Deutsche Bank
Markets Research

North America
United States

Quantitative Strategy
Signal Processing

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Quant 3.0

Rochester Cahan, CFA
rochester.cahan@db.com

Zongye Chen
john.chen@db.com

Yin Luo, CFA
yin.luo@db.com

Miguel-A Alvarez
miguel-a.alvarez@db.com

Javed Jussa
javed.jussa@db.com

Sheng Wang
sheng.wang@db.com

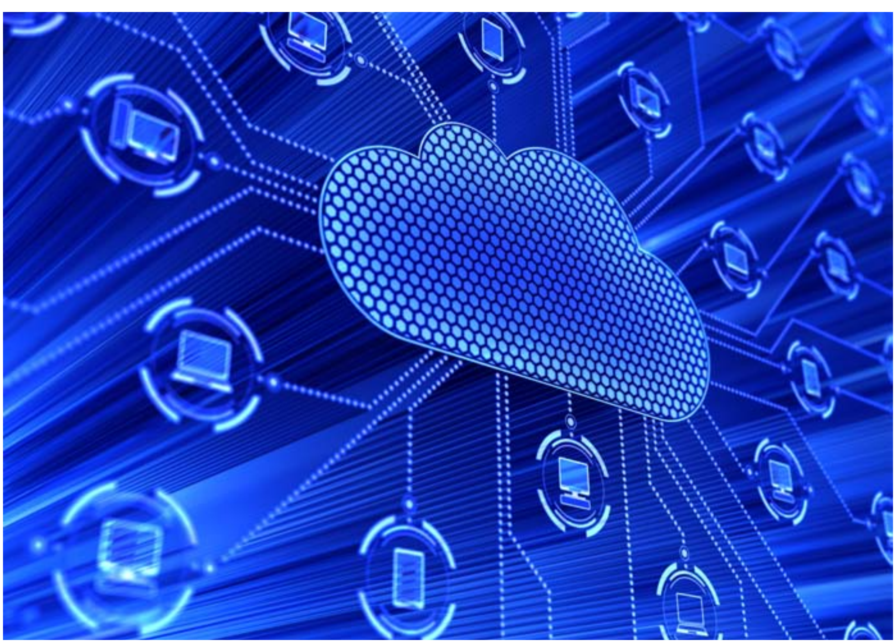
North America: +1 212 250 8983
Europe: +44 20 754 71684
Asia: +852 2203 6990

Trawling the web for new alpha opportunities
This is our third report in a series of papers studying the use of unstructured data in stock selection. In this paper we propose three ways to enhance traditional quant signals by overlaying information from unstructured web and news data.

Casting the net wider
The web is a challenge and an opportunity for quantitative investors. For a data-driven discipline like ours, the vast volume of data available online is a potential gold mine. But like all mining, getting at the treasure is harder than it looks. In this research we use a new database of internet and social media sentiment to try to untangle the web into something useful for systematic investors.

Use web and news flow to condition simple quant factors
We show how simple price-based strategies like momentum and reversal are closely tied to web and news flow. Reversal factors work much better in stocks with little or no news, whereas momentum is more effective when there is a lot of news about a stock.

News-aware momentum and reversal factors
Using these results, we suggest simple but effective ways to improve momentum and reversal by using the volume of web and news mentions to tilt the signal towards parts of the universe where it will be the most effective.



Deutsche Bank Securities Inc.

Table Of Contents

A letter to our readers

Harnessing unstructured data in quantitative strategies

The next frontier

Many of you have been following our research for a number of years now, so most of you will no doubt recall that unstructured data is one of our favorite topics. This report is our third on the topic since we launched our quant research here at Deutsche Bank. In our first report in the series, way back in 2010, we showed how to use non-linear, learning models to convert news sentiment into an alpha signal. Last year we expanded our analysis to web data and showed that co-mentions of two companies on the web can be a useful way to uncover relationships between companies that often transcend the usual sector or industry lines. In this report, we combine news and web sentiment into one data set via an interesting new database: Thomson Reuters News Analytics for Internet News and Social Media. This database uses the same natural language processing algorithms that are used in the Thomson Reuters News Analytics database. The beauty of this is that it allows us to make a fairer comparison between the two content sets, while keeping the sentiment algorithms constant.

Living up to its promise?

When we first started researching news sentiment signals in early 2009, news sentiment and natural language processing was the one of the hottest topic in quant. However, as the initial buzz died down, uptake among quantitative investors has been slower than many expected, at least at the longer-term end of the rebalancing curve. Does this mean news sentiment has been a flop? We don't think so. However, we do think there is perhaps a mismatch between expectations and reality. Often, when a new data source shows up, quants (ourselves included) breathlessly expect it will add instant alpha to their models – the fabled "orthogonal alpha source". In reality it is never so easy. If alpha came off the shelf in a pretty shrink-wrapped box, there wouldn't be much for us to do every day. News sentiment, like any data set, requires a great deal of effort to find ways it can add value.

