehicle and parts dealers*, *Food and beverage stores*, *General merchandise stores*, and *Other retail*.

To address these issues, we first construct a baseline set of broader industries by combining the following post-1997 summary level industries: *Truck transportation* with *Other transportation and support activities* and *Warehousing and storage*; *Motor vehicle and parts dealers* with *Food and beverage stores*, *General merchandise stores*, and *Other retail*; *Federal Reserve banks, credit intermediation, and related activities* with *Funds, trusts, and other financial vehicles*; *Data processing, internet publishing, and other information services* with *Computer systems design and related services*; *Housing* with *Other real estate*; and *Rental and leasing services and lessors of intangible assets* with *Management of companies and enterprises*. This process reduces the number of post-1997 industry groups to 49. Next, we use the SIC-NAICS cross-walk to match each pre-1997 SIC-based industry with one of these resultant 49 post-1997 NAICS-based industries.

After this mapping, some of the pre-1997 industries still remain matched to several of the constructed post-1997 industries. For each such industry, we identify and match by name a corresponding industry in the detail level 1997 input-output datafile, and map it to a summary level industry using the 1997 summary-to-detail level mapping table provided by the BEA. Since the name of industries in the IO accounts prior to 1997 differ slightly in different updates (e.g., in 1982 vs 1987), we make use of the BEA's IO industry codes (which are consistent in all pre-1997 years) to match industries with the pre-1997 industries that are successfully assigned a post-1997 industry.

Having identified the 49 industries that span the overall sample period, we turn to measuring their economic links. We construct aggregated *Make* and *Use* tables by combining all sectors in each of the 49 industries we identify. To account for the effect of imports and exports of commodities at the level of dependence between industries in the economy, we modify the *Make* table by multiplying the value of each commodity produced by each industry by an adjustment ratio whose numerator is the total value of the commodity used by all industries, and whose denominator is the total value of that commodity produced in the economy. This way, an industry's exports would result in its lower dependence as a supplier to other industries. For the commodities whose total value used by other industries is larger than its total value produced in the economy, we set the adjustment ratio to 1. The resultant matrix represents the equivalent dollar value of each commodity produced by each industry that is being used in the economy.

We next normalize the dollar value of each commodity used by each industry in the *Use* table by dividing it by the total value of that commodity used by the industries in the economy. Hence, the normalized matrix represents the value of each commodity used by each industry as a percentage of the total value of that commodity used in the economy. Multiplying the modified *Make* matrix with the normalized *Use* matrix obtains the IO matrix, which is a square matrix representing the total dollar value of the trade flow from each industry (presented in row) to any other industry (presented in column).

