The Analyst Matrix: Profiting from Sell-Side Analysts' Coverage Networks

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Prior studies document profitable investment strategies arising from lead-lag relationships between fundamentally connected firms.[1] These studies identified fundamental linkages between firms either explicitly (customers and suppliers) or implicitly (companies in the same industry). Sell-side analyst coverage data provides a new and rich source of establishing connections between firms, as analysts (given their industry expertise) are likely to cover fundamentally related firms. This report uses sell-side analysts' coverage data to build a *connected-firm network (CFN)* - a portfolio of companies that are covered by analyst(s) that follow a focal firm. This network has three broad applications: measuring the "strength" of economic relationships between companies; forecasting fundamentals of companies in the network; and as a stock selection signal. Key insights include:

- **Connected-firm networks quantify the strength of relationships between companies in the network (Figure 1), unlike sector relationships which are binary.** This distinction is important because the strength of company relationships is related to the degree to which information pertinent to one company impacts other companies in the network.

- **Models used to forecast EPS estimate revisions can be improved by incorporating the prior month's estimate revisions for all the stocks in the company's connected-firm network (networkRev3MFY1)**. The coefficient for networkRev3MFY1 is economically significant in a forecast model that includes control variables for size, value, price momentum and negative earnings (Section 6).

- **The alpha signal constructed from the CFN ("Analyst Network Momentum" or "AN-MOM")[2] is effective across most developed markets, with long-short returns ranging from 4.08% (Europe ex-UK) to 7.78% (US).** Long-only excess returns[3] are over 400 basis points in the US and Asia ex-Japan (Table 2, Table 3).

- **The long-short return within a universe of firms with the most complex networks is 9.69%, vs. 6.02% for a universe of stocks with simple networks.** The difference is significant at the 5% level (Table 4), and it is an indication that investors need more time to process all related-firm news for a network with many connections.

- **AN-MOM's performance is not subsumed by analyst EPS revisions or industry momentum (Table 8). However, its efficacy is concentrated in the small cap spectrum (Table 2),** suggesting that new information emanating from CFNs are quickly (slowly) incorporated in the stock prices of large (small) cap stocks.

[1] Lead-lag relationships arise when a company's stock price reacts slowly to relevant information about other firms to which it is economically connected. See Cohen and Frazzini (2007), Grinblatt and Moskowitz (1999), and, Parsons et al (2016).
[2] The factor value for each company is the weighted sum of prior-month returns of all stocks in its connected-firm network.
[3] Long- short excess return is the equal-weighted return of the top quintile minus the equal-weighted return of the bottom quintile. Long-only excess return is the equal weighted return of the top quintile of stocks minus the equal-weighted return of the universe.

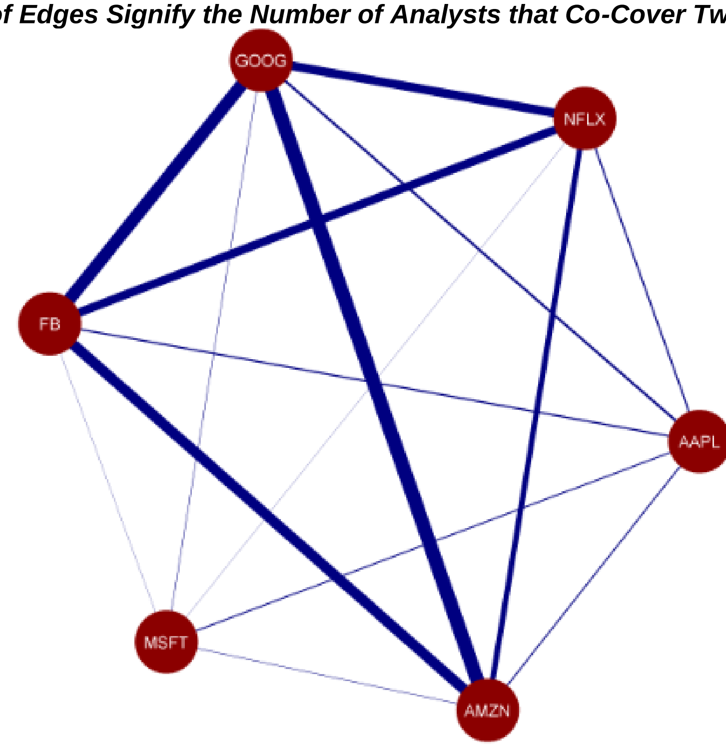
1. Introduction

Investors' inability to quickly update asset prices with new value-relevant information has been well documented. Most of these studies attribute the gradual (rather than instantaneous) incorporation of new information in asset prices to investors' limited attention and capacity to process information. Cohen and Frazzini (2007) documented a lead-lag effect between customers and their suppliers. They found that a strategy of buying firms whose customers had the most positive returns in the previous month, and selling short firms whose customers had the most negative returns yielded an annualized return in excess of 18%. Other studies that utilized lead-lag relationships between stocks include Grinblatt and Moskowitz (1999), Parsons et al (2016) and Lee et al (2017). These studies determined company linkages using industry relationships, geographic location and technology similarity, respectively.

