S&P CAPITAL IQ

QUANTITATIVE RESEARCH
AUGUST 2012

Authors

Paul Fruin
Quantitative Analyst
617 530-8107
paul_fruin@spcapitaliq.com

Jim Osiol
Quantitative Analyst
312 233-7128
josiol@spcapitaliq.com

Kirk Wang
Director, Quantitative Research
312 233-7149
kwang@spcapitaliq.com

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

Material events affecting entities in an economic system should introduce ripple effects to related entities through various types of relationships. Supply chain relationships are among the most visible and measurable, as revenues and costs shape the realized economic and financial performance of connected companies. Studies have shown that events within a supply chain do introduce these ripple effects, and theories incorporating this information into an investment process have garnered attention in recent years. Menzly & Ozbas (2007) examine cross-predictability of industries using BEA (the U.S. Bureau of Economic Analysis) Input-Output data, and Shahrur et al (2010) extend the methodology to international markets.

Leveraging input-output accounts from the BEA and Compustat, which use North American Industry Classification System (NAICS) codes, we construct a map quantifying industry level connections along the supply chain. Using this map, and trailing industry returns as a proxy for industry level information shocks, we construct inter-industry momentum signals similar to the methodology proposed by Menzly and Ozbas. These signals exhibit lead-lag relationships over short horizons, as the information shocks diffuse through the market and manifest themselves in the performance of related industries. We find:

- Significant lead-lag return relationships between connected industries exist in the US. Using a simple equal weight model of industry supply chain momentum signals to form long-short industry portfolios generates significant positive return spreads of 0.6% per month from 1987 to 2011.

- We test the methodology across a number of scenarios for sensitivity to common quantitative biases. We find supply chain momentum to be a sufficiently unique source of information as well as a significant predictive signal even when adjusting for beta or testing in a large cap universe.

- A model combining monthly and weekly industry supply chain signals, using expanding window regression signal weighting, produces a backtested strategy with long-short industry return spreads of 0.9% per month from 1990 to 2011. The long and short quintiles contribute symmetrically with active returns just over 0.4% per month relative to an average industry return benchmark.

- We test the sensitivity to supply chain signals across industries. Implementation of an industry-specific time series model for industries is appealing intuitively, but due to the unstable nature it underperforms a simple pan-industry model.

1 Information Diffusion across Industries

Grounded in the limited attention hypothesis, our research looks to exploit a systematic inability to incorporate all relevant information as it enters the system. Individual investors are limited in their ability to instantly process the entirety of new information and typically focus on the entities that are impacted directly. The delay to incorporate data represents a possible inefficiency in the pricing of securities.

Investors are potentially slow to recognize information introduced by related entities tied through business relationships. Supply chain interactions are an example of this tangential information which may be slow to enter into an investment process but can have a direct impact on performance. This is likely the case where industry connections are not readily apparent, high profile, or within the common coverage portfolio of analysts. Fortunately, the BEA compiles quantified inter-industry trade information, which helps identify industry supply chain connections in the US economy. Utilizing this map, we trace relevant information flows through these economic relationships.

We expand on the work of recent academic papers which examine the predictability of returns using cross-momentum signals between connected industries. We test the cross-momentum signal under the BEA's NAICS classification, explore the effect across longer and shorter timelines, enhance the traditional monthly signal with weekly momentum, and examine the predictive power of the relationships in an industry selection backtest.

1.1 Industry Relationships – BEA Map and Industry Returns

The BEA is the arm of the US Department of Commerce charged with the collection and analysis of economic statistics. As part of its data collection edict, the BEA captures annual industry Summary Input-Output Accounts, which provide quantified sales links between industries. This map is available with a one year lag on an annual basis starting in 1998, and currently uses NAICS as the defined groups. Prior to the 1998 Input-Output tables, the BEA provided 'Benchmark Input-Output Data' on years ending in 2 and 7, starting in 1982, and used the SIC classification system prior to the official switch to the current NAICS code basis.

Similar to Menzly and Ozbas (2007) (M&O) in their working paper "Cross-Industry Momentum", we construct monthly inter-industry momentum signals using the BEA map and cap weighted industry returns (outlined in more detail below). This model serves as our base case from which we derive variations. The Summary Use Annual I-O (Input-Output) table, with an appropriate lag, serves as the map to assign relative importance of connected industries. For simplicity, we assume the 1998 connections back to the start of our test period (1987) based on prior work and the assumption that these relationships are sufficiently stable. This allows us to preserve the same NAICS industry identifiers throughout. We weight connected industries by their inter-industry sales relative to the total of all inter-industry sales for the target industry. Relationships are in two directions: each industry consumes products that are produced by others (upstream connections), and produces products that are bought by other industries (downstream connections). We refer to each connection as a relationship weight. (An example of the calculation of relationship weighting between connected industries is available in Figure 10 of the Appendix) Using this relationship weighted map and industry returns, we construct supply chain momentum signals with relationships in both upstream and downstream directions. The industry signals are the relationship-weighted-average of connected industry trailing returns. We interpret these signals as measures of trailing information shocks (assuming abnormal returns are driven by new information). We anticipate that good (bad) news in upstream and downstream industries beget good (bad) returns in connected industries. In other words, industries that are connected to industries that had weak returns last month may have weak returns themselves later. In order to reduce issue level size effects and better gauge aggregate news within an industry, we use industry cap weighted returns in our analysis.

2 Base Case – Monthly Model

Three monthly signals are constructed for industry momentum: own momentum (**Own**), upstream momentum (**Up**), and downstream momentum (**Down**). The Own signal is simply the trailing return of the industry without relationship weights. The upstream and downstream signals are the relationship weighted average cap weight returns of industries connected in relationship map described above. To begin, we focus only on raw monthly returns as inputs to the signal.

2.1 Regression

We first test the cross-sectional predictive power of the three monthly signals using Fama-MacBeth style monthly panel regressions. The monthly regression takes the following form:

$$R_{i,t} = \alpha + \beta_{own}\, x\, R_{i,t-1} + \beta_{Down}\, x\, R^{Down}_{i,t-1} + \beta_{Up}\, x\, R^{Up}_{i,t-1}$$

$$R_{i,t} = Forward\ Return\ of\ Industry\ i$$

$$R_{i,t-1} = Trailing\ Return\ of\ Industry$$

$$R^{Down}_{i,t-1} = Trailing\ Relationship\ Weighted\ Return\ of\ DownStream\ (Customer) Industry$$

$$R^{Up}_{i,t-1} = Trailing\ Relationship\ Weighted\ Return\ of\ UpStream\ (Supplier) Industry$$

Each month in our time window (from January 1987 through September 2011) has its own set of monthly regression coefficients. We calculate the average coefficient for each signal across months, and calculate the t-statistic to test whether each coefficient is statistically different from zero. Our universe for this base model is all stocks which are primarily traded on US exchanges, with minimum price threshold of $1. The results of this test are shown below in Table 1.

Table 1 : Fama-Macbeth Regression Coefficients

US Stock Universe, 1/1987-9/2011

	Multivariate Regression				Univariate Regressions					
	Inter-cept	β_{Own}	β_{DS}	β_{US}	Inter-cept	β_{Own}	Inter-cept	β_{DS}	Inter-cept	β_{US}
Avg. Mo. Coef.	.009***	-0.001	.079**	.137***	.015***	0.004	.014***	.095***	.010***	.148***
(T-Stat)	(2.8)	(-0.0)	(2.4)	(3.9)	(5.4)	(0.3)	(4.6)	(2.7)	(3.1)	(4.0)

*p-value < 10% **p-value < 5% ***p-value < 1%

Source: S&P Capital IQ Quantitative Research. Past performance is not an indication of future results

We confirm that Downstream (Customer industries) and Upstream (Supplier industries) trailing returns have a statistically significant positive relationship with forward industry returns. This is in line with our thesis and is consistent with previous work. We also find that Own industry momentum does not have a significant loading in either the multifactor regression, or as a standalone signal in this framework.

