Supply Chain Interactions Part 2: Companies

Connected Company Returns Examined as Event Signals

In nature we never see anything isolated, but everything in connection with something else which is before it, beside it, under it and over it.
Johann Wolfgang von Goethe

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On January 16th, the FAA grounded all flights for the Boeing 787. The news broke prior to the market open, and Boeing (NYSE: BA) opened 4% below the previous day's close. Precision Castparts Corp (NYSE: PCP), a major supplier to Boeing, opened just slightly under its previous day's close, but quickly dropped around 2% within the first hour. While the major headlines of the day focused on Boeing, electrical problems, and the grounding, there was little mention of Precision Castparts Corp, a supplier of unrelated parts to the same Boeing 787 Dreamliner. This suggests the market forecasted reduced business for PCP as a supplier to BA; but it did not react to the news as quickly as it had for Boeing.

Boeing and PCP is an example of a high attention event with fast transfer of information along the supply chain in less than a day. Existing academic research has found that this diffusion lag may take longer, on the order of days, weeks, or months depending on the market's level of inattention. In our August 2012 research piece we examined lead-lag properties in industry returns. This month we extend this analysis to the level of economically linked companies. We build upon the work done by Cohen and Frazzini in their 2008 paper, "Economic Links and Predictable Returns", to examine signals based on lead-lag supply chain relationships over recent years. We assess the significance of relationships and examine how the information embedded in returns may carry from customers to suppliers in the days, weeks, and months following news events.

Leveraging Compustat customer segment data, we construct a map of significant company level supply chain connections in the United States based on the revenue a supplier derives from its customers[1]. Using this map, we investigate the impact of news for customers and subsequent stock returns for their suppliers, over the time period May 2000 through April 2011 and find that[2]:

- Shares of suppliers with major customer relationships reacted to positive and negative earnings surprise of their customers with a statistically significant 0.93% to 1.97% abnormal spread in the 5 to 60 trading days following the surprise.
- A monthly rebalanced backtest of long-short supplier portfolios based on customer momentum would have resulted in a statistically significant 0.81% average monthly return, or 0.70% after controlling for common risk factor exposures.
- The customer momentum signal historically performs best in cyclical sectors such as Materials and Consumer Discretionary, where post signal return spreads are statistically significant.

[1] SFAS 131 requires US filers to report segment sales information in their 10K for relationships where a customer comprises more than 10% of the supplier's total revenue.

[2] Note that backtest results provide only a hypothetical historical analysis.

1. Supply Chain Connections

1.1 The Customer – Supplier Map

We link customer/supplier pairs historically using Compustat's customer segment file, which identifies suppliers who reported the names of customer companies comprising more than 10% of their annual sales. Suppliers that report linkages are identified using Compustat's unique GVKEY identifier, which is easily matched to other financial and security data. Customer identification poses a greater difficulty, as they are simply identified by a non-standard text name, which requires greater manual intervention to link. For researching this piece, we manually mapped these customer text names to GVKEY.[3] The Capital IQ Business Relationships data set, which is in production, identifies these relationships with unique identifiers, but historical records are not available for backtesting research.

For our research we do not assume that the market "knew" about these supply chain connections until the relationship has been disclosed in the supplier's 10K filing. We apply a conservative lag of 4 months following the annual period end date to account for filing lag and collection of this relationship data. For example, Precision Castparts Corp (GVKEY = 008717, NYCE:PCP) identifies "Boeing" as a major company in their 10K filing for the year ended March 31, 2010. For our research we map "Boeing" over to GVKEY=002285 (NYSE:BA) and consider this link to be known 4 months later on July 31, 2010. To account for inactive relationships, we "expire" links in our backtest 12 months later, on July 31, 2011 for the previous example. Links persist only if a subsequent 10K filing re-identifies the link the following year. Our research relies on filings from the years 1999 through 2010. To allow for reporting lag, our event studies and backtests cover the period May 2000 through April 2011.

Our map construction derives from suppliers that identify customers that are significant to them. However, this does not guarantee that those suppliers are necessarily significant to their customers. Hence, for this research we focus on one side of the relationship, transference of signals from the customer to the supplier. Also for simplicity in our signal construction, we weight all identified customer-supplier relationships equally, rather than weighting based on magnitude of the relationship, since the exact level of sales attributable to the customer is not always available.

1.2 Cap and Industry Characteristics of Linked Suppliers

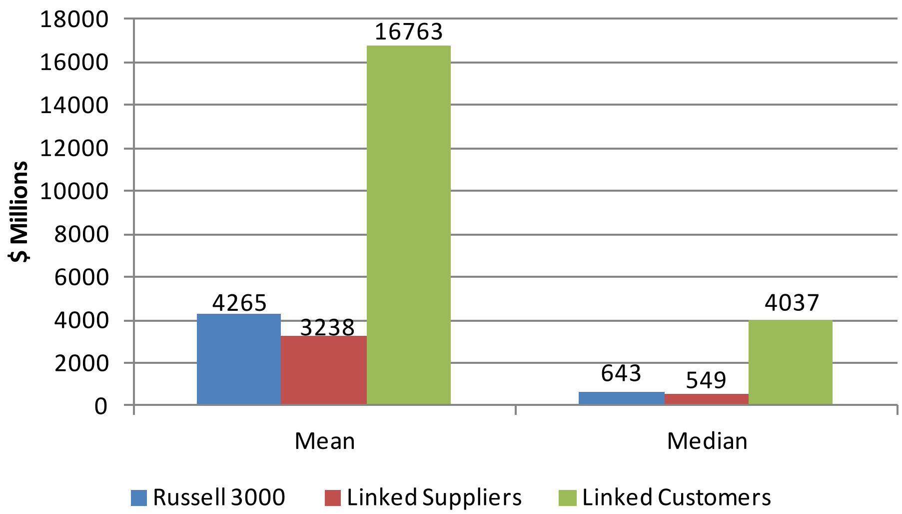
Suppliers that report customers with greater than 10% of its revenue comprise a small subset of the universe of public companies. Over our research period, approximately 22% by count and 17% by market cap of the Russell 3000 companies were identified as suppliers to other Russell 3000 companies. On the linked customer end, approximately 17% by count and 67% by market cap of the Russell 3000 companies are identified as customers. Intuitively, we expect that these relationships may be more concentrated in certain sectors, and also have skewed market

[3] A saleable mapping of these customer text names to GVKEY is planned, but not currently in production.

capitalizations relative to the index. This is confirmed when comparing descriptive statistics for portfolios made up solely of linked suppliers and customers to the rest of the Russell 3000 index.