Ali and Hirshleifer (2019) argue that the stronger the linkages between firms, the more pronounced the lead-lag effect will be, as there would be more relevant news for investors to underreact to. They propose that the strongest economic linkages between firms are best established using sell-side analyst coverage, as analysts are likely to cover firms that provide similar products or services.

Figure 1 describes the process of building a network using analyst coverage data for six stocks, collectively named FAANGM - Facebook (FB), Apple (AAPL), Amazon (AMZN), Netflix (NFLX), Alphabet (GOOG) and Microsoft (MSFT).

Figure 1: Analyst-Network for FAANGM Stocks as of 12/31/2019
Width of Edges Signify the Number of Analysts that Co-Cover Two Stocks



Source: S&P Global Market Intelligence Quantamental Research. Data as at 02/28/2020

The thicker the width of the edges in Figure 1, the higher the number of analysts that co-cover connected firms, and the stronger their economic connection. ***Figure 1 demonstrates the value of a connected-firm network. AMZN is not in the same sector as GOOG, FB and NFLX, but the CFN suggests it has strong economic links to all three companies (streaming, advertising)***. While AAPL and MSFT are both in the information technology sector, the economic linkage between the two stocks is weak.

2. Signal Construction and Test Results

Table 1 describes the construction of the alpha signal ("Analyst Network Momentum" or "AN-MOM") for GOOG as at the end of December 31, 2019 (assuming that the universe of stocks is restricted to FAANGM). AN-MOM's value for Google is the weighted return of all the five connected stocks, where the weight is the # of analysts that co-cover GOOG and each connected stock. Similar to Ali and Hirshleifer (2019), the calculation for AN-MOM is given by:

$$\text{AN-MOM}_{jt} = \sum_{i=1}^{n} W_{it} \; R_{it} \qquad \text{Equation 1}$$

Where *W* is the (# of analysts that co-cover the focal firm j and connected firm i) divided by the total # of connections in the network; *t* is the index for time and R_i is the return of stock i in a given month.

Table 1: AN-MOM Calculation for GOOG for 12/31/2019, Assuming Universe of Stocks is FAANGM

Focal Stock	Connected Firm	# of Analysts that co-cover both Stocks	1-month Return of Connected Firm (Dec 2019)	Weighted Return of Connected Firm
GOOG	AMZN	30	2.6%	0.9%
GOOG	FB	31	1.8%	0.6%
GOOG	MSFT	2	4.2%	0.1%
GOOG	AAPL	5	9.9%	0.6%
GOOG	NFLX	21	2.8%	0.7%
		AN-MOM Value		**2.8%**

Source: S&P Global Market Intelligence Quantamental Research. Data as at 02/28/2020

The above process is repeated for each of the other five connected companies, and the calculated value for each stock represents its alpha forecast for January 2020. *Companies with higher AN-MOM values as of December 31 2019 are expected to outperform firms with lower values in January 2020*.

All returns in this report are equal-weighted, Winsorized at 3-standard deviations, and adjusted for market, size, value, momentum and 1-month reversal risk factors.[4]

[4] Given that the factor value for each stock is calculated using the 1-month return of all companies in its connected-firm network, it is important to ensure that the performance of AN-MOM is not subsumed by the 1-month reversal factor. Our results are qualitatively similar if we adjust returns by market, size, value and momentum risk factors only.

2.1. U.S Test Results

Backtests for the Russell 3000, Russell 1000 (large cap) and Russell 2000 (small cap) universes are shown in Table 2. The strategy is effective in the broad-based Russell 3000 universe, with all performance metrics significant at the 1% level. The returns of both the long (4.28%) and long-short (7.78%) portfolios indicate that AN-MOM can be used by portfolio managers pursuing long-only and/or long-short equity strategies.

AN-MOM is not effective in the large cap spectrum, but efficacy improves in the small cap space. This suggests that new information emanating from connected-firm networks is quickly (slowly) incorporated in the stock prices of large (small) cap stocks. Because sell-side analysts play an important role in information gathering and dissemination, low analyst coverage (an attribute of small cap stocks) often impedes the information efficiency of small cap stocks.[5]

Table 2: Analyst Network Momentum: Performance in the U.S (June 1999 – Dec. 2019)

Test Universe	Average Quintile Count	1-month Information Coefficient (IC)	Annualized Long-Only Active Return	Annualized Information Ratio (Long Only Active Return	Hit Rate (Long-Only Active Return)	Annualized Long-Short Return	Annualized Information Ratio (Long-Short Return)	Hit Rate (Long-Short Return)
Russell 3000	515	0.017***	4.28%***	1.48	62%***	7.78%***	1.54	68%***
Russell 1000	183	0.005	0.63%	0.19	53%	1.04%	0.18	52%
Russell 2000	332	0.023***	5.81%***	1.73	66%***	9.65%***	1.71	68%***

*** Statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.
Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as at 02/29//2020.