If there is a common theme that runs through all our research on this topic, it is that one needs to do more than just buy positive sentiment stocks and sell negative sentiment stocks. While this is an obvious starting point – indeed it is where we start in this report – we do want to encourage quants to look deeper than this. Sentiment, like any quantity tied to human emotions, is a complex beast. A story could have very positive sentiment linguistically, but if it is less positive than the market expected it could lead to a negative price reaction. We think textual sentiment needs to be evaluated in the context of the market reaction to that sentiment, and indeed the learning models we have proposed in the past try to do exactly this.

Web and news flow as a conditioning tool

In this paper we suggest some additional ways to use web and news data in quant investing. We show how news flow is a useful conditioning tool for simple, price-based strategies like momentum and reversal. Even though the web and news data sets are complex, the strategies we suggest are simple but effective.

Regards,

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

The story so far

Part three in an ongoing research series

Before diving into our analysis, it is worth pausing for a moment to recap the story so far. In our past research, we have studied a number of ways to use unstructured data in quantitative strategies. Specifically, we have published two in-depth white papers on the subject, one in 2010 and one last year.

Beyond the headlines

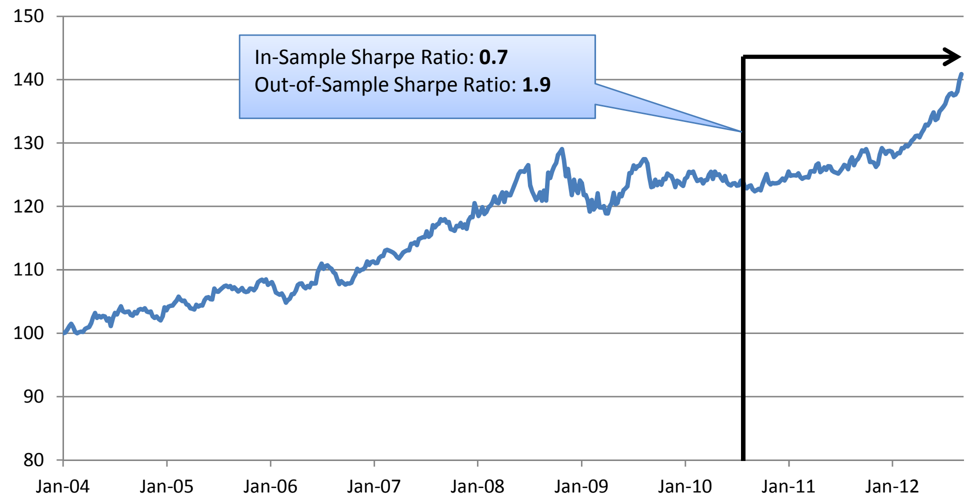
Shortly after we launched our quantitative research at Deutsche Bank, we published a report called "Beyond the Headlines" where we studied using news sentiment data as an alpha signal (see Cahan et al. [2010]). In that paper, we made two key points:

- Non-linear models are an effective way to capture the predictive power in news sentiment. The impact of news on future stock returns is often non-linear; for example a really positive story might be so newsworthy that it is plastered all over CNBC, Bloomberg, etc. and hence is priced in immediately, leaving little post-event drift for quant models to harvest. On the other hand, a moderately positive story might be initially overlooked by the market but potentially detected immediately be a news sentiment signal – leaving the opportunity for the quant model to profit from any subsequent price drift as the market slowly prices in the news.
- News sentiment is best interpreted in conjunction with the market reaction to that sentiment. In finance, it is not so much the absolute positivity or negativity of a news story that matters; it is how the sentiment compared to market expectations. Two stories with exactly the same sentiment could lead to very different price reactions, depending on what the market was expecting.

In our research, we proposed using a non-linear, learning model – the Random Forest – to address these two issues. By feeding the model a combination of sentiment variables (e.g. the sentiment of the news story, the relevance of the story to the company in question, the volume of recent news on the same subject) and market variables (e.g. the abnormal volume and return on the day the news came out) the model was able to learn which combinations of factors lead to the best post-news drift.

In the two years since we published the model, we have been tracking performance in a true out-of-sample sense. Figure 1 shows the performance of a decile spread portfolio in the in-sample and out-of-sample period. Unlike many models that look great on paper but fall over in actual trading, this one has actually done better out-of-sample, with a Sharpe ratio (pre-costs) of 1.9 compared to 0.7 for the in-sample period.

