Quantitative Strategy
North America United States

Deutsche Bank

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Signal Processing
Quant 2.0

Global Markets Research

Research Summary
In this research we explore a unique new database of structured web data. This data is collected from a wide range of sources, from traditional media sites to blogs and Twitter feeds. We suggest a range of trading strategies based on this data.

Harnessing the power of the web in quantitative investing

Bringing structure to the web
In this report we explore a new frontier for quantitative investors: web-based data. Historically web data has been difficult for quants to use, given its unstructured nature, and the difficulty in procuring a history for backtesting. However, advances in natural language processing techniques now make it possible to transform text-based information into a structured, machine-readable form in real-time. At the same time, new data vendors are stepping up to offer products that automate the data collection and interpretation process. As a result, the time is ripe for quants to take a look at this cutting-edge new data source.

Trading on web-based sentiment and momentum
We show that short-term trading strategies, based on how prominently a company is trending on the web and the sentiment of that trend, can add value after costs. Such a strategy is uncorrelated with traditional short-term factors like one-day reversal and abnormal volume.

Untangling a web of relationships
For longer-term investors, we show how to use web data to identify a stock's "peer group", which often crosses sector lines. We build a promising new momentum factor based on the difference between a stock's past returns and those of its web-based peers. We find that buying stocks that have been outperforming their peers is a fruitful longer-term strategy.
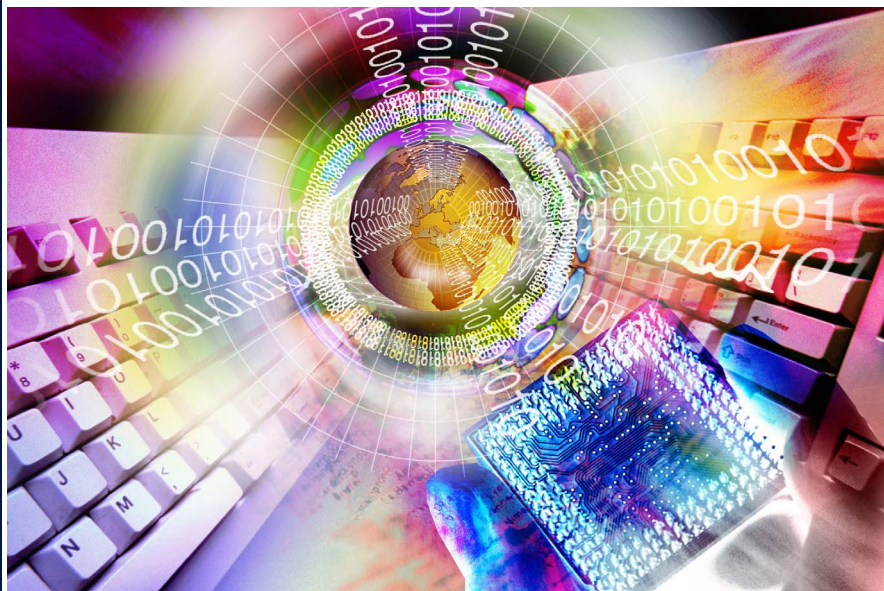
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A letter to our readers

Quant 2.0 – The next big thing?

There is a tremendous amount of data available on the web, but most of it is "unstructured"

To most of us, the internet has become such an integral part of our lives that it hardly warrants second thought. From mundane status updates to secure online financial transactions, there are few activities that haven't been touched, transformed, or even created by the internet. Of course, it goes without saying that this ubiquity leads to a tremendous amount of data, most of which is what we might call "unstructured", i.e. text-based as opposed to machine-readable.

A blessing and a curse

Academic researchers are beginning to explore the link between web-based sentiment and stock returns

For quantitative investors, this is a blessing and a curse. More data is good of course, but unstructured information, which is often qualitative in nature, can be challenging to use in a systematic investing framework. Nonetheless, quant researchers are beginning to make headway. In the last few months, we have noticed a growing number of papers looking at ways to use web-based data in a systematic investment process. For example, in the September edition of our *Academic Insights* report we flagged a paper that used aggregate sentiment from the daily status updates of over 100 million U.S. Facebook users to predict equity market returns and volumes.[1] In similar vein, another recent paper argued that the sentiment in Twitter posts, or "tweets", can be used to predict day-ahead excess returns and trading volume at the stock level.[2]

Beyond the headlines… again

This paper continues a series of papers we have published looking at the use of text-based data in quant investing

Our own interest in using unstructured data stems from the pioneering work we did on the subject of news sentiment. Since 2009, we have published a number of research papers studying how news sentiment metrics, gleaned from the text of financial news stories, can be used as an alpha signal.[3] In this research, we cast our net wider and consider the whole breadth of the web. We will make the argument that finance-specific stories are already widely scrutinized by human investors, and consequently may be more efficiently priced than less obvious – but perhaps equally pertinent – information from, say, a financial blog.

Tomorrow today

We introduce a new database of structured web data

Specifically, in this report we introduce an interesting new database of structured web data, provided by a company called Recorded Future. A novel feature of this database is the ability to identify future events before they happen. For example, suppose a (hypothetical) blog post reads "Apple is expected to release the iPhone 5 on November 5th, 2012". The technology behind the Recorded Future database can identify and extract this future date, and store it as a structured record in a standardized format.

How might stocks react to such future events? Can we build an alpha strategy that chases such future events? For the answers to these questions and more, read on.

Regards,

Yin, Rocky, Miguel, Javed, John, and Sheng
Deutsche Bank North American Equity Quantitative Strategy

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[1] For more details, see: Cahan et al., 2011, "Academic Insights", *Deutsche Bank Quantitative Strategy*, 28 September 2011, p. 10

[2] For more details, see: Cahan et al., 2011, "Quantum", *Deutsche Bank Quantitative Strategy*, November 2010

[3] See for example Cahan et al., 2010, "Signal Processing: Beyond the headlines", *Deutsche Bank Quantitative Strategy*, 20 July 2010; and Salvini et al., 2011, "Introducing the MIR", *Deutsche Bank Quantitative Strategy*, 10 November 2011

A peek into the future

Adding structure to the web

We use a database of structured we by data provided by a company called Recorded Future

In this research, we use a database of structured web data from a company called Recorded Future. The database begins at the start of 2009, and contains structured information extracted from around 40,000 different web sources, ranging from traditional media sites and government portals to blogs and Twitter feeds. The idea is to extract certain elements of information from each source, and store those elements in a structured, machine-readable fashion. The most obvious type of information that one might want to extract is references to *entities* (e.g. people, places, companies) and *events* (e.g. acquisitions, legal issues, management changes). However, Recorded Future goes beyond entity detection and also introduces a *temporal* element, i.e. when was the entity reference made, or when will the event occur?

The basic process is depicted in Figure 1. Recorded Future describes the data storage mechanism as a "cube" with three dimensions: structure, time, and metrics. We elaborate on each of the three dimensions below.[4]

Figure 1: Adding structure to an unstructured web
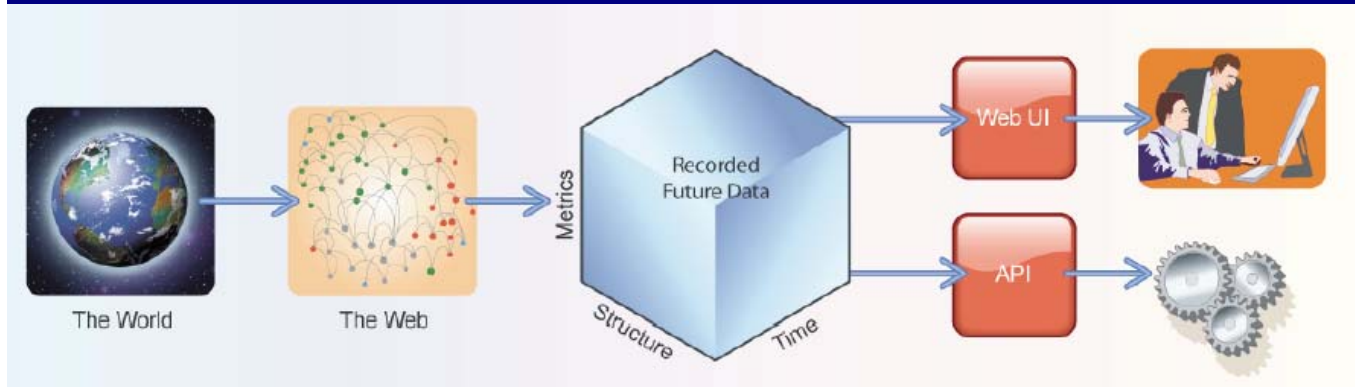
Source: Recorded Future, reproduced with permission from Truve, S., 2011, "Big data for the future: Unlocking the predictive power of the web"

The data collection process involves identifying entities and events, along with any temporal information

- **Structure** – This involves taking unstructured data from the web, and extracting information about entities and events, as mentioned above. These events and entities are then combined with what is called *ontological* information, which is basically a specification of the relationships that can exist between entities and events. For example, what country is a certain city located in, who is the leader of a certain company, etc.

- **Time** – This requires the identification of when things happen, both in the past and in the future. This is a non-trivial task, because dates are often non-specific (e.g. "the end of 2012") or relative (e.g. "tomorrow", "yesterday"). Thus a set of rules is needed to convert a wide range of potential types of date reference into a timestamp.

- **Metrics** – These are computed by Recorded Future to help determine which entities or events are important. For example, one such metric is a concept called *momentum*, which effectively measures the online "buzz" around an entity. Other metrics measure the positivity or negativity of the sentiment around the entity. We expand on these metrics in the next section where we backtest some of them.

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[4] For more detailed information on the data collection process, see: Truve, S., 2011, "Big data for the future: Unlocking the predictive power of the web", *Recorded Future,* October 2011

Key items in the database include companies that are mentioned together with the main entity (coentities), sentiment and momentum metrics, and temporal information

A snapshot of the database
Putting this all together, Figure 2 shows a snapshot of what the data actually looks like (note here we are displaying only select columns for illustrative purposes only). Some of the most interesting columns include:

- **Fragment Coentities** – Lists other entities that are mentioned in the same sentence fragment as the main company. We will expand on this point when we explore a concept called coentity momentum later in this report.

- **Positive, Negative, Momentum** – Measures the positive sentiment, negative sentiment, and the "buzz" associated with the stock. We will examine these metrics in more detail in the next section.

- **Type** – Indicates the type of reference made to the company. For example, EntityOccurrence means the company was mentioned, whereas CompanyCompetitor means the stock was mentioned in reference to a competitor. We will expand on these types in more detail when we look at how stocks react to different events later in this report.

- **Future Start, Future Stop** – The start and end date of any future events detected (note how these are after the publication date). For less precise events, the start and stop dates may be different, e.g. "…in the third quarter of 2011" would appear as start = 1-Jul-2011; stop = 30-Sep-2011. In the snapshot below, all the events happen to be one-day events (i.e. start = stop).

Figure 2: Selected columns and rows from Recorded Future database

Stock	Fragment Coentities	Positive	Negative	Media Type	Type	Momentum	Fragment	Published	Future Start	Future Stop
Apple	Apple,Steve Jobs	NA	NA	News Agency	EntityOccurrence	0.32	Apple's Jobs takes medical leave, shares tumble.	14-Jan-09	21-Jan-09	21-Jan-09
Apple	Apple,Steve Jobs	NA	NA	Mainstream	EntityOccurrence	0.19	Apple Inc chief and tech visionary Steve Jobs is set to take a medical leave of absence until the end of June because of health problems that are more complex than thought, backtracking on reassurances, stunning investors and sending its shares skidding 10 percent on Wednesday.	15-Jan-09	21-Jan-09	21-Jan-09
Apple	Apple,Steve Jobs	NA	NA	News Agency	EntityOccurrence	0.21	Apple Inc chief and tech visionary Steve Jobs will take a leave of absence till end-June because of health problems more complex than thought, backtracking on reassurances, stunning investors and sending its shares skidding 10 percent on Wednesday.	15-Jan-09	21-Jan-09	21-Jan-09
Apple	Apple,Steve Jobs	NA	NA	News Agency	EntityOccurrence	0.44	Apple chief and tech visionary Steve Jobs will take a leave of absence till end-June because of health problems more complex than thought, backtracking on reassurances, stunning investors and sending its shares skidding 10 percent on Wednesday.	15-Jan-09	21-Jan-09	21-Jan-09
Apple	Steve Jobs,Apple	NA	NA	News Agency	EntityOccurrence	0.38	Apple chief and tech visionary Steve Jobs will take a leave of absence till end-June because of health problems more complex than thought, backtracking on reassurances, stunning investors and sending its shares skidding 10 percent on Wednesday.	15-Jan-09	21-Jan-09	21-Jan-09
Apple	Apple,CEO	NA	NA	Mainstream	EntityOccurrence	0.19	Apple shares slump as CEO goes on medical leave.	15-Jan-09	21-Jan-09	21-Jan-09
Apple	Apple	0.21	NA	Blog	EntityOccurrence	0.47	AAPL - news - people) did little to address these questions on its quarterly earnings call Wednesday, letting stronger than expected sales and earnings speak for themselves amidst a quarter that wrecked much of the rest of the tech industry.	21-Jan-09	28-Jan-09	28-Jan-09
Apple	Research in Motion,Apple	NA	NA	Blog	CompanyCompetitor	0.23	Comparing shares of RIM to its biggest rival, Apple Inc. (NASDAQ:	27-Mar-09	2-Apr-09	2-Apr-09
Apple	Apple,senior vice president of worldwide product marketing,Phil Schiller	NA	NA	Blog	PersonCareer	0.05	Apple will kick off its annual Worldwide Developers Conference (WWDC) with a keynote address on Monday, June 8 at 10:00 a.m. A team of Apple executives, led by Philip Schiller, Apple's senior vice president of Worldwide Product Marketing, will deliver the keynote.	14-May-09	8-Jun-09	8-Jun-09
Apple	Apple,Intel	0.69	NA	Mainstream	Alliance	0.25	With the purchase, is Intel picking up some cues with its partnership with Apple?	4-Jun-09	3-Jun-10	3-Jun-10

Source: Recorded Future, Deutsche Bank

Mining the web for alpha

Testing a new quant factor based on web data

Our first step is to backtest some linear alpha factors based on the data

We start our analysis where we often do, with some basic backtesting to get a feel for what the data looks like. As a first pass, we consider the factors listed in Figure 3. These factors are all what we might call aggregate factors, in the sense that they are computed for each stock based on multiple web mentions over the course of a trailing aggregation window.

Figure 3: Quant factors from the Recorded Future (RF) database

| Factor	Definition
RF Momentum Score	Provided by Recorded Future (RF). Proprietary measure of online "buzz". The momentum score is related to a number of factors, including the change in the number of references about a company and the credibility of sources mentioning that company.
RF Positive Sentiment	Provided by RF. Computed using a statistical model based on n-gram frequencies of particular words and phrases in positive business language.
RF Negative Sentiment	Provided by RF. Computed using a statistical model based on n-gram frequencies of particular words and phrases in negative business language.
RF Factor	Calculated as *RF Momentum Score * (RF Positive Sentiment - RF Negative Sentiment)*. Essentially captures sentiment weighted by the amount of online "buzz" the stock is getting.
Count	Number of references to the company in the aggregation window.