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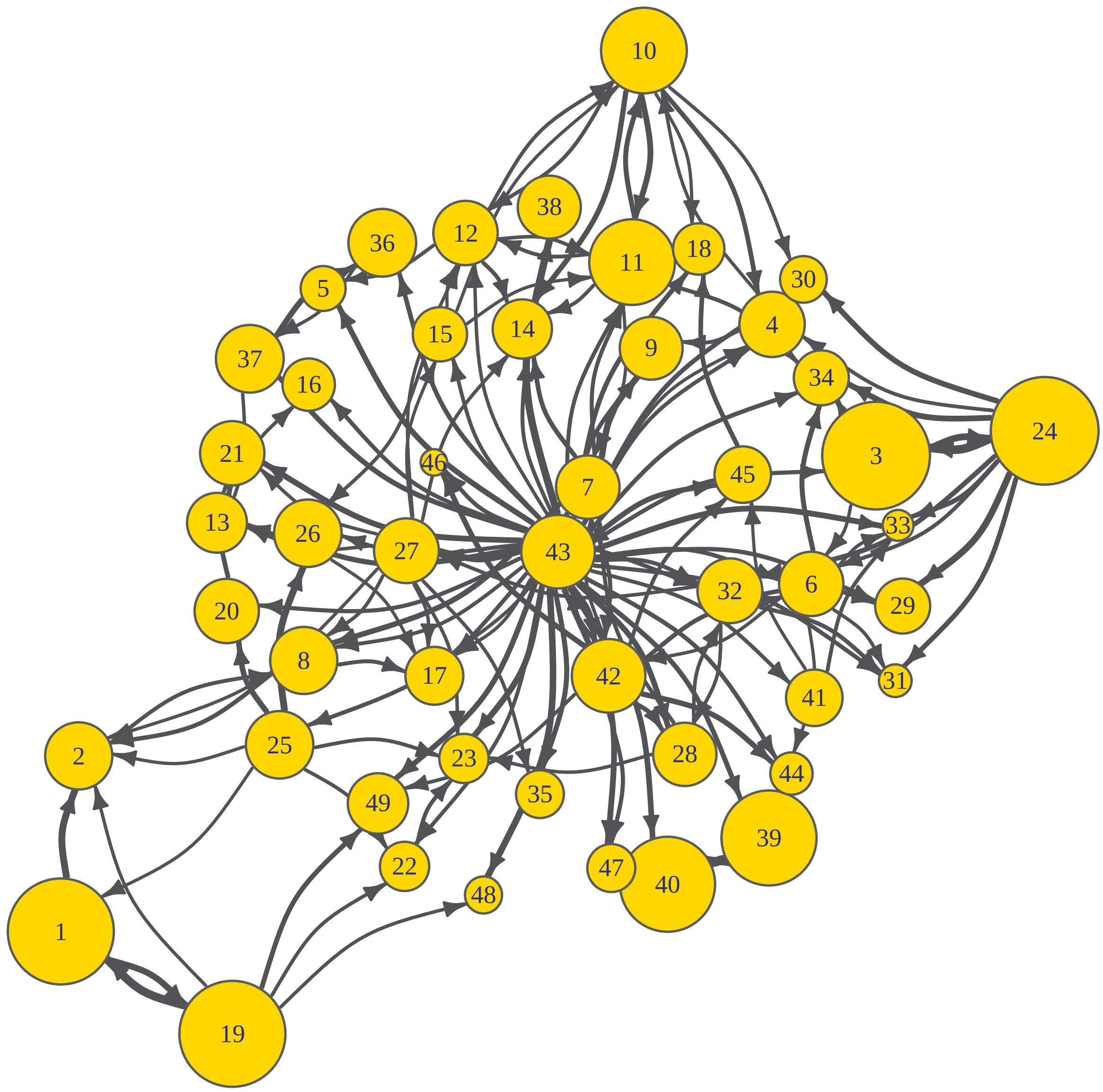

Figure 1. Trade Network of 49 Industries in 2013
This figure plots the customer-supplier trade network of the 49 industries defined on Ken French's website. The size of the circles represents the size of the industry, and the thickness of lines captures the magnitude of trade connections between industry pairs. The network is depicted for 2013.