Figure 1:FOREST news sentiment model: Cumulative performance of long-short decile spread portfolio, pre-costs



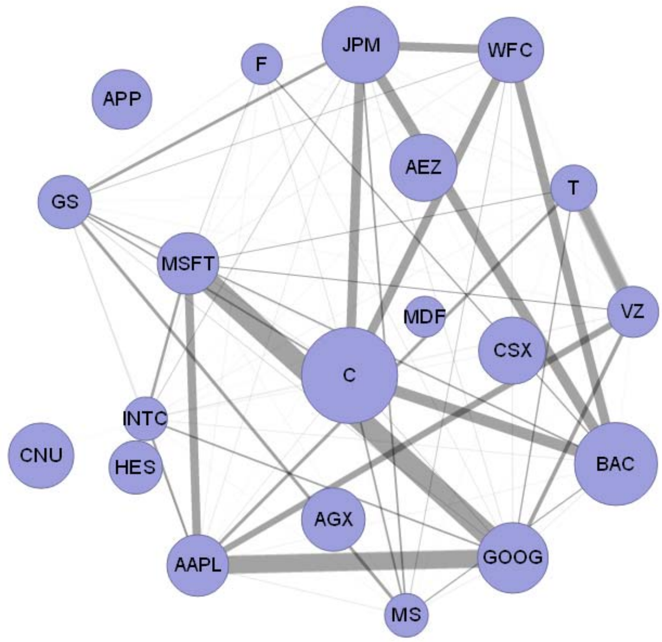
Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Quant 2.0

Last year we followed up our initial work in the unstructured data space with another report, called "Quant 2.0". In that paper, we studied various applications for web data in stock selection (see Cahan et al. [2011]). We found that:

- Web momentum – a measure of the positive or negative "buzz" a stock is generating across the spectrum of the web (e.g. news sites, social media, blogs, etc.) – is a short-term predictor of future returns. Stocks with positive buzz outperform in the following day.
- Automatically detecting upcoming events on the web can be useful for event-based trading strategies. For example, knowing that company XYZ will close a factory on 25 December 2012 or that company ABC will release a new product on 15 January 2013 can allow a systematic model to react to some of the stock-specific events that were previously the domain of fundamental stock-pickers.
- The proximity of companies on the web is a useful way of understanding the relationship between companies. For example, companies that are frequently mentioned together in the same web story, blog post, or tweet are likely to be connected in some way – perhaps as customer/supplier or as fierce competitors (see Figure 2 for an example – the thickness of the lines between companies is a visual illustration of how frequently they appear together on the web). We used these relationships to build an interesting peer-based momentum factor.

Figure 2: A network graph of the "proximity" of companies to each other on the web



Source: Recorded Future, Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Quant 3.0

In this paper we build on our past research by considering some other ways we might use unstructured data in quantitative strategies. In particular, we look at how news flow (defined broadly as both mentions on the web as well as mentions in traditional financial newswires) interacts with simple quantitative strategies like momentum and reversal. Such price-based strategies are fundamental building-blocks of many quantitative models, but are themselves at least partly driven by news flow and market sentiment. We argue that using web/news data can help us get at the root of these phenomena, and as a result can help us better exploit them. For more, read on.

Why the web?

Is it really so different from financial newswires?

As we mentioned in the introduction, news sentiment data has been on the radar screen for quants for at least five years now. A number of data vendors– Thomson Reuters, RavenPack, Alexandria, SemLab to name a few – have released products or data feeds in the space, some of which have gained traction with quantitative investors. Initially, most vendors focused their efforts on traditional financial newswires (e.g. Thomson Reuter's product uses the Reuters newswires; RavenPack's product uses the Dow Jones newswire). This was a logical place to start since the content of these professionally written and edited stories tends to be timely, accurate, company-specific, and widely read within the investment community. Ironically though, as we argued in Cahan et al. [2011], these characteristics can also be disadvantages. Because financial news stories are widely circulated among investment professionals and convey timely, company-specific information, the information content can be priced very quickly. This is problematic for quantitative news sentiment models, which typically try to profit by predicting post-news drift.

A new database of internet sentiment

But suppose we cast the net wider? The volume of information on the internet is enormous, but so too is the noise to signal ratio. Can we filter through the cacophony to find something useful? In this paper, we will try to do just that by leveraging a unique data set: Thomson Reuters News Analytics for Internet News and Social Media. This data feed is actually a partnership between two companies, Moreover Technologies and Thomson Reuters. Readers of our past papers will be familiar with the Thomson Reuters News Analytics product – essentially a set of algorithms that score the textual content of a news story across three dimensions: sentiment (how positive or negative is the story?), relevance (how specific to a given company?), and novelty (how similar to past stories?). In the Internet News and Social Media feed, these same natural language processing algorithms are directed at a broad spectrum of internet content provided by Moreover Technologies. The Moreover Technologies feed comprises real-time scanning of around 50,000 internet news sites and four million social media channels that are piped into the Thomson Reuters algorithms and quantified in real-time into a machine-readable format.[1]

In this sense, the database is not dissimilar to the Recorded Future database we explored in Cahan et al. [2011]. However, because that database used different natural language processing algorithms to those used in Thomson Reuters News Analytics, it was difficult to do a direct apples-for-apples comparison between the information content of news sentiment and that of web sentiment. In this research, by using the same Thomson Reuters algorithms on both news and web content, we can better isolate differences between the two sources of information.