2.2 Backtest

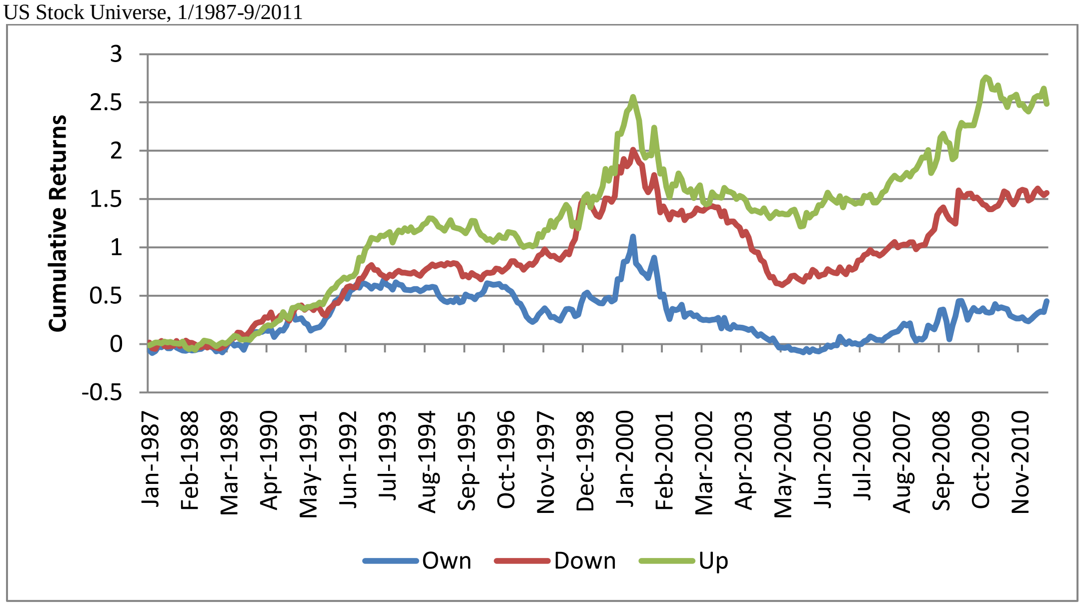
Given the encouraging regression results, we test these same industry level factors as a cross sectional investment strategy. We group industries into quintiles based on Own, Up, or Down momentum and long (short) the industries with highest (lowest) momentums. We treat each industry as an investable entity, using the cap weighted industry return as the realized return. The backtest results are outlined below (Table 2 & Figure 1).

Table 2 : Base 1-Month Supply Chain Momentum Backtest
US Stock Universe, 1/1987-9/2011

	Own	Down	Up
Average Monthly Spread	0.21%	0.36%	0.47%
Spread T-Stat	0.88	2.18	2.69
Annualized IR	0.18	0.44	0.54
Average IC	0.016	0.026	0.034
IC T-Stat	1.29	2.67	3.38

Source: S&P Capital IQ Quantitative Research. Backtested results provide only a hypothetical historical analysis. Past performance is not an indication of future results.

Figure 1 : Cumulative Returns from 1-Month Supply Chain Momentum Signals
US Stock Universe, 1/1987-9/2011



Source: S&P Capital IQ Quantitative Research. Backtested results provide only a hypothetical historical analysis. Past performance is not an indication of future results.

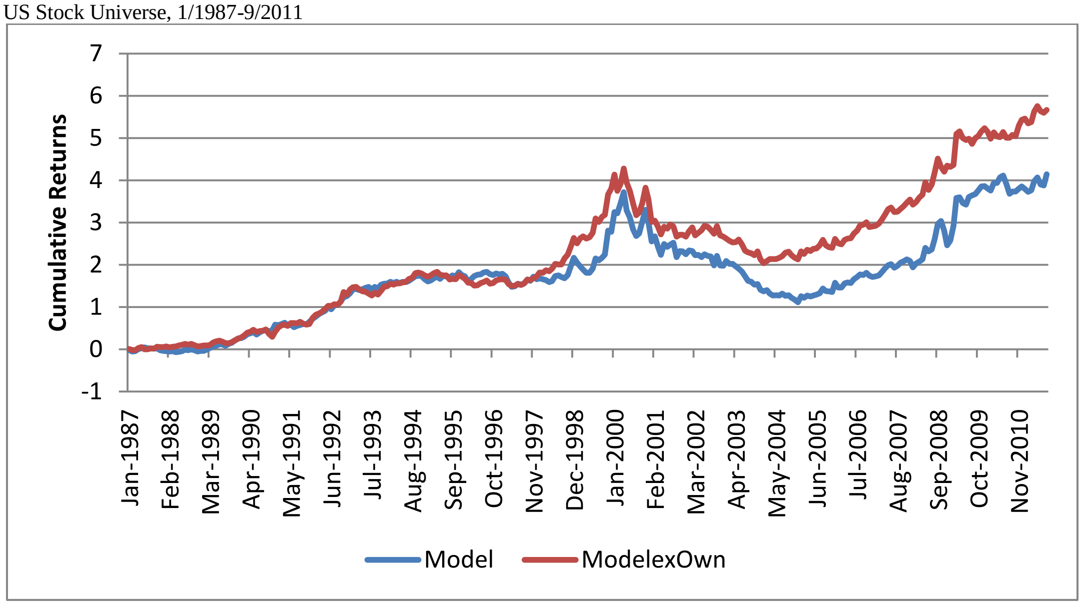
We also combine these industry signals to create two models. The models are the equal weight combination of the signal ranks. Considering both the regression results and single factor backtest results, we evaluate an equal weight model of all three signals (**MODEL**), and an equal weight model of just the Up and Down signals (**MODEL exOwn**). We find that both of these models outperform the individual industry signals in both return spread and IC space (Table 3 & Figure 2).

Table 3 : Base 1-Month Supply Chain Momentum Models Backtest
US Stock Universe, 1/1987-9/2011

	Model	Model exOwn
Average Monthly Spread	0.62%	0.69%
Spread T-Stat	2.94	3.76
Annualized IR	0.59	0.76
Average IC	0.039	0.037
IC T-Stat	3.22	3.56

Source: S&P Capital IQ Quantitative Research. Backtested results provide only a hypothetical historical analysis. Past performance is not an indication of future results.

Figure 2: Cumulative Return from 1 Month Supply Chain Momentum Models
US Stock Universe, 1/1987-9/2011



Source: S&P Capital IQ Quantitative Research. Backtested results provide only a hypothetical historical analysis. Past performance is not an indication of future results.

3 Sensitivity to Size and Beta

We proceed to test these signals across several permutations to validate our previous results. Namely, as industries are simply collections of functionally related securities, we want to ensure the results are not being overly influenced by small or high beta securities. Utilizing the same framework to test the original signals and models, we evaluate these permutations both for cross sectional predictive power with regression, and as a long short investment strategy.

3.1 Size

A common concern with quantitative models is potential overexposure to small cap stocks. This can lead to strategies that perform well in broad, hypothetically investable universes but that do not generate positive results in more investable large cap universes. We test the monthly signals in more restricted large cap and broad cap universes to observe their behavior in different size contexts. The results are promising regardless of the cap associated with the given index. We present our results in the large cap Russell 1000 and broad Russell 3000 universes using cap weight industry returns in Table 4 below.

Table 4 : Fama-Macbeth Regression Coefficients for Russell Universe

Russell 1000 Universe, 1/1987-9/2011

	Multivariate Regression				Univariate Regressions					
	Inter-cept	β_{Own}	β_{Down}	β_{Up}	Inter-cept	β_{Own}	Inter-cept	β_{Down}	Inter-cept	β_{Up}
Avg. Mo. Coef.	.010**	.006	.0394	.125***	.013***	.012	.013***	.060*	.008*	.135***
(T-Stat)	(2.9)	(0.4)	(1.5)	(3.7)	(4.6)	(0.8)	(4.5)	(2.1)	(2.4)	(3.82)

Russell 3000 Universe, 1/1987-9/2011

	Multivariate Regression				Univariate Regressions					
	Inter-cept	β_{Own}	β_{Down}	β_{Up}	Inter-cept	β_{Own}	Inter-cept	β_{Down}	Inter-cept	β_{Up}
Avg. Mo. Coef.	.009**	.013	.096**	.128***	.015***	.020	.014***	.108**	.010**	.139***
(T-Stat)	(2.6)	(0.8)	(3.3)	(3.9)	(5.1)	(1.2)	(4.4)	(3.4)	(2.9)	(3.9)