The market capitalization of linked suppliers is slightly lower than for our benchmark as a whole, and capitalization for linked customers is much larger, as shown in Figure 1. Through the nature of our map, which identifies relationships where a customer purchases more than 10% of a supplier's revenue, it is natural to expect that those customers are larger than the suppliers.

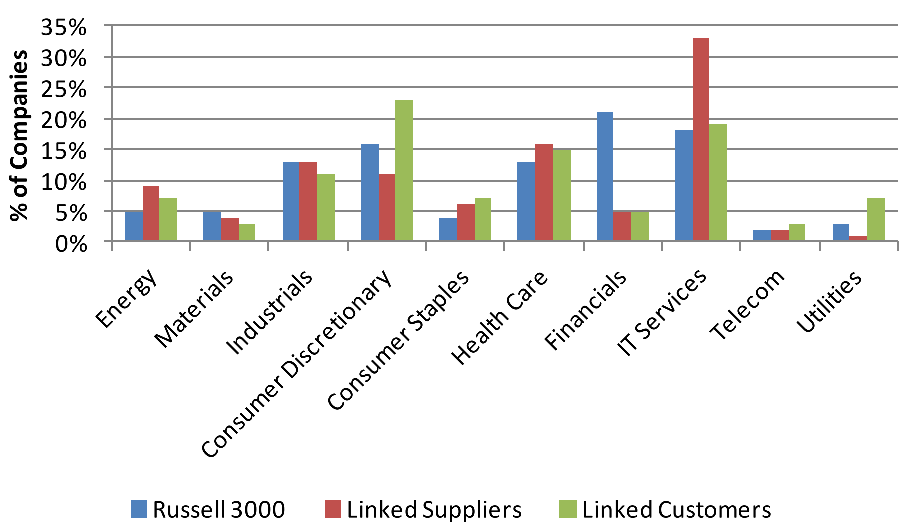
Figure 1: Average Market Cap Across Time for Linked Suppliers, Customers, and Russell 3000



Source: S&P Capital IQ Quantamental Research, Average and Median Caps, May 2000 – April 2011

Figure 2 shows the sector makeup, averaged across time by number of companies, of the benchmark Russell 3000 over our test period, compared with portfolios of all "linked" suppliers and customers over the same test period.

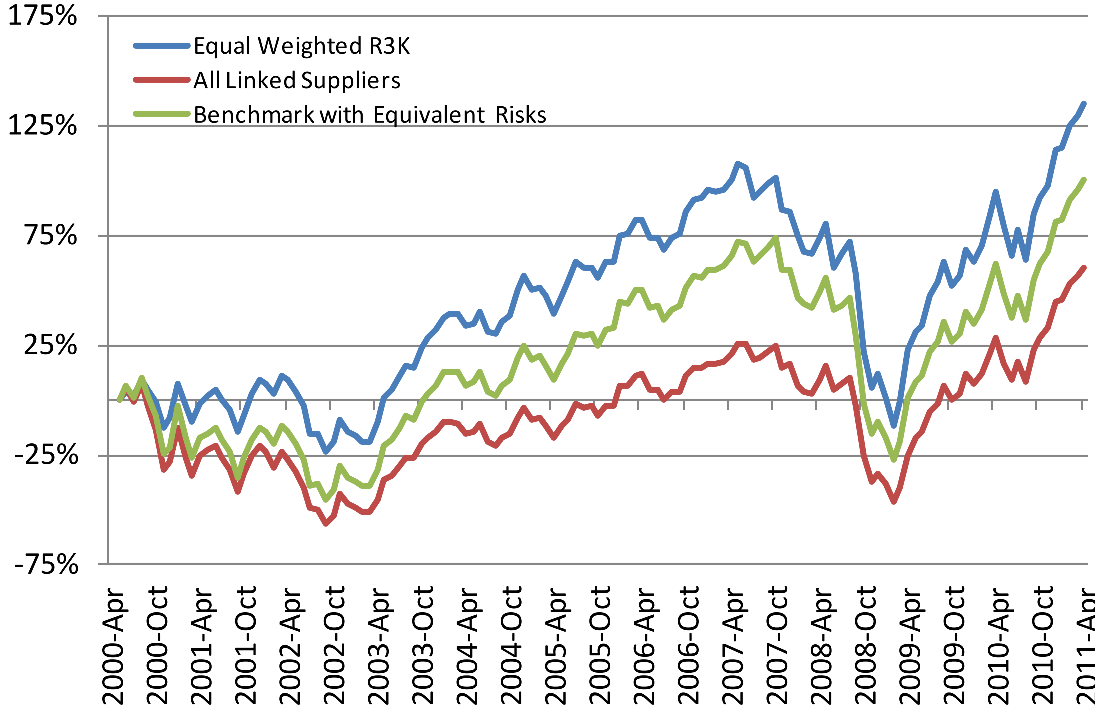
Figure 2: Sector Comparison for Linked Suppliers, Customers, and Russell 3000



Source: S&P Capital IQ Quantamental Research, Average and Median Caps, May 2000 – April 2011

It's important to be aware of these universe differences when comparing event and backtest results to the benchmark. Our research focuses on investment strategies within the universe of linked suppliers, and we find that investing in a portfolio comprised solely of this subset universe performed quite differently from the benchmark as a whole. Over our test period of May 2000 through April 2011, we find that a portfolio made up of linked suppliers within the Russell 3000 underperformed the full benchmark by 0.18% per month on average, Figure 3. We also compare to a benchmark of returns adjusted for equivalent risk exposures to Market, Style, and Industry.

Figure 3: Cumulative Return – Russell 3000, Suppliers, and Risk Equivalent Benchmark



Source: S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future results

This underperformance can be partly attributed to GICS, market, and risk factor exposures of the supplier universe relative to the benchmark in this period. Table 1 summarizes the returns for the benchmark and linked supplier portfolios, the active difference, and attribution of the differences to stock-specific, market exposure, sector, and alpha style exposures of the portfolio using the S&P Capital IQ US Short-Term Risk Model. The full risk model methodology is outlined in our July 2010 work 'Introducing Capital IQ's Fundamental US Equity Risk Models'.