A closer look at the data

One of our key questions in this research is whether news sentiment and web sentiment capture similar information. After all, a newsworthy event is almost certain to appear in financial newswires as well as the web, probably simultaneously. To get a feel for what the data looks like, Figure 3 shows the 20 most positive news stories at a given date, in this case 29 June 2012.

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[1] See Cahan [2010], pages 4-6, for more details on how these algorithms work.

Figure 3: Top 20 positive news stories on 29 June 2012

Ticker	Relevance	Net Sentiment	Headline
ITRI.O	1.00	0.82	Itron`s Water Technology Selected by Sydney Water, Australia`s Largest Water Utility <ITRI.O>
LSCC.O	1.00	0.82	Lattice Is Honored With Huawei Quality Award <LSCC.O>
FCH.N	1.00	0.81	FelCor Declares Current Quarterly and Accrued Preferred Dividends <FCH.N>
AM.N	1.00	0.80	Local Greeting Card Aisle just Got Awesome with justWink <AM.N>
BRKL.O	1.00	0.80	Eastern Funding Drives New Financing for Tow Trucks <BRKL.O>
MMM.N	1.00	0.80	BUZZ-Short end HKD vols spurt but spot steady
MRVL.O	1.00	0.80	Marvell Enables the Launch of a New Generation of Google TVs <MRVL.O>
NOC.N	1.00	0.80	Northrop Grumman Awards Grants to Los Angeles Area Schools to Promote Science, Technology, Engineering and Mathematics <NOC.N>
STZ.N	1.00	0.80	Moody's affirms Constellation Brands Ba1 ratings after acquisition announcements; outlook stable <STZ.N>
TWC.N	1.00	0.80	Warm up Your Voice and Sing Along to Your Favorite Musicals on Time Warner Cable Movies On Demand <TWC.N>
UTX.N	1.00	0.80	Three Pratt & Whitney Rocketdyne RS-68A Engines Power Delta IV Heavy Upgrade Vehicle on Inaugural Flight <UTX.N>
ACN.N	1.00	0.79	Accenture and Out & Equal Honor Green Chimneys with First Skills to Succeed LGBT Award <ACN.N>
DOW.N	1.00	0.79	Dow AgroSciences, The Royal Barenbrug Group Announce Strategic Relationship <DOW.N>
EV.N	1.00	0.79	Eaton Vance Enhanced Equity Income Fund June 2012 Distribution <EOI.N><EV.N>
GCI.N	1.00	0.79	Gannett to Webcast Second-Quarter 2012 Earnings Conference Call <GCI.N>
LINTA.O	1.00	0.79	Liberty Interactive Seeks New Class for Women's eCommerce Network <LINTA.O><LINTA.OQ>
MCHP.O	1.00	0.79	Top Tech Analyst Issues Special Report on 'Triple Crown' Tech Stocks that Deliver Dividends, Exploring Altera, Microchip Technology, Linear Technology, and More
SCHL.O	1.00	0.79	Storia, the eReading App for Kids Created by Scholastic, to Offer National Geographic for Kids Titles <SCHL.O>
SO.N	1.00	0.79	Southern Company and Ted Turner Acquire Second Solar Photovoltaic Power Project <SO.N><WFR.N>
SRSL.O	1.00	0.79	SRS Completes Integration of TruMedia onto Hexagon DSP based Snapdragon Platforms <SRSL.O>

Source: Thomson Reuters, Moreover, Deutsche Bank

As a comparison, Figure 4 shows the 20 most positive mentions on the web, for the same date. At this particular date, only three stocks overlap LSOC.O, FCH.N, and BRKL.O (see rows highlighted in grey in each table). In each of those three cases, the headline is almost exactly the same. The second and third columns show the relevance and sentiment for each story. The relevance score ranges from 0 to 1, with 1 being most relevant to that particular company. The sentiment score is measured as the net sentiment, i.e. probability of positive sentiment minus probability of negative sentiment (again, see Cahan et al. [2010] for complete details of the scoring system).

For the three stories that overlap, not only are their headlines the same, the body of the stories also appears to be similar given the similar relevance and sentiment scores in the two databases.