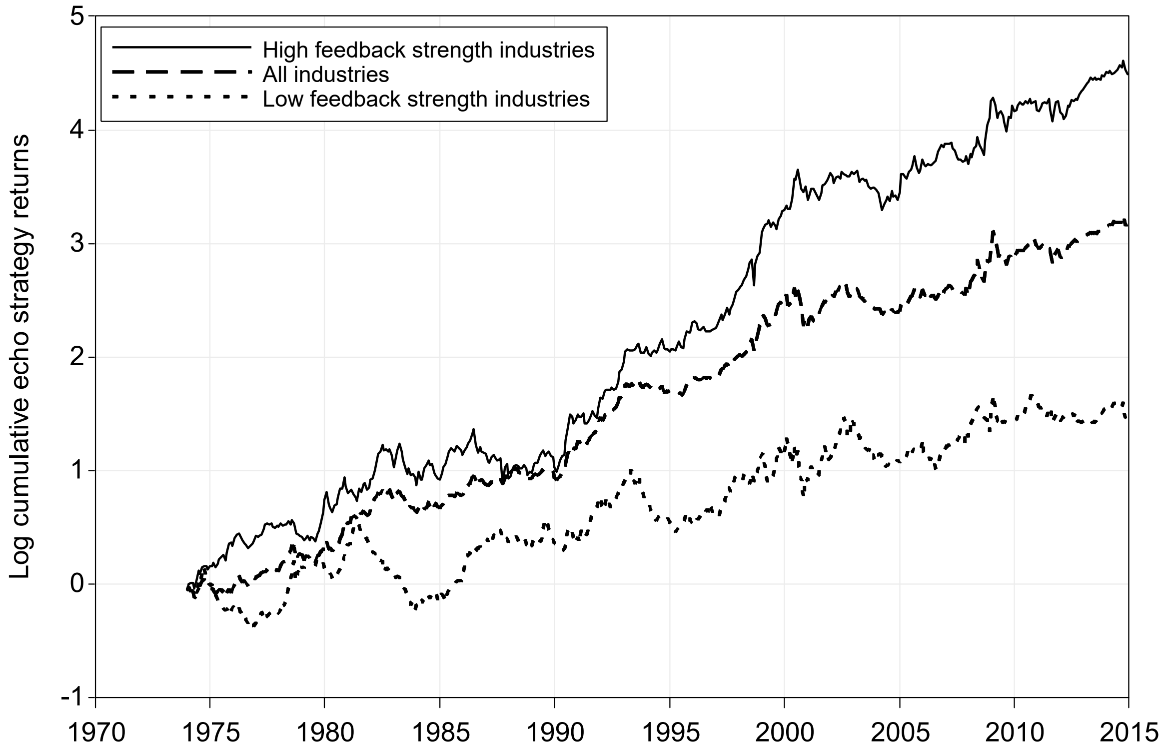

Figure 2. Cumulative Returns of Industry Echo Strategies

This figure plots log cumulative returns of echo strategies that invest in high-FS industries, low-FS industries, or all industries without conditioning on FS. At the end of each month $t-1$, industries are sorted into terciles by their FS, computed as in section 4.1. Within each tercile, they are sorted into quintiles by their cumulative intermediate-horizon returns ($t-11$ through $t-7$, inclusive). The resultant winner-minus-loser value-weighted portfolio is held during month t. The sample covers January 1973 through December 2014.

Table 1
Industry Feedback Strength Summary Statistics

This table reports summary statistics for the 49 industries in the sample, ranked by their feedback strength (FS). Each month, an industry's FS is calculated by applying Dijkstra's algorithm on the matrix of direct inter-sectoral supply chain connections as described in section 4.1. The table reports the time-series mean, standard deviation, minimum and maximum values of FS for each industry from January 1973 to December 2014.