*p-value < 10% **p-value < 5% ***p-value < 1%

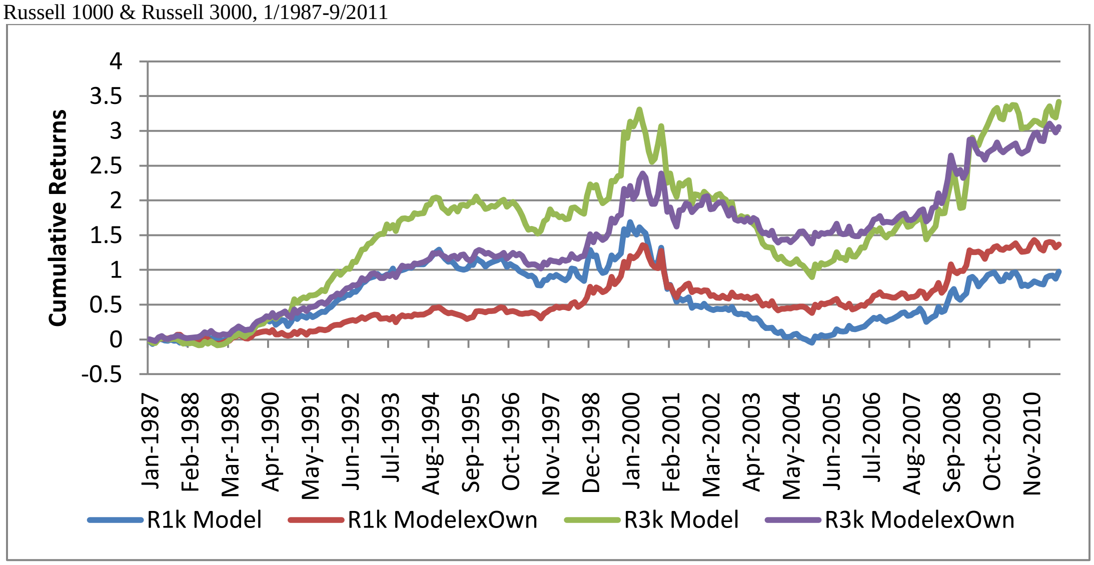
Source: S&P Capital IQ Quantitative Research. Past performance is not an indication of future results.

We find that within the large cap Russell 1000 universe, both the Up and Down signal are statistically significant as univariate factors. In the multivariate regression, the Up signal dominates the Down signal, which weakens slightly and narrowly loses significance at the 90% level. Within the broader Russell 3000, the Down and Up regression coefficients are both strong, as standalone factors and in combination.

In a long-short strategy for the large cap space, the Up supply chain signal yields the strongest performance, which is consistent with the regression results. However, the Down signal performed considerably worse in context, even as a standalone signal. Long-short results on a broader universe show more equal performance across all of the supply chain momentum signals. The Up and Down signals are both significant for the broad index in our test period. In line with the regression, we do receive some benefit from combining our signals into models.

Figure 3: Backtest Model Comparison – Large Cap & Broad Cap

Russell 1000 & Russell 3000, 1/1987-9/2011



Source: S&P Capital IQ Quantitative Research. Backtested results provide only a hypothetical historical analysis. Past performance is not an indication of future results.

While there seem to be some differences, the general conclusions from our regressions and backtests hold in both large and broad cap universes. We find that the Up and Down supply chain signals to be significant factors when regressed against forward industry returns. Additionally, these signals generate similar backtest results and return patterns when evaluated as a simple model (Figure 3).

3.2 Beta

We test these signals using Beta-adjusted industry level returns (calculation outlined below). This provides additional insight for the relative performance of the industries and does not simply key in on industries comprised predominantly of high beta securities which typically have the extreme highest or lowest returns in any given month. If the industry constituents simply deliver the expected return implied by their beta, then, it is likely that the industry did not experience an information shock that should ripple into other industries. The Beta-adjusted industry returns are calculated as follows:

$$Stock\ BetaAdjRtn = Stock\ Total\ \mathrm{Re}turn - 60M\ \ Beta \times Index\,\mathrm{Re}turn$$

$$Industry\ BetaAdjRtn = \sum Stock\ BetaAdjRtn \times MktCapWgt$$

These Beta-adjusted industry returns are used as both the signal and response variables in this regression. We find the two supply chain factors to be significant independently and jointly in our regressions when using Beta-adjusted returns. Please refer to Table 8 in the Appendix for comparison of Beta-adjusted regression coefficients with the base case raw returns. We find that the UP signal is stronger relative to the other signals using the Beta-adjusted returns when compared to the original signal construction. However, we still find the same signals to be significant on their own and jointly in a 3-factor model.

Table 5 : Fama-Macbeth Regression Coefficients for Beta-adjusted Returns

US Universe, Beta-adjusted Industry signals Jan 1987 - Sep 2011

	Multivariate Regression				Univariate Regressions					
	Inter-cept	β_{Own}	β_{Down}	β_{Up}	Inter-cept	β_{Own}	Inter-cept	β_{Down}	Inter-cept	β_{Up}
Avg. Mo. Coef.	.006***	0.007	0.067*	.112**	.007***	.007	.007***	.081*	.006***	.128***
(T-Stat)	(4.6)	(0.4)	(2.1)	(3.2)	(6.2)	(0.4)	(5.8)	(2.4)	(4.5)	(3.4)

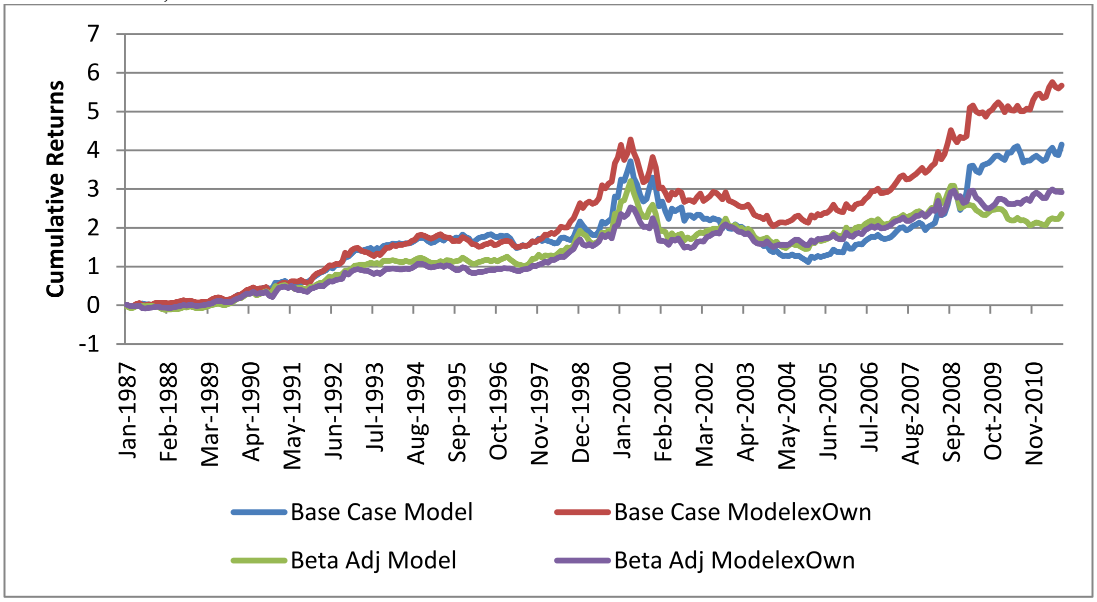
*p-value < 10% **p-value < 5% ***p-value < 1%

Source: S&P Capital IQ Quantitative Research. Past performance is not an indication of future results

We test the Beta-adjusted signals in a backtest with forward returns measured as the raw cap weight industry returns. The results of these backtests are very similar to the original backtests. We find that the simple model combining these signals generates statistically significant returns through our period (Figure 4).

Figure 4: Backtest Model Comparison – Base Case vs. Beta-adjusted

US Stock Universe, 1/1987-9/2011



Source: S&P Capital IQ Quantitative Research. Backtested results provide only a hypothetical historical analysis. Past performance is not an indication of future results.

Again, the general conclusions from our regressions and backtests hold when adjusting for Beta in our signal construction. The Up and Down supply chain signals consistently drive the performance of this industry strategy.

4 Enhancements

These simple checks make us feel more comfortable that we are capturing a real phenomenon at the industry level. However, these checks did not lead to improved performance in excess to the original specifications. We dig deeper in an attempt to enhance the original strategy. With this in mind, we augment our signals and models by incorporating data with different frequencies, relationship maps, and signal weighting schemes to further refine our process within the same investment thesis.

4.1 Higher Frequency and Frequency Combinations

Within the story of information diffusion along the supply chain, two somewhat conflicting hypotheses relating to the possible speed of diffusion can be constructed. The realized economic impact for industries can be long lived or delayed depending on the nature of relationship. For example, an airline orders new planes from an airplane manufacturer. The manufacturer realizes an immediate economic impact by increasing its current production, but the airline is not able to deploy the new planes until they are delivered which can take a significant amount of time (years in the case of the Boeing 787). This suggests that a longer lookback horizon may contain information that is still relevant to the supply chain relationship and by extension, forward returns. However, markets are reasonably efficient. While our investment thesis is predicated on the speed of information diffusion, the market most likely incorporates this information at varying speeds and takes into consideration the long term impact of the relationship. This would suggest that a shorter lookback than 1 month may be appropriate. We test these signals with both longer and shorter horizons to evaluate these hypotheses.