Table 1: Linked Supplier Universe Return Attribution

Monthly Return Component	mean	t-stat
R3000 Equal Weight Return	0.88%	1.50
Linked Suppliers Portfolio	0.70%	0.98
Active Return, R3k vs. Linked Suppliers	-0.18%	-0.93
Active Stock Specific Return	-0.14%	-1.78 *
Active Risk Exposure Return	-0.04%	-0.24
Market	0.01%	0.23
Sector	0.00%	-0.06
Style	-0.05%	-0.42

***, **, and * denote statistical significance at the 1% 5%, and 10% levels
Source: S&P Capital IQ Quantamental Research, US Risk Models, and Clarifi Portfolio Attribution
Past performance is not a guarantee of future results

We find that active risk exposure for commonly known factors accounts for 0.04% of the underperformance of the linked supplier universe relative to the benchmark. The remaining 0.14% of average monthly underperformance is due to other unidentified factors related to the supplier universe. This underperformance is unattributed to standard factors in our US risk model, which accounts for 33 different Market, Industry, and Style factor effects. The knowledge that these are supplier companies with concentrated business links with their customer is the common denominator, which suggests that these suppliers are exposed to additional effects transferred from their customers, or that these linkages have imposed a return penalty on these suppliers.

2. Event Studies of Connected Signals

The nature of connected companies who may be influenced by news events for their customer lends itself well to an event study methodology. Event studies allow us to view the price response of securities before and after an event and when the responses develop relative to the event date. Following event study methodologies suggested by MacKinlay (1997), we examine the Cumulative Average Abnormal Return (CAAR) of companies in the days prior to and following a trigger event. CAAR is the security level return in excess of an implied "normal" return for that security attributable to market or other factors independent to the event.

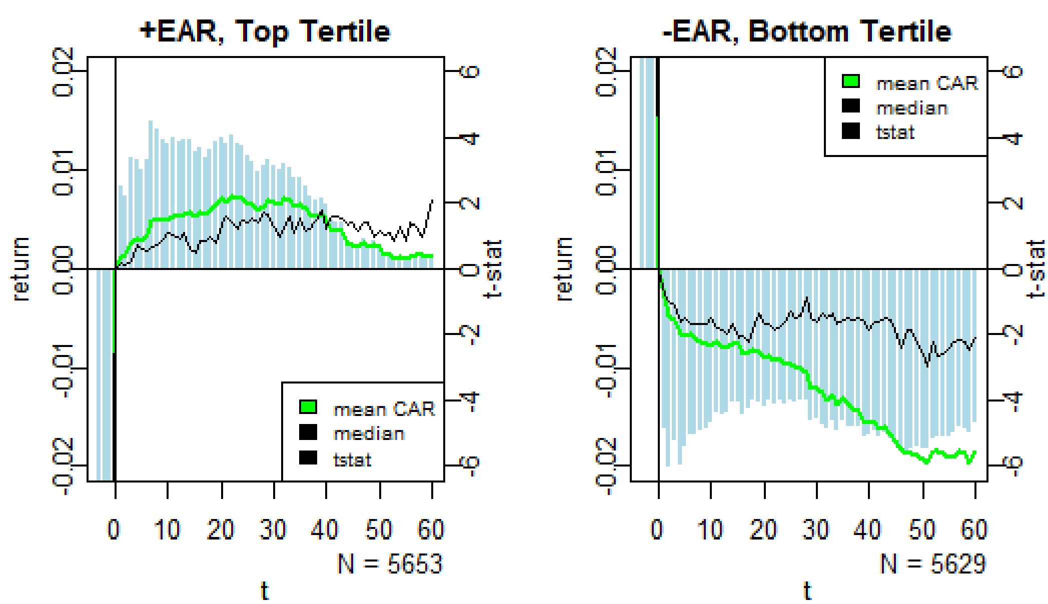
For this research, we define abnormal return as return of a stock in excess of normal return after accounting for exposures to a factor model of market and GICS subsector returns, and to size and value effects. For example: if a stock has a daily Beta to market return of 1.5, and market return on a given day in the event window is 1%, the estimated "normal" return of that stock attributable to the market is 1.5%. Abnormal returns of the stock are calculated as the daily return in excess of that estimated normal return. We estimate daily Beta exposures to market, GICS, size, and value effects using a 252 day regression window on returns prior to the event. The intent of stripping away these normal returns is to isolate as much as possible, the abnormal return resulting from the event signal, without incorporating external market effects that may be coincident with the event date.

2.1 Surprise Event Study: Earnings Announcement Return

In our September 2012 research, we investigated the Earnings Announcement Return (EAR) Factor as an intelligent signal to identify cases of true market surprise around a quarterly earnings announcement. EAR (Earnings Announcement Return) is simply the 3-day return for a stock surrounding the day of company's announcement of quarterly earnings. The return of the stock over those 3 days is a proxy for the market's reaction to the news contained in that announcement. The reaction may incorporate more than just EPS surprise relative to consensus, such as revenues, margins, major developments, and guidance. We use large EAR returns as a trigger for an event study. To set a threshold for significant positive surprise, we compare the magnitude of positive EAR returns with positive EAR returns for all companies over the past year, and likewise compare negative EARs with all negative EARs over the past year. We consider a positive EAR as a significant event trigger if it scores in the top tertile (top 33%) relative to all other positive EARs over the prior year, and likewise we consider a negative EAR as a negative event if it scores in the bottom tertile of all negative EARs in the prior year.

We initially test this surprise factor in an event study following the return response of the announcing company, Figure 4. We then examine the response of connected suppliers to the same EAR event signals when present in their customer companies. After assembling a list of both positive and negative events, we calculate the daily cumulative abnormal returns to each stock in the days following the event. We standardize the dates by, converting calendar days to a number of trading days following the event at time t = 0. We aggregate results by aligning days and computing the median, mean, and t-stat of abnormal returns for each day in the event window.

Figure 4: EAR Events on Standalone Companies



Source: S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future results

We find that strong positive EAR event signals began with extremely positive abnormal returns in the 3 days leading up to day 0. This is due to the way the event trigger is constructed – we only consider companies where the 3-day EAR was extremely high or small, and we define our t=0 as immediately following calculation of this 3-day return. Notably, the positive abnormal returns continue on in the days following the event. This is consistent with prior research – that positive EAR is followed by positive returns. Significantly negative EAR signals are likewise followed by significantly negative returns for the stock.

A strategy of going long stocks with a positive EAR event and short negative EAR events performs quite well. From our backtesting period of May 2000 – April 2011, we choose a random sample of approximately five thousand eligible events on both the long and short side and calculate the sample CAAR, Table 2. The difference in mean CAAR (Cumulative Average Abnormal Return) between the long and short event sets is a statistically significant 1.97% spread after 60 trading days.