		Feedback strength			
Rank	Industry	Mean	St. dev	Min	Max
1	Petroleum and coal products	0.135	0.015	0.117	0.160
2	Oil and gas extraction	0.135	0.015	0.117	0.160
3	Food and beverage and tobacco products	0.119	0.007	0.106	0.128
4	Farms	0.119	0.007	0.106	0.128
5	Fabricated metal products	0.074	0.004	0.063	0.078
6	Primary metals	0.074	0.004	0.063	0.078
7	Textile mills and textile product mills	0.062	0.020	0.015	0.082
8	Apparel and leather and allied products	0.062	0.020	0.015	0.082
9	Funds, trusts, Fed. banks, credit intermediation	0.061	0.023	0.034	0.100
10	Securities, commodity contracts, and investments	0.060	0.024	0.025	0.100
11	Utilities	0.056	0.015	0.035	0.080
12	Wood products	0.055	0.008	0.039	0.070
13	Forestry, fishing, and related activities	0.055	0.008	0.039	0.070
14	Mining, except oil and gas	0.052	0.018	0.025	0.080
15	Services	0.047	0.006	0.039	0.058
16	Chemical products	0.044	0.005	0.037	0.053
17	Plastics and rubber products	0.044	0.005	0.037	0.053
18	Pipeline transportation	0.044	0.018	0.018	0.069
19	Real Estate	0.044	0.008	0.033	0.058
20	Construction	0.043	0.005	0.034	0.051
21	Food services and drinking places	0.042	0.010	0.026	0.052
22	Nonmetallic mineral products	0.040	0.005	0.031	0.048
23	Machinery	0.039	0.006	0.029	0.047
24	Printing and related support activities	0.039	0.010	0.016	0.051
25	Paper products	0.038	0.010	0.016	0.051
26	Wholesale trade	0.037	0.005	0.032	0.048
27	Motion picture and sound recording industries	0.036	0.006	0.029	0.046
28	Broadcasting and telecommunications	0.036	0.006	0.029	0.046
29	Retail trade	0.032	0.005	0.022	0.039
30	Publishing industries, except internet (includes software)	0.031	0.010	0.014	0.043
31	Furniture and related products	0.029	0.003	0.025	0.037
32	Motor vehicles, bodies and trailers, and parts	0.027	0.005	0.021	0.036
33	Truck transportation, warehousing and support activities	0.025	0.008	0.016	0.036
34	Computer systems design, Data proc., other info. srvcs	0.025	0.010	0.000	0.035
35	Electrical equipment, appliances, and components	0.024	0.003	0.021	0.030
36	Health	0.022	0.005	0.011	0.028
37	Air transportation	0.021	0.004	0.012	0.029
38	Support activities for mining	0.020	0.013	0.006	0.047
39	Insurance carriers and related activities	0.018	0.003	0.014	0.025
40	Computer and electronic products	0.018	0.003	0.016	0.029
41	Rail transportation	0.016	0.003	0.011	0.022
42	Miscellaneous manufacturing	0.016	0.004	0.010	0.021
43	Other transportation equipment	0.015	0.002	0.011	0.023
44	Amusements, gambling, recreation, performing arts	0.013	0.002	0.010	0.016
45	Accommodation	0.010	0.001	0.008	0.012
46	Educational services	0.010	0.003	0.006	0.016
47	Water transportation	0.006	0.001	0.005	0.008
48	Transit and ground passenger transportation	0.004	0.001	0.003	0.006
49	Social assistance	0.004	0.001	0.003	0.006

Table 2
Recent- and intermediate-horizon momentum in industry returns

This table reports results of time series regressions of monthly returns of industry momentum portfolios. At the end of each month $t-1$, industries are ranked into quintiles by their cumulative intermediate-horizon returns (IR, $t-11$ through $t-7$, inclusive) or recent-horizon returns (RR, $t-6$ through $t-2$, inclusive), and the resultant winner-minus-loser momentum (MOM) portfolios are held during month t. Returns of these portfolios, MOM_{RR} and MOM_{IR}, as well as their difference, $\text{MOM}_{\text{IR}} - \text{MOM}_{\text{RR}}$, are regressed on the market excess return (MKT), the HML factor, and the SMB factor. The sample covers January 1973 through December 2014.

	Intercept (% monthly), slope coefficients, and [t-statistics] from regressions where the dependent variable is								
Independent	intermediate-horizon (past 11 to 7 mo) momentum return, MOM_{IR}			recent-horizon (past 6 to 2 mo) momentum return, MOM_{RR}			return difference of two strategies, $\text{MOM}_{\text{IR}} - \text{MOM}_{\text{RR}}$		
variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.67	0.67	0.78	0.08	0.14	0.19	0.60	0.53	0.59
	[4.55]	[4.51]	[5.22]	[0.40]	[0.74]	[0.96]	[2.72]	[2.42]	[2.66]
MKT		0.00	-0.04		-0.12	-0.15		0.13	0.12
		[0.08]	[-1.15]		[-3.02]	[-3.48]		[2.67]	[2.24]
HML			-0.21			-0.10			-0.11
			[-4.11]			[-1.51]			[-1.45]
SMB			-0.02			0.05			-0.07
			[-0.34]			[0.77]			[-0.90]

Table 3
Industry momentum spanning tests

This table reports results of time series regressions of monthly returns of industry momentum portfolios. At the end of each month $t-1$, industries are ranked into quintiles by their cumulative intermediate-horizon returns (IR, $t-11$ through $t-7$, inclusive), recent-horizon returns (RR, $t-6$ through $t-2$, inclusive), or returns over both horizons ($t-11$ through $t-2$, inclusive). The resultant winner-minus-loser momentum (MOM) portfolios are held during month t. Returns of these portfolios, MOM_{RR}, MOM_{IR}, and $\text{MOM}_{\text{IR,RR}}$, are regressed on the market excess return (MKT), the HML factor, the SMB factor, MOM_{RR}, and MOM_{IR}. The sample covers January 1973 through December 2014.