4.1.1 12-month & 3-month lookback horizons

We construct 12 month and 3 month trailing return signals using the same methodology from the monthly test (relationship weighted average of the 12 and 3 month trailing returns of connected industries). Please refer to Table 6 below. We find that in our regressions the statistical significance of the trailing signals drops considerably at longer horizons. The 3-month trailing Down and Up momentum coefficients are weaker than the 1 month signals. Only the 3-month Up signal remains significant at the 95% level, and Down drops out of significance. At the 12-month horizon, the signals are also weaker, with all coefficients dropping out of significance in multivariate, and only marginally significant as univariate factors. Note we are looking at one month forward holding periods to avoid biasing the t-tests with overlapping forward periods.

Table 6 : Fama-Macbeth Regression Coefficients for Longer Trailing Horizons

US Universe, 12 month trailing vs. 1 month forward Jan 1987 - Sep 2011

	Multivariate Regression				Univariate Regressions					
	Inter-cept	β_{Own}	β_{Down}	β_{Up}	Inter-cept	β_{Own}	Inter-cept	β_{Down}	Inter-cept	β_{Up}
Avg. Mo. Coef.	.008***	.009*	.011	.009	.009***	.010*	.011***	.017*	.012***	.016*
(T-Stat)	(2.6)	(1.7)	(1.2)	(1.0)	(3.2)	(1.9)	(3.5)	(1.8)	(3.7)	(1.7)

US Universe, 3 month trailing vs. 1 month forward Jan 1987 - Sep 2011

	Multivariate Regression				Univariate Regressions					
	inter-cept	β_{Own}	β_{Down}	β_{Up}	Inter-cept	β_{Own}	Inter-cept	β_{Down}	Inter-cept	β_{Up}
Avg. Mo. Coef.	.009***	.018*	.017	.035*	.010***	.018*	.012***	.026	.011***	.039**
(T-Stat)	(3.1)	(1.9)	(1.0)	(1.9)	(3.5)	(2.0)	(4.0)	(1.5)	(3.8)	(2.0)

*p-value < 10% **p-value < 5% ***p-value < 1%

Source: S&P Capital IQ Quantitative Research. Past performance is not an indication of future results.

4.1.2 1 Week horizon

Conversely, we do find statistically significant industry supply chain momentum at shorter time horizons. At the 1 week trailing versus 1 week forward return horizons, we find all the signals to be stronger, with all coefficients at > 99% confidence level. Notably, we find a significantly negative Own signal see Table 7 below.

Table 7 : Fama-Macbeth Regression Coefficients for 1 Week Horizon

US Universe, 1 week trailing vs. 1 week forward Jan 1987 - Sep 2011

	Multivariate Regression				Univariate Regressions					
	Inter-cept	β_{Own}	β_{Down}	β_{Up}	Inter-cept	β_{Own}	Inter-cept	β_{Down}	Inter-cept	β_{Up}
Avg. Mo. Coef.	.003***	-.030***	.049***	.056***	.004***	-.028***	.003***	.043***	.004***	.064***
(T-Stat)	(3.9)	(-3.9)	(3.1)	(3.1)	(5.5)	(-3.6)	(4.6)	(2.7)	(4.3)	(3.5)

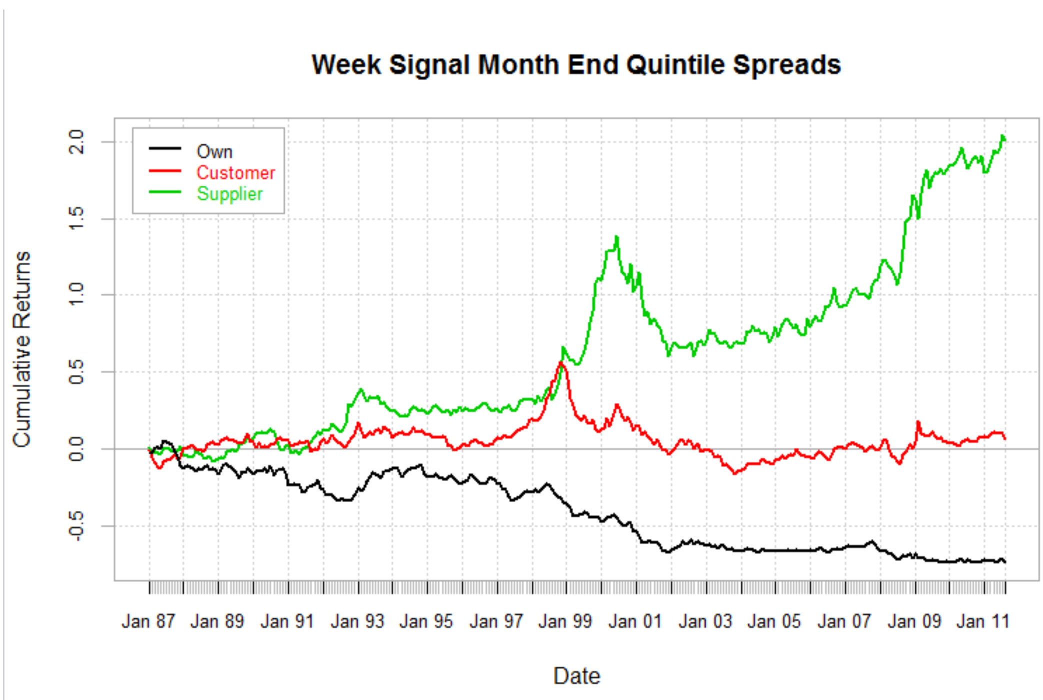
*p-value < 10% **p-value < 5% ***p-value < 1%

Source: S&P Capital IQ Quantitative Research. Past performance is not an indication of future results.

With these promising results at the 1 week level, we test a combination model using both 1 month and 1 week trailing signals. In order to synchronize the signals, we regress 1 month forward returns against the trailing 1 month and 1 week signals, with 1 month sampling frequency. Please refer to Table 15 in the Appendix, where we compare regression coefficients of 1 month forward returns versus a variety of combinations of 1 month and 1 week trailing signals.

Figure 5: Cumulative Return Spreads from 1-Week Signals

US Stock Universe, 1/1987-9/2011



Source: S&P Capital IQ Quantitative Research. Past performance is not an indication of future results.

Since both 1 month and 1 week trailing supply chain signals are useful in predicting 1 month forward returns, we combine the signals into a 6 factor regression using the three monthly and three weekly signals.

Note regression # 9 in Table 15 shows the regression coefficients for a full 6 factor model, with the Up, Down, and Own signals at both the monthly and weekly frequencies. To avoid overfitting, we simplify this and construct another model (regression #10 in Table 15) by removing the two signals that are not statistically significant as standalone: 1-month Own and 1-week Down. This leaves us a refined 4-factor model incorporating monthly and weekly signals. We find that these four factors are all significant at the 95% level when considered jointly. We present the results for this refined model (model #10 from Table 15) in condensed form in Table 8 below.

Table 8: Fama-Macbeth Regression of Refined Monthly and Weekly Signal List

US Stock Universe, 1/1987-9/2011

		1 Month		1 Week	
	Intercept	β_{Down}	β_{Up}	β_{Up}	β_{Own}
Avg. Mo Coef	.009**	.078**	.092**	.206**	-.070**
(T-Stat)	(2.5)	(2.2)	(2.2)	(2.1)	(-2.0)

*p-value < 10% **p-value < 5% ***p-value < 1%

Source: S&P Capital IQ Quantitative Research. Past performance is not an indication of future results.

The Up signal is represented at both the 1 month and 1 week trailing horizons. The average monthly Spearman correlation between these two signals is 0.4. As a side test of multicollinearity, we tried removing the overlap by replacing the 1 month signal with a (1month - 1week) differential to neutralize the correlation. However, the results are similar; the 1 month and 1 week Up signals are both independently significant, so we present the simpler model here.

We apply these combined monthly and weekly models to a long short investment strategy. We rank industries based on equal weight combinations of the individual signal ranks. These models perform similarly well in both return and IC space. Given the additional signals, the 6-factor model outperforms in raw IC space, but the refined model generates more significant return spreads, higher risk adjusted returns, and more significant average IC.