2.2. International Test Results

The results for developed equity markets are displayed in Table 3. Overall, AN-MOM is effective in three of four developed equity markets: UK, Europe ex-UK and Asia ex-Japan. All performance metrics in the table are significant, at the 5% level or better, across all three equity markets. While the signal has an annualized long-only return (1.76%) that is statistically significant in Japan, the average 1-month IC (0.005) is poor and suggests the factor is weak at separating stocks in the cross-section in Japan.

[5] Elgers, P., Lo, M., and Pfeiffer, R., 2001, "Delayed Security Price Adjustments to Financial Analysts' Forecasts of Annual Earnings". *The Accounting Review*, 76(4), 613-632.

Table 3: Analyst Network Momentum:
International Performance, Developed Markets (June 2004 – Dec. 2019)

Universe	Average Quintile Count	1-month Information Coefficient (IC)	Annualized Long-Only Active Return	Annualized Information Ratio (Long Only Active Return	Hit Rate (Long-Only Active Return)	Annualized Long-Short Return	Annualized Information Ratio (Long-Short Return)	Hit Rate (Long-Short Return)
S&P UK BMI	81	0.024***	3.81%***	1.00	60%***	6.51%***	1.05	61%***
S&P Developed Europe Excluding UK BMI	250	0.021**	1.84%***	0.75	63%***	4.08%***	0.91	63%***
S&P Japan BMI	198	0.005	1.76%**	0.63	57%*	2.23%*	0.42	50%
S&P Developed Asia Ex Japan BMI	150	0.014**	4.85%***	1.07	61%***	5.87%***	0.73	58%**

*** Statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.
Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as at 02/28//2020.

3. Network Complexity

When a company has a complex (large) connected-firm network, information flow may be slower, as investors need to put in more time/effort to process all related-firm news. Focal companies with more complex connected-firm networks should therefore see a much slower incorporation of network information in their stock prices, while stock prices should be updated more rapidly for focal companies with simple networks.

To test the above hypothesis, we divide the Russell 3000 into two halves using the median total number of analyst connections based on the equation below. This process adjusts for size bias, as large cap companies tend to have more analyst connections than small cap companies.[6]

$$numConnections_{it} = \beta_0 + \beta_1 logmakcap_{it} + \varepsilon_{it} \qquad \text{Equation 2}$$

Where numConnections is the standardized # of connections for a given company, β_0 is the regression constant, and ε is the regression residual. The residuals from equation 2 serve as a proxy for network complexity.[7]

AN-MOM is effective in both high and low network complexity groups, with statistically significant 1-month information coefficients (ICs), long-only returns, long-short returns and hit rates in both complexity groups. However, performance is stronger in the high complexity group, as the 1-month long-only and long-short returns in this half are about 60% larger than those of the low complexity group. The difference in average annualized 1-month long-only (1.97%) and long-short returns (3.67%) between the high and low complexity groups are significant at the 10% and 5% levels respectively. The long-short return information ratio (IR) in the high complexity group is also about 45% higher than the IR in the low complexity group.

[6] The average rank correlation between the number of analyst connections and market capitalization (Russell 3000, Jun 1996 – Dec 2019) is 0.66.
[7] The average correlation between the residuals and market cap is -0.08.

Table 4 : Analyst Network Momentum: Performance in High vs Low Network Complexity (Russell 3000 Universe: June 1999 – December 2019)

Level of Complexity	Average Quintile Count	1-month Information Coefficient (IC)	Annualized Long-Only Active Return	Annualized Information Ratio (Long Only Active Return	Hit Rate (Long-Only Active Return)	Annualized Long-Short Return	Annualized Information Ratio (Long-Short Return)	Hit Rate (Long-Short Return)
High	260	0.018***	5.36%***	1.28	65%***	9.69%***	1.46	67%***
Low	255	0.010***	3.39%***	0.98	61%***	6.02%***	1.02	65%***
High - Low			1.97%*			3.67%**		

*** Statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.
Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as at 02/28//2020.

4. Factor Weight, Connected-Firm Network Horizon and Signal Decay

As a robustness check, this section examines the impact of the following on AN-MOM's performance:

- Using an equal-weighted approach to calculate factor values.
- Re-specifying the horizon window used in the construction of the network.
- Applying a 1 to 3 month lag before acting on the signal.

4.1. Factor Weighting Method

Equal weighting the returns of all the stocks in a connected-firm network (rather than weighting by the # of analysts) may not reflect the "strength" of the economic relationships between a focal company and firms in its network. However, performance metrics for both the equal and # of analyst weighted methods are similar (Table 5), suggesting that both methods can be used to determine linkages between companies.