	Intercept (% monthly), slope coefficients, and [t-statistics] from regressions where the dependent variable is								
Independent	intermediate-horizon (past 11 to 7 mo) momentum return, MOM_{IR}		recent-horizon (past 6 to 2 mo) momentum return, MOM_{RR}		recent- and intermediate-horizon (past 11 to 2 mo) momentum return, $\text{MOM}_{\text{IR,RR}}$				
variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	0.67	0.78	-0.22	-0.16	0.51	-0.09	-0.06	0.45	0.51
	[4.28]	[4.89]	[-1.24]	[-0.87]	[2.63]	[-0.69]	[-0.45]	[3.67]	[4.09]
MKT		-0.05		-0.12			-0.04		0.00
		[-1.31]		[-2.85]			[-1.35]		[-0.05]
HML		-0.21		0.00			0.00		-0.13
		[-3.84]		[0.01]			[-0.01]		[-3.02]
SMB		0.02		0.02			-0.03		-0.04
		[0.34]		[0.41]			[-0.77]		[-0.89]
WML_{IR}			0.43	0.42		0.86	0.86		
			[9.16]	[8.86]		[25.6]	[25.0]		
WML_{RR}	0.34	0.33						0.79	0.79
	[9.16]	[8.86]						[27.4]	[27.2]

Table 4
Momentum in industry returns: Panel regressions

This table reports the results of panel regressions of industry raw or factor-adjusted returns in month t on its return in month $t-1$, average intermediate-horizon returns (IR, $t-11$ through $t-7$, inclusive), and average recent-horizon returns (RR, $t-6$ through $t-2$, inclusive). Factor-adjusted returns are the sum of the intercept and residuals from the in-sample regression of industry excess returns on the factors. All regressions include industry fixed effects. The t-statistics, shown in square brackets, are based on standard errors clustered by time. The sample period is from January 1973 to December 2014.

	Slope coefficients and [t-statistics] from regressions where the dependent variable is industry			
	Raw return	CAPM alpha	3-factor alpha	4-factor alpha
Independent variable	(1)	(2)	(3)	(4)
Last month's return	0.049	0.039	0.032	0.033
	[2.87]	[2.39]	[2.06]	[2.25]
Intermediate-horizon return, IR	0.089	0.093	0.078	0.079
	[2.71]	[2.82]	[2.50]	[2.52]
Recent-horizon return, RR	-0.027	-0.010	-0.029	-0.019
	[-0.67]	[-0.24]	[-0.62]	[-0.52]

Table 5
Determinants of industry feedback strength

This table reports results of panel regressions of industry feedback strength on contemporaneous industry characteristics. Industry centrality is computed following Ahern (2013). Market shares is the proportion of market capitalization of firms in an industry relative to the market value of all industries. The *t*-statistics are based on standard errors are clustered by industry and are shown in square brackets. All regressions include time fixed effects. The sample covers January 1973 through December 2014.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Centrality of industry	0.467						0.348	0.362
	[2.45]						[1.86]	[1.92]
Log count of firms in industry		0.008					0.004	0.005
		[3.86]					[1.95]	[2.23]
Log average firm size			0.003				0.001	
			[1.73]				[0.37]	
Industry market share				0.192			0.034	
				[3.64]			[0.48]	
Log age of firms in industry					0.001		0.002	
					[0.69]		[0.89]	
Industry Hirfindahl index						-0.020	-0.007	
						[-2.68]	[-1.16]	
R^2	0.23	0.19	0.08	0.11	0.06	0.11	0.27	0.27

Table 6
Momentum profits of industry portfolios sorted on feedback strength

This table reports raw and factor-adjusted monthly returns of industry momentum portfolios conditional on feedback strength (FS). At the end of each month $t-1$, industries are sorted into terciles by their FS, computed as in section 4.1. Within each tercile, they are sorted into quintiles by their cumulative intermediate-horizon returns ($t-11$ through $t-7$, inclusive) or recent-horizon returns ($t-6$ through $t-2$, inclusive). The resultant winner-minus-loser value-weighted portfolio is held during month t. Reported are excess returns and alphas from the CAPM, 3-factor, and 4-factor models, all in percent monthly, as well as the associated t-statistics in square brackets. The sample covers January 1973 through December 2014.