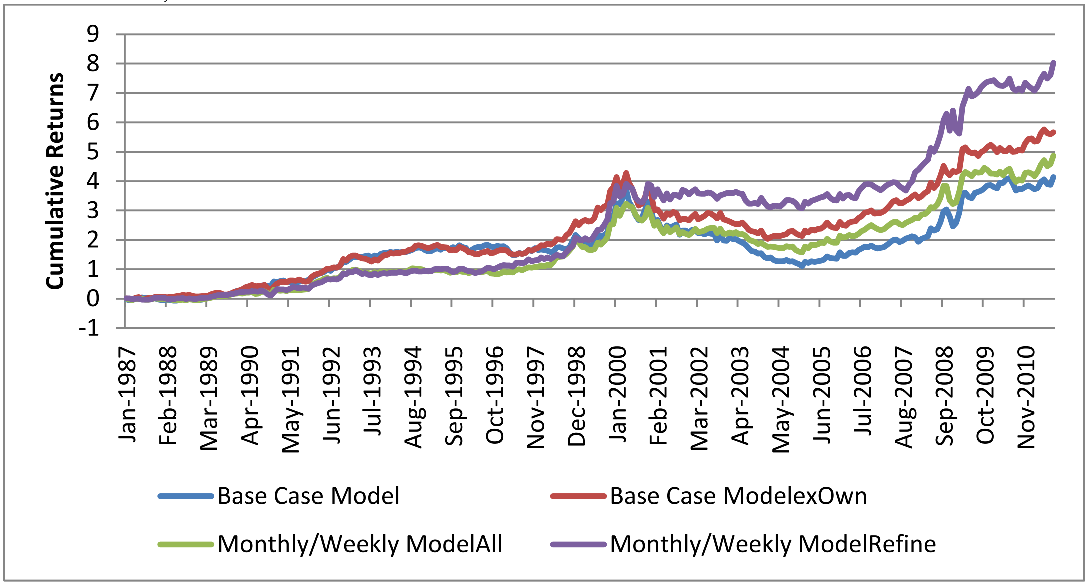
Table 9: Backtest of Models Combining Monthly and Weekly Signals

US Stock Universe, 1/1987-9/2011

	Model All	Model Refined
Average Monthly Spread	0.66%	0.80%
Spread T-Stat	3.35	4.18
Annualized IR	0.67	0.84
Average IC	0.045	0.043
IC T-Stat	4.18	4.19

Source: S&P Capital IQ Quantitative Research. Backtested results provide only a hypothetical historical analysis. Past performance is not an indication of future results.

Figure 6: Cumulative Returns of the Combined Monthly and Weekly Models
US Stock Universe, 1/1987-9/2011



Source: S&P Capital IQ Quantitative Research. Backtested results provide only a hypothetical historical analysis. Past performance is not an indication of future results.

4.2 Squared Relationship Weights

Our original signals assume a linear relationship between industries: a customer industry that consumes 20% of an industry output is given 20% weight in the downstream momentum signal, and an industry that consumes 1% of output is given 1% weight in the signal. But it's likely that the relative significance of industry supply chain relationships is nonlinear, since greater customer/supplier concentration often leads to greater marginal influence. We test the performance of the signals by altering the underlying relationship weighting used in the signal construction to reflect this nonlinearity. We squared the relationships covered in the BEA Map to put greater weight on larger relationships to emphasize deeper industry connections:

$$(Dowstream\ Squared\ \%)_{i,j} = \frac{(p_{i,j})^2}{\sum_{(all\ targets\ j)}(p_{i,j})^2}$$

$$(Upstream\ Squared\ \%)_{i,j} = \frac{(p_{i,j})^2}{\sum_{(all\ sources\ i)}(p_{i,j})^2}$$

With this construction, a customer industry with 2x the consumption % will have 4x the amount of influence on returns. We construct new upstream/downstream signals using this methodology, and found it improved the consistency of the signal across time. Please see Table 12 in the Appendix comparing the strength of the signals using squared relationship weights versus the original construction with linear proportions. The average regression coefficient is slightly diminished, but we observe higher t-stats from our panel regression due to the increased stability.

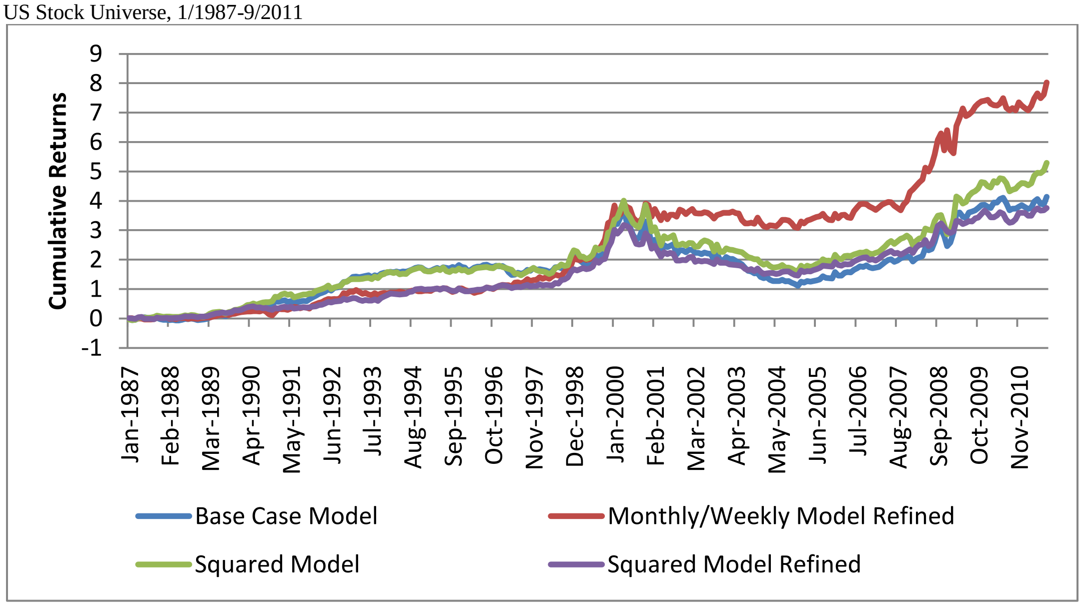
This map generates solid performance in both return and IC-space. The improvement is most apparent in the 3-factor Monthly Model. While this methodology improves the 4-factor Monthly and Weekly Model in terms of IC, we find that the original map generates larger and more significant returns.

Table 10: Backtest Models with Squared Relationship Signals
US Stock Universe, 1/1987-9/2011

	Month Model	Model Refined
Average Spread	0.68%	0.58%
Spread T-Stat	3.53	3.72
Annualized IR	0.67	0.71
Average IC	0.043	0.045
IC T-Stat	3.78	4.68

Source: S&P Capital IQ Quantitative Research. Backtested results provide only a hypothetical historical analysis. Past performance is not an indication of future results.

Figure 7: Backtest Model Comparison – Original Map vs. Squared Map
US Stock Universe, 1/1987-9/2011



Source: S&P Capital IQ Quantitative Research. Backtested results provide only a hypothetical historical analysis. Past performance is not an indication of future results.

We also tried to include deeper relationships into our map by incorporating the extended supply chain of an industry's first level customers and suppliers (ex: customer's other customers and suppliers). However, this addition did not provide sufficient information beyond the squared map due to the increased noise and decreased relevance.

4.3 Predictive Backtest

In addition to incorporating shorter term signals in our models, we test an alternative approach to combine these supply chain momentum signals. To this point, we have shown simple equal weighted model signals, but we now incorporate a regression based weighting scheme. Beginning with a 3-year training window, we construct coefficients based on an expanding window average of the monthly regression coefficients. We lag by one month, and apply regression weights to the latest signals to predict a forward one month return for each industry. To minimize the complexity, we refrain from using the squared relationship weights in this model, and stick with the original linear relationships.

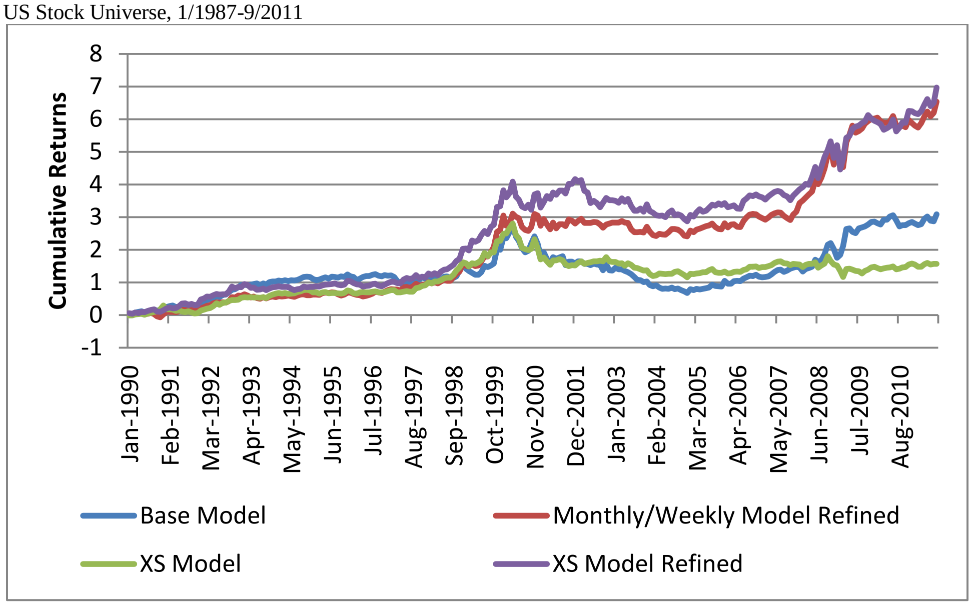
We test this methodology for both the 3-factor Monthly Model and the 4-Factor Monthly/Weekly refined model. We compare the performance of the predictive models using regression-weighted coefficients, versus predictive models using simple equal-weighting of signals in Table 11. Using this regression based weighting improves the 4-Factor Monthly/Weekly refined model. But regression-weights underperform the simpler equal weight 3-factor monthly model. All of these models generate statistically significant positive returns. As always, equal weight is hard to beat.