Figure 4: Top 20 positive web mentions on 29 June 2012

Ticker	Relevance	Net Sentiment	Headline
SWFT.N	1.00	0.82	Swift Transportation Offers Driver Quarterly Performance Pay Incentive
FES.O	0.85	0.81	Friday 6/29 Insider Buying Report: BAS, FES
LSCC.O	1.00	0.81	Lattice Is Honored With Huawei Quality Award
CBR.N	1.00	0.81	Infor and Ciber Team to Offer Clients New Customized Solutions
FCH.N	1.00	0.81	FelCor Declares Current Quarterly and Accrued Preferred Dividends
HRZN.O	1.00	0.81	Horizon Technology Finance Leads $8 Million Venture Loan Facility for Semprius
LUFK.O	1.00	0.81	Bullish Moving Average Cross by Lufkin Industries (LUFK)
NCMI.O	1.00	0.80	National CineMedia Brings in Celebration! Cinema as a Network Affiliate
VG.N	1.00	0.80	Vonage Appoints Barbara Goodstein as Chief Marketing Officer
TGI.N	1.00	0.80	Goldman Sachs Starts Triumph Group (TGI) at Buy
BRKL.O	1.00	0.80	Eastern Funding Drives New Financing for Tow Trucks
HSC.N	1.00	0.80	Harsco Shares Climbing Higher, Up 3.4%
EME.N	1.00	0.80	EMCOR Group, Inc. Declares Regular Quarterly Dividend Business Wire
ANSS.O	1.00	0.80	ANSYS Making Electric Vehicle Batteries More Practical And Efficient
ADS.N	1.00	0.80	Alliance Data Systems: The Winning Streak Continues (ADS)
THOR.O	1.00	0.80	Thoratec Launches Cloud-Based Mechanical Circulatory Support Program Management System
KRG.N	1.00	0.80	Kite Realty Group Trust Goes Ex-Dividend Soon
IBI.N	1.00	0.79	Interline Brands, Inc. Announces Receipt of Requisite Consents in Its Consent Solicitation Relating to the 7.00% Senior Subordinated Notes Due 2018
BEAV.O	1.00	0.79	BE Aerospace Crosses Above its 10-day MA (BEAV)
JOSB.O	1.00	0.79	JOS A Bank Clothiers Crosses Above its 10-day MA (JOSB)

Source: Thomson Reuters, Moreover, Deutsche Bank

Repeating the exercise for negative stories, we see that there is no overlap among the top 20 negative news stories and web mentions on this particular date (Figure 5 and Figure 6).

Figure 5: Top 20 negative news stories on 29 June 2012

Ticker	Relevance	Net Sentiment	Headline
CBS.N	1.00	-0.76	High court agrees no indecency fine for CBS "wardrobe malfunction"
MAKO.O	1.00	-0.76	Faruqi & Faruqi, LLP Encourages Investors Who Suffered Losses to Contact the Firm <MAKO.O>
AA.N	1.00	-0.75	Alcoa says grant to help keep Aus smelter running
EL.N	1.00	-0.75	STOCKS NEWS US-Option bears target Estee Lauder puts
GOOG.O	1.00	-0.75	US investigating Google unit over patent licensing
OB.N	1.00	-0.75	OneBeacon Schedules Second Quarter 2012 Earnings Release And Webcast <OB.N><WTM.N>
X.N	1.00	-0.72	TEXT-S&P revises United States Steel outlook to negative
C.N	1.00	-0.67	Ex-Citigroup VP gets 8 years for stealing $22 mln
ACE.N	1.00	-0.65	ACE Publishes 2011 Global Loss Triangles <ACE.N>
MSFT.O	1.00	-0.65	EXCLUSIVE-Microsoft tie-up, network sale among RIM options-sources
ANR.N	1.00	-0.64	TEXT-S&P revises Alpha Natural Resources outlook to negative
CXW.N	1.00	-0.64	CCA to Modify Contract With California Reducing Total Population <CXW.N>
MSFT.O	1.00	-0.64	Greek militant group claims Microsoft attack
GOOG.O	1.00	-0.62	FACTBOX-Crunch time for Google as EU deadline looms
NDAQ.O	1.00	-0.60	SEC may order Nasdaq to upgrade trading systems - WSJ
FRX.N	1.00	-0.58	Icahn suing Forest, cites succession plan worries
NKE.N	1.00	-0.51	STOCKS NEWS EUROPE-Adidas down after Nike profit disappoints
WMT.N	1.00	-0.51	Pittsburgh Law Office of Alfred G. Yates Jr., PC Announces Shareholder Lead Plaintiff Deadline for Walmart (WMT) Shareholders <WMT.N>
ALL.N	1.00	-0.51	Allstate encourages homeowners to take steps to reduce wildfire risk <ALL.N>
BA.N	1.00	-0.51	Boeing says U.S. plant won't excuse Airbus subsidy

Source: Thomson Reuters, Moreover, Deutsche Bank

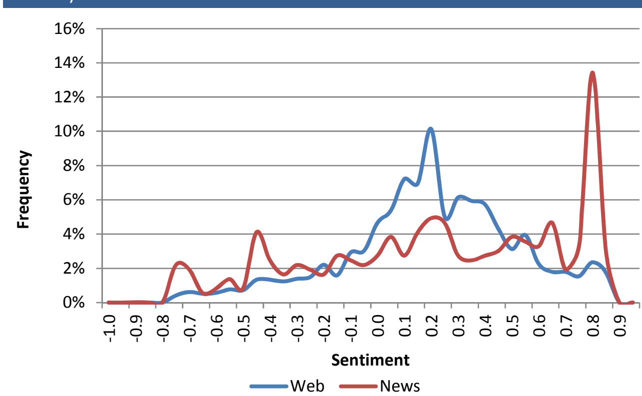
Figure 6: Top 20 negative web mentions on 29 June 2012

