# Internet Appendix to:

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

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## A. Motivating 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 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 extend this prior work by showing that when an industry is connected to itself via an inter-industry supply chain, its returns will exhibit an echo: intermediate-term autocorrelation in returns.

### A.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 $\eta$. 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.[1] 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 $t = 3$.

## A.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 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 $\eta$ is within the above-mentioned boundary, $cov(R_{X,1}, R_{X,3})$

[1] 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).

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.

## B. 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 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 challenge 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 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 $t$.

### B.1. Portfolio Sorts

At the end of each month $t-1$, we sort industries into quintiles by their IR or RR returns. To form the intermediate-horizon momentum portfolio, $\text{MOM}_{\text{IR}}$, 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, $\text{MOM}_{\text{RR}}$. As in Novy-Marx (2012), stocks within an industry are value-weighted, and industries in the momentum portfolios are equally weighted.

Table A.1 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 0.70% ($t$=4.16) and 0.84% ($t$=4.95) 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 0.57% ($t$=2.81) and 0.64% ($t$=3.11).

## B.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.[2]

The large and significant intercepts in regressions (1) and (2) of Table A.2 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 industry returns. In particular, while specification (5) shows that this momentum portfolio generates an average monthly return of 0.49% ($t$=2.49), it is spanned by the IR-based strategy, as evidenced by the insignificant intercepts 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 A.2 suggest that the echo component in industry returns is strong and spans both the short-horizon and long-horizon industry momentum strategies.

## B.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 month fixed effects and cluster standard errors by month. 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

[2]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.

are computed as sums of the intercept and residuals from in-sample regressions of industry excess returns on the factors.

Table A.3 summarizes the results of panel regressions. We find that 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.

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**Table A.1**
**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, $\text{MOM}_{\text{RR}}$ and $\text{MOM}_{\text{IR}}$, 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 2016.

| | Intercept (% monthly), slope coefficients, and [t-statistics] from regressions where the dependent variable is | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Independent | intermediate-horizon (past 11 to 7 mo) momentum return, $\text{MOM}_{\text{IR}}$ | | | recent-horizon (past 6 to 2 mo) momentum return, $\text{MOM}_{\text{RR}}$ | | | return difference of two strategies, $\text{MOM}_{\text{IR}} - \text{MOM}_{\text{RR}}$ | | |
| variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Intercept | 0.70 | 0.73 | 0.84 | 0.09 | 0.16 | 0.20 | 0.62 | 0.57 | 0.64 |
| | [4.16] | [4.27] | [4.95] | [0.45] | [0.84] | [1.06] | [3.07] | [2.81] | [3.11] |
| MKT | | -0.04 | -0.10 | | -0.14 | -0.17 | | 0.09 | 0.07 |
| | | [-1.22] | [-2.61] | | [-3.38] | [-3.77] | | [2.15] | [1.39] |
| HML | | | -0.25 | | | -0.10 | | | -0.14 |
| | | | [-4.13] | | | [-1.55] | | | [-1.97] |
| SMB | | | 0.03 | | | 0.04 | | | -0.01 |
| | | | [0.53] | | | [0.59] | | | [-0.11] |

**Table A.2**
**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 $MOM_{IR,RR}$, 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 2016.

| | 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, $MOM_{IR,RR}$ | | | | |
| variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Intercept | 0.67 | 0.77 | -0.21 | -0.15 | 0.49 | -0.13 | -0.09 | 0.42 | 0.48 |
| | [4.30] | [4.89] | [-1.20] | [-0.80] | [2.49] | [-0.99] | [-0.67] | [3.60] | [4.03] |
| MKT | | -0.05 | | -0.12 | | | -0.07 | | -0.02 |
| | | [-1.29] | | [-3.00] | | | [-2.21] | | [-0.66] |
| HML | | -0.21 | | 0.00 | | | 0.00 | | -0.13 |
| | | [-3.82] | | [-0.03] | | | [0.04] | | [-3.06] |
| SMB | | 0.02 | | 0.03 | | | -0.01 | | -0.01 |
| | | [0.34] | | [0.42] | | | [-0.12] | | [-0.26] |
| $MOM_{IR}$ | | | 0.43 | 0.42 | | 0.88 | 0.88 | | |
| | | | [9.23] | [8.92] | | [26.00] | [25.46] | | |
| $MOM_{RR}$ | 0.34 | 0.33 | | | | | | 0.83 | 0.83 |
| | [9.23] | [8.92] | | | | | | [30.77] | [30.35] |

**Table A.3**
**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 month 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 2016.