	Profits (% monthly) of momentum strategies based on industry returns over							
Performance	intermediate horizon (past 11 to 7 mo)				recent horizon (past 6 to 2 mo)			
measure	Low FS	Med FS	High FS	High-Low	Low FS	Med FS	High FS	High-Low
Excess return	0.33	0.44	0.97	0.64	0.12	0.23	-0.22	-0.35
	[1.41]	[2.14]	[4.10]	[1.91]	[0.48]	[1.01]	[-0.89]	[-0.97]
CAPM alpha	0.33	0.40	0.95	0.62	0.17	0.29	-0.17	-0.33
	[1.39]	[1.96]	[4.00]	[2.31]	[0.65]	[1.28]	[-0.65]	[-1.17]
3-factor alpha	0.43	0.60	1.02	0.60	0.26	0.33	-0.15	-0.41
	[1.81]	[2.96]	[4.24]	[2.20]	[1.02]	[1.43]	[-0.56]	[-1.42]
4-factor alpha	0.01	0.30	0.57	0.56	-0.35	-0.19	-0.76	-0.41
	[0.04]	[1.55]	[2.57]	[2.03]	[-1.62]	[-0.97]	[-3.45]	[-1.39]

Table 7
Industry momentum profits and feedback strength: Panel regressions

This table reports the results of panel regressions of industry raw or factor-adjusted returns in month t on its return in month $t-1$, average intermediate-horizon returns (IR, $t-11$ through $t-7$, inclusive), average recent-horizon returns (RR, $t-6$ through $t-2$, inclusive), feedback strength, computed as in section 4.1, and cross terms. We use either simple returns, or factor-adjusted returns, which are are computed as the sum of the intercept and residuals from the in-sample regression of industry excess returns on the three factors of Fama and French (1993). All regressions include industry fixed effects. The t-statistics, shown in square brackets, are based on standard errors clustered by time. The sample period is from January 1973 to December 2014.

	Slope coefficients and [t-statistics] from regressions where the dependent variable is industry					
	Raw return			3-factor alpha		
Independent variable	(1)	(2)	(3)	(4)	(5)	(6)
Last month return	0.049	0.048	0.050	0.032	0.031	0.032
	[2.87]	[2.81]	[2.90]	[2.06]	[1.98]	[2.08]
Intermediate-horizon return, IR	0.089	0.043		0.078	-0.017	
	[2.71]	[1.10]		[2.50]	[-0.50]	
Recent-horizon return, RR	-0.027		-0.036	-0.023		-0.005
	[-0.67]		[-0.77]	[-0.62]		[-0.11]
Feedback strength, FS		-0.103	-0.102		-0.090	-0.106
		[-2.27]	[-2.25]		[-2.12]	[-2.49]
FS × IR		1.143			2.124	
		[2.28]			[3.48]	
FS × RR			0.223			-0.441
			[0.46]			[-0.67]

Table 8

Momentum profits of industry portfolios sorted on feedback strength: Conditioning on the winner portfolio formation-period feedback strength

This table reports raw and factor-adjusted monthly returns of industry momentum portfolios conditional on feedback strength (FS). At the end of each month $t-1$, industries are sorted into terciles by their FS, computed as in section 4.1. Within each tercile, they are sorted into quintiles by their cumulative intermediate-horizon returns ($t-11$ through $t-7$, inclusive) or recent-horizon returns ($t-6$ through $t-2$, inclusive). The resultant winner-minus-loser value-weighted portfolio is held during month t. Reported are excess returns and alphas from the CAPM, 3-factor, and 4-factor models, all in percent monthly, as well as the associated t-statistics in square brackets. The sample covers January 1973 through December 2014.