Table 5: Analyst Network Momentum: Performance with Different Factor Formulation (Russell 3000, June 1999 – December 2019)

Weighting Method	Average Quintile Count	1-month Information Coefficient (IC)	Annualized Long-Only Active Return	Annualized Information Ratio (Long Only Active Return	Hit Rate (Long-Only Active Return)	Annualized Long-Short Return	Annualized Information Ratio (Long-Short Return)	Hit Rate (Long-Short Return)
# of Analyst	515	0.017***	4.28%***	1.48	62%***	7.78%***	1.54	68%***
Equal	515	0.016***	4.37%***	1.48	68%***	7.69%***	1.51	67%***

*** Statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.
Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as at 02/28//2020.

4.2. Connected-Firm Network Horizon Window

A connection between two companies is established once an analyst starts to jointly cover two stocks. The base case discussed so far assumes this connection "expires" after 12-months (row 1, Table 6), unless the analyst updates his/her forecast before the expiration of the 12-month window. Changing the network horizon window has minimal impact on performance as the results of using a shorter window (6 or 9-months) or a longer window (15-months) are similar to those of the 12-month base case (Table 6).

Table 6: Analyst Network Momentum: Varying Network Connection Window
Russell 3000, June 1999 – December 2019

Network Connection Window	Average Quintile Count	1-month Information Coefficient (IC)	Annualized Long-Only Active Return	Annualized Information Ratio (Long Only Active Return	Hit Rate (Long-Only Active Return)	Annualized Long-Short Return	Annualized Information Ratio (Long-Short Return)	Hit Rate (Long-Short Return)
12-months	515	0.017***	4.28%***	1.48	62%***	7.78%***	1.54	68%***
6-months	485	0.017***	4.23%***	1.50	63%***	7.61%***	1.49	67%***
9-months	513	0.017***	4.36%***	1.56	64%***	7.81%***	1.54	70%***
15-months	517	0.017***	4.38%***	1.50	63%***	7.72%***	1.53	66%***

*** Statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.
Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as at 02/28//2020.

4.3. Signal Decay

Annualized long-short (3.37%) and long-only (2.22%) returns are still significant when signal implementation is delayed by 1-month (Table 7). The decay in performance is likely because news itself is short-term in effect, and is typically incorporated quickly by the market. Long-short returns are no longer significant if the delay is extended to 3-months, with an accompanying information ratio (0.36) that is about a third of the signal with no lag (1.54).

Table 7: Analyst Network Momentum: Signal Decay
Russell 3000, June 1999 – December 2019

Signal Lag Window	Average Quintile Count	1-month Information Coefficient (IC)	Annualized Long-Only Active Return	Annualized Information Ratio (Long Only Active Return	Hit Rate (Long-Only Active Return)	Annualized Long-Short Return	Annualized Information Ratio (Long-Short Return)	Hit Rate (Long-Short Return)
No Lag	515	0.017***	4.28%***	1.48	62%***	7.78%***	1.54	68%***
1-month	513	0.011**	2.22%***	0.78	57%**	3.37%***	0.64	54%
2-months	509	0.008	1.88%***	0.64	57%**	2.75%**	0.52	55%*
3-months	506	0.006	1.55%**	0.52	57%**	1.92%	0.36	57%**

*** Statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.
Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as at 02/28//2020.

5. Is AN-MOM Different from Industry Momentum and Analyst Revisions?

Ali and Hirshleifer argue that AN-MOM is superior to industry momentum because the former uses a better method to determine economic relationships between companies.[8] Also, given that an important function of analysts is to provide company forecasts, it is prudent to confirm that the results in Table 2 are not subsumed by analyst revisions[9] (Equation 3).

$$\text{AN-MOM}_t = \alpha + \beta_1 earningsRevision_t + \beta_2 industryMomentum_t + \varepsilon_t \qquad \text{Equation 3}$$

Where AN-MOM, earningsRevision and industryMomentum are monthly long-short returns.

[8] Industry Momentum is based on the 24 industry groups according to the Global Industry Classification System (GICS®). Each month we rank all 24 industries based on their prior 6-month return. Long-short return are calculated using tertiles.
[9] Earnings revision is calculated as the 3-month change in consensus FY1 earnings per share divided by price.

The average monthly long-short return to AN-MOM is 0.62% (significant at the 1% level) after regressing out the long-short returns to both earnings revision and industry momentum (Table 8), indicating that the excess returns to AN-MOM are not subsumed by these factors

Table 8: AN-MOM Monthly Long-Short Excess Return Adjusted for Earnings Revisions and Industry Momentum Russell 3000 (June 1999 – December 2019)

Variable	Coefficient
Intercept	0.62%***
industryMomentum	0.05***
earningsRevision	-0.04

*** Statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.
Source: S&P Global Market Intelligence Quantamental Research. For all exhibits, all returns and indices are unmanaged, statistical composites and their returns do not include payment of any sales charges or fees an investor would pay to purchase the securities they represent. Such costs would lower performance. It is not possible to invest directly in an index. Past performance is not a guarantee of future results. Data as at 02/28/2020.

6. Forecasting FY1 EPS Estimate Revisions

Unlike investors, sell-side analysts may incorporate news about related firms in their forecasts quickly. If this is true, the EPS estimate revisions of all the stocks in a connected-firm network should *not be* useful in forecasting the EPS estimate revisions of the focal company.