Table 11: Model Comparison – Equal Weight to Regression Weight
US Stock Universe, 1/1987-9/2011

	Monthly Model Regression Weighted	Monthly Model Equal Weighted	Model Refined Regression Weighted	Model Refined Equal Weighted
Avg. Mo Spread	0.41%	0.62%	0.85%	0.69%
Spread T-Stat	2.08	2.94	3.88	3.76
Annualized IR	0.44	0.59	0.83	0.76
Average IC	0.032	0.039	0.044	0.037
IC T-Stat	2.87	3.22	3.81	3.56

Source: S&P Capital IQ Quantitative Research. Backtested results provide only a hypothetical historical analysis. Past performance is not an indication of future results.

Figure 8: Backtest Model Comparison – Equal Weight to Regression Weight
US Stock Universe, 1/1987-9/2011



Source: S&P Capital IQ Quantitative Research. Backtested results provide only a hypothetical historical analysis. Past performance is not an indication of future results.

5 Considerations – Time Series Regressions

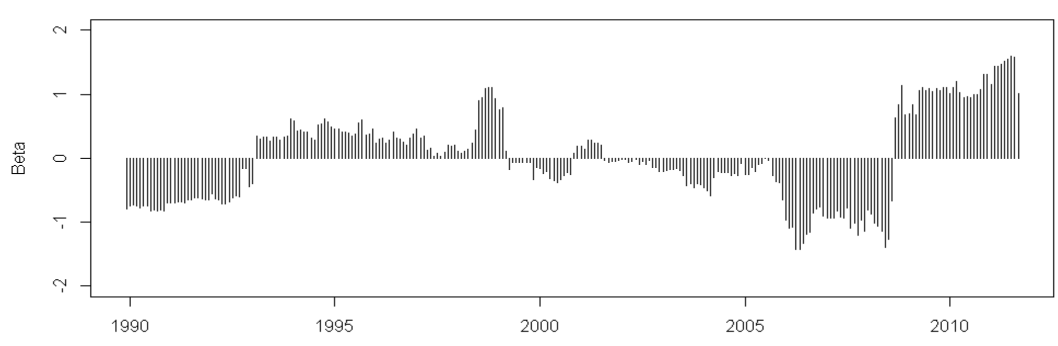
We see that good news for upstream and downstream industries, in aggregate, is good news for connected industries. However, for some industries this may be counter-intuitive. For example, good news for the oil & petroleum industry may spell bad news for customers in the transportation industries. It's also reasonable to assume that industry relationships have varying amounts of analyst awareness, leading to varying diffusion speed. Some industry links are more obvious, which will most likely compress the diffusion lag from monthly to weekly, daily, or nonexistent.

We test industry-specific exposures to the supply chain signals in an attempt to apply this intuition. For each industry, we perform stepwise time series regression versus the six signals (monthly & weekly) to measure industry-specific supply chain exposures. After doing this, we confirm intuition and find that all industries are indeed not the same when it comes to supply-chain exposure. The full period results of the regressions are reported in Table 13 in the Appendix. Notable: The petroleum and coal industry (NAICS 324) returns show no net statistically significant exposure to any of the Up or Down signals. As another example, the apparel and leather industry (NAICS 315AL) has significant exposures to all of the supply chain signals, but with a negative sign for the two Down signals, which differs from the cross-section of all industries on average.

We test the usefulness of this intuition on a predictive model by calculating the 5 year rolling time series Beta to the supply chain signals for each industry. To simplify the model for each industry, we perform stepwise regression for each industry, beginning with a 6-factor model for each industry (Up, Down, and Own signals, 1 month and 1 week). Statistically insignificant factors for each industry are removed based on AIC. We then calculate the final time-varying Betas for each industry to the supply chain signals.

Although the time-series exposure model does identify industries where cross-sectional momentum does not work, or is perverse, we find that it also identifies unstable relationships, where coefficients continually change and may reverse sign over time.

Figure 9: Time Series Beta of Primary Metals (NAICS 331) to Downstream Signal Across Time
US Stock Universe, 1/1987-8/2011



Source: S&P Capital IQ Quantitative Research. Past performance is not an indication of future results.

We find this instability makes the industry-specific model weak for out-of-sample prediction. Although the more sophisticated model with industry-specific sensitivities is appealing, the simpler model where the same coefficient is applied to every industry appears stronger and more consistent for out-of-sample prediction across time

6 Conclusions

We confirm that supply chain momentum effects do exist between cap-weighted industry groups which are connected economically along the supply chain. In addition to monthly momentum observed by previous researchers, we also find significant supply chain momentum at weekly frequencies. In fact we observe positive weekly momentum from connected industries, in contrast to significant negative momentum within industry. It appears that longer-term frequency signals at the three and twelve month levels are not statistically significant enough for short term prediction.

These monthly and weekly signals may be combined to drive a moderately profitable industry rotation strategy. We find that using an expanding window regression weighting of the supply chain industry signals, applying the same signal weighting to all industries, rather than trying to fit a model to each industry, provides the most consistent performance.

In future research we will turn to investigating supply chain interactions at the issue level. We intend to test the practical considerations of using these cross-industry momentum signals as an overlay with other issue-level selection strategies. We will also dig into company-level supply chain linkages, using company-level supplier-to-customer segment data.

Appendix

Table 12 Fama-Macbeth Regression Coefficients, Jan 1987 - Sep 2011
Regression using Raw Returns versus Market Beta-Adjusted Excess Returns

Base US Universe All US Traded Stocks > $1

		Raw Returns				Market Beta-Adjusted Excess Returns				
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	coefficient
1 Month Trailing Raw Returns	Intercept	0.009***	0.015***	0.014***	0.010***	.006***	.007***	.007***	.006***	mean
		(2.8)	(5.4)	(4.6)	(3.1)	(4.6)	(6.2)	(5.8)	(4.5)	(T-Stat)
	β_{Own}	-0.001	0.004	-	-	.007	.007	-	-	mean
		(-0.04)	(0.26)			(0.4)	(0.4)			(T-Stat)
	β_{Down}	0.079**	-	0.095***	-	.067**	-	.081**	-	mean
		(2.38)		(2.69)		(2.1)		(2.4)		(T-Stat)
	β_{Up}	0.137***	-	-	0.148***	.112***	-	-	.128***	mean
		(3.86)			(3.97)	(3.2)			(3.4)	(T-Stat)

(1) Regression of Own, Down, and Up signals together
(2) Regression of Own signal alone
(3) Regression of Down signal alone
(4) Regression of Up signal alone

* : p-value < 10%
** : p-value < 5%
***: p-value < 1%

Source: S&P Capital IQ Quantitative Research. Past performance is not an indication of future results.

Table 13 Fama-Macbeth Regression Coefficients, Jan 1987 - Sep 2011
Regression Coefficients for Large Cap and Broad Cap universes.

Signals Constructed Using Cap-Weighted Industry Raw Returns

		Russell 1000 Large Cap				Russell 3000 Broad Cap				
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	coefficient
1 Month Trailing Raw Returns	Intercept	0.01***	.013***	.013***	.008**	.009***	.015***	.014***	.010***	mean
		(2.9)	(3.7)	(4.5)	(2.4)	(2.6)	(5.1)	(4.4)	(2.9)	(T-Stat)
	β_{Own}	.006	.012			.013	.020			mean
		(0.38)	(.79)			(0.8)	(1.2)			(T-Stat)
	β_{Down}	.0394		.060**		.096***		.108***		mean
		(1.51)		(2.1)		(3.3)		(3.4)		(T-Stat)
	β_{Up}	.125***			.135***	.128***			.139***	mean
		(3.72)			(3.8)	(3.8)			(3.9)	(T-Stat)

(1) Regression of Own, Down, and Up signals together
(2) Regression of Own signal alone
(3) Regression of Down signal alone
(4) Regression of Up signal alone

* : p-value < 10%
** : p-value < 5%
***: p-value < 1%

Source: S&P Capital IQ Quantitative Research. Past performance is not an indication of future results.