	Profits (% monthly) of momentum strategies based on industry returns over							
	intermediate horizon (past 11 to 7 mo)				recent horizon (past 6 to 2 mo)			
	Low FS	Med FS	High FS	High-Low	Low FS	Med FS	High FS	High-Low
A. Winner portfolio formation-period FS *in the top quartile of its time-series distribution*								
Winners and losers based on	0.23	0.37	0.88	0.66	-0.23	0.27	-0.58	-0.35
sorts into runup terciles	[0.86]	[2.12]	[3.63]	[1.84]	[-0.88]	[1.28]	[-1.88]	[-0.86]
Winners and losers based on	0.04	0.72	1.51	1.47	-0.08	0.37	-0.49	-0.40
sorts into runup deciles	[0.09]	[2.63]	[2.93]	[2.10]	[-0.15]	[1.17]	[-0.85]	[-0.51]
Number of months	123	246	123	246	124	247	124	248
B. Winner portfolio formation-period FS *in the top decile of its time-series distribution*								
Winners and losers based on	0.02	0.42	1.22	1.21	-0.26	0.02	-0.64	-0.38
sorts into runup terciles	[0.04]	[3.00]	[3.29]	[2.24]	[-0.54]	[0.14]	[-1.52]	[-0.59]
Winners and losers based on	-0.59	0.86	1.23	1.82	0.37	0.01	-0.07	-0.44
sorts into runup deciles	[-0.76]	[3.63]	[1.40]	[1.55]	[0.41]	[0.05]	[-0.11]	[-0.41]
Number of months	49	397	49	98	49	397	49	98

Table 9
Industry momentum profits and feedback strength:
Role of limited information

This table reports the results of panel regressions of industry factor-adjusted returns in month t on its return in month $t-1$, average intermediate-horizon returns (IR, $t-11$ through $t-7$, inclusive), average recent-horizon returns (RR, $t-6$ through $t-2$, inclusive), feedback strength, computed as in section 4.1, analyst coverage along the feedback loop, and cross terms. For each industry, analyst coverage is defined as the average of the number of analysts covering at least one firm in each two industries that belong to the strongest feedback loop for that industry, normalized by the total number of firms in the departure industry. All returns are factor-adjusted, computed as the sum of the intercept and residuals from the in-sample regression of industry excess returns on the three factors of Fama and French (1993). All regressions include industry fixed effects. The t-statistics, shown in square brackets, are based on standard errors clustered by time. The availability of analyst coverage data restricts the sample to the period from January 1984 to December 2014.

	Slope coefficients and [t-statistics] from regressions where the dependent variable is industry 3-factor alpha				
Independent variable	(1)	(2)	(3)	(4)	(5)
Last month return	0.004	0.005	0.004	0.004	0.005
	[0.24]	[0.27]	[0.22]	[0.23]	[0.28]
Intermediate-horizon return, IR	-0.022		-0.116	-0.036	
	[-0.51]		[-2.09]	[-0.75]	
Recent-horizon return, RR		-0.003			-0.014
		[-0.05]			[-0.20]
Feedback strength, FS	-0.113	-0.130	-0.114	-0.114	-0.126
	[-2.37]	[-2.72]	[-2.39]	[-2.40]	[-2.68]
FS × IR	1.797		3.407	1.585	
	[2.46]		[2.95]	[2.18]	
FS × RR		-0.710			0.018
		[-0.94]			[0.01]
Analyst coverage			-0.001	-0.001	-0.001
			[-0.30]	[-0.30]	[-0.28]
Analyst coverage × FS			0.007	0.006	0.001
			[0.26]	[0.21]	[0.03]
Analyst coverage × IR			0.226	0.061	
			[2.28]	[0.72]	
Analyst coverage × RR					-0.004
					[-0.04]
Analyst coverage × FS × IR			-3.013		
			[-2.25]		
Analyst coverage × FS × RR					-0.867
					[-0.67]