Source: Recorded Future, Deutsche Bank

The data starts in 2009, and coverage increases over time

Because of the short data history, which starts in 2009, we focus on daily backtesting. This means that we need to exercise extra care to ensure we don't accidentally introduce a look-ahead bias. To this end, all of the factors are snapped using data up to 3.30pm EST each day. We then assume we can execute the trade at the close on that day, and hold the position until the close on the following day.

In Figure 4 we can see the coverage for the S&P 500 universe over the data history. Coverage starts at about 200 stocks per day and rises to around 400 by the end of the sample. This is a reflection of the fact that, even in the large cap universe, not all companies are mentioned on the web every day. Indeed, as Figure 5 shows, large companies are of course much more likely to be mentioned than smaller companies.

Figure 4: Number of S&P 500 stocks with Recorded Future data
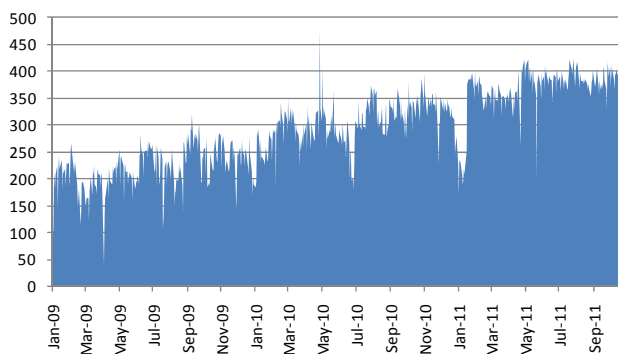
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

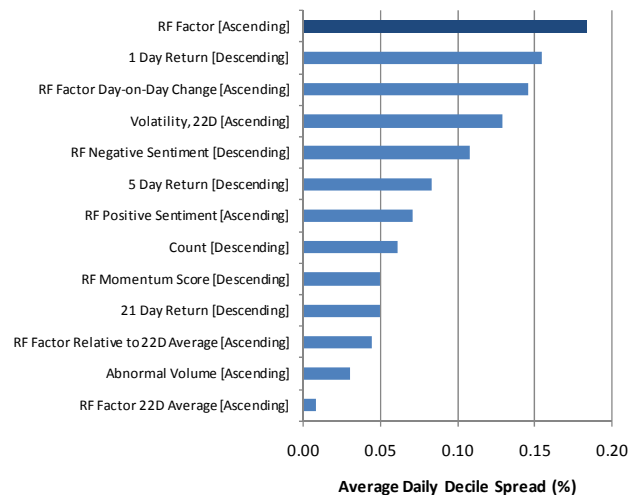**Figure 5: Relationship between market cap and number of mentions, as at 30 Sep 2011**
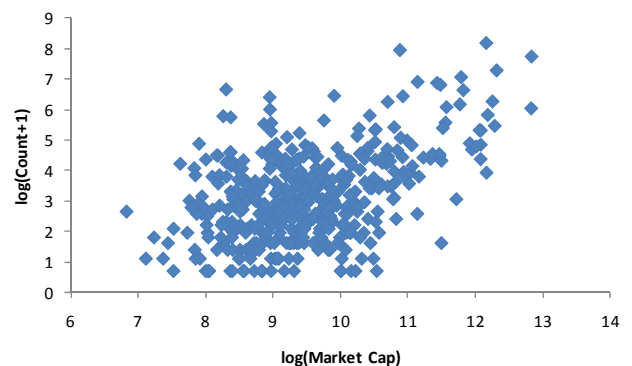
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

The RF Factor outperforms other common daily quant factors like 1-Day Reversal
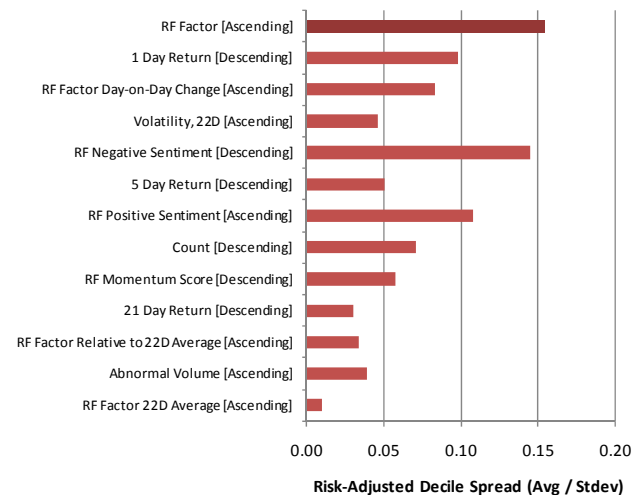
Basic backtesting statistics

Figure 6 shows the average top decile minus bottom decile return spread for the RF factors, along with some other common "short-term" factors for comparison purposes. Interestingly, the RF Factor, which blends web momentum with web sentiment, is the best performing of all the factors we considered over this backtest period. In other words, stocks that have good web "buzz" and positive sentiment tend to outperform on a one day horizon. This is also true on a risk-adjusted basis (Figure 7). In both raw and risk-adjusted terms, the RF Factor outperforms the 1 Day Reversal factor, which is typically one of the strongest factors on a one day basis.

Figure 6: Comparison of decile return spread versus other common short-term factors

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 7: Comparison of risk-adjusted decile spread versus other common short-term factors

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

The time-series of decile spread returns is shown in Figure 8, and the cumulative performance in Figure 9. Note that both these results are pre-costs; we will address the crucial question of transaction costs shortly.

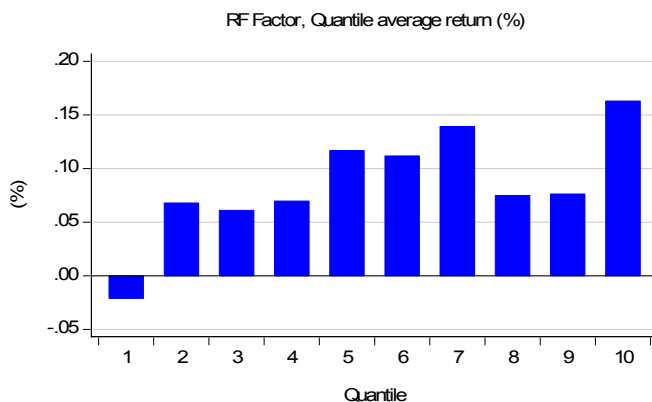**Figure 8: RF Factor, average daily decile return spread**

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 9: RF Factor, cumulative decile spread return
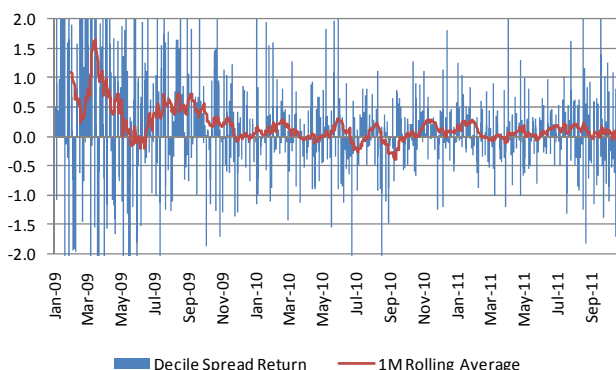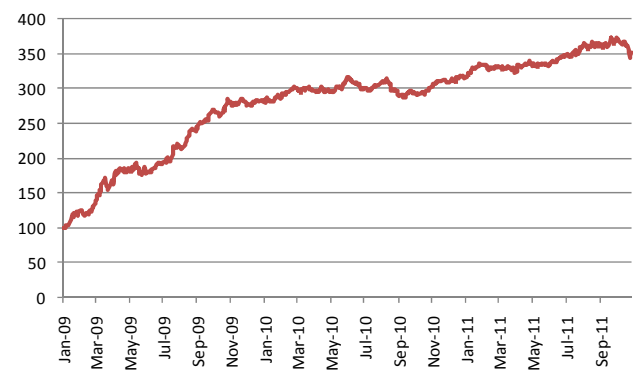
Source: Recorded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank
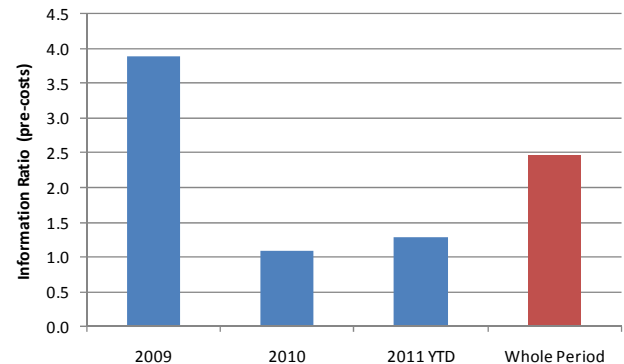
The factor also shows a relatively monotonic pattern of average decile returns, which is promising (Figure 10). However, on the negative side, we do notice a decline in factor efficacy from about 2010 onwards – this can be seen clearly in the time-series charts and also in Figure 11, which shows the information ratio of the strategy by calendar year.
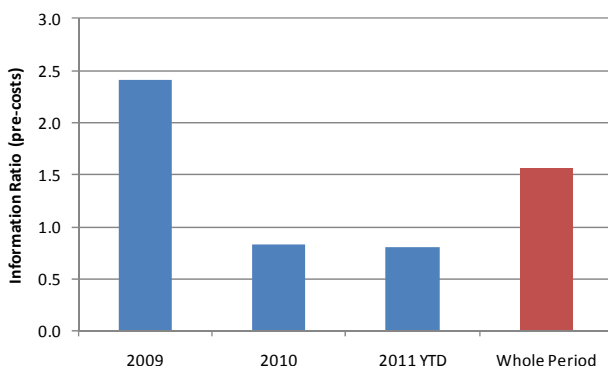
Figure 10: RF Factor, average daily decile returns

RF Factor, Quantile average return (%)

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 11: RF Factor: Information ratio (pre-costs)

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

The factor has lost some efficacy in 2010-11, but the decay has been no worse than for other short-term quant factors

Which such a short history, it is difficult to determine the cause of this slowdown. One could speculate that perhaps the increase in interest in news sentiment based strategies in the last two years has precipitated some of the decline as the forces of arbitrage come into play. Having said that, the RF Factor was certainly not alone in seeing a decline in efficacy in 2010 and 2011. For example, two of the other top performing factors – 1 Day Reversal (Figure 12) and Trailing Volatility (Figure 13) – experienced very similar declines in predictive power. This suggests there are larger forces at play. We would hypothesize that the likely culprit is the macro-dominated environment that has characterized recent years; it's hard to play stock-specific factors when everyone is pricing assets based on their exposure to macro risk.

Figure 12: 1 Day Reversal: Information ratio (pre-costs)

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 13: 22D Volatility: Information ratio (pre-costs)

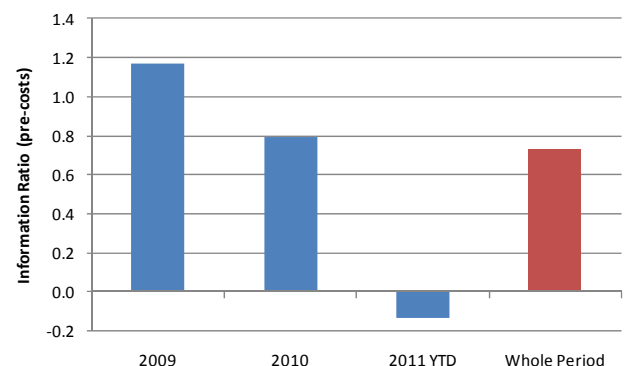
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Correlation analysis shows the RF Factor is not highly correlated with typical daily quant factors

A proxy for momentum or abnormal volume?

In the higher-frequency world (intraday to one day rebalancing), there are arguably even less factors to play compared with the traditional lower-frequency world (monthly rebalancing and up). This is because at higher frequencies, company fundamentals matter very little; hence almost all signals are tied to some degree to either price action (e.g. short-term momentum or reversal), volume (e.g. abnormal volume), or some combination of the two (e.g. technical trading rules).

As a result, the question of correlation is even more important than in the low-frequency world. With such a finite set of factors, there is a good chance any new factor will just be a proxy for some of the other price or volume based factors. In Figure 14 we show the correlation matrix for our set of factors. The correlations are computed as time-series correlations based on the daily long-short decile spread returns for each strategy.

Figure 14: Correlation of daily decile spread returns

	RF Momentum Score	RF Positive Sentiment	RF Negative Sentiment	RF Factor	1 Day Return	5 Day Return	21 Day Return	RF Factor Relative to 22D Average	RF Factor Day-on-Day Change	RF Factor 22D Average	Abnormal Volume	Count	Volatility, 22D
RF Momentum Score	1	0.11	0.18	0.06	-0.06	-0.18	-0.15	-0.14	0.00	0.18	0.14	0.82	-0.31
RF Positive Sentiment		1	0.14	0.36	-0.02	-0.08	-0.16	0.04	0.08	0.32	0.19	0.18	-0.26
RF Negative Sentiment			1	0.52	-0.12	-0.07	0.11	0.12	0.17	-0.12	0.07		-0.34
RF Factor				1	-0.20	-0.16	-0.04	0.06	0.45	0.32	0.08	0.03	-0.32
1 Day Return					1	0.45	0.08	-0.11	-0.16	0.03	0.03	-0.01	0.02
5 Day Return						1	0.47	0.20	-0.03	-0.18	-0.03	-0.16	0.18
21 Day Return							1	0.09	0.22	-0.40	-0.26	-0.20	0.30
RF Factor Relative to 22D Average								1	0.09	-0.02	0.11	-0.02	0.10
RF Factor Day-on-Day Change									1	-0.09	0.03	-0.05	0.10
RF Factor 22D Average										1	0.24	0.22	-0.59
Abnormal Volume											1	0.21	-0.12
Count												1	-0.26
Volatility, 22D													1

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

The RF Factor is not just a proxy for short-term momentum or reversal

The results are encouraging. The section of the matrix highlighted shows the correlation of the RF Factor with each of the other factors. The correlations with non web-based factors tend to be fairly low, or even negative. Notably, the correlation with 1-Day Return is -0.2, which suggests the RF Factor is not just a proxy for 1-day price reversal.[5] The correlation is also negative with 5-Day and 21-Day Momentum, which reinforces the idea that the RF Factor is different from simple price momentum.

It is also uncorrelated with abnormal volume, but negatively correlated with volatility

The other correlations worth noting are the 0.08 and -0.32 correlations with Abnormal Volume and Volatility, respectively. Abnormal Volume measures today's volume divided by the average volume of the stock over the past month. Therefore we can conclude that the RF Factor is not just buying stocks that see a pop in volume. On the other hand, Volatility measures the standard deviation of daily returns over the past 22 days. In our backtesting, this is a positive factor at the 1-day horizon, i.e. higher volatility leads to higher returns the next day. So the negative correlation with the RF Factor is telling us that the factor is more likely to be buying low volatility stocks rather than high volatility stocks, i.e. the strategy tends to be short volatility.