Ticker	Relevance	Net Sentiment	Headline
CTIC.O	0.82	-0.76	Deckers Outdoor, Diamond Foods Among Stocks hitting 52-Week Lows Thursday
DPS.N	1.00	-0.76	Zacks Sell List Highlights: Biglari Holdings, Systemax, Dr Pepper Snapple Group and Leggett & Platt
SWY.N	1.00	-0.75	Safeway (SWY) Showing Bearish Technicals With 4.04% Dividend Yield
WFR.N	1.00	-0.75	MEMC Electronic Materials (WFR) Breaks Through Resistance at $2.15
BGC.N	1.00	-0.74	General Cable (BGC) Showing Bearish Technicals With Resistance At $25.63
ADTN.O	1.00	-0.72	ADTRAN (ADTN) Showing Bearish Technicals With Resistance At $30.05
VNO.N	1.00	-0.72	Vornado Announces its Share of Toys "R" Us` First Quarter Financial Results
BKD.N	1.00	-0.71	Brookdale Senior Living (BKD) Showing Bearish Technicals But Could Break Through $17.48 Resistance
EML.O	0.82	-0.68	Deckers Outdoor, Diamond Foods Among Stocks hitting 52-Week Lows Thursday
AEE.N	1.00	-0.68	BRIEF: Power restored to customers affected by outage in Collinsville area
FNB.N	1.00	-0.64	Possible Bearish Inside Day Candle Pattern Detected for FNB (NYSE:FNB)
AIQ.N	1.00	-0.64	Garland healthcare worker gets nearly three years for paying patients to bilk Medicare
LL.N	1.00	-0.63	Lumber Liquidators (LL) Could Fall Through $31.32 Support Level
NVEC.O	1.00	-0.63	This Metric Says You're Smart to Own NVE Corp.
TXRH.O	1.00	-0.63	Texas Roadhouse (TXRH) Could Break Through $18.19 Resistance Level
GGS.N	1.00	-0.60	How Should You Be Playing Global Geophysical Services?
IDXX.O	1.00	-0.58	IDEXX Laboratories (IDXX) Showing Bullish Technicals But Could Break Through $97.13 Resistance
ODFL.O	1.00	-0.57	Potential Old Dominion Freight Line (ODFL) Trade Targets 19.25% Return
PGTI.O	1.00	-0.55	PGT Added to Russell 2000 Index
LOPE.O	1.00	-0.53	Grand Canyon (LOPE) Showing Bullish Technicals But Could Fall Through $20.09 Support

Source: Thomson Reuters, Moreover, Deutsche Bank

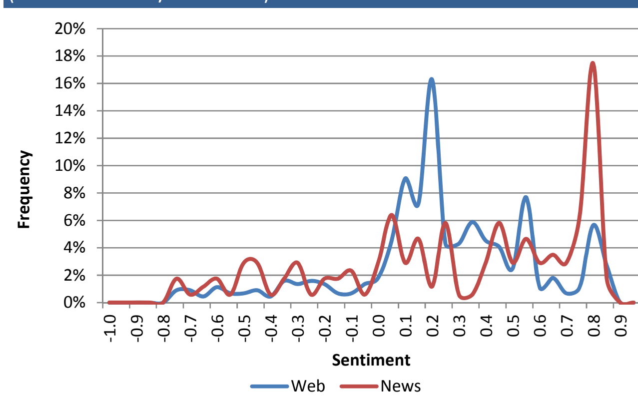
Expanding the picture beyond the top and bottom 20 stories, consider Figure 7 and Figure 8. These two charts show the cross-sectional distribution of news and web sentiment on 29 June 2012. The left chart shows the distribution with no filters, and the right chart shows how this changes when we focus only on stories that are highly relevant to a company and unique.[2] It turns out the distributions are quite different, regardless of what filters we apply. This suggests the two data sets are indeed capturing something quite different.

Figure 7: Sentiment distribution as at 29 June 2012 (no filters)



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 8: Sentiment distribution as at 29 June 2012 (RLVN > 0.75, CNT < 1)