Table 14 Fama-Macbeth Regression Coefficients, Jan 1987 - Sep 2011
Comparision of Time Horizons. Regression Coefficients of 12 Month, 3 Month, and 1 Week Signals
Universe = All US Traded Stocks with Price > $1

	1 Month Forward Returns vs 12 Month Trailing Signals				1 Month Forward Returns vs 3 Month Trailing Signals				1 Week Forward Returns vs 1 Week Trailing Signals				
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	coef.
Intercept	.008***	.009***	.011***	.012***	.009***	.010***	.012***	.011***	.003***	.004***	.003***	.004***	mean
	(2.6)	(3.2)	(3.5)	(3.7)	(3.1)	(3.5)	(4.0)	(3.8)	(3.9)	(5.5)	(4.6)	(4.3)	(T-Stat)
β_{Own}	.009*	.010*			.018*	.018*			-.030***	-.028***			mean
	(1.7)	(1.9)			(1.9)	(2.0)			(-3.9)	(-3.6)			(T-Stat)
β_{Down}	.011		.017*		.017		.026		.049***		.043***		mean
	(1.2)		(1.8)		(1.0)		(1.5)		(3.1)		(2.7)		(T-Stat)
β_{Up}	.009			.016*	.035*			.039**	.056***			.064***	mean
	(1.0)			(1.7)	(1.9)			(2.0)	(3.1)			(3.5)	(T-Stat)

(1) Regression of Own, Down, and Up signals together
(2) Regression of Own signal alone
(3) Regression of Down signal alone
(4) Regression of Up signal alone

* : p-value < 10%
** : p-value < 5%
***: p-value < 1%

Source: S&P Capital IQ Quantitative Research. Past performance is not an indication of future results.

Table 15 Fama-Macbeth Regression Coefficients, Jan 1987 - Sep 2011
Comparison of Monthly & Weekly Models, and Combination Frequency Models

		Base US Universe All US Traded Stocks > $1										
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	coef.
	Intercept	.009***	.015***	.014***	.010***	.014***	.016***	.016***	.012***	.010***	.009**	mean
		(2.8)	(5.4)	(4.6)	(3.1)	(4.1)	(5.7)	(5.2)	(2.8)	(2.6)	(2.5)	(T-Stat)
1 Month Trailing	β_{Own}	-.001	.004	-	-	-	-	-	-	.021	-	mean
		(-0.04)	(0.26)							(1.3)		(T-Stat)
	β_{Down}	.079**	-	.095***	-	-	-	-	-	.055	.078**	mean
		(2.38)		(2.69)						(1.4)	(2.2)	(T-Stat)
	β_{Up}	.137***	-	-	.148***	-	-	-	-	.081*	.092**	mean
		(3.86)			(3.97)					(1.9)	(2.2)	(T-Stat)
1 Week Trailing	β_{Own}	-	-	-	-	-.07*	-.07**	-	-	-.080**	-.070**	mean
						(-2.0)	(-2.0)			(-2.2)	(-2.0)	(T-Stat)
	β_{Down}	-	-	-	-	.023	-	.058	-	-.040	-	mean
						(0.3)		(0.9)		(-0.6)		(T-Stat)
	β_{Up}	-	-	-	-	.261***	-	-	.229***	.206**	.206**	mean
						(3.1)			(2.8)	(2.1)	(2.1)	(T-Stat)

(1) Regression of Monthly Own, Down, and Up signals together
(2) Regression of Monthly Own signal alone
(3) Regression of Monthy Down signal alone
(4) Regression of Monthly Up signal alone
(5) Regression of Weekly Own, Down, and Up signals together
(6) Regression of Weekly Own signal alone
(7) Regression of Weekly Down signal alone
(8) Regression of Weekly Up signal alone
(9) Regression of all Monthly and Weekly Signals Together
(10) Regression of the 4 significant factors together - 1 Month Down & Up, 1 Week Self & Up

Source: S&P Capital IQ Quantitative Research. Past performance is not an indication of future results.

Table 16 Fama-Macbeth Regression Coefficients, Jan 1987 - Sep 2011
Comparison of Signals Construction using Original Linear Weights versus Squared Relationship Weights

3-Factor Monthly Model

		Original Signals	Squared Relation Wts	coef.
	Intercept	0.009*** (2.8)	.013*** (4.4)	mean coefficient (T-Stat)
1 Month Trailing	β_{Own}	-0.001 (-0.04)	.009 (0.6)	mean coefficient (T-Stat)
1 Month Trailing	β_{Down}	0.079** (2.38)	.056*** (3.1)	mean coefficient (T-Stat)
1 Month Trailing	β_{Up}	0.137*** (3.86)	.079*** (4.4)	mean coefficient (T-Stat)

4-Factor Combined Monthly/Weekly Model

		Original Signals	Squared Relation Wts	coef.
	Intercept	.009** (2.5)	.013*** (4.6)	mean coefficient (T-Stat)
1 Month Trailing	β_{Own}	-		mean coefficient (T-Stat)
1 Month Trailing	β_{Down}	.078** (2.2)	.058*** (3.0)	mean coefficient (T-Stat)
1 Month Trailing	β_{Up}	.092** (2.2)	.054** (2.5)	mean coefficient (T-Stat)
1 Week Trailing	β_{Own}	-.070** (-2.0)	-.06* (-1.9)	mean coefficient (T-Stat)
1 Week Trailing	β_{Down}	-	-	mean coefficient (T-Stat)
1 Week Trailing	β_{Up}	.206** (2.1)	.134** (2.4)	mean coefficient (T-Stat)

Source: S&P Capital IQ Quantitative Research. Past performance is not an indication of future results.

Figure 10 – Example Calculation of BEA Upstream/Downstream Percentages

Using the 2009 BEA "Use" table for NAICS industries 212 and 331:

In 2009 the "Primary Metals" (NAICS 331) industry consumed $11,194 million worth of "Mining ..." commodities (NAICS 212). The total amount of external commodities consumed that year by NAICS 331 was $77,343 million (the sum of the industry column less self-produced primary metals commodities).

BEA Use Table, 2009 (Millions of Dollars)

		NAICS Code	...	212	...	331	...	
NAICS Code	Commodity Description	Industry Description	...	Mining, except oil and gas	...	Primary metals	...	**Sum of Commodity row, less Self**
...	...	...	...	...	...	...	...	**...**
212	Mining, except oil and gas	...	...	7,037	...	11,194	...	**59,962**
...	...	...	...	...	...	...	...	**...**
331	Primary metals	...	...	932	...	47,839	...	**155,858**
...	...	...	...	...	...	...	...	**...**
	Sum of Industry Column, less self			**25,649**		**77,343**		

Therefore, NAICS 212 supplies 11194/77343 = 14.5% of the commodities used by NAICS 331. We consider this to be a 14.5% upstream relationship.

Upstream Percentages of Input Consumed

		NAICS Code	...	212	...	331	...
NAICS Code	Commodity Description	Industry Description	...	Mining, except oil and gas	...	Primary metals	...
...	...	...	...	...	...	...	...
212	Mining, except oil and gas	...	...	n/a	...	14.5%	...
...	...	...	...	...	...	...	...
331	Primary metals	...	...	3.6%	...	n/a	...
...	...	...	...	...	...	...	...
	Sum of Industry Column, less self	..	..	**100%**	..	**100%**	..

Similarly, the total amount produced by NAICS 212 for external industry use that year was $59,962 million (the sum of the industry row less mining commodities, which are self-consumed). NAICS 331 was the ultimate user of 11194/59,962 = 18.7% of the commodities produced by NAICS 212. We consider this to be an 18.7% downstream relationship.