The model used to forecast the 3-month change in FY1 EPS estimates (Rev3MFY1) for a firm is detailed in Equation 4.[10] The independent variables used in the model include the FY1 EPS estimate revisions of all the companies in a CFN (networkRev3MFY1), log of market cap (logSize), and 12-momentum (12MPMOM). See Appendix A for variable definitions.

$$Rev3MFY1_{it+1} = \beta_0 + \beta_1 logBP_{it} + \beta_2 networkRev3MFY1_t + \beta_3 lossFlag_{it} + \beta_4 logSize_{it} + \beta_5 12MPMOM_{it} + \beta_6 1MReversal_{it} + \varepsilon_{it} \quad \text{Equation 4}$$

The coefficient of networkRev3MFY1 is economically significant (Table 9), confirming that analysts are also slow to adjust their forecasts across all stocks in their coverage universe.

Table 9: Average Coefficients of Predictors of 3-month Change in Analyst FY1 EPS: Russell 3000 (January 2000 – December 2019)

Variable	Coefficient
Intercept	-0.171***
logBP	-0.026***
Network_Rev3MFY1	0.237***
LossFlag	-0.131***
logSize	0.013***
12MPMOM	0.059***
1MMOM	0.053***

*** statistically significant at 1% level; ** statistically significant at 5% level; * statistically significant at 10% level.
Source: S&P Global Market Intelligence Quantamental Research. Adjusted R^2 = 0.09. Data as at 02/15/2020.

[10] Equation 4 is similar to that used by Ali and Hirshleifer (2019).

7. Data

The data used to construct connected-firm networks in this report is drawn from the S&P Capital IQ Estimates database. This database includes analyst forecasts for over 75 data items including company fundamentals (EPS, revenue, dividends etc.), industry estimates (REITs, oil & gas, and retail) and commodity estimates (fossils and precious metals). The database covers over 56,000+ companies (active and inactive) in over 110 countries. Estimates are sourced from more than 600 contributors. The S&P Global Estimate database also captures over 37 guidance data items for 10,000+ companies. Data history starts in 1999 for the U.S, and 1995 for other countries.

S&P Global Market Intelligence's Capital IQ Premium Financials and Compustat® North America packages were the sources of fundamental data for this study. Both are point-in-time databases, eliminating any look-ahead bias in our back-tests.

8. Conclusion

Profitable investment strategies arising from lead-lag relationships between fundamentally connected firms have been documented in prior studies. This report proposes three broad applications for a network derived from sell-side analysts' coverage data – quantifying economic linkages between companies, forecasting fundamentals of companies in the network, and as a stock selection signal. The alpha signal presented in this report (AN-MOM) delivers statistically significant long-only and long-short returns in the US, UK, Europe ex-UK and Asia ex-Japan equity markets. AN-MOM's returns are stronger in a universe of stocks with the most complex networks, supporting the hypothesis that the strategy exploits investors' and analysts' inability to quickly update asset prices due to limited attention and capacity to process information. Finally, AN-NOM's returns are not subsumed by industry momentum and analyst earnings revisions.

APPENDIX A

- Rev3MFY1 is the 3-month difference in FY1 mean estimates divided by the absolute value of the beginning period FY1 EPS
- logBP is the log of book-to-price
- networkRev3MFY1 is the average Rev3MFY1 of all the stock's in a company's connected-firm network. This value is standardized.
- lossdFlag is set to 1 if net income is negative and zero otherwise.
- logSize is the log of market capitalization.
- 12MPMOM is the standardized 11-month stock return skipping the most recent month
- 1MMOM is the standardized past 1-month return.

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Our Recent Research

June 2020: The Information Supply Chain Begins Recovering From COVID

The COVID-19 shockwaves emanating through the global supply chain continue to reverberate. The information that decision makers have traditionally relied have also been disrupted but is slowly showing signs of normalizing. S&P Global Market Intelligence processes 64,000 financial documents each day, placing it in a central position in the information supply chain with a unique view into the specific areas and magnitude of information disruption.

May 2020: Never Waste a Crisis: Following the Smart Money Through Beneficial Ownership Filings

Investors looking for ideas amid the recent market downturn may profit from reviewing beneficial ownership filings: SEC schedules 13D and 13G. These purchases often represent high conviction buys by activists, industry insiders, hedge funds, etc. Our previous investor activism research shows that investors can benefit by following activists' lead: a portfolio of stocks that activists had targeted outperformed the market by over 8% annually.

This report examines recent 13D and 13G filings, and spotlights four purchases of target companies with high historical operating cash flows and below average dividend payments, characteristics of companies typically targeted by activists.

May 2020: Risky Business: Foot Traffic, Vacancy Rates and Credit Risks

The COVID-19 pandemic has led to widespread closures of retail stores, offices and hotels. Foot traffic data can be combined with traditional financial ratios to provide a more holistic view of business health for both credit and equity investors. This report extends our prior analysis of foot-traffic data by setting foot traffic figures in the context of a screen for identifying where risks may be highest.