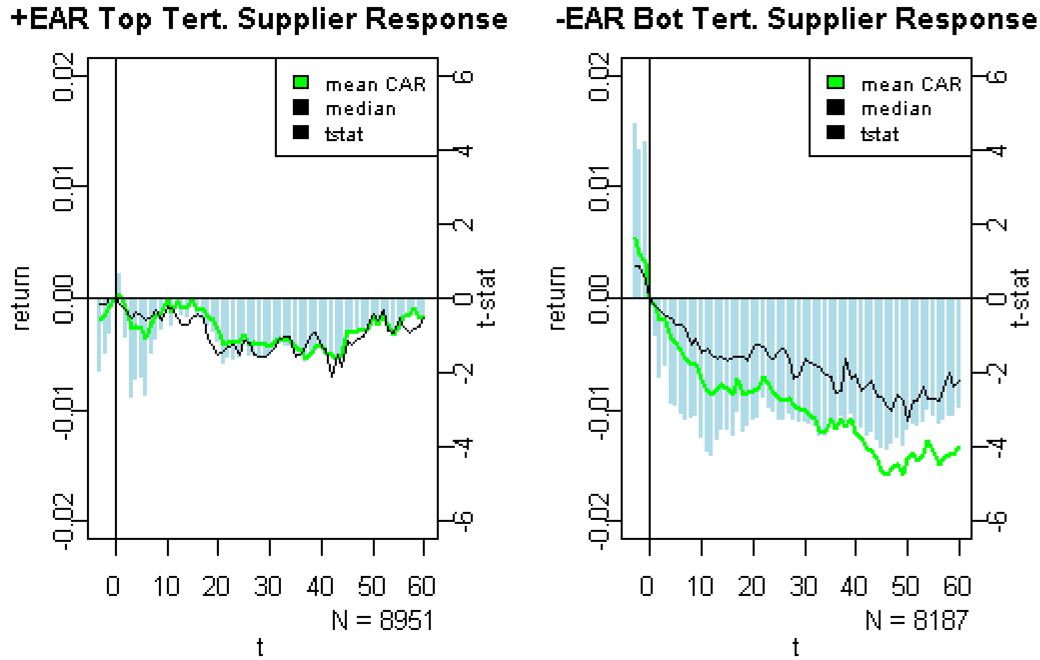
Table 2: EAR Long-Short Event Performance on Standalone Companies

	LONG		SHORT		DIFFERENCE Long-Short	
t	Median	Mean	Median	Mean	Median	Mean
-3	-9.51%***	-11.08%***	10.34%***	13.20%***	-19.85%***	-24.28%***
0	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
5	0.21%***	0.28%***	-0.43%***	-0.65%***	0.64%***	0.93%***
20	0.50%***	0.73%***	-0.54%***	-0.84%***	1.05%***	1.58%***
40	0.44%***	0.54%**	-0.61%***	-1.46%***	1.04%***	2.00%***
60	0.70%	0.11%	-0.71%***	-1.86%***	1.41%***	1.97%***

***, **, and * denote statistical significance at the 1% 5%, and 10% levels
Significance levels of medians based on Wilcoxon rank sum test
Source: S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future results

With these baseline event results for EAR as event for the announcing company, we test whether this signal transfers through the supply chain from customer to suppliers. We take this same positive and negative EAR signal and observe how the linked suppliers (where they exist) responded to the EAR signal of their customer. We tested a set of all eligible events, (approximately eight to nine thousand) where a supplier is linked to a customer with a significant EAR event, Figure 5.

Figure 5: Linked EAR Events – Supplier Response to Customer EAR Event



***, **, and * denote statistical significance at the 1% 5%, and 10% levels
Source: S&P Capital IQ Quantamental Research
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The 3 days prior to t=0, which are the 3 days of extreme customer return surrounding the customer announcement, the suppliers show CAAR returns of the same sign, though very much more muted (-11% and 13% vs. -0.2% and .58% on the long and short side respectively). The strongest connection seems to be on the short side with negative EAR events.

Interestingly, we find both the long and short side populations show a negative CAAR following the event, Table 3. This may be attributable to difficulty in estimating the "normal" return for stocks in an event study. We found a slight underperformance to estimated "normal" for the supplier universe over the test period. We find it more informative to look at the difference in means between the two sides. While we find considerable return differences out to 60 days, the difference in mean CAARs between suppliers with positive and negative customer EAR events is most statistically significant at t10, which is 10 trading days (2 weeks) following the original signal.

Table 3: Linked Supplier Response to Customer EAR Event

	LONG		SHORT		DIFFERENCE Long-Short	
t	Median	Mean	Median	Mean	Median	Mean
-3	-0.06%**	-0.20%**	0.29%***	0.58%***	-0.35%***	-0.77%***
0	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
5	-0.14%**	-0.20%	-0.21%***	-0.33%**	0.06%	0.13%
10	-0.07%	0.09%	-0.45%***	-0.59%***	0.39%**	0.68%***
20	-0.43%**	-0.19%	-0.34%***	-0.69%***	-0.09%	0.50%
40	-0.32%	-0.32%	-0.67%***	-1.20%***	0.34%	0.89%**
60	-0.18%	-0.17%	-0.73%**	-1.34%***	0.54%**	1.16%**

***, **, and * denote statistical significance at the 1% 5%, and 10% levels
Significance levels of medians based on Wilcoxon rank sum test
Source: S&P Capital IQ Quantamental Research
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The results suggest that information can transfer through this economic link and be realized in terms of returns. While the return from the EAR signal persists for the customer company, it seems to have a more muted impact from customer to supplier. We believe this may be due to the high level of attention surrounding earnings announcements and that this information impacts only a portion of the connected companies revenue generating operations. The market prepares for the arrival of prescheduled new information and possibly re-familiarizes itself with major suppliers of the announcing company. This may lead to a weaker signal being driven more by the co-movement for these connected companies rather than a lead-lag as the market prices in this information throughout the event window for both entities.