| | 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 | 0.045 | 0.036 | 0.032 | 0.032 |
| | [2.69] | [2.27] | [2.11] | [2.19] |
| Intermediate-horizon return, IR | 0.101 | 0.102 | 0.102 | 0.097 |
| | [3.13] | [3.22] | [3.35] | [3.21] |
| Recent-horizon return, RR | -0.016 | -0.007 | -0.002 | -0.004 |
| | [-0.41] | [-0.17] | [-0.05] | [-0.10] |

**Table A.4**
**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 2.1 of the paper, and cross terms. We use either simple returns, or factor-adjusted returns, which 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 month 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 2016.

| | 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 | 0.045 | 0.045 | 0.047 | 0.032 | 0.031 | 0.034 |
| | [2.69] | [2.65] | [2.78] | [2.11] | [2.05] | [2.22] |
| Intermediate-horizon return, IR | 0.101 | 0.054 | | 0.102 | 0.004 | |
| | [3.13] | [1.44] | | [3.35] | [0.12] | |
| Recent-horizon return, RR | -0.016 | | -0.024 | -0.002 | | 0.022 |
| | [-0.41] | | [-0.52] | [-0.05] | | [0.54] |
| Feedback strength, FS | | -0.019 | -0.009 | | 0.000 | 0.001 |
| | | [-1.28] | [-0.60] | | [-0.01] | [0.08] |
| FS × IR | | 1.173 | | | 2.212 | |
| | | [2.38] | | | [3.76] | |
| FS × RR | | | 0.237 | | | -0.455 |
| | | | [0.50] | | | [-0.72] |

**Table A.5**
**Feedback strength and the term structure of momentum: Cross-sectional regressions**

This table reports the results of Fama-MacBeth regressions of month $t$ returns of portfolios of industries with different feedback strengths (FS) on their returns in month $t-k$. Feedback strength is computed as in section 2.1 of the paper at the end of month $t-1$. We use either simple returns, or factor adjusted returns, which are calculated 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). The $t$-statistics are shown in square brackets. The sample period is from January 1973 to December 2016.

| | Slope coefficients and [t-statistics] from Fama MacBeth regressions based on industry | | | | | |
|---|---|---|---|---|---|---|
| | Raw returns | | | 3-factor adjusted returns | | |
| Lag, $k$ | Low FS | Med FS | High FS | Low FS | Med FS | High FS |
| 1 | 0.099 | 0.084 | 0.076 | 0.078 | 0.101 | 0.116 |
| | [2.34] | [2.12] | [1.67] | [1.92] | [2.62] | [2.46] |
| 2 | 0.051 | 0.052 | -0.019 | 0.026 | 0.094 | 0.037 |
| | [1.17] | [1.29] | [-0.41] | [0.62] | [2.31] | [0.79] |
| 3 | 0.026 | 0.080 | 0.001 | -0.002 | 0.123 | 0.081 |
| | [0.54] | [1.99] | [0.02] | [-0.06] | [3.16] | [1.76] |
| 4 | 0.035 | 0.053 | 0.004 | 0.027 | 0.094 | 0.049 |
| | [0.81] | [1.33] | [0.08] | [0.65] | [2.46] | [1.01] |
| 5 | 0.072 | 0.080 | 0.066 | 0.050 | 0.120 | 0.114 |
| | [1.70] | [2.03] | [1.44] | [1.22] | [3.08] | [2.47] |
| 6 | 0.098 | 0.082 | 0.172 | 0.083 | 0.103 | 0.208 |
| | [2.34] | [2.07] | [3.83] | [2.02] | [2.67] | [4.61] |
| 7 | 0.105 | 0.115 | 0.167 | 0.060 | 0.123 | 0.208 |
| | [2.60] | [3.00] | [3.79] | [1.50] | [3.19] | [4.73] |
| 8 | 0.103 | 0.145 | 0.161 | 0.062 | 0.15 | 0.192 |
| | [2.48] | [3.57] | [3.42] | [1.52] | [3.67] | [4.13] |
| 9 | 0.095 | 0.108 | 0.154 | 0.044 | 0.133 | 0.187 |
| | [2.36] | [2.60] | [3.19] | [1.11] | [3.17] | [3.91] |
| 10 | 0.069 | 0.080 | 0.101 | 0.036 | 0.106 | 0.102 |
| | [1.81] | [1.96] | [2.17] | [0.93] | [2.61] | [2.22] |
| 11 | 0.020 | 0.053 | 0.020 | 0.012 | 0.081 | 0.069 |
| | [0.52] | [1.31] | [0.47] | [0.31] | [1.93] | [1.49] |
| 12 | -0.001 | 0.049 | -0.045 | 0.030 | 0.081 | 0.008 |
| | [-0.01] | [1.27] | [-1.03] | [0.76] | [2.02] | [0.19] |