Overall, the backtesting results and correlation results are promising, but a big question mark remains. Will the performance survive transaction costs?

Transaction costs: A silent killer?

In high frequency trading, costs are the crucial question

In Figure 15 we show the information decay profile for the RF Factor. As expected, it is a high turnover factor; all the alpha is gone after the first day. This suggests that harnessing the full potential of the factor will be challenging in the presence of transaction costs. Another way to look at the potential turnover of the factor is to consider the signal autocorrelation, i.e. how much do the factor scores change from one day to the next. Figure 16 shows the results. The average autocorrelation is around 30%, which is actually quite high for a short-term factor (by way of comparison, 1-Day Reversal has an average autocorrelation of zero).

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[5] Note we take 1-Day Return to be a reversal factor, hence the RF Factor acts in the opposite direction to a strategy that buys yesterday's losers and sells yesterday's winners; this is expected since the RF Factor is something of a momentum metric rather than a reversal signal.

Figure 15: Information decay profile, decile spread returns
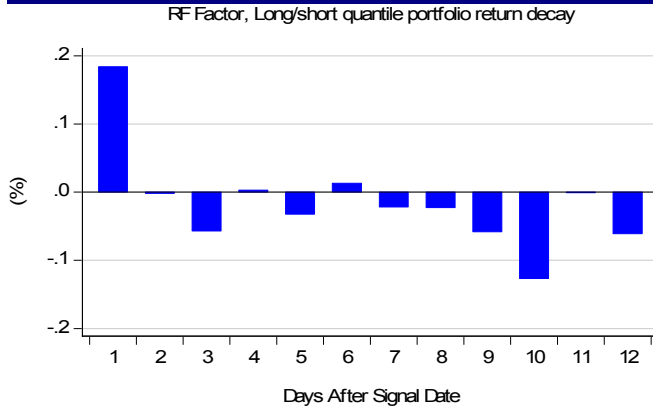
RF Factor, Long/short quantile portfolio return decay

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 16: Signal autocorrelation from day *t*-1 to day *t*

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

We run a fully optimized weekly backtest, and consider the after-cost performance at various levels of transaction costs

To evaluate whether we can extract any after-cost alpha out of the signal, we conduct a real-world simulation. Specifically, we conduct a weekly backtesting using the Axioma portfolio optimizer to construct a mean-variance optimal, market neutral portfolio each week. The alpha signal is of course the RF Factor, and we apply sector and beta neutrality constraints. We leave turnover unconstrained, but set the objective function to maximize expected return and minimize transaction costs. The portfolio targets a risk level of 15% annualized.
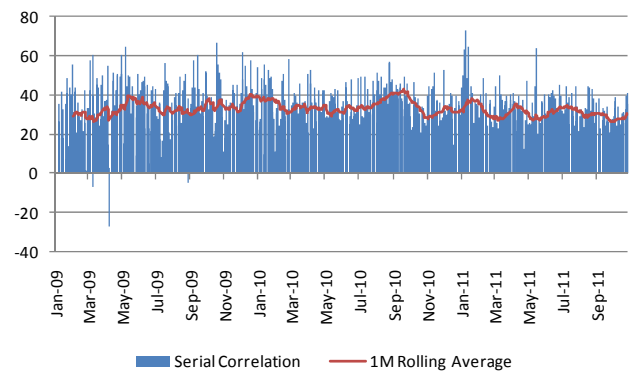
Figure 17 shows the weekly turnover of the portfolio. As expected it is very high, and averages around 250% (note this is two-way turnover for a market neutral portfolio, so the maximum turnover in a given period is 400%). Next, we evaluate the impact of transaction costs by assuming varying degrees of linear transaction costs (Figure 18).

Figure 17: Two-way turnover of RF factor optimized portfolio, rebalanced weekly
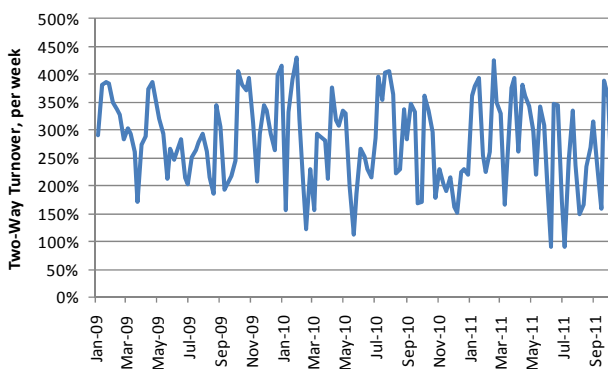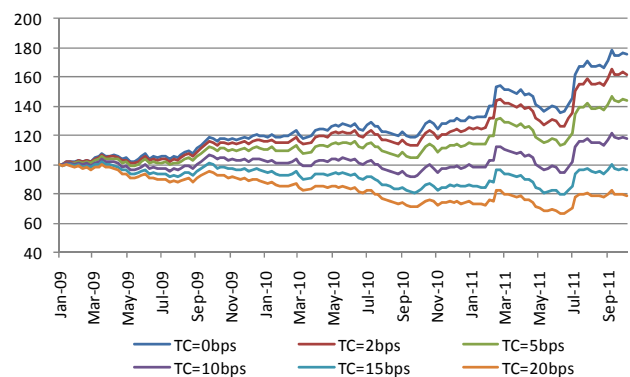

Source: Recoded Future, Axioma, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 18: Cumulative returns for varying degrees of one-way, linear transaction costs

Source: Recoded Future, Axioma, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

We find breakeven costs of around 15bps; we think this is achievable

To make the breakeven point easier to see, we show the after-cost, annualized information ratio of the strategy under each cost assumption in Figure 19. Based on these results, the breakeven cost is around 10-15bps for a one-way trade. With the rise in cheap electronic execution, and the fact the strategy is only trading liquid, S&P 500 names, we would argue that achieving execution costs in this ballpark is not unattainable for higher-frequency traders.
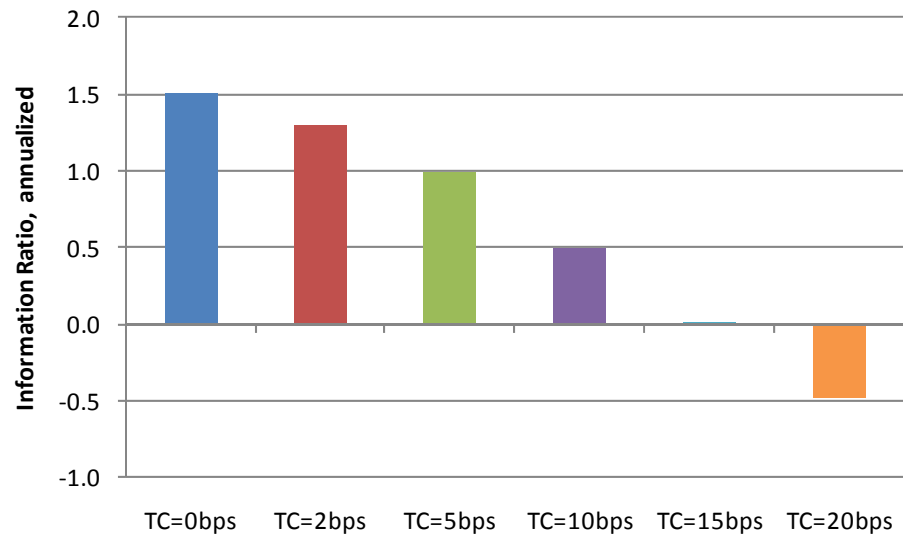
Figure 19: After-costs, annualized information ratio at various levels of one-way transaction costs (i.e. these costs are charged twice for a round-trip rebalance)

Source: Recoded Future, Axioma, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

What about long-term investors?

For longer-term investors, the RF Factor is a good candidate to use as a trade-timing tool, given it outperforms other common tools like 1-Day Reversal

So far we have focused on nimble, short-term investors who can rebalance at least weekly with relatively low costs. In the following sections we will discuss some ways to use the web data with a longer investment horizon, but before we do we would argue the results above can also be useful for long-term investors who are looking for trade-timing tools.

A growing area of research is the idea of using short-term signals to help time a longer-term buy or sell decision. For example, a recent paper by Isrealov and Katz [2011] shows how even long-term investors can benefit from using short-term signals to better time long-term trades. The beauty of such an approach is that one can capture some of the alpha in the short-term signal, without any incremental turnover (after all, you have to make the trade anyway).

This is an area that we plan to do more research in going forward, but for now suffice it to say that the RF Factor appears to be a good candidate for such a trade-timing tool.

Event horizon

How do stocks react around future events?

In this sector we study how we can use the web data to detect and trade events

In the previous section we evaluated how signals from the web could be used as stand-along alpha factors. In this section we explore what we think is the most interesting aspect of the Recorded Future (RF) database: the ability to detect specific event types and the timing of those events. Figure 20 shows the frequency of various event types in the RF database. The most prevalent is the PersonCareer type, which is used when an individual, say a company CEO, is mentioned along with the company.

Figure 20: Frequency of events (greater than 1,000 occurrences)
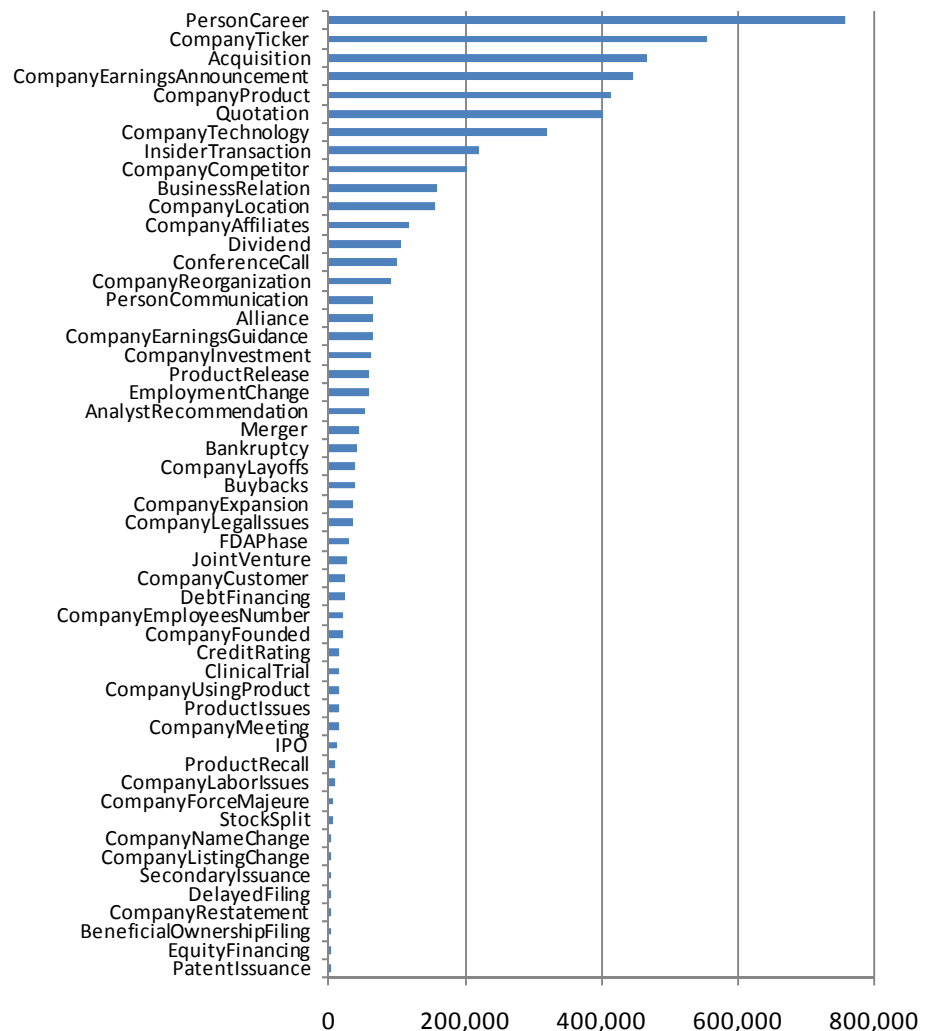
Source: Recorded Future, Deutsche Bank

To make things more concrete, Figure 21 shows some examples of different event types for Apple (AAPL). For example, the top row is an example of the PersonCareer type we previously mentioned. In this case a reference is made to Steve Jobs, the late CEO of Apple. Other examples include the CompanyTicker event which is used when the company ticker is mentioned, for example in a market commentary report, and the Acquisition event, which obviously applies to content that mentions takeovers or mergers.

Figure 21: Some examples of events for Apple (AAPL)			
Ticker	Predefined Event Type	Publication Date	Event Fragment
AAPL	PersonCareer	2-Mar-11	"Apple CEO Steve Jobs once again took the center stage and made a surprise appearance at the launch of the new iPad at an event in San Francisco."
AAPL	CompanyTicker	10-Sep-09	"Apple Inc. (NASDAQ: AAPL) Raised to Outperform at JMP Securities."
AAPL	Acquisition	22-Apr-10	"As rumors go, it doesn't get more shocking than the whisperings Wednesday night, that gadget maker Apple Inc. was mulling a move to buy British chip shop ARM Ltd."
AAPL	CompanyEarningsAnnouncement	2-Apr-11	"We may finally get some answers on April 20, when Apple reports its earnings for the second quarter of 2011."
AAPL	CompanyProduct	5-Mar-10	"Apple Inc., expanding beyond the iPhone and Macintosh desktops and laptops, plans to start selling its iPad tablet computer in the U.S. on April 3 and will take preorders for the device next week."

Source: Recorded Future, Deutsche Bank

Note that there is also an event type called EntityOccurrence, which is actually the most common of all events as it is used whenever an entity is mentioned. In fact, a single piece of web content can lead to multiple records, one of which will be an EntityOccurrence reference. For example, the CompanyTicker event above would also give rise to an EntityOccurrence event (not shown) and also potentially an AnalystRecommendation event (also not shown).

Look to the future

A key feature of the database is the ability to detect future events with some precision

So far we have said nothing about timing, but to our mind this is one of the most interesting aspects of the database. In traditional financial event studies, the date of interest is usually the announcement date. For example, when a takeover is announced, the target company will typically rally on the day of the announcement; in an efficient market this new piece of information should be priced immediately. However, not all events are so clear-cut. Sometimes, we might be interested not in the announcement-day reaction, but in the reaction on the actual future event day. For example, consider the events in Figure 22.