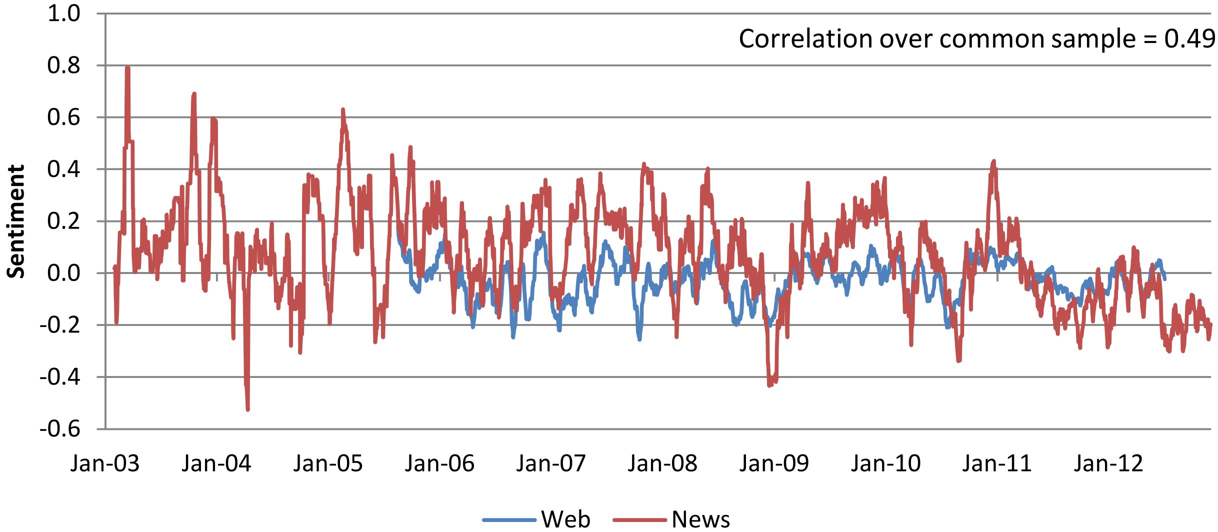


Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

[2] RLVN is a score between 1 and 0 measuring how specific the story is to a particular company (1 being very specific) and CNT measures how many similar stories there have been in the past 24 hours (so a lower CNT means the story is "more novel"). See Cahan et al. [2010] for more details.

Another piece of anecdotal evidence to support this view is to consider a single stock example. Figure 9 shows the time-series of web and news sentiment for Apple (AAPL). Overall the two series show some correlation, but over the common sample it is around 50%.

Figure 9: News and web sentiment for AAPL (21 day rolling)

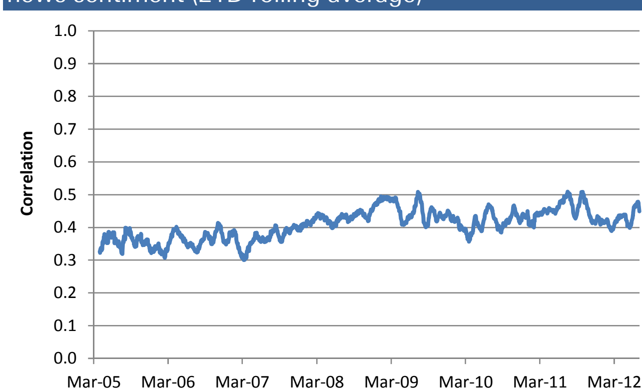


Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Cross-sectional comparison

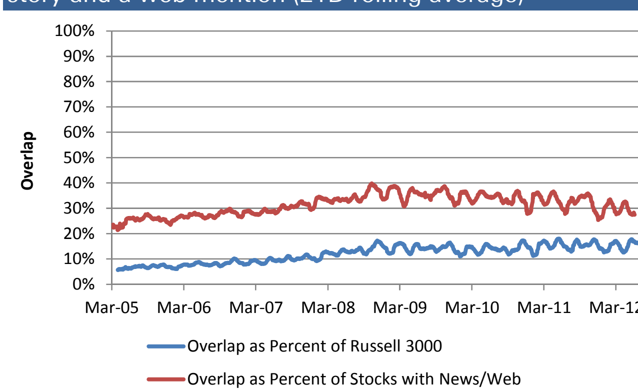
To generalize this comparison, we can compute the cross-sectional correlation of web sentiment and news sentiment at each point in time, as shown in Figure 10. Over time, the correlation tracks at around 40%, which suggests the two sources of sentiment are capturing information that is not identical. In fact, if we look at the overlap, i.e. stocks that have both a web mention and a news mention on the same day, we see it is quite low (Figure 11). Only around 20% of stocks in the Russell 3000 have a web mention *and* a news mention on the same day (the blue line). However that understates the overlap a little because on average only around 1,000 stocks in the Russell 3000 have a web *or* news mention on the same day. The red line shows the overlap as a percent of the stocks that have at least one mention on either the web or in the news that day. Even this number is quite low, at around 40%.

Figure 10: Cross-sectional correlation of daily web and news sentiment (21D rolling average)



Source: Thomson Reuters, Moreover, Deutsche Bank

Figure 11: Percent of stocks each day that have a news story and a web mention (21D rolling average)