The analysis in this report can help: i) Creditors identify customers that require additional credit facilities to support growth, or companies where existing credit lines need to be reassessed given bleak prospects; and ii) Equity investors identify companies where revenues may be accelerating or firms that may have difficulty meeting financial obligations.

May 2020: Finding the Healthy Stocks in Health Care During Lockdown

Elective and non-essential medical procedures are on an indefinite hold in many places. Simultaneously, essential medical services are in high demand, and likely to remain in demand for the near future. This dynamic creates winners and losers among Health Care device manufacturers and distributors. Investors can identify potential opportunities in the Health Care Equipment and Services subsector by analyzing 510(k) premarket notifications, which are filings required by the U.S. Food and Drug Administration (FDA) for any company seeking to market a medical device in the United States.

May 2020: No More Walks in the (Office) Park: Tying Foot Traffic Data to REITs

Foot traffic data provides investors and corporate managers with key insights on the level of activity at properties and the demographic profile of visitors to these locations. Corporate managers can use this information to pinpoint properties at greater risk of tenant defaults, while investors can use foot traffic data to identify REITs managing properties where activity remains robust. More importantly, once the nationwide lockdown eases, foot traffic can serve as a leading indicator of a return of economic activity across industries.

May 2020: Do Markets Yearn for the Dog Days of Summer: COVID, Climate and Consternation

Stakeholders are turning to untraditional data sources to quantify the impact of the COVID-19 shutdown. While no single variable can forecast which locations will be most susceptible to the virus, mounting scientific literature suggests that there is a correlation between temperature and viral propagation. If correct, regions in the temperature 'target zone' may need to implement more stringent lockdown policies for a longer period to achieve comparable mitigation.

Investors can combine weather data with property data, to expose one dimension of risk for Real Estate Investment Trusts (REITs) of prolonged closures, as well as areas that may see a resurgence of the virus later this year.

April 2020: Cold Turkey - Navigating Guidance Withdrawal Using Supply Chain Data

A recent surge in corporate earnings guidance withdrawals has left decision-makers missing a wrench in their toolbox. Corporate guidance was already declining, in 2018, when the number of companies in the Russell 3000 providing guidance peaked at 1,721, dropping 6.9% year over year in 2019 to 1,632 companies. Guidance has been further impacted by the Coronavirus pandemic – 173 companies withdrew their previous guidance in the first quarter. This leaves decision-makers looking for alternative forward-looking information on a company's prospects.

April 2020: Data North Star - Navigating Through Information Darkness

Crisis creates uncertainty. Familiar landmarks lose their value and decision makers are left to navigate on partial information. Following the outbreak of the COVID-19 pandemic, this is the environment in which investors and corporate decision-makers now suddenly find themselves. The S&P Global Quantamental Research team has launched a series of research briefs that will aid decision-makers in navigating this uncertain environment. Utilizing non-traditional datasets across the entire S&P Global Market Intelligence product suite, these briefs will provide market participants with analysis on COVID-19's impact to the financial markets geared to fill the current information gap.

March 2020: Long Road to Recovery: Coronavirus Lessons from Supply Chain and Financial Data

COVID-19 continues to disrupt global supply chains in unprecedented ways. Leveraging maritime shipping data from Panjiva, this report includes a review of trade and financial data to analyze the impact of the SARS-CoV-2 / COVID-19 coronavirus outbreak. Findings include:

- Second-order supply chain effects are also emerging with the apparel industry now seeing a shortage of materials globally due to earlier outages in China.
- Retailers including Costco and Target are gaining from increased sales of health- and personal care products. Yet, supply shortages are rapidly emerging in part due to medical supply export restrictions in several countries.
- There is a notable, but not statistically significant, relationship with firms with higher exposure to Asia having seen a weaker sector neutral stock price performance.

February 2020: Ship to Shore: Mapping the Global Supply Chain with Panjiva Shipping Data in Xpressfeed™

World merchandise trade accounted for an estimated $19.7 trillion in 2018, about 90% of which is by sea. While financial data tells us "how a company has done in the past," shipping data provides a closer-to-real time indicator of "what a company is doing now." Panjiva's shipping data allows investors to track trends, identify anomalies, and assess risks for companies engaged in international trade. This paper illustrates how to find investment insights in Panjiva's US seaborne and Mexican datasets using the US auto parts industry as a case study.

Findings include:

- Shipment trends often lead fundamentals: Rising shipments amid flat or declining fundamentals may signal future financial trend reversal
- Growth in the number of a company's suppliers and in the types of products it imports may signal strengthening demand and/or product line diversification.
- Tracking industry-level product-line trends can help identify companies with significant exposure to rising or declining product lines.

January 2020: Natural Language Processing – Part III: Feature Engineering Applying NLP Using Domain Knowledge to Capture Alpha from Transcripts

Unstructured data is largely underexplored in equity investing due to its higher costs. One particularly valuable unstructured data set is S&P Global Market Intelligence's machine readable earnings call transcripts.