Figure 22: Some examples of "future events" for Apple (AAPL)				
Ticker	Predefined Event Type	Publication Date	Event Fragment	Future Date
AAPL	CompanyEarningsAnnouncement	2-Apr-11	"We may finally get some answers on April 20, when Apple reports its earnings for the second quarter of 2011."	20-Apr-11
AAPL	CompanyCompetitor	25-Oct-10	"On November 14 Sprint, the No. 4 U.S. mobile service will kick of sales for $400 for the Tab, which is seen as the most credible competitor so far to Apple Inc's popular iPad, which has on sale for $630 since earlier this year."	14-Nov-10
AAPL	BusinessRelation	28-Sep-09	"Given that the first-generation iPhone originally went on sale in the UK on November 9th 2007, as an exclusive to O2, it seems a reasonable prediction that Orange will begin selling their version on November 9th 2009."	9-Nov-09
AAPL	CompanyLegalIssues	12-Aug-11	"Samsung will have the opportunity to defend itself against Apple in a German court on August 25th."	25-Aug-11
AAPL	ConferenceCall	30-Mar-11	"Mark your calendars: Apple has announced that it will hold its quarterly financial results conference call on Wednesday, April 20, 2011 at 2 p. m. Pacific, 5 p. m. Eastern."	20-Apr-11
AAPL	CompanyExpansion	1-Jul-10	"Apple will open the store in the Lujiazui area in Pudong New Area on July 10."	10-Jul-10
AAPL	CompanyLaborIssues	27-May-11	"...reports that Apple is being targeted for protests by US Uncut, an organization seeking to stop companies from avoiding taxes, with the organization planning a series of protests at Apple's retail stores on June 4th."	4-Jun-11

Source: Recorded Future, Deutsche Bank

Take the second row as an example. Here is a somewhat complicated CompanyCompetitor event. As shown in the text snippet, the article makes reference to the future date when Sprint will begin offering Samsung's Galaxy Tab, a competitor to Apple's iPad tablet. Note the publication date for this story: October 25th, 2010. This was almost a month before the actual event date, which the Recorded Future algorithms successfully extracted as November 14th, 2010. The interesting question we can now pose is: how might the stock price of Apple (and indeed Samsung) react on the day that Sprint starts selling Samsung's iPad rival?

In theory, most of the market reaction to an event should come on the announcement date, not the event date

Efficient market aficionados would argue that the information was known a month in advance, so there should be little reaction on the day of the event itself; the market should have had plenty of time to price in the implications. However, a growing body of literature argues that investors suffer from limited attention, and as a result bits and pieces of useful information are overlooked in the daily deluge of news that investors are confronted with. In this example, one could reasonably assume that for a high profile stock like Apple, and a flagship product like the iPad, there will be plenty of investors keeping close watch on the stock and events like this one. But every day there are thousands of such events mentioned in far flung places all over the web. As a quantitative investor, the natural question is whether there are patterns in the way stocks trade around certain events that can be exploited.
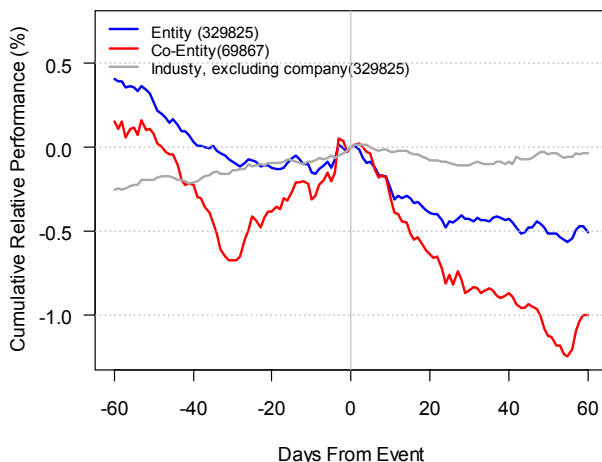
Stock returns around future events

We track the performance of the entity, its coentities, and its sector around future events of different types

To help answer this question, we ran event studies around the 52 different event types listed in Figure 20, as well as the EntityOccurrence event (again, think of this as capturing all events, regardless of type). We limit our analysis to events that meet two important criteria:

- **Event is one day long** -- As mentioned previously, some events have imprecise timing, e.g. "third quarter of 2011". Therefore we limit our analysis only to events that can be precisely defined as one day long (i.e. start date = end date).

- **Event is at least five days in the future** – We limit ourselves to events that are at least five days in the future, to ensure that we would have time to take a position *before* the event occurs. As a result, unlike a traditional event study, where the event-day return is typically hard to capture, our event studies are tradable from day *t*-4 onwards.

Figure 23: Excess returns around EntityOccurrence events

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 24: Excess returns around PersonCareer events
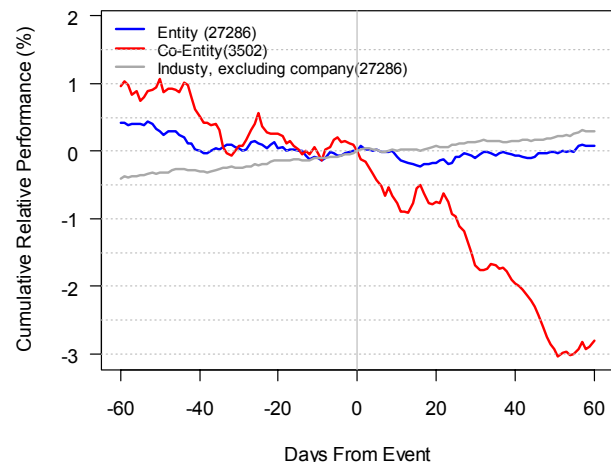
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

*On average over the sample, events lead to negative returns for entities and also coentities*

Figure 23 and Figure 24 show the results for the two most populous event types: EntityOccurrence and PersonCareer. In each chart we use the Russell 3000 universe, and all returns are excess returns over the equally-weighted Russell 3000 benchmark. In each chart we show three lines: the blue line shows the cumulative returns to the entity that is involved in the event, the red line shows the cumulative returns to the coentities that are mentioned in the same sentence fragment as the main entity, and the grey line shows the return of the GICS Industry Group (i.e. level 2) for the entity. The idea of the latter two lines is to see if there are any contagion effects that flow on from the main entity to other stocks that are closely mentioned on the web or in the entity's sector.

Interestingly, for the EntityOccurrence events in Figure 23 above, the average entity company underperforms the market both before and after the future event. Furthermore, the stock's coentities actually underperform by even more. This interesting coentity result is also seen in the PersonCareer event type. However, given the diverse range of possible events that are captured by these two categories, it is hard to come up with an intuitive explanation for the results.

For some events, the main reaction is on the announcement day as expected, but for others the move is on the event day

Instead, consider two of the more specialized event types: Acquisitons (Figure 25) and BusinessRelation (Figure 26). In the Acquisition chart we see a result that confirms that for some events, the announcement date not the event date is all that matters. The big jump around day *t*-5 comes by construction; because we are limiting ourselves to events that occur at least five days in the future, we end up getting a lot of announcement dates clustered around day *t*-5 in the chart, hence the big jump. In contrast, for the BusinessRelation event, there does seem to be some movement, particularly for coentities, on the event date. This is where things start to get interesting, because recall again that the event date was in fact known before the fact.

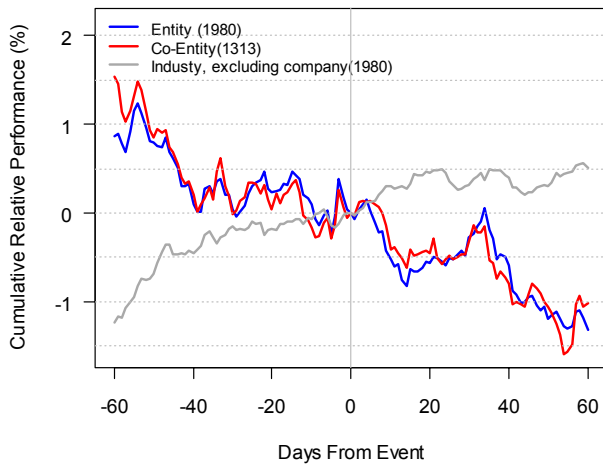**Figure 25: Excess returns around Acquisition events**
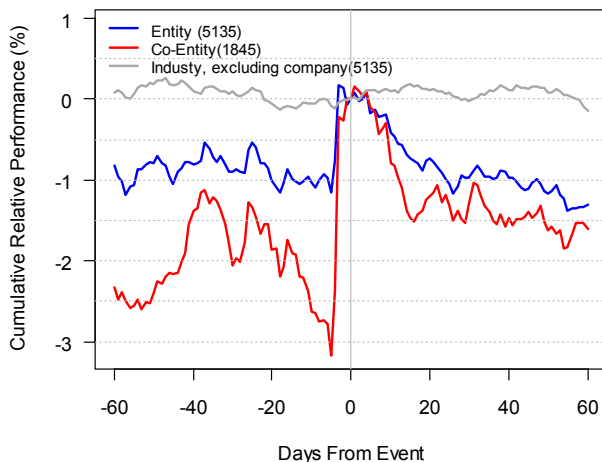
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

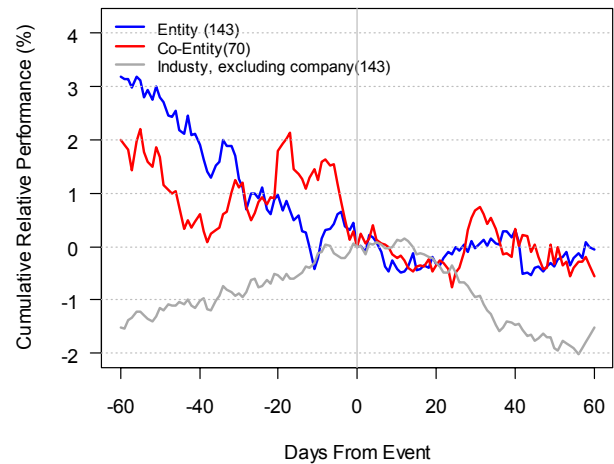**Figure 26: Excess returns around BusinessRelation events**
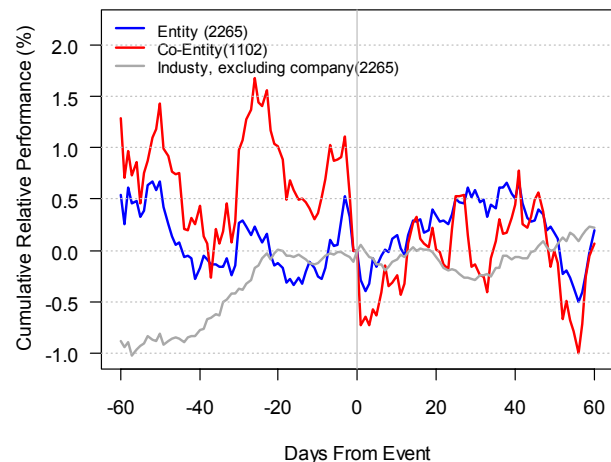
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

In the following charts, we show the results for a number of other event types. If you would like the complete set of charts for all event types, please let us know and we would be happy to provide them.

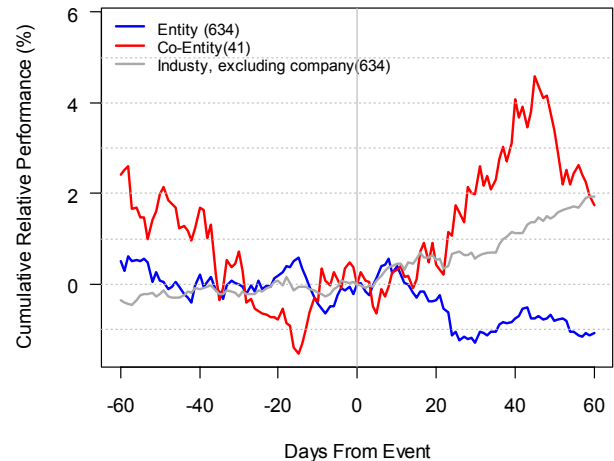**Figure 27: Excess returns around CompanyCompetitor events**

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

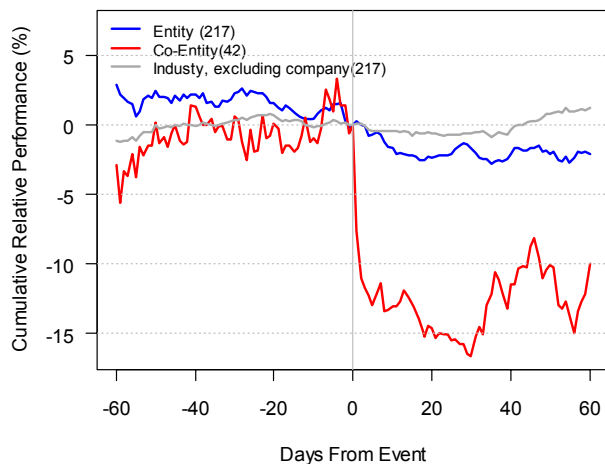**Figure 28: Excess returns around CompanyCustomer events**

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 29: Excess returns around CompanyEarningsAnnouncement events
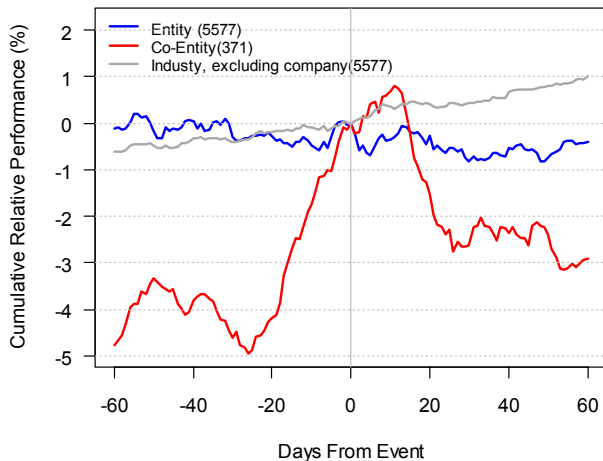
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank
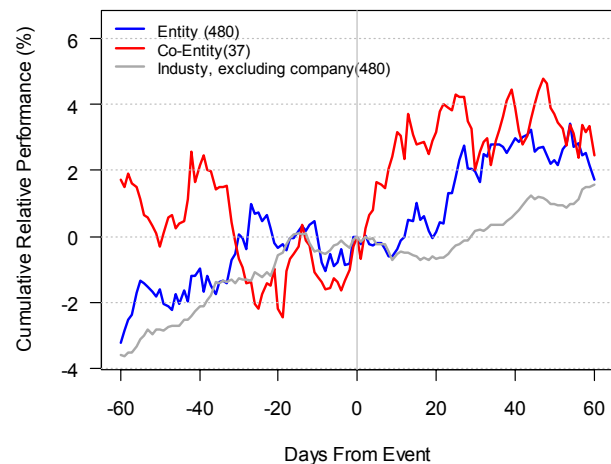
Figure 30: Excess returns around EarningsGuidance events

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 31: Excess returns around CompanyLaborIssues events

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 32: Excess returns around CompanyLayoffs events

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

It is hard to see a clear pattern in the event study charts; some events are positive on average and some are negative

Overall, the results are something of a mixed bag. Some charts show intriguing features, for example Figure 27 shows returns around CompanyCompetitor events. Here we see that the average entity returns and the coentity returns track each other very closely, suggesting a tight correlation between stocks that are competitors to each other. Thinking back to the Apple and Samsung example earlier, this is perhaps not surprising.
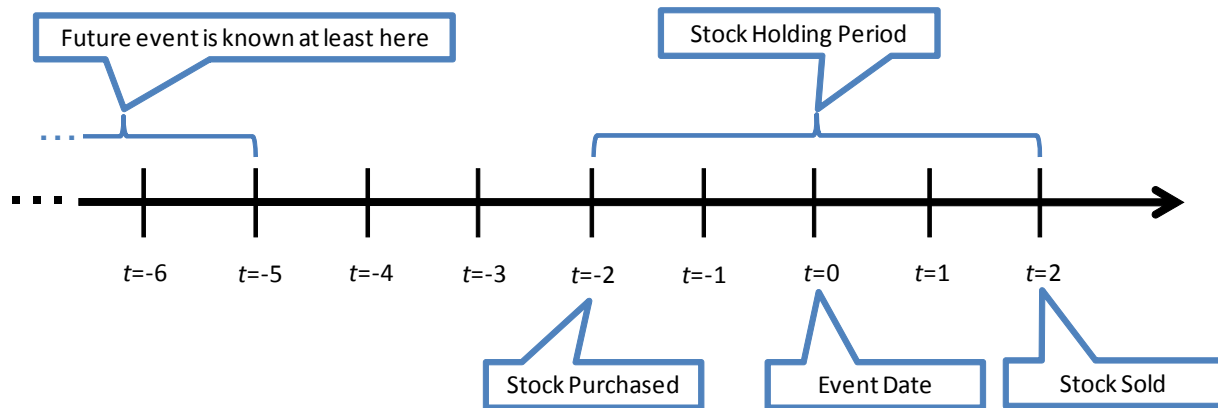
Another interesting example is the CompanyLaborIssues chart in Figure 31. In that chart we see significant underperformance from the coentities when a fellow company suffers from labor issues (e.g. a strike). This hints strongly at a contagion effect from the affected company into other "similar" (in the sense they are mentioned together frequently on the web) companies.