2.2 Return Momentum Event Study – 1 Month

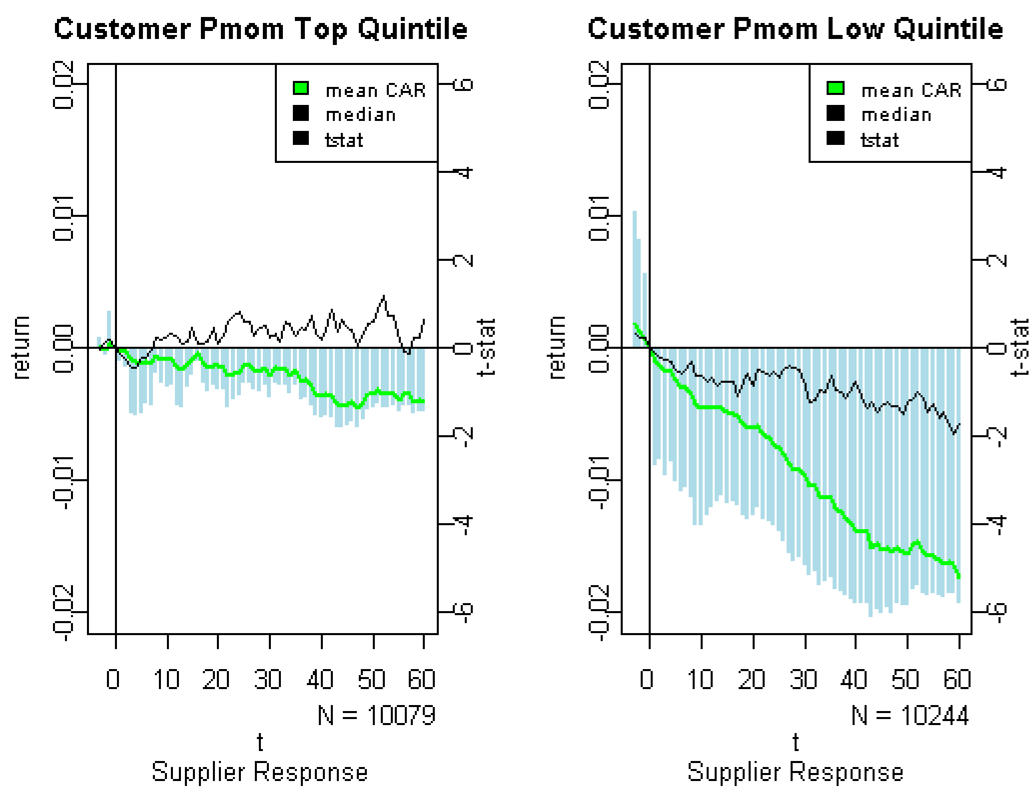
Given the possible limitations of transference with pre-scheduled events, we test the supply chain event methodology on rolling period momentum factors. We look at momentum at non-company specific intervals, specifically trailing 1 month momentum, measured at each month end. This is meant to be a more flexible signal, capturing momentum effects from unscheduled news events or indirect economic news, while still allowing company specific returns to signal important informational events.

In part one of our supply chain series, August 2012, we used 1 month momentum to study the lead-lag effects of monthly momentum from industry to industry. Similarly, we look at how one month momentum transfers at the company level, from customer to suppliers as identified in a direct company connection map. We begin simply, by calculating 1-month trailing price momentum for all companies in the Russell 3000 for our backtest period, May 2000 – April 2011. We align our calculation with calendar month ends, and place each company into one of five quintile buckets each month based on trailing momentum scores.

We interpret strong/weak company returns over the past month (top/bottom quintile of momentum) as an indication of positive/negative information arriving for the company. This can include news such as product press releases, catastrophes, or industry favorability in general that would not follow any well defined schedule. We study the effect of this month-end signal as a proxy for favorable market events for the linked suppliers.

We use the same event study methodology as the previous section (events aligned at t=0 with a normal return model accounting for market, industry, size and value effects). Supplier companies with customers with the strongest/weakest trailing returns (top/bottom quintile) are incorporated into long/short event sets. In cases where a supplier has multiple customers, we consider an event to be triggered if any one of their customers has a positive or negative signal. However, we do not double count a supplier if more than one customer has the same positive or negative signal on the same day.

Figure 6: Linked Supplier Response to Customer Momentum Event



***, **, and * denote statistical significance at the 1% 5%, and 10% levels
Source: S&P Capital IQ Quantamental Research
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We again find a slight negative tilt in the CAAR for both the long and short event portfolios as in our EAR event. Due to this, we focus on the difference in means between the two event sets. We see a significant difference between suppliers whose customer experienced positive momentum last month and those whose customer experienced negative momentum in the prior month, Table 4. This signal shows stronger persistence with steadily increasing spread, from 0.32% abnormal spread after 5 days up to 1.67% abnormal spread after 60 trading days.

Table 4: Linked Supplier CAAR Resposne to Customer Momentum

	LONG		SHORT		DIFFERENCE Long-Short	
t	Median	Mean	Median	Mean	Median	Mean
0	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
5	-0.06%	-0.08%	-0.15%**	-0.20%**	0.09%	0.11%
10	0.13%	-0.03%	-0.19%***	-0.40%***	0.32%***	0.37%**
20	0.07%	-0.06%	-0.27%**	-0.56%***	0.34%***	0.50%**
40	0.08%	-0.29%	-0.24%***	-1.31%***	0.31%***	1.03%***
60	0.21%	-0.41%	-0.57%***	-1.75%***	0.78%***	1.34%***

***, **, and * denote statistical significance at the 1% 5%, and 10% levels
Significance levels of medians based on Wilcoxon rank sum test
Source: S&P Capital IQ Quantamental Research
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Given possible return correlation between customers and suppliers, we wanted to make sure we weren't capturing the effect of the supplier's own momentum. Table 5 shows a two way sort, counting the candidate events based on the trailing return of both the customer and supplier over the previous month.

Table 5: Distribution of Events in Customer and Own Momentum Quintiles

		Event Counts Supplier Momentum Quintile				
		High	>	>	>	Low
Customer		**1**	**2**	**3**	**4**	**5**
Momentum	**High**	4016	2672	2270	2171	2271
Quintile	**Low**	2420	2276	2447	3018	4491

Source: S&P Capital IQ Quantamental Research

There is a possible exposure to own momentum with a disproportionate number of suppliers sharing the same momentum quintile as their connected customers (High/High and Low/Low). In the same way you can neutralize for beta or sector, we attempt to neutralize based on a company's own trailing momentum. We start by first sorting all of the suppliers into 5 quintile buckets based on their trailing momentum. Then, within each supplier quintile, we apply the customer momentum signal and quintile again to create a 5x5 double sort matrix. This allows us to identify suppliers with the strongest customer momentum within their own momentum quintiles. We aggregate all securities that were in the top quintile based on customer momentum from the 5 original own momentum quintiles.]. After neutralizing for the suppliers own momentum, we get a more balanced and comparable exposure to their own 1 month momentum on both the long and short side, Table 6.