- Topic Identification – Firms that referenced the most positive descriptors around their financials outperformed historically.
- Transparency – Firms that provided greater call transparency exhibited by executives' behaviors and decisions outperformed historically.
- Weighted Average Sentiment – Quantifying call sentiment using a weighted average construct led to better returns and less volatility historically.

- Additive Forecasting Power – The newly introduced signals demonstrated additive forecasting power above commonly used alpha and risk signals historically.

December 2019: <u>The "Trucost" of Climate Investing: Managing Climate Risks in Equity Portfolios</u>

Does sustainable investing come at a "cost", and is the fear of investors around the performance concessions of "green" portfolios warranted? Our latest research suggests investors' fears are misplaced – carbon-sensitive portfolios have similar returns and significantly better climate characteristics than portfolios constructed without carbon emission considerations. Other findings include:

- Highly profitable firms are likely to be leaders in reducing their carbon emission levels.
- There is no degradation in fundamental characteristics for the carbon-sensitive portfolios compared to the baseline portfolio, even though the difference in constituents can be as high as 20%.
- Carbon-sensitive portfolios were observed as having significant reductions in water use, air pollutants released and waste generated.

October 2019: <u>#ChangePays: There Were More Male CEOs Named John than Female CEOs</u>

This report examines the performance of firms that have made female appointments to their CEO and CFO positions. Our research finds that firms with female CEOs and/or CFOs:.

- Are more profitable and generated excess profits of $1.8 trillion over the study horizon.
- Have produced superior stock price performance, compared to the market average.
- Have a demonstrated culture of Diversity and Inclusion, evinced by more females on the company's board of directors.

June 2019: <u>Looking Beyond Dividend Yield: Finding Value in Cash Distribution Strategies</u>

June 2019: <u>The Dating Game: Decrypting the Signals in Earnings Report Dates</u>

May 2019: <u>Bridges for Sale: Finding Value in Sell-Side Estimates, Recommendations, and Target Prices</u>

February 2019: <u>U.S Stock Selection Model Performance Review</u>

February 2019: <u>International Small Cap Investing: Unlocking Alpha Opportunities in an Underutilized Asset Class</u>

January 2019: <u>Value and Momentum: Everywhere, But Not All the Time</u>

November 2018: <u>Forging Stronger Links: Using Supply Chain Data in the Investing Process</u>

September 2018: <u>Their Sentiment Exactly: Sentiment Signal Diversity Creates Alpha Opportunity</u>

September 2018: <u>Natural Language Processing – Part II: Stock Selection: Alpha Unscripted: The Message within the Message in Earnings Calls</u>

July 2018: **A Case of 'Wag the Dog'? - ETFs and Stock-Level Liquidity**

June 2018: **The (Gross Profitability) Trend is Your Friend**

May 2018: **Buying the Dip: Did Your Portfolio Holding Go on Sale?**

March 2018: **In the Money: What Really Motivates Executive Performance?**

February 2018: **The Art of the (no) Deal: Identifying the Drivers of Canceled M&A Deals**

January 2018: **U.S Stock Selection Model Performance Review**

September 2017: **Natural Language Processing - Part I: Primer**

July 2017: **Natural Language Processing Literature Survey**

June 2017: **Research Brief: Four Important Things to Know About Banks in a Rising Rate Environment**

April 2017: **Banking on Alpha: Uncovering Investing Signals Using SNL Bank Data**

March 2017: **Capital Market Implications of Spinoffs**

January 2017: **U.S. Stock Selection Model Performance Review 2016**

November 2016: **Electrify Stock Returns in U.S. Utilities**

October 2016: **A League of their Own: Batting for Returns in the REIT Industry - Part 2**

September 2016: **A League of their Own: Batting for Returns in the REIT Industry - Part 1**

August 2016: **Mergers & Acquisitions: The Good, the Bad and the Ugly (and how to tell them apart)**

July 2016: **Preparing for a Slide in Oil Prices -- History May Be Your Guide**

June 2016: **Social Media and Stock Returns: Is There Value in Cyberspace?**

April 2016: **An IQ Test for the "Smart Money" – Is the Reputation of Institutional Investors Warranted?**

March 2016: **Stock-Level Liquidity – Alpha or Risk? - Stocks with Rising Liquidity Outperform Globally**

February 2016: **U.S. Stock Selection Model Performance Review - The most effective investment strategies in 2015**

January 2016: **What Does Earnings Guidance Tell Us? – Listen When Management Announces Good News**

November 2015: **Late to File - The Costs of Delayed 10-Q and 10-K Company Filings**

October 2015: **Global Country Allocation Strategies**

September 2015: **Research Brief: Building Smart Beta Portfolios**

September 2015: **Research Brief – Airline Industry Factors**

August 2015: **Point-In-Time vs. Lagged Fundamentals – This time i(t')s different?**

August 2015: **Introducing S&P Capital IQ Stock Selection Model for the Japanese Market**

July 2015: Research Brief – Liquidity Fragility

May 2015: Investing in a World with Increasing Investor Activism

April 2015: Drilling for Alpha in the Oil and Gas Industry – Insights from Industry Specific Data & Company Financials

February 2015: U.S. Stock Selection Model Performance Review - The most effective investment strategies in 2014

January 2015: Research Brief: Global Pension Plans - Are Fully Funded Plans a Relic of the Past?