But how can we trade this?

We devise a simple trading strategy, where we hold event-stocks for a five day window around know future events

While we could eyeball the event study charts all day, and spin plausible stories to explain them ad nauseum, the whole point of quantitative investing is to be as objective as possible. Therefore, our main interest is coming up with a systematic trading strategy that might be able to exploit some of the interesting trading patterns highlighted above. With this in mind, we examine the events from another angle: suppose we form a simple, long-only trading strategy that buys a stock two days before a certain event occurs, and sells it two days after. At the risk of belaboring the point, we stress again that such a strategy does not suffer look-ahead bias, because we are limiting ourselves to events that are known today, but will actually occur at least five days in the future, as illustrated in Figure 33.

Where there are multiple events occurring simultaneously, we equally weight our capital among the stocks.

Figure 33: Simple strategy for trading future events

Future event is known at least here

Stock Holding Period

t=-6 t=-5 t=-4 t=-3 t=-2 t=-1 t=0 t=1 t=2

Stock Purchased

Event Date

Stock Sold

Source: Deutsche Bank

For some events, there is quite a difference between the trading strategy returns in large versus small caps

Figure 36 shows the cumulative returns to such a strategy, focusing on the EntityOccurrence event type (which captures all events). We test a Russell 3000 strategy as well as an S&P 500 strategy. Note that both strategies are long-only, and the returns shown are excess returns over the benchmark. The chart shows an interesting difference between events in Russell 3000 stocks and S&P 500 names: on average the strategy outperforms over the whole Russell 3000, but underperforms in large caps.

In contrast, if we look at another event type, in this case the Acquisition event, we see that the strategy on average underperforms significantly in both universes (Figure 35). This is effectively saying that on average, if we buy stocks that are taking part in acquisitions (either as the acquirer or acquire) on average we will underperform. Perhaps more evidence that mergers are value-destructive on average?

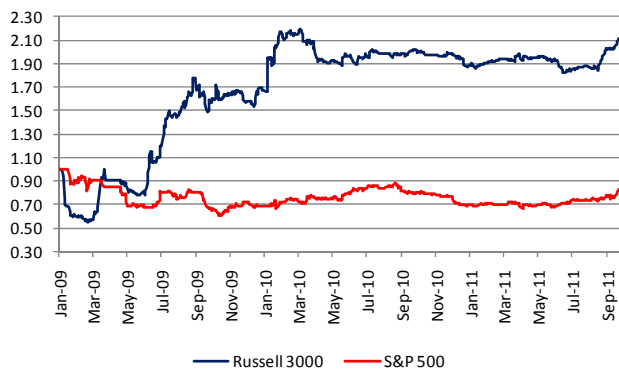**Figure 34: Cumulative relative performance of EntityOccurrence event strategy**
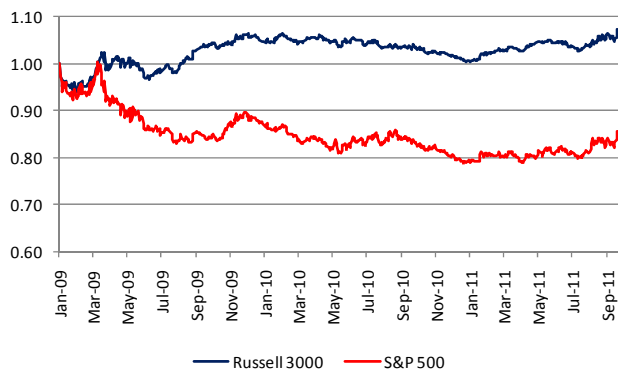
Figure 35: Cumulative performance of Acquisition event strategy
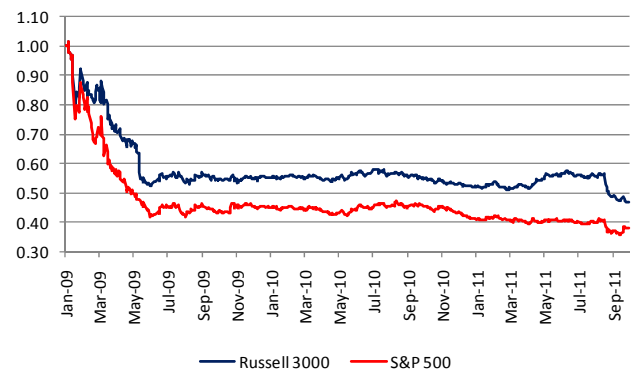
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank
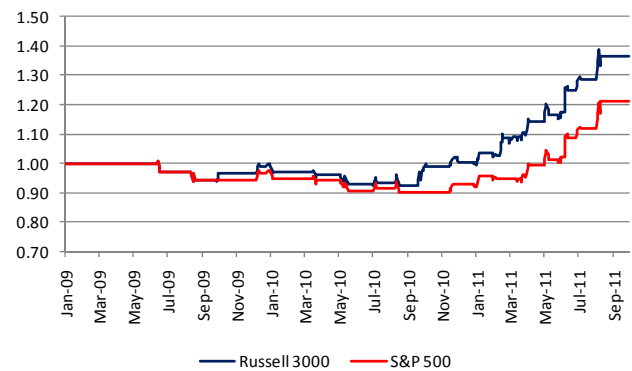
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

One of the best performing event types is related to buying stocks around disaster events

Figure 36 and Figure 37 show two other event types, ConferenceCall events and CompanyForceMajeure events respectively. Interestingly, for the former we again see a marked difference between large cap stocks and the whole universe. One hypothesis would be that the information released on management conference calls matters a lot more for less heavily covered small cap stocks. For CompanyForceMajeure events, which capture disasters which befall companies (e.g. the Japanese earthquake disrupting Apple's supply chain for example), the results suggest that these stocks tend to be oversold and recover on average after the event.

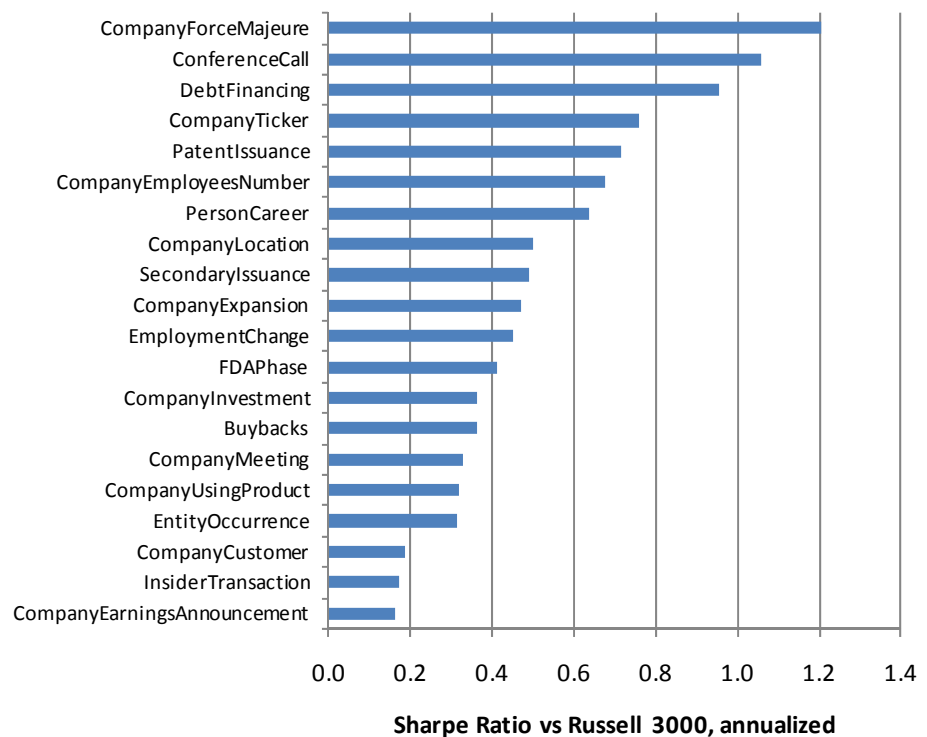**Figure 36: Cumulative relative performance of ConferenceCall event strategy**

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 37: Cumulative performance of CompanyForceMajeure event strategy

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

We rank events by the performance of our event trading strategies over the sample period

In the interests of space, we do not reproduce charts for all the event types here – these are available on request. Instead, Figure 38 shows the 20 most profitable event-based strategies, based on the Russell 3000 universe. Performance is measured as the annualized Sharpe ratio of each strategy, relative to the Russell 3000 benchmark.

Figure 38: Top 20 event types by risk-adjusted excess returns, Russell 3000 universe

Sharpe Ratio vs Russell 3000, annualized

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

It turns out two of the best strategies are the two mentioned previously: trading around CompanyForceMajeure events and ConferenceCall events. A number of other strategies also yield attractive returns.

However, in this type of analysis the risk of data mining is very real. In the same way that picking factors for a multifactor model after the fact will tend to inflate model performance (because we are almost certain to pick the factors that worked best up to that point), so too will picking the best events after the fact. This problem is exacerbated here because we have such a short history to test our strategies over. The question we need to ask ourselves is: would we have really known that ConferenceCall and CompanyForceMajeure events would turn out to be the best strategies if we were standing back in 2009?

Out-of-sample trading tests

The problem is, how can we be sure the events that worked in the past will continue to work?

A more conservative test is to evaluate whether we can profit from event trading strategies using only information we had at each point in time. To this end, we test two momentum-based strategies:

- **Cross-sectional strategy** – Each day, we evaluate the past returns to individual strategies trading each of 53 event types. We then use these past returns to determine the weight of capital we are willing to allocate to each strategy in the next day. Because we are in a long-only world, we allocate zero capital to the event strategies that have had negative past returns in the formation period. We test different formation periods ranging from one month to one year.

- **Time-Series strategy** – In this strategy we treat each event as a separate portfolio, and use the past returns of each strategy to determine whether we go long the event portfolio or hold cash for the following day.

In both strategies, we assume one-way trading costs of 10 bps (these are charged twice for a round-trip trade) and assume a one-day lag from signal date to implementation. The charts below show the cumulative performance for each of the two strategies, using both three and twelve month momentum as our signal.
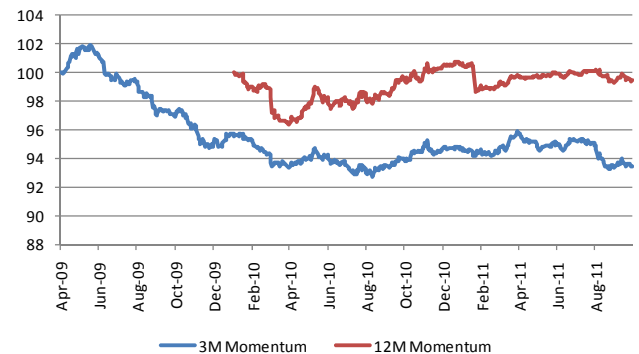
Figure 39: Cross-sectional: After-cost excess returns to long-only event momentum strategy
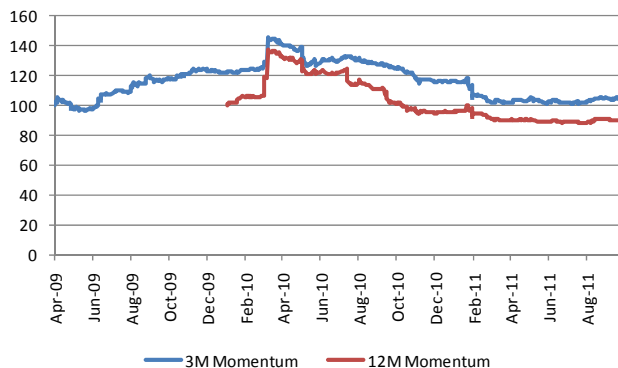
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 40: Time-series: After-cost excess returns to long-only event momentum strategy

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

We show that it is difficult to pick which events to allocate capital to, based solely on the past performance of the event strategies

Overall, the results tell us is that using the past returns to pick the events to allocate capital towards is not a fruitful strategy. This is analogous to what we typically find in the more familiar world of quant factors; in our research on style rotation, we found that past factor performance was an ineffective way to predict future factor performance.[6] In fact, we showed that it was only when we injected exogenous information into the problem – in that case economic and capital market indicators – that we were able to achieve good predictive power. It seems plausible that a similar argument applies here.

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[6] Luo et al, 2010, "Signal Processing: Style rotation", *Deutsche Bank Quantitative Strategy*, 7 September 2011

For example, consider the ConferenceCall event. Clearly, the returns around such an event will somewhat depend on the current market environment – if times are tough and firms are struggling, then we can reasonably expect that on balance the average management earnings call will have more negative information surprises than positive. Hence, on average returns to a strategy that chases this type of event might be negative under these conditions. On the other hand, if times are good and there are more surprises to the upside on the call, then returns to the event strategy are more likely to be positive.

Future directions

Future research should focus on ways to use macro variables to pick which events will work at different points in the business cycle

What this implies is that we also need a directional indicator when trading events. Many of the event types listed back in Figure 20 could reasonably be expected to move stocks in both directions, depending on the information released on the event day. A classic example is an event quants are all familiar with: the earnings surprise. A naïve strategy of simply buying stocks in the five days around their earnings announcement date is clearly not going to work without some ex ante indicator to predict the expected direction of the earnings surprise. This is an area we plan to expand on in future reports. If we can find indicators that help us predict the direction a stock will trade around common events, then perhaps we can expand the breadth of the traditional earnings surprise strategy to other event types.