Table 6: Distribution of Events following Own Momentum Neutralization

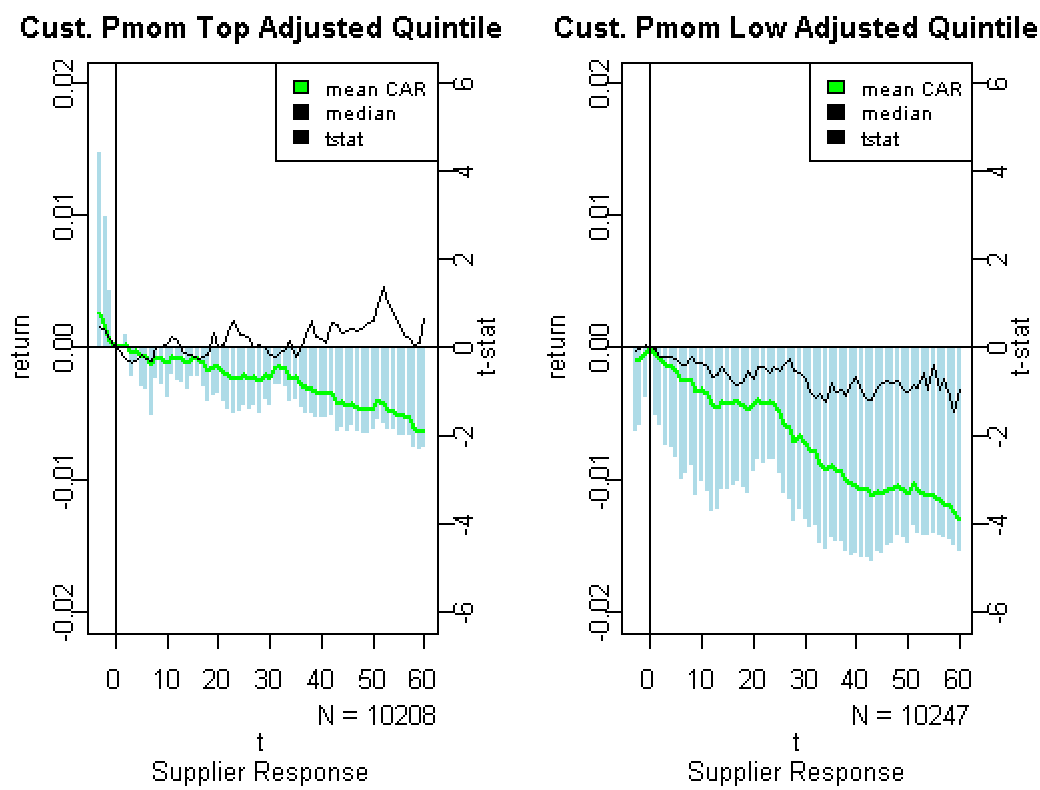
Company Counts:

		Supplier Momentum Quintile				
Customer		High	>	>	>	Low
Momentum	High	4153	3736	3524	3830	4331
Quintile	Low	4263	3841	3630	3939	4441

Source: S&P Capital IQ Quantamental Research

We then retest our customer momentum event with this new bucketing, Figure 7. As before, we see a statistically significant spread between the long (positive customer momentum) and short (negative customer momentum) sets of events, even after adjusting the scores to avoid over-exposure to the supplier's own momentum, Table 7.

Figure 7: Linked Supplier Response - Customer Momentum Adjusted Signal



Source: S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future results

Table 7: Linked Supplier CAAR – Customer 1Mo Momentum Adjusted Signal

	LONG		SHORT		DIFFERENCE Long-Short	
t	Median	Mean	Median	Mean	Median	Mean
0	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
5	-0.04%	-0.04%	-0.09%	-0.16%**	0.05%	0.12%
10	0.05%	-0.07%	-0.10%**	-0.28%***	0.15%**	0.20%
20	0.05%	-0.07%	-0.23%**	-0.39%**	0.27%**	0.31%
40	0.10%	-0.28%	-0.21%***	-1.01%***	0.32%**	0.73%**
60	0.21%	-0.62%**	-0.32%***	-1.30%***	0.53%**	0.67%**

***, **, and * denote statistical significance at the 1% 5%, and 10% levels
Significance levels of medians based on Wilcoxon rank sum test
Source: S&P Capital IQ Quantamental Research
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We find that after adjusting our scoring to account for relative differences in the supplier's own momentum, there is still a statistically significant difference in returns when using the customer's trailing momentum as a buy or sell signal.

2.3 Return Momentum Event Study – 1 Week

We also look at momentum effects at the one week level to view the effect of this concept at higher frequency momentum signals. We use a one week momentum approach similar to the one month signal discussed above. The 1-week momentum signals are calculated at the end of each trading week, and we apply the same neutralizing methodology as outlined above to ensure we are capturing effects more specifically attributable to customer momentum.

Table 8: Linked Supplier CAAR –Customer 1Wk Momentum Adjusted Signal

	LONG		SHORT		DIFFERENCE Long-Short	
t	Median	Mean	Median	Mean	Median	Mean
0	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
5	-0.01%	-0.01%	-0.10%**	-0.20%***	0.10%**	0.19%**
10	0.06%	-0.03%	-0.24%***	-0.50%***	0.30%***	0.47%***
15	0.02%	-0.11%	-0.12%**	-0.58%***	0.14%**	0.47%**
20	0.00%	-0.19%	-0.10%**	-0.61%***	0.10%**	0.42%**

***, **, and * denote statistical significance at the 1% 5%, and 10% levels
Significance levels of medians based on Wilcoxon rank sum test
Source: S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future results

We find statistically significant spreads between the long and short event sets by using a one week trailing customer momentum signal as well. This higher frequency signal produces a higher mean Long-Short spread at the t20 horizon than when using the 1 month signal. In Table 8 we find a statistically significant spread of 0.42% mean CAAR after 20 trading days, compared to the monthly signal, with a statistically insignificant 0.31% spread after 20 days, as noted in Table 7 on the previous page.

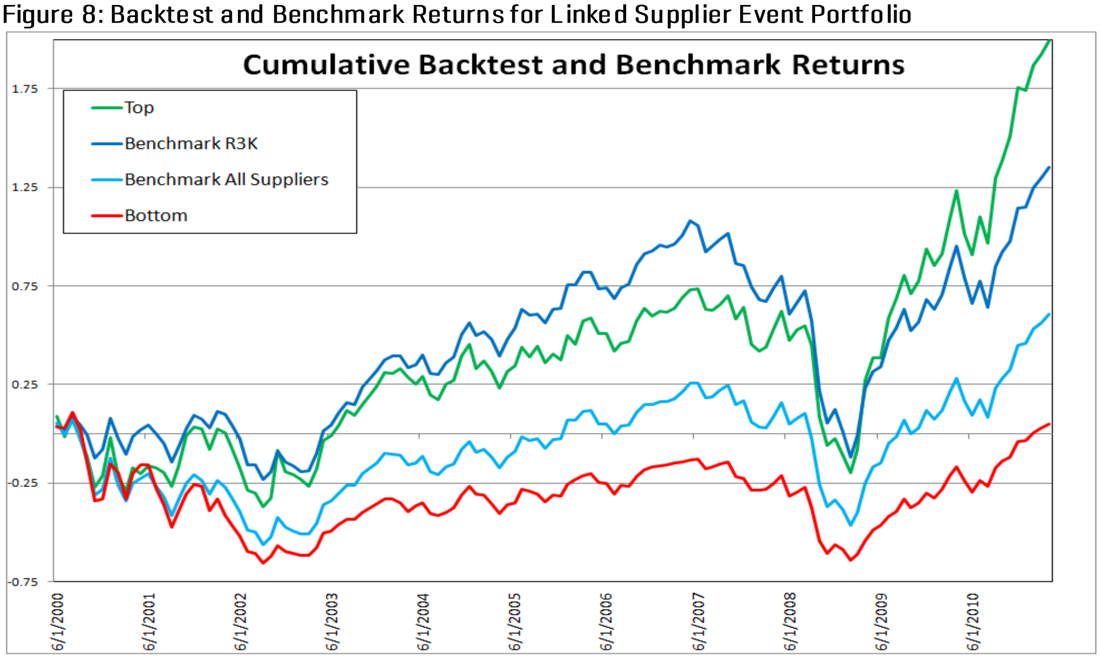
2.4 Return Momentum Portfolio Strategy – 1 Month