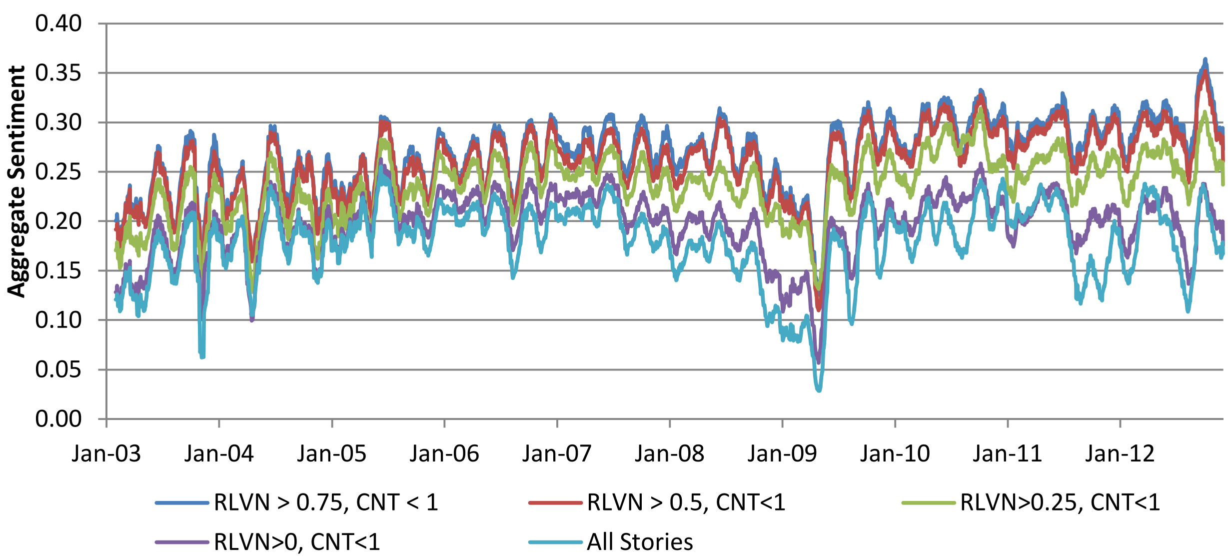


Source: Thomson Reuters, Moreover, Deutsche Bank

Aggregate sentiment

As we've seen, the overlap between news sentiment and web sentiment is moderate, which lends support to our hypothesis that these two data sets are picking up on somewhat different information. Another way to examine this question is to aggregate news and web sentiment up to the market level. In Figure 12 we show aggregate news sentiment for the Russell 3000 using various filters on relevance (RLVN) and novelty (CNT). In general, news sentiment is skewed positive – even during the depths of the financial crisis it remained above zero. Interestingly, the more specific the stories are (i.e. higher RLVN filter) the higher the aggregate sentiment.

Figure 12: Aggregate news sentiment (rolling 21 days) for various relevance filters

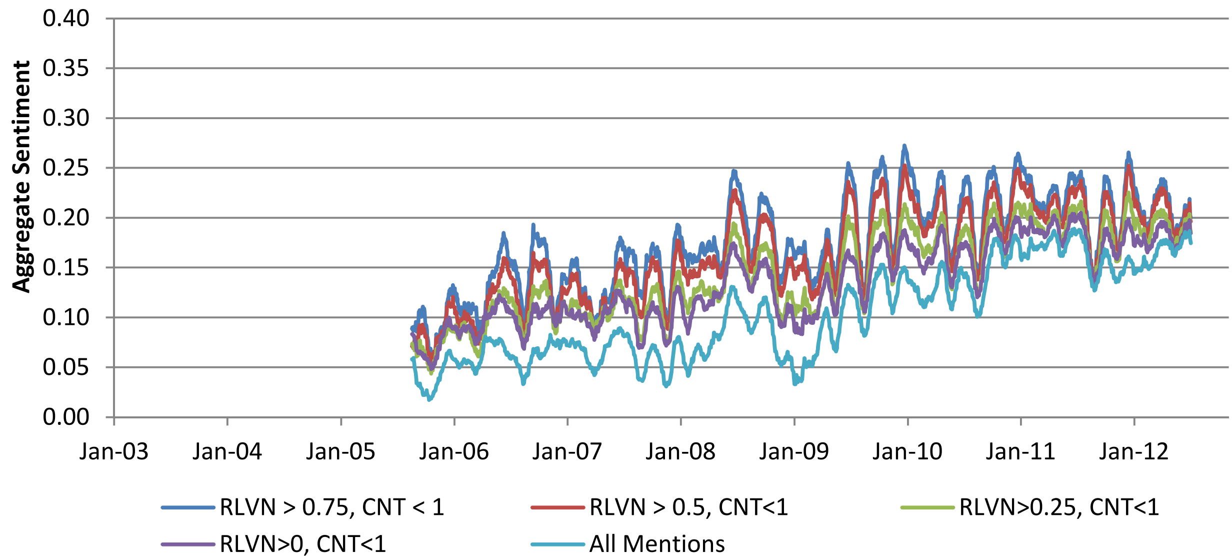


Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 13 shows the same chart for the web sentiment. Note that we are using a first cut of this new database in this research, so the sample period is from January 2005 to June 2012. However, for ease of comparison we keep the x-axis the same on both charts.

Even just eyeballing the two charts, it is clear that news sentiment and web sentiment are not perfectly correlated; this corroborates with what we saw cross-sectionally in the previous charts. One of the most noticeable differences is the steady upwards trend in aggregate web sentiment, something we don't see in the news sentiment time-series. One potential explanation could be that financial reporters purposely write