Don't forget about risk

Risk is another dimension where knowing about upcoming events can be useful

However, there is one dimension where direction does not matter – risk prediction. Regardless of the positivity or negativity of the news, we might reasonably expect that there will be an increase in volatility on the future event day. To test this hypothesis, we repeat our previous event study charts, except this time we focus on volatility. Because we want a point estimate of volatility on each day, we use intraday 1-minute bar returns to compute realized volatility on each trading day. We then normalize the intraday volatility of each stock on each day by dividing it by the equally-weighted average intraday volatility of all stocks on that day. As before, we also include the impact on coentities and the entity's sector.

For example, Figure 41 shows the results for the EntityOccurrence event (recall this captures all event types). There is indeed a sharp spike in realized volatility around the event date. Interestingly, the volatility also appears to spill over into the coentities as well.

Figure 41: Relative volatility around EntityOccurrence events
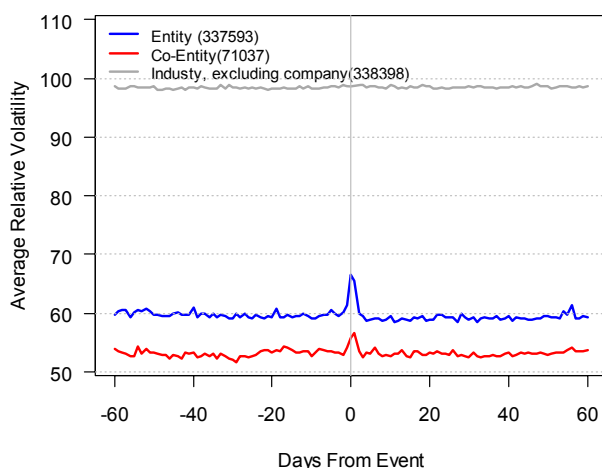
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

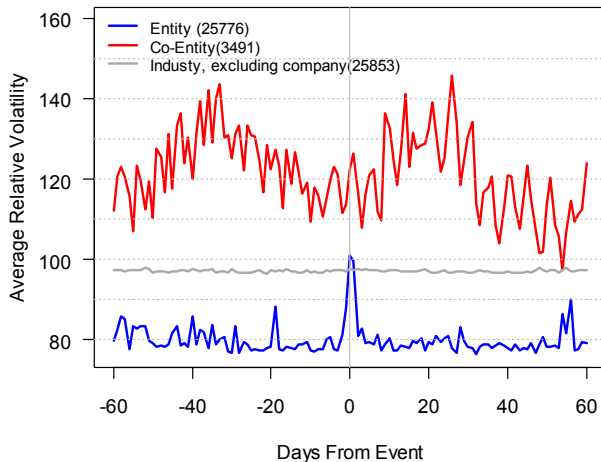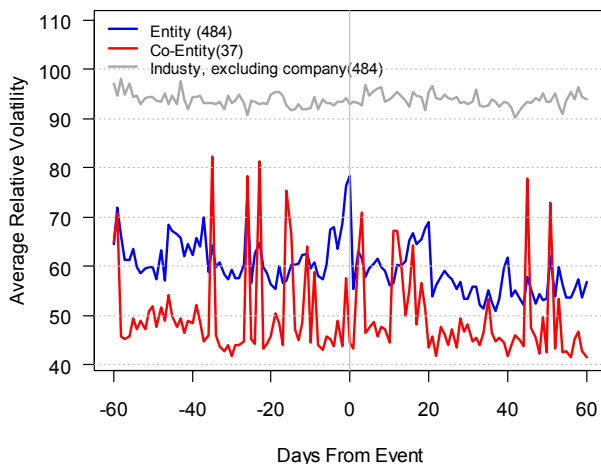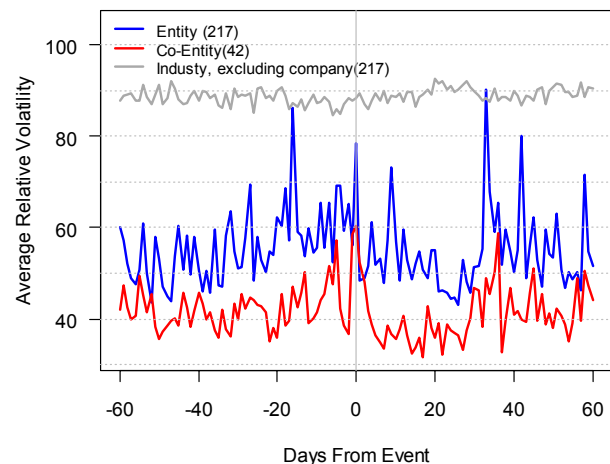**Figure 42: Relative volatility around CompanyEarningsAnnouncement events**
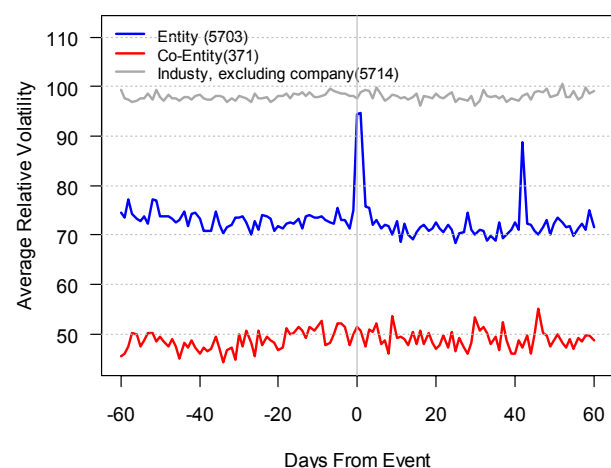
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

We track the change in intraday volatility for stocks around future event dates

Note that in the chart, the reason the red and blue lines have average relative volatilities of 50-60% is because of the size bias in event frequency. Large cap stocks (which on average have lower volatility) tend to have more events; hence these stocks dominate the averages and push the relative volatility well below 100% (which is effectively market volatility). Nonetheless, we mainly care about the change in volatility on the event date relative to the rest of the period.

The following charts show the volatility around some of the other comment events. Again, the complete set of charts is available on request.

Figure 43: Relative volatility around ConferenceCall events

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 44: Relative volatility around PersonCareer events
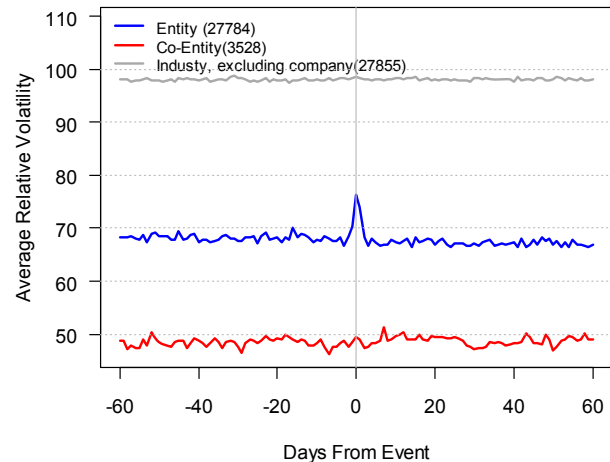
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 45: Relative volatility around CompanyLayoff events

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 46: Relative volatility around CompanyLaborIssues events

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

For many event types, we see a clear jump in volatility on the event day

For many of the event types, there is a clear jump in volatility around the event day for the entity, and often for coentities as well. Again, it is worth remembering that these are events that we would have known about at least five days in advance, so we would have had time to take a position well before the event actually occurred. This suggests there is scope for some interesting options strategies designed to exploit the sudden but predictable jump in volatility around future events. This is beyond the scope of this paper, but something we will look at in future research.

Building a better risk model

Back in the plain vanilla equity world, risk prediction is also important. The asset-by-asset covariance matrix is a crucial ingredient in the portfolio construction process for most quants. With the above results in mind, one interesting question is whether we can improve our risk prediction, and hence the accuracy of our risk model, by incorporating the expected volatility spike due to future events into our model. For example, we could upweight the risk of stocks that we know will have a future event within our forecast horizon. We could also tweak the covariance of stocks that are coentities of those stocks, given our finding that many events seem to have a contagion effect into related (in a web sense) names.

A suggestion for future research: can we use the information about upcoming events to tweak our risk model?

Again, a full analysis is worthy of its own report, so here we focus on a single result that hints at the possibility on this front. Suppose we are running a very simple risk model, where we assume our best guess for the future volatility of each stock is its historical volatility. Next, supposed we define the following cross-sectional regression:

$$\frac{\sigma_{i,[t-1,t]}}{\sigma_{i,[t-M-1,t-2]}} - 1 = c_t + \beta_{event,t} D_{event,t} + \varepsilon_t$$

where $\sigma_{i,[a,b]}$ is the volatility of daily returns from month a to month b for stock i, and $D_{event,t}$ is a dummy variable denoting if stock i will experience an event in month t.

In more intuitive terms, the expression to the left of the equal sign is just the percentage change in volatility for each stock in the latest month, relative to its past volatility in the previous M months. For example, if $M = 3$ then we are just computing the percentage increase or decrease in the stock's daily volatility over this month, compared to the prior three months. We then regress this percentage change cross-sectionally on a dummy variable that takes on a value of 1 if the stock had an event in the most recent month, and 0 otherwise. If the $\beta_{event,t}$ coefficient is positive and significant, then we know that stocks with events do indeed have a larger change in volatility in the event-month compared to their past volatility, versus the change for stocks with no events.

Figure 47: Beta coefficient from cross-sectional volatility regression
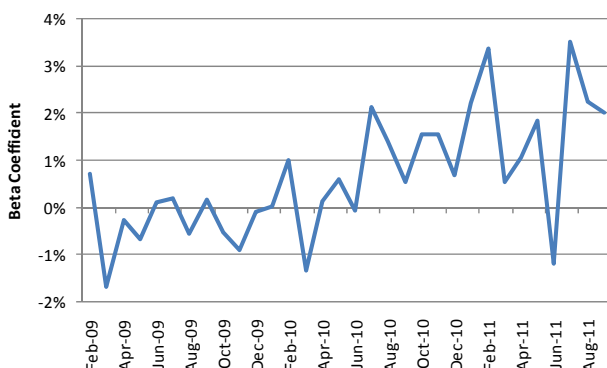
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 48: T-statistic for beta coefficient from cross-sectional volatility regression
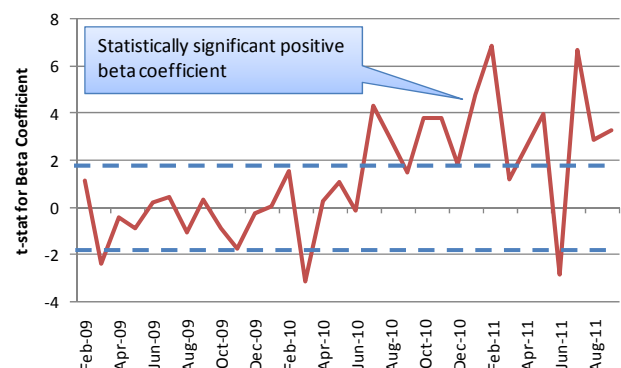
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

We find some evidence that future events are positively related to a larger than average increase in month-ahead volatility

In the charts above, Figure 47 shows the value of the beta coefficient through time, and Figure 48 shows the corresponding t-statistic. Interestingly, there is some evidence in the more recent years that events are indeed associated with a higher change in volatility in the month where the event occurs.[7] Note that a crucial point in this analysis is that we only include events in the dummy variable if they were known at time t-1. This means that this analysis is forward looking. For example, suppose we observed the beta coefficient was consistently positive over time, i.e. we knew that past volatility consistently under-predicted future volatility for stocks that have future events. Then at time t-1 we could take our volatility estimates from t-M-1 to t-1, and then increase the volatility estimates for those stocks with known future events coming up in month t-1 to t by β_{event} percent. If events continue to lead to higher volatility in the future, then such a process should lead to a better ex ante estimate of risk for those stocks with upcoming events.

Future work could examine whether we can use future events to tweak our risk forecast

Clearly the analysis above is grossly simplified – after all a good risk model is not going to rely purely on past volatility to predict the future – but we think the concept has some merit. For example, if we are using a vendor-provided risk model, we could perturb the stock-specific risk component for those stocks that we know have events upcoming. Similarly, we could delve deeper and try to use the fact that there is volatility spillover into coentities to modify the covariances between web-related stocks.

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[7] Given the rather short-lived spike in volatility around event days, we are probably understating the result here by using a monthly frequency. Using a weekly frequency would probably have been a better idea, but that would have necessitated using intraday returns (since five days of daily returns is too little to compute realized volatility over).

Untangling the web

Network analysis

In this section we study the performance of stocks that are closely related on the web, i.e. they are often mentioned together

In this section, we focus on ways to trade, and hopefully profit from, the way companies are related on the web. In the previous section we touched on the idea of coentities, i.e. other companies that are mentioned in the same sentence fragment as the entity itself. We showed how sometimes events that affect the entity can spill over and impact the returns of the coentities as well. Of course, as quants we have seen this effect before under a different guise: stocks in the same sector tend to move together, and are often impacted by contagion events. However, the web data offers a way to move beyond rigid sectors, and generalize the idea of company "connectedness" in a more natural way. If two companies are frequently mentioned together on the web, it stands to reason there is some link between them in the physical world.

To illustrate this idea, consider the network graph in Figure 49. Here we use the entire Recorded Future (RF) database to tease out the strongest relationships between companies. The size of each circle effectively indicates how often a company is mentioned on the web from 2009 to now, and the thickness of the connecting lines indicates how frequently two companies are mentioned together in the same sentence fragment.