A common concern with event driven investing is the difficulty in turning irregularly timed events into investable portfolios. The event study framework provides a tool to derive insight from the market reaction to an event. However, it has some fundamental challenges with implementing in an investment process. With events occurring with individual securities on irregular days and intervals, it is difficult to react with a regularly rebalanced portfolio.

One solution is to form portfolios of all companies that have experienced events within a lookback horizon, with a regular rebalancing schedule. The downside of this is when the rebalance period and lookback horizon don't align with event days, you lose alpha as it decays waiting for rebalance. To account for this, and to test a more practical implementation of the signal, we test an event signal that can be generated at a regular rebalance intervals and observe the effectiveness of this approach. All companies within our linked universe have scores every month which allows us to have increased breadth without compromising the timeliness of the information about market sentiment at a given date. We test the practicality of this approach by performing a backtest over the test period May 2000 - April 2011.

Each month, we form two portfolios of linked supplier companies. The "Top" portfolio is suppliers whose customers' momentum was in the top quintile of momentum (relative to the supplier's own momentum quintile). And the "Bottom" portfolio contains suppliers whose customers were in the bottom quintile, adjusted for supplier's own quintile.

Figure 8: Backtest and Benchmark Returns for Linked Supplier Event Portfolio



Source: S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future results

Table 9: Linked Supplier Event Portfolio Returns and Attribution

		Portfolio Returns		Attribution of Active Returns			
		Portfolio	Benchmark R3K EW	Market Risk Exposure	Sector Risk Exposure	Style Risk Exposure	Stock Selection Return
All Linked Suppliers	mean	0.70%	0.88%	0.01%	0%	-0.05%	-0.14%
	t.stat	0.98	1.5	0.23	(0.06)	(0.42)	(1.78)*
Suppliers, Top Customer Pmom	mean	1.24%	0.88%	0.09%	-0.01%	-0.06%	0.35%
	t.stat	1.55	1.5	1.1	(0.12)	(0.46)	1.78*
Suppliers, Bottom Customer Pmom	mean	0.43%	0.88%	-0.04%	0%	-0.06%	-0.35%
	t.stat	0.56	1.5	(0.35)	0.03	(0.39)	(1.92)*
Top Minus Bottom	mean	0.81%	-	0.12%	0%	0.00%	0.70%
	t.stat	2.04*	-	1.32	(0.11)	0	2.51**

***, **, and * denote statistical significance at the 1% 5%, and 10% levels
Significance levels of medians based on Wilcoxon rank sum test
Source: S&P Capital IQ Quantamental Research
Past performance is not a guarantee of future results

We find statistically significant returns to both the top (long) and bottom (short) customer momentum portfolios relative to the equal-weighted Russell 3000, after accounting for risk factor exposures to Market, Sector, and Style factors. We calculate these exposures and attribution using Clarifi Portfolio Attribution and the S&P Capital IQ US Short Term Risk Model.

Table 10: Long-Short Portfolio Return Exposures to Alpha Factor Library Style Returns

	Coefficient	t-stat
(Intercept)	0.86%	2.15*
MARKET	-0.05	(0.47)
Analyst Expectation	-0.31	(0.7)
Capital Efficiency	-0.16	(0.28)
Earnings Quality	0.66	0.49
Historical Growth	-0.15	(0.27)
Price Momentum	-0.67	(1.3)
Size	-0.17	(0.72)
Valuation	-0.88	(1.74)*
Volatility	-0.21	(0.64)

***, **, and * denote statistical significance at the 1% 5%, and 10% levels
Source: S&P Capital IQ Quantamental Research, US Risk Models, and Clarifi Portfolio Attribution
Past performance is not a guarantee of future results

2.5 Return Momentum Event Study - Performance across Sectors

We look at the performance of the 1 month customer momentum event signal by sector, to examine the differences between the customer-to-supplier momentum transfer among supplier industries, Table 11. We exclude Financials from this study since the coverage of Financial sector suppliers in our map is low, and our intuition that the nature of the customer supplier interactions is quite different for Financials, which makes them inappropriate for this type of signal.

Table 11: Linked Supplier CAAR Response to Customer Trailing 1 Mo Momentum by Sector

Sector	Energy 10	Materials 15	Industrials 20	Cons. Disc. 25	Cons. Staples 30	Healthcare 35	IT 45	Telecom 50	Utils 55
t	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
5	0.51%*	0.63%*	0.04%	0.24%	0.44%*	0.04%	(0.03%)	0.61%	(0.24%)
10	0.40%	1.43%***	0.36%	0.83%***	0.31%	0.26%	0.06%	(0.12%)	(0.70%)
15	0.34%	2.13%***	0.28%	1.02%***	0.15%	0.32%	0.01%	(0.80%)	0.35%
20	0.42%	2.52%***	0.61%	0.78%*	0.31%	0.47%	0.12%	(1.04%)	(0.23%)
40	0.42%	3.68%***	0.91%	1.40%**	(0.15%)	0.18%	0.55%	0.35%	(0.73%)
60	0.28%	3.58%**	0.78%	1.63%*	(0.29%)	0.78%	0.14%	2.84%	(2.28%)

***, **, and * denote statistical significance at the 1% 5%, and 10% levels

Source: S&P Capital IQ Quantamental Research

Past performance is not a guarantee of future results

Across our test period, the long-short 1 month customer momentum event produced positive spreads after 60 days in 7 of the 9 sectors we examined. Consumer staples and Utility suppliers showed negative spreads on the customer momentum signal, although with high variability making them statistically insignificant. The most promising sectors for this strategy, in terms of the magnitude and significance of the spread were the Materials and Consumer Discretionary sectors over longer horizons, and Energy and Consumer Staples at the shorter 5 trading day horizon. The performance difference among sectors seems to align with supplier sectors which provide hard goods to their customers, in the form of consumer discretionary goods sold to retailers or raw materials to upstream manufacturers. This is consistent with the economic power of supply chain links flowing through inventory and production purchases. If a customer has good news and increases business, they are likely to place orders for inventory from their suppliers to support their growth. Conversely, bad news and soft sales are likely to be followed by reducing inventory, and cutting off orders of goods from their suppliers. The customer momentum signal does not perform well on suppliers in the more service oriented and defensive sectors such as healthcare, where sudden swings in customer demand may be less severe.