Source: S&P Capital IQ Quantitative Research

Table 17: T-Stat of Time Series Exposures of Each Industry to the Supply Chain Signals

NAICS	Industry Name	Intercept	1M Own	1MDown	1M Up	1W Own	1WDown	1W Up
111CA	Farms	4.34		-1.88		-1.86		
113FF	Forestry, fishing, and related	3.46				-2.73		
211	Oil and gas extraction	3.63				-1.58		
212	Mining, except oil and gas	4.27	-2.84	2.87				
213	Support activities for mining	2.92	1.42					
22	Utilities	4.37			-1.73			1.60
23	Construction	3.74				-1.51		
311FT	Food, bev., & tobacco	5.37						
313TT	Textile mills and textile product mills	2.93	-1.74	2.30		2.01		-2.56
315AL	Apparel and leather and allied products	4.26	2.30	-2.64	1.65	-1.87	-1.82	2.05
321	Wood products	2.36						
322	Paper products	2.79	-2.03				-2.49	2.17
323	Printing and related support activities	1.88		2.13				
324	Petroleum and coal products	4.16	-1.58					
325	Chemical products	5.87						
326	Plastics and rubber products	3.73						
327	Nonmetallic mineral products	3.81		2.31	-1.42			
331	Primary metals	3.21	-1.76	2.11				
332	Fabricated metal products	4.24						
333	Machinery	4.26	2.55					
334	Computer and electronic products	4.13		-2.70	1.56			
335	Elec. Equip., appl., & components	4.13						
3361MV	Motor vehicles, bodies, trailers, & parts	2.65						
3364OT	Other transportation equipment	4.15			1.51			
337	Furniture and related products	4.11	1.93					-2.00
339	Miscellaneous manufacturing	6.11						
42	Wholesale trade	5.09					-1.61	1.59
44RT	Retail trade	4.87	1.45			-2.08		
481	Air transportation	2.37						
482	Rail transportation	4.69			2.00			-1.94
483	Water transportation	3.45						1.84
484	Truck transportation	3.50		1.74	-1.56			
485	Ground passenger transportation	1.04	5.85			-2.63		
486	Pipeline transportation	4.28						-1.57
487OS	Other transportation and support	3.11						
493	Warehousing and storage	2.39			-1.69	-1.82	-2.45	2.74
511	Publishing industries (includes software)	4.68						
512	Motion picture and sound recording	3.62		-1.57	1.95			
513	Broadcasting and telecommunications	3.90						
514	Information and data processing	4.50						
521CI	Federal Reserve banks, and related	4.17			2.61			-1.57
523	Securities and investments	3.69						
524	Insurance carriers and related activities	4.25		-1.67	1.85			
525	Funds, trusts, and other financial	4.59	-2.71		2.10	2.49		
531	Real estate	3.04	-3.05		3.09	2.41		
532RL	Rental and leasing of intangible assets	4.39		1.71			-3.26	2.42
5411	Legal services	1.31	-1.48			-1.45	2.56	
5412OP	Misc. prof.l, scientific, & tech. services	5.08		2.27	-2.32		-2.33	1.74
5415	Computer systems design and related	3.39						
561	Administrative and support services	4.14	2.26	2.11	-2.75		-1.50	1.98
562	Waste management and remediation	2.56		-1.75	2.80		1.51	
61	Educational services	4.04	-1.68					
621	Ambulatory health care services	5.37				1.65		
622HO	Hospitals and residential care facilities	2.86						
624	Social assistance	1.14	-1.52			-2.77		
711AS	Performing arts, sports, museums	1.94					-1.51	2.19
713	Amusements, gambling, and recreation	3.73		3.18	-1.86			
721	Accommodation	3.46		4.09	-3.28	-2.08		
722	Food services and drinking places	4.91			-1.42			
81	Other services, except government	3.13		1.96			2.08	-2.23

Source: S&P Capital IQ Quantitative Research. Past performance is not an indication of future results.

References

Kewei Hou, "Industry Information Diffusion and the Lead-Lag Effect in Stock Returns [2007] The Review of Financial Studies, Vol 20, Issue 4, pp. 1113-1138

Lauren Cohen and Andrea Frazzini, "Economic Links and Predictable Returns" [August 2008], Journal of Finance, 63[4]: pp 1977-2011

Eugene Fama and James MacBeth, "Risk, Return, and Equilibrium: Empirical Tests" [1973] Journal of Politcal Economy 81, pp 607-636

Lior Menzly and Oguzhan Ozbas , "Cross-Industry Momentum" [2006], Working Paper, University of Chicago and University of Southern California

Lior Menzly and Oguzhan Ozbas , "Market Segmentation and Cross-Predictability of Returns" [2009], Journal of Finance, Forthcoming

Mark Grinblatt and Tobias J. Moskowitz, "Do Industries Explain Momentum" [October 1999] Journal of Finance, 54[4]: pp 1249-1290

Li Ma and Kirk Wang, "Riding Industry Momentum" [June 2012] , S&P Capital IQ Quantitative Research

Husayn Shahrur, Ying L. Becker, and Didier Rosenfeld, CFA, "Return Predictability along the Supply Chain: The International Evidence" [May/June 2010], Financial Analysts Journal, Volume 66[3], 60-77

Our Recent Research

July 2012: Releasing S&P Capital IQ's Regional and Updated Global & US Equity Risk Models
Over the course of the last two years we released our Global and US Fundamental Equity Risk Models. As a natural progression we are releasing the first set of Regional Models – the Pan-Asia ex. Japan and the Pan-Europe Fundamental Equity Risk Models. This document will explain some of the salient aspects of the process adopted for constructing the Regional Models. We have also made additional improvements to our US & Global Equity Risk Models, and we shall explain these changes.

June 2012: Riding Industry Momentum – Enhancing the Residual Reversal Factor
Unlike individual stocks whose short-term returns tend to revert from one month to the next, industry portfolios exhibit return momentum even at a one-month horizon. We examine a strategy that takes advantage of both industry level momentum and stock level reversal. We combine our residual reversal factor with an industry momentum score, and find that the factor performance is greatly enhanced in the Russell 3000 universe between January 1987 and February 2012. The decile return spread is increased by 42 bps per month on average.

May 2012: The Oil & Gas Industry - Drilling for Alpha Using Global Point-in-Time Industry Data
In the oil & gas industry, a key determinant of value and future cash flow streams is the level of oil & gas reserves a firm holds. While most fundamental analysts/investors take into consideration a company's reserves in arriving at price targets, a majority of systematic driven processes do not. Using S&P Capital IQ's Global Point-in-Time database, we investigate the importance of reserve and production information provided by oil & gas companies.

May 2012: Case Study: S&P Capital IQ – The Platform for Investment Decisions
Ten years ago, AAPL traded just below $12 and closed at $583.98 on April 30, 2012. That is an average annual return of 48.1% over the period. During this same time the S&P 500 grew at an annual rate of only 2.65%. On April 2nd, Topeka Capital Markets initiated coverage of AAPL with a price target of $1001. If achieved, this would make AAPL the first company to ever reach a $1 trillion market cap. In this case study, we highlight some key S&P Capital IQ functionality in analyzing AAPL hypothetically reaching $1000:

March 2012: Exploring Alpha from the Securities Lending Marker – New Alpha Stemming from Improved Data
Numerous studies have examined the information content of short interest and found that heavily shorted stocks tend to underperform and liquid stocks with low levels of short interest subsequently outperform. Most studies relied on short interest data obtained directly from the exchanges available with a significant delay.

January 2012: S&P Capital IQ Stock Selection Model Review – Understanding the Drivers of Performance in 2011
In this report, we review the performance of S&P CIQ's four U.S stock selection models in 2011. These models were launched in January 2011, and this analysis will assess the underlying drivers of each model's performance over the last 12 months.

January 2012: Intelligent Estimates – A Superior Model of Earnings Surprise
As residual stakeholders, equity investors place enormous importance on a company's earnings. Analysts regularly forecast companies' future earnings. The prospects for a company's future earnings then become the basis for the price an investor will pay for a company's shares. Market

participants follow sell side analysts' forecasts closely, identifying those analysts that demonstrate forecasting prowess and track those analysts' forecasts going forward.

December 2011: Factor Insight – Residual Reversal
Many investors employ price reversal strategies (strategies that buy "losers" and sell "winners" based on short-term price changes) in their stock selection decisions. One popular reversal strategy is constructed as the change in 1-month stock price over the most recent month. This report compares the performance of this factor to a "residual reversal" signal proposed by Blitz, Huij, Lansdorp and Verbeek in their 2011 paper, "Short-Term Residual Reversal".

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

October 2011: The Banking Industry
Investors can improve model and portfolio risk adjusted returns using various approaches, including incorporating new alpha signals in an existing investment process. In this research piece, we build on our earlier work (See "Is your Bank Under Stress? Introducing our Dynamic Bank Model", November 2010), to determine if bank specific data provided by financial institutions regulatory bodies (FFIEC standardized data), can yield alpha signals orthogonal to those found in most stock selection models.

September 2011: Methods in Dynamic Weighting
In this report, we introduce a powerful discovery tool in Alphaworks and provide a pragmatic survey covering the identification and potential dynamic techniques to handle financial regimes and security level context. With increasingly volatile factor performance, the ability to implement adaptive strategies is paramount in maximizing factor efficacy.

September 2011: Research Brief: Return Correlation and Dispersion - Tough Times for Active Managers
July 2011: Research Briefs- 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