Figure 49: Example network graph, weighted by "PageRank" algorithm on frequency of co-mentions
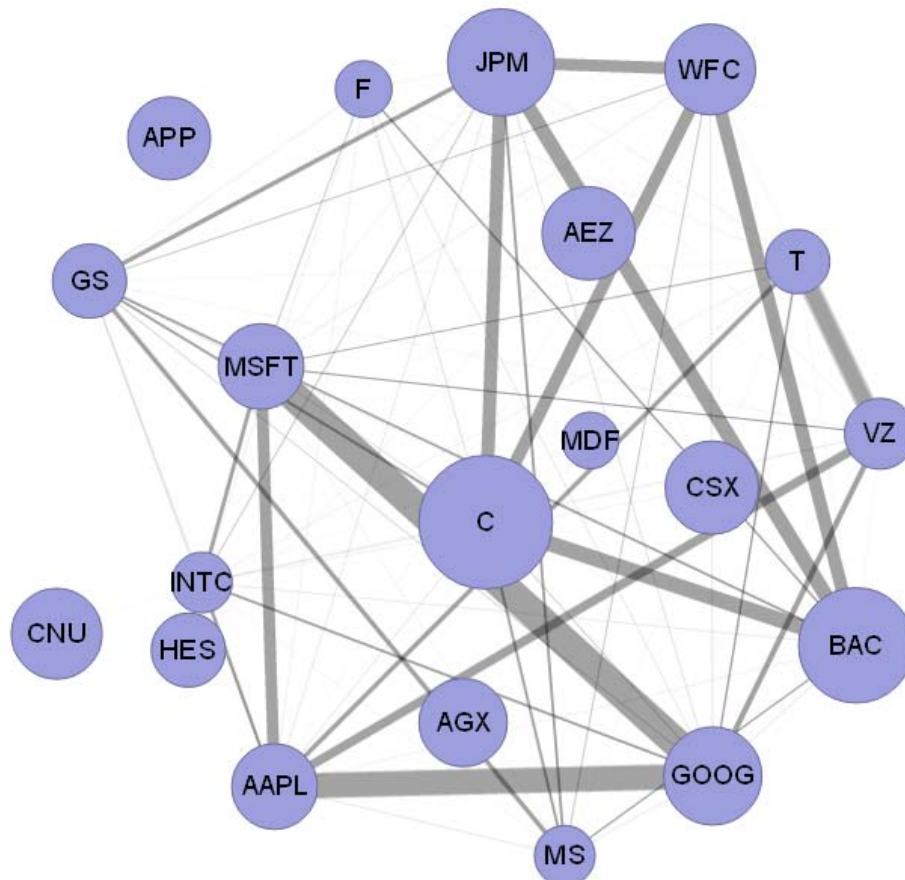
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

A network graph is a useful way to visualize relationships

You can think of this as a "PageRank" of sorts, similar to what Google uses to measure the importance of web pages, i.e. stocks are most prominently displayed if they have lots of links to other important stocks in the universe. The results are quite intuitive. For example, Google (GOOG), Apple (AAPL), and Microsoft (MSFT) form a triumvirate of tech stocks; it should come as no surprise that these three names are frequently mentioned together on the web. Similarly, Citigroup (C), Bank of America (BAC), JP Morgan (JPM), and Wells Fargo (WFC) are tightly connected. Both these results make sense, and indeed would be picked up by traditional sector links.

Cross-sector connections between stocks are particularly interesting

Things get more interesting when we have relationships that cross sector lines. For example, Ford (F) has a reasonably strong link to Bank of America (BAC). This is interesting as the reason for such a link is not obvious. Perhaps Bank of America has provided financing to Ford? Whatever the reason, this type of result suggests there might be a hidden relationship here between the stocks, that the market may be overlooking.

Introducing coentity momentum

In the September edition of our *Academic Insights* paper, we reviewed an interesting paper by Nguyen [2011] that proposed a concept called "geographic momentum". The idea behind geographic momentum is simple. Many companies derive a significant proportion of their revenue offshore, a fact that often seems to be overlooked by the market. Nguyen builds a simple momentum factor that is constructed as the revenue-weighted average of the past market returns in each country where the firm does business. The argument is that investors, faced with a dizzying array of information, often overlook the impact of business conditions in markets where the firm does crucial business. He shows that this geographic momentum factor has strong predictive power, even after controlling for the standard Fama-French, Carhart, and Pastor-Stambaugh factors.

We propose a new factor called Coentity Momentum, which is the weighted average of the momentum of a stock's web-determined peers

Our idea is to generalize this concept. Perhaps investors also overlook the importance of past returns to closely related firms, particularly if these relationships cross sector lines. For example, maybe the past returns to a supplier – perhaps located in a completely different industry – can tell us something about future returns to the end user. In essence, can we use the past returns to coentities to predict the future returns of the entity?

We define a simple momentum metric, which we will call Coentity Momentum (CoMo), as follows:

$$CoMo_{F,i,t} = \sum_{j=1}^{J} w_{L,i,j,t} Mo_{F,j,t}$$

where $CoMo_{F,i,t}$ is the Coentity Momentum for stock i at time t using a formation period F, $Mo_{F,j,t}$ is the momentum of stock j at time t over formation period F, $w_{L,i,j,t}$ is the weight applied to the momentum of stock j, and $j=1...J$ is the set of coentities of stock i as determined over a lookback period L. We define the weight as

$$w_{L,i,j,t} = C_{L,i,j,t} / \sum_{j=1}^{J} C_{L,i,j,t}$$

where $C_{L,i,j,t}$ is the number of times stock j appears as a coentity of stock i over the lookback period L.

If this sounds a bit confusing, a simple example is probably an easier way to understand our formulation. Supposed we want to compute the 12-month CoMo for Apple. The first thing we need to do is determine how far we want to look back to find coentity relationships. Since we are interested in 12-month price momentum (i.e. $F=12$), it seems natural to also look back 12 months to find coentities (i.e. $F=L=12$). Now, suppose over the past 12 months, we find that Google has appeared five times as a coentity to Apple, and AT&T has appeared 10 times as a coentity to Apple. Further, suppose the 12-month momentum scores today for
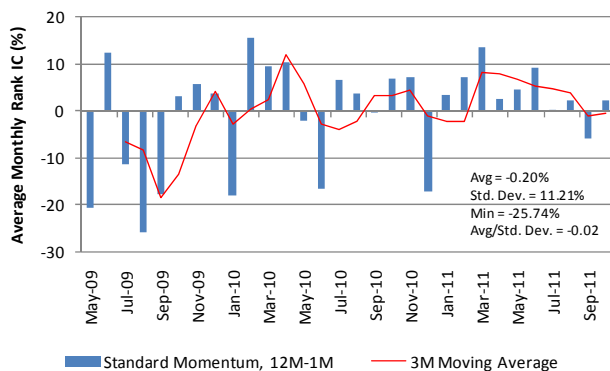
Google and AT&T are 20% and 30% respectively. Then the computation of CoMo for Apple is straightforward. The weight on Google's momentum will be 5 / (5+10) = 0.33 and the weight on AT&T's momentum will be 10 / (5+10) = 0.67. Hence Apple's 12-month CoMo today is 0.33*20% + 0.67*30% = 26.7%.

Empirical results

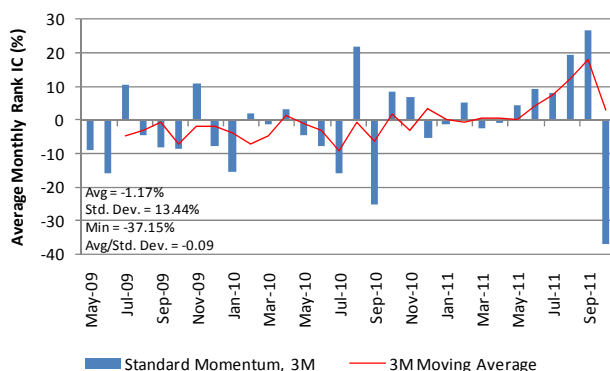*We backtest the performance of CoMo and compare it to the equivalent standard momentum*

Our first step is to backtest the CoMo factor, and compare it with standard momentum. We do this for three different flavors of momentum/reversal: 12M-1M momentum, 3M momentum, and 1M reversal. In each instance, we use a lookback period of 12 months to find coentities. The charts below show the monthly rank information coefficients for each periodicity of momentum; on the left is standard momentum and on the right is CoMo. Note that in each case we start our analysis *after* the start of the junk rally in March 2009. Because of the short history, if we include the massive March 2009 drawdown in our backtest, then that single month completely dominates the results. This is arguably data mining, but the alternative is to have all our results determined exclusively by whether the factor did better or worse than standard momentum on that single month.

Figure 50: 12M-1M Price Momentum, rank IC

Avg = -0.20%
Std. Dev. = 11.21%
Min = -25.74%
Avg/Std. Dev. = -0.02

Standard Momentum, 12M-1M   3M Moving Average

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 51: 12M-1M Coentity Momentum, rank IC
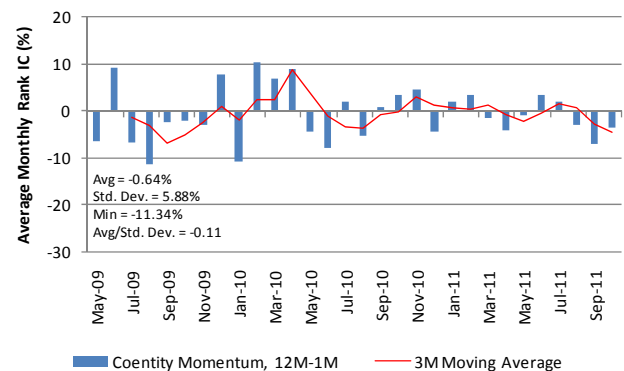
Avg = -0.64%
Std. Dev. = 5.88%
Min = -11.34%
Avg/Std. Dev. = -0.11

Coentity Momentum, 12M-1M   3M Moving Average

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 52: 3M Price Momentum, rank IC

Avg = -1.17%
Std. Dev. = 13.44%
Min = -37.15%
Avg/Std. Dev. = -0.09

Standard Momentum, 3M   3M Moving Average

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 53: 3M Coentity Momentum, rank IC
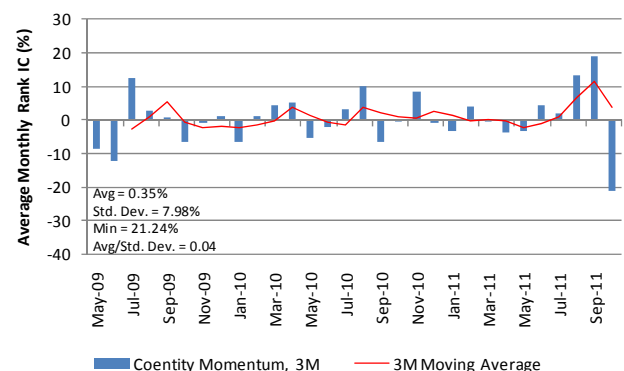
Avg = 0.35%
Std. Dev. = 7.98%
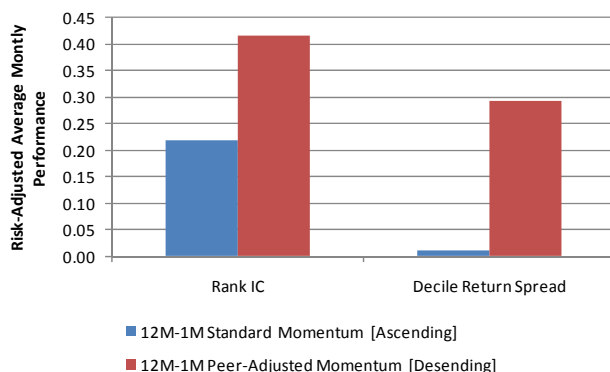Min = 21.24%
Avg/Std. Dev. = 0.04

Coentity Momentum, 3M   3M Moving Average

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 54: 1M Price Reversal, rank IC
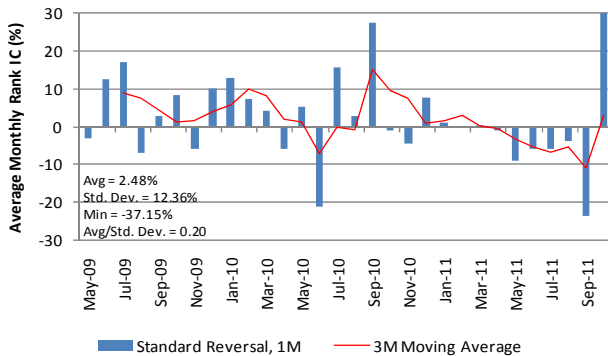
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 55: 1M Coentity Reversal, rank IC
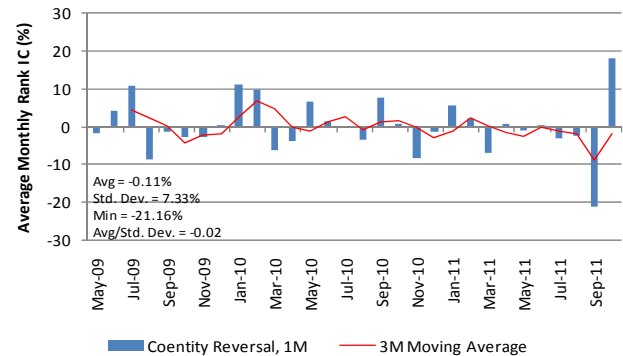
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Overall, the results are disappointing at face value. Only in the 3M momentum case does CoMo do better than standard momentum. This result is easier to see in Figure 56, which compares the risk-adjusted average ICs for each of the strategies.

Figure 56: Risk-adjusted average IC for standard and coentity momentum factors
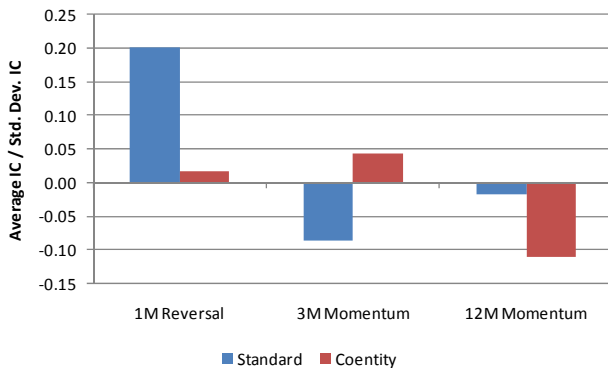
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 57: 12M-1M Coentity Momentum versus 12M-1M Standard Momentum, as at 31 October 2011
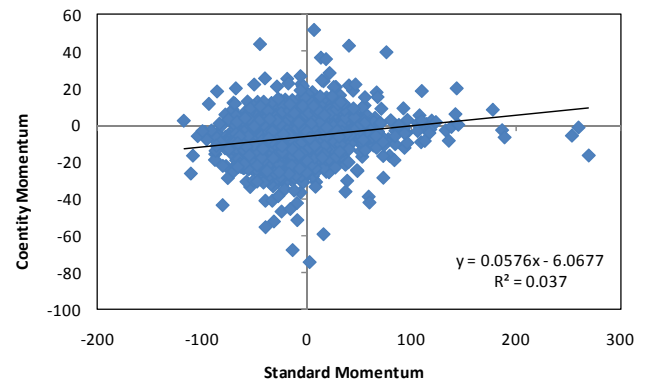
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

We find that CoMo does not consistently outperform standard momentum, so we study the difference between CoMo and standard momentum

Peer-adjusted momentum

However, we are not quite ready to give up. If we consider Figure 57, we can see that CoMo and standard momentum are indeed positively related, but also that their correlation is low enough to suggest that they are picking up on different information. With this in mind, we test a new strategy where we backtest the difference between CoMo and standard momentum. To do this, at each point in time we z-score the CoMo factor and the standard momentum factor, and then define a new, peer-adjusted momentum factor as

$$PeerMo_{i,t} = Z(CoMo_{i,t}) - Z(Mo_{i,t})$$

where $Z(CoMo_{i,t})$ and $Z(Mo_{i,t})$ are the cross-sectionally z-scored CoMo and standard momentum scores for stock i at time t.

In Figure 58 we compare the monthly rank IC of 12M-1M standard momentum versus 12M-1M peer-adjusted momentum (PeerMo), and in Figure 59 we do the same with the top decile minus bottom decile return spread. In both cases we focus on the period from 2010 onwards, which is where longer-term momentum started to work again after the dislocation in the post-risk rally period.[8]

Figure 58: Rank IC comparison between 12M-1M Standard Momentum and Peer-Adjusted Momentum
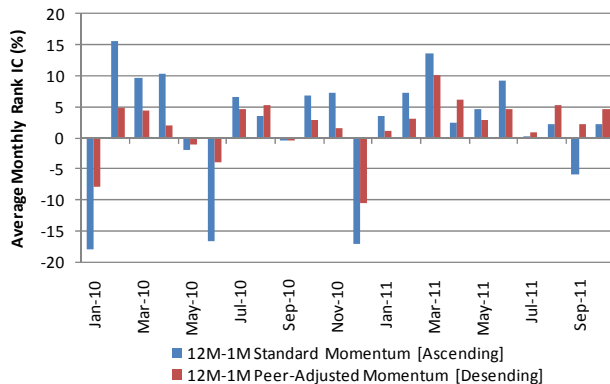
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 59: Decile spread comparison between 12M-1M Standard Momentum and Peer-Adjusted Momentum
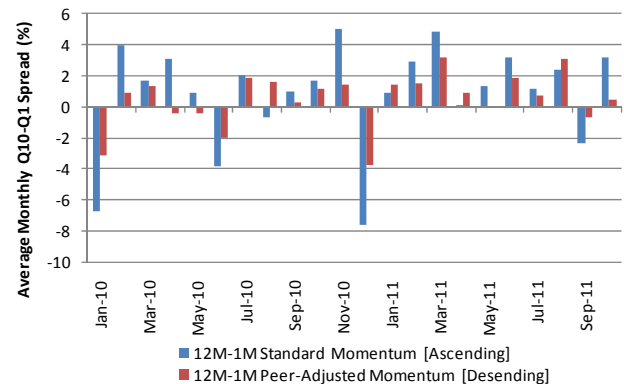
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

We do find evidence that peer-adjusted momentum outperforms standard momentum

To summarize the findings, Figure 60 compares the risk-adjusted average monthly rank IC and risk-adjusted monthly decile spread return for the two strategies. On both metrics, the PeerMo momentum factor outperforms. Furthermore, as shown in Figure 61, this outperformance does not come at the cost of too much extra turnover, as the signal autocorrelations are not significantly different over the life of the backtest.

Figure 60: Average monthly risk-adjusted performance, 2010-present

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 61: Average monthly signal autocorrelation for alterative momentum strategies, 2010-present
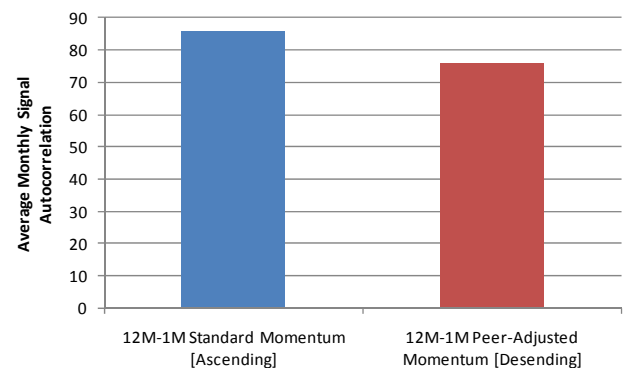
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

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[8] This looks a bit like data mining, and it is to some extent, but we do note that even if we include 2009, peer-adjusted momentum marginally outperforms standard moment (risk-adjusted IC of 0.04 versus 0.02). But given the massive drawdowns of both strategies, we argue it is more sensible to evaluate both over a time-frame where at least momentum was working, otherwise we are just comparing noise to noise.

The direction of the factor is that we are buying stocks that have outperformed their web-related peer group

Another interesting point is the direction that the PeerMo factor works in: stocks with lower PeerMo actually outperform in the following month. Recall that we compute PeerMo as CoMo minus standard momentum, so this is effectively saying that stocks with high standard momentum and low CoMo tend to do best (because a large negative factor score leads to outperformance). In other words, we are buying stocks that have been significantly outperforming their web-identified peers in the last 12 months, and shorting stocks that have been underperforming their peers.

Is this just a sector effect?

A critical question is whether we can capture the peer effect more easily by considering sector-adjusted momentum

The directionality of the factor is somewhat intuitive. Unlike standard momentum, which buys stocks that have been outperforming other stocks in an absolute sense, our PeerMo factor is buying stocks that have outperformed their peers. However, the obvious question is whether we could replicate this effect by simply buying stocks that have outperformed their sector. After all, we would expect a lot of the coentities found on the web would be from the stock's sector.

To test this, we construct a third momentum factor which we call sector-adjusted momentum (Figure 62). This is simply the z-score of the stock's GICS Industry Group momentum minus the z-score of the stock's own momentum. As shown in the chart, this strategy also does better than simple momentum, but not as well as PeerMo. In fact, it turns out the correlation between PeerMo and sector-adjusted momentum is 55%, so there is actually some scope to diversify by including both factors in a model.

We find the sector-adjusted and peer-adjusted momentum are different

As a further example of the difference between the two factors, we show the time-series of the factor scores for IBM's peer-adjusted and sector-adjusted momentum scores in Figure 63.

Figure 62: Average monthly risk-adjusted performance, 2010-present
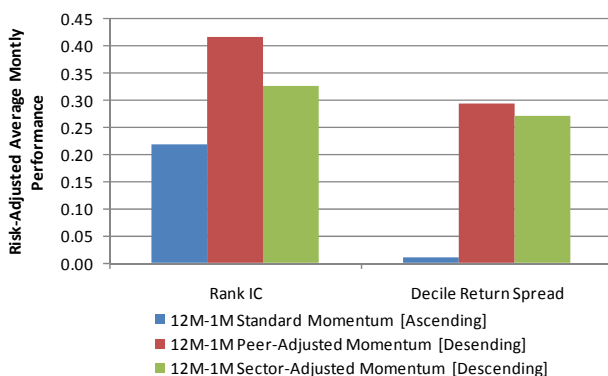
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 63: Example of Sector-Adjusted versus Peer-Adjusted Momentum for IBM
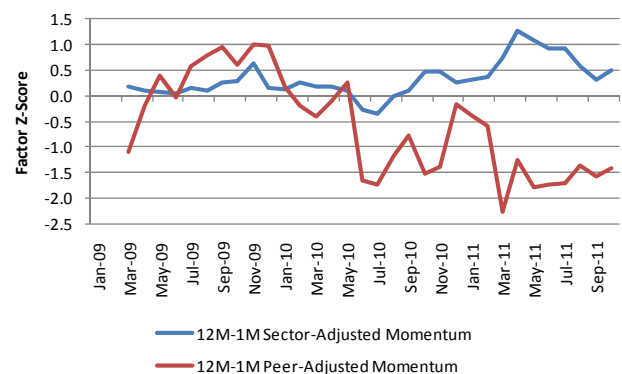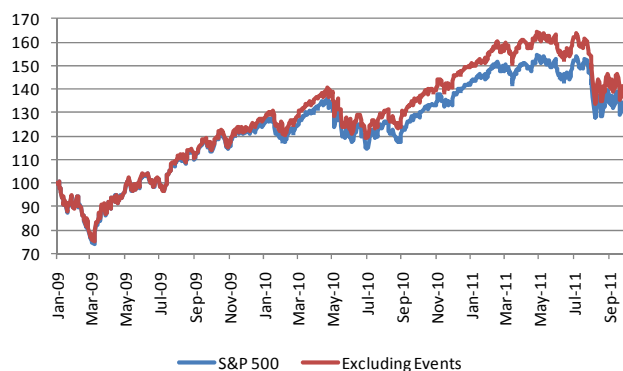

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

But wait, there's more

Future research could consider a refined version of the PeerMo metric that only incorporates cross-sector coentities

Overall, we think these results are quite interesting. While we obviously have to be careful not to jump to conclusions based on a short time-series, we do think this analysis has touched on a very powerful feature of web data, namely the ability to detect relationships between companies that might not be obvious based on traditional sector delineations, or the past correlation of returns. We can envision an enhanced version of PeerMo momentum that only gives weights to coentities that cross sector lines. Such a factor would further reduce the correlation with sector-adjusted momentum, yielding a more orthogonal alpha source.

Another idea would be to use the event types to refine which coentities are included in the CoMo computation

Another exciting idea would be to try to incorporate some directionality into the signal. Currently we buy stocks that have outperformed their peers, i.e. which have higher individual momentum than their web-defined peer group. However, suppose a stock's coentities are mainly suppliers. In that case, we might expect that we actually want to buy stocks that are *underperforming* their suppliers, because we expect eventually the good business momentum that the suppliers are enjoying will flow on into the customer company. Indeed an interesting paper by Cohen and Frazzini [2008] found this is precisely the case: good returns in U.S. supplier companies eventually flow into the customer company. In a subsequent study, Shahrur, Becker, and Rosenfeld [2010] showed the same is true in international markets. With this in mind, one can imagine using the event classifications in the previous section (event types like CompanyCustomer, CompanyAffiliates, CompanyCompetitor, and CompanyUsingProduct spring to mind) to refine which coentities are included in the CoMo calculation, and even the sign to be placed on the momentum of each coentity's momentum. We think this is an area ripe for further research.

Enhanced indexing

Tilt away from event stocks

Lastly, we study an enhanced indexing strategy where we avoid stocks with future events for a five day window around the event day

As our final case study on ways to use web data in quantitative investing, we explore an area that at first seems far removed from the active investing world we have explored so far: enhanced indexing. Motivated by the results in the previous sections where we saw that events tend to lead to higher volatility (Figure 41 on page 21) and, for large cap stocks, lower returns on average (Figure 34 on page 18), we explore a simple index-hugging strategy where we underweight stocks around future event days.

Specifically, our strategy holds stocks at the S&P 500 weight, except we do not hold any stocks in a period +/- 2 days around a known future event. Similar to our previous analysis, we only sell out for events that were known at least five days in advance, so that we have ample time to set our positions.

Figure 64 shows the annualized information ratio for each strategy, and Figure 65 shows the contribution that return and risk makes to that information ratio. A somewhat surprising result is that the strategy actually helps on the return side more than the risk side. Our expectation was that, given the large jump in volatility around an event, we would see a reduction in volatility for the enhanced strategy compared to the index strategy. However, this does not appear to be the case.[9]

Figure 64: Change in information ratio when excluding event stocks
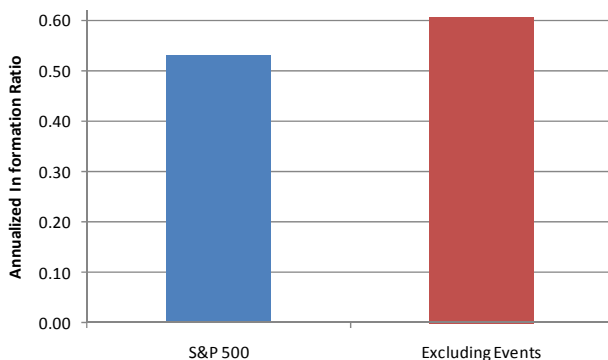
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 65: Change in annual returns and risk when excluding event stocks
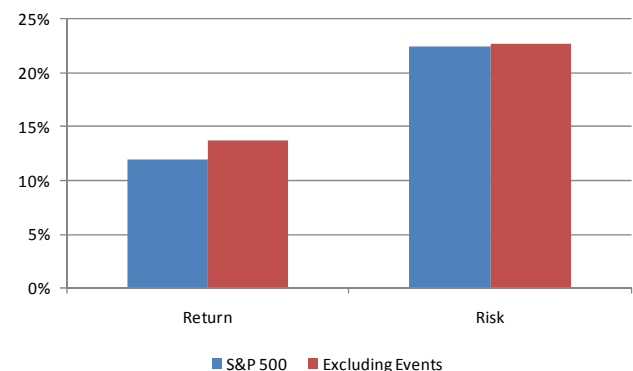
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

The strategy adds about 2% per annum on top of the S&P 500 return, for a 2.5% tracking error

In terms of cumulative performance, Figure 66 shows the performance of both strategies, while Figure 67 shows the cumulative relative performance of the enhanced strategy. Over the backtest period, the enhanced strategy delivers a Sharpe ratio versus the S&P 500 benchmark of 0.71 (a 1.8% annualized outperformance for a tracking error of 2.5%). The relative performance has been quite consistent over time, although recently the strategy appears to have struggled a little.

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[9] Interestingly, this is a similar result to what we found in Alvarez et al., 2011, "Portfolios Under Construction: Minimum variance – Exposing the magic", *Deutsche Bank Quantitative Strategy*, 9 February 2011. There too we found that, somewhat counterintuitively, a better risk model surprisingly seemed to improve the return side of the equation more than the risk side.

Figure 66: Cumulative performance of strategies benchmark and anti-event strategy

Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Figure 67: Cumulative relative performance of anti-event strategy
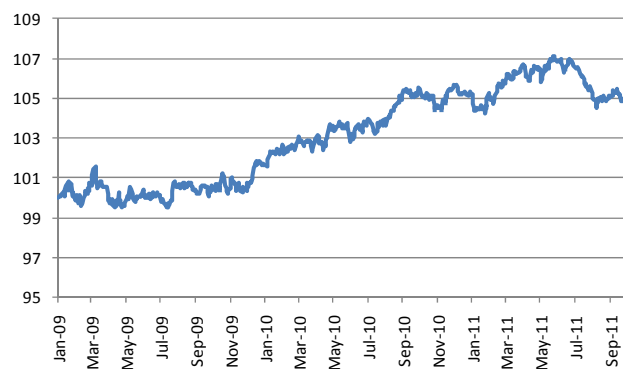
Source: Recoded Future, Bloomberg Finance LP, Compustat, Haver, IBES, Russell, Thomson Reuters, Thomson SDC, Deutsche Bank

Conclusion

Web data: worth a closer look

We think web data is a fruitful area for quants to explore; we hope this paper has offered some of the trading strategies that are possible

In this paper we have touched on a number of strategies that we think are fruitful areas for future research. Our initial impression is that web data is a promising new source of data for quantitative investors. As more and more of the world's data moves online, it is inevitable that quants will increasingly have to tap into this vast repository. As we have illustrated in this paper, the technology to extract structured data from the tangle of text-based information on the web exists today, and more importantly is getting even better every day. Anyone who has tried Siri, the voice-activated digital assistant on Apple's latest iPhone, has probably caught a glimpse of what the future holds.

Going forward, we hope to explore many of the questions raised in this paper in more detail. Like any new data source, one of the biggest criticisms we will face is the lack of history with which to backtest our strategies. This is a trade-off that is becoming increasingly relevant for quants, as they look to balance the need to innovate with dangers of data mining a short history. There are no easy answers here, and every quant investor will have to reach their own conclusion about how much history they need to get comfortable with a new factor.

We hope this paper has offered some ideas on first steps in this exciting new field, and we look forward to discussing some of them with you.

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Appendix 1

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