Table 10

Momentum profits of industry portfolios sorted on augmented feedback strength

This table reports raw and factor-adjusted monthly returns of industry momentum portfolios conditional on augmented feedback strength (FS*). At the end of each month $t-1$, industries are sorted into terciles by their FS*, computed based on the PageRank algorithm as described in section 6.1. Within each tercile, they are sorted into quintiles by their cumulative intermediate-horizon returns ($t-11$ through $t-7$, inclusive) or recent-horizon returns ($t-6$ through $t-2$, inclusive). The resultant winner-minus-loser value-weighted portfolio is held during month t. Reported are excess returns and alphas from the CAPM, 3-factor, and 4-factor models, all in percent monthly, as well as the associated t-statistics in square brackets. The sample covers January 1973 through December 2014.

	Profits (% monthly) of momentum strategies based on industry returns over							
Performance	intermediate horizon (past 11 to 7 mo)				recent horizon (past 6 to 2 mo)			
measure	Low FS*	Med FS*	High FS*	High-Low	Low FS*	Med FS*	High FS*	High-Low
Excess return	0.21	0.38	1.09	0.88	0.42	-0.11	-0.26	-0.69
	[0.90]	[1.99]	[4.38]	[2.56]	[1.60]	[-0.51]	[-1.05]	[-1.88]
CAPM alpha	0.23	0.41	1.03	0.81	0.49	-0.03	-0.25	-0.74
	[0.95]	[2.13]	[4.11]	[2.81]	[1.82]	[-0.16]	[-0.99]	[-2.55]
3-factor alpha	0.32	0.53	1.15	0.83	0.59	-0.02	-0.21	-0.80
	[1.32]	[2.74]	[4.51]	[2.87]	[2.19]	[-0.10]	[-0.82]	[-2.75]
4-factor alpha	-0.16	0.18	0.78	0.94	-0.05	-0.53	-0.80	-0.75
	[-0.76]	[1.01]	[3.18]	[3.20]	[-0.21]	[-2.72]	[-3.55]	[-2.53]

Table 11

Industry momentum profits and feedback strength: Robustness to controlling for industry centrality and size

This table reports the results of panel regressions of industry factor-adjusted returns in month t on its return in month $t-1$, average intermediate-horizon returns (IR, $t-11$ through $t-7$, inclusive), average recent-horizon returns (RR, $t-6$ through $t-2$, inclusive), feedback strength, computed as in section 4.1, industry centrality, computed following Ahern (2013), log of the count of firms in the industry, and cross terms. All returns are factor-adjusted, computed as the sum of the intercept and residuals from the in-sample regression of industry excess returns on the three factors of Fama and French (1993). All regressions include industry fixed effects. The t-statistics, shown in square brackets, are based on standard errors clustered by time. The sample period is from January 1973 to December 2014.

	Slope coefficients and [t-statistics] from regressions where the dependent variable is industry 3-factor alpha				
Independent variable	(1)	(2)	(3)	(4)	(5)
Last month return	0.031	0.031	0.032	0.029	0.031
	[1.98]	[1.97]	[2.08]	[1.87]	[1.97]
Intermediate-horizon return, IR	-0.017	-0.024		-0.151	
	[-0.50]	[-0.61]		[-1.48]	
Recent-horizon return, RR			-0.006		-0.196
			[-0.14]		[-1.83]
Feedback strength, FS	-0.090	-0.075	-0.090	-0.030	-0.043
	[-2.12]	[-1.79]	[-2.14]	[-0.75]	[-1.08]
FS × IR	2.124	2.034		2.034	
	[3.48]	[3.04]		[3.33]	
FS × RR			-0.452		-0.598
			[-0.62]		[-0.88]
Centrality		-0.040	-0.043		
		[-1.19]	[-1.29]		
Centrality × IR		0.572			
		[0.50]			
Centrality × RR			0.085		
			[0.07]		
Log firm count				-0.005	-0.005
				[-4.02]	[-4.19]
Log firm count × IR				0.033	
				[1.34]	
Log firm count × RR					0.047
					[1.74]