3. Conclusion

We find significant value incorporating information about companies linked within a supply chain into an investment process. Using an event study framework, we find that market moving earnings announcements and large returns from Customers have historically been predictive of future returns for the linked Supplier (significant long-short event return spreads). Supply chain connections are most effective in sectors where suppliers provide hard goods to their customers (ex: Materials) where the success of their customers (increased demand for end products) also directly impacts their success (increased demand for production inputs). The effectiveness of this signal is also related to the difficulty in identifying significant information that will pass through this map. This is exacerbated by the fact that Suppliers tend to be smaller cap names with lower analyst coverage.

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Our Recent Research

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

In this paper, we revisit the asset growth anomaly by extending global results to the end of December 2012 and providing additional behavior-based arguments on why investors seem to persistently misprice the growth rates of total assets, one of the most readily available pieces of financial information. Our results indicate:

- Asset growth demonstrates return predictive power globally with and without controlling for size, value, 12-month price momentum, and 1-month price reversal factors.
- Information coefficient correlation analyses indicate that there are potential diversification benefits from adding asset growth to other alpha factors.
- The companies that demonstrated the highest asset growth show subsequent deterioration in their top-line and bottom-line growth rates while companies that had the lowest asset growth experience subsequent improvement in their top-line and bottom-line growth rates.

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

This month we build upon the work done by Cohen and Lou in their 2010 paper, "Complicated Firms", to determine if we can exploit industry level information from pure-play firms to predict the future performance of multi-industry, complicated firms. Leveraging Compustat segment data and Standard Industrial Classification (SIC) 2 digit codes, we exploit the lag in incorporating industry level information between simple and complicated firms to forecast the future performance of complicated firms. This is done by constructing pseudo-conglomerate returns, revisions, and valuation signals that combine the relevant information of all the industries in which a complicated firm operates. These pseudo-conglomerate signals simply weight industry level information (ex: industry return) proportionately to the complicated firm's reported sales in each industry.

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

Equity Risk models are subject to a common criticism. We examined three techniques to further enhance the S&P Capital IQ Fundamental Factor risk models: Utilized the cross sectional dispersion of stock and factor returns by adjusting model factors and stock specific volatilities, change the model production frequency from monthly to daily to capture recent data, and shorten data look back window (1 year as opposed to 2 years) resulting in a more reactive model. Dispersion based adjustments, and high frequency of model generation both improved model results, while a shortened calibration window showed no appreciable improvement.

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

Can profits be made by following the actions of activists? One month after the commencement of activism, the strategy yielded a market-adjusted excess return of 3.4%. After controlling for market, size, value, and industry, the excess return was 2.7. Twelve months after the disclosure of activist involvement, the strategy produced an average excess return of 14.1% after controlling for market, size, value, and momentum. We did not find evidence of return reversal up to two years after activism or of diminished excess returns in 2008 -- 2012 vis-à-vis those in 2003 -- 2007.

February 2013: [Stock Selection Model Performance Review: Assessing the Drivers of Performance in 2012]
In this report, we review the performance of S&P Capital IQ's four U.S. stock selection models in 2012. These models were launched in January 2011, and this analysis will assess the underlying drivers of each model's performance over the 12 months ended December 31, 2012.

January 2013: Research Brief: Exploiting the January Effect Examining Variations in Trend Following Strategies
At the beginning of every year, one topic frequented by many institutional investors is the January Effect. Investors often point to January as the most pronounced example of seasonality, where longer term trend following strategies suddenly underperform and short-term reversal and mean-reversion dominate. But which strategies have performed well in January and is this performance sustainable? With several studies in the Literature documenting the January Effect on company capitalization, we decided to undertake our own review using our S&P Capital IQ Alpha Factor Library (AFL), to examine various strategies' effectiveness during the month.

December 2012: Do CEO and CFO Departures Matter? - The Signal Content of CEO and CFO Turnover
In October of this year, the US equity market was caught off guard with the seemingly sudden departure of Citibank CEO Vikram Pandit. While CEO departures are almost always headline news, CFO departures are not often accompanied with such recognition. We explore the impact of CEO and CFO departures and find consistent results in the US and the Developed World. CEO and CFO departures often signify a turning point in both the company's stock performance and the company's operating metrics.

November 2012: 11 Industries, 70 Alpha Signals -The Value of Industry-Specific Metrics
Investors routinely utilize industry intelligence in their investment process. But which information is relevant? Which is irrelevant? Our work yields some surprising results. This work complements our previous industry work on Retail [June 2011], Banking [Oct 2011], and Oil & Gas [May 2012]. Using S&P Capital IQ's Global Point-in-Time database and Compustat Industry-Specific data, we look at 70 factors in 11 industries: airlines, hospitals & facilities, managed healthcare, pharmaceuticals & biotechnology, homebuilding, insurance, telecommunications, utilities, gold miners, hotels & gaming, and restaurants

October 2012: Introducing S&P Capital IQ's Fundamental Canada Equity Risk Models
In July 2012 we released our regional risk models -- the Pan-Asia ex. Japan and the Pan-European Models, and updated versions of our US and Global Risk Models. Continuing in our efforts to provide a broad set of models to the asset management community, we are now releasing our second single country risk model -- Canada Fundamental Equity Risk Model.

September 2012: Factor Insight: Earnings Announcement Return – Is A Return Based Surprise Superior to an Earnings Based Surprise?
In this report, we compare the performance of SUE to one based on returns around a firm's earnings announcement date (EAR), proposed by Brandt et al (2008). We test both factors globally

and find EAR dominates SUE in the U.S in the post Reg FD era on both a long-short return and top quintile excess return basis.

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

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 Market – 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 predictive prowess and track those analysts' forecasts going forward.

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 - Tough Times for Active Managers

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