January 2015: Profitability: Growth-Like Strategy, Value-Like Returns - Profiting from Companies with Large Economic Moats

October 2014: Lenders Lead, Owners Follow - The Relationship between Credit Indicators and Equity Returns

July 2014: Factor Insight: Reducing the Downside of a Trend Following Strategy

May 2014: Introducing S&P Capital IQ's Fundamental China A-Share Equity Risk Model

April 2014: Riding the Coattails of Activist Investors Yields Short and Long Term Outperformance

March 2014: Insights from Academic Literature: Corporate Character, Trading Insights, & New Data Sources

February 2014: Obtaining an Edge in Emerging Markets

February 2014: U.S Stock Selection Model Performance Review

January 2014: Buying Outperformance: Do share repurchase announcements lead to higher returns?

October 2013: Informative Insider Trading - The Hidden Profits in Corporate Insider Filings

September 2013: Beggar Thy Neighbor – Research Brief: Exploring Pension Plans

August 2013: Introducing S&P Capital IQ Global Stock Selection Models for Developed Markets: The Foundations of Outperformance

July 2013: Inspirational Papers on Innovative Topics: Asset Allocation, Insider Trading & Event Studies

June 2013: Supply Chain Interactions Part 2: Companies – Connected Company Returns Examined as Event Signals

June 2013: Behind the Asset Growth Anomaly – Over-promising but Under-delivering

April 2013: Complicated Firms Made Easy - Using Industry Pure-Plays to Forecast Conglomerate Returns.

March 2013: Risk Models That Work When You Need Them - Short Term Risk Model Enhancements

March 2013: Follow the Smart Money - Riding the Coattails of Activist Investors

February 2013: **Stock Selection Model Performance Review: Assessing the Drivers of Performance in 2012**

January 2013: **Research Brief: Exploiting the January Effect Examining Variations in Trend Following Strategies**

December 2012: **Do CEO and CFO Departures Matter? - The Signal Content of CEO and CFO Turnover**

November 2012: **11 Industries, 70 Alpha Signals -The Value of Industry-Specific Metrics**

October 2012: **Introducing S&P Capital IQ's Fundamental Canada Equity Risk Models**

September 2012: **Factor Insight: Earnings Announcement Return – Is A Return Based Surprise Superior to an Earnings Based Surprise?**

August 2012: **Supply Chain Interactions Part 1: Industries Profiting from Lead-Lag Industry Relationships**

July 2012: **Releasing S&P Capital IQ's Regional and Updated Global & US Equity Risk Models**

June 2012: **Riding Industry Momentum – Enhancing the Residual Reversal Factor**

May 2012: **The Oil & Gas Industry - Drilling for Alpha Using Global Point-in-Time Industry Data**

May 2012: **Case Study: S&P Capital IQ – The Platform for Investment Decisions**

March 2012: **Exploring Alpha from the Securities Lending Market – New Alpha Stemming from Improved Data**

January 2012: **S&P Capital IQ Stock Selection Model Review – Understanding the Drivers of Performance in 2011**

January 2012: **Intelligent Estimates – A Superior Model of Earnings Surprise**

December 2011: **Factor Insight – Residual Reversal**

November 2011: **Research Brief: Return Correlation and Dispersion – All or Nothing**

October 2011: **The Banking Industry**

September 2011: **Methods in Dynamic Weighting**

September 2011: **Research Brief: Return Correlation and Dispersion**

July 2011: **Research Brief - A Topical Digest of Investment Strategy Insights**

June 2011: **A Retail Industry Strategy: Does Industry Specific Data tell a different story?**

May 2011: **Introducing S&P Capital IQ's Global Fundamental Equity Risk Models**

May 2011: **Topical Papers That Caught Our Interest**

April 2011: **Can Dividend Policy Changes Yield Alpha?**

April 2011: **CQA Spring 2011 Conference Notes**

March 2011: **How Much Alpha is in Preliminary Data?**

February 2011: **Industry Insights – Biotechnology: FDA Approval Catalyst Strategy**

January 2011: **US Stock Selection Models Introduction**

January 2011: **Variations on Minimum Variance**

January 2011: **Interesting and Influential Papers We Read in 2010**

November 2010: **Is your Bank Under Stress? Introducing our Dynamic Bank Model**

October 2010: **Getting the Most from Point-in-Time Data**

October 2010: **Another Brick in the Wall: The Historic Failure of Price Momentum**

July 2010: **Introducing S&P Capital IQ's Fundamental US Equity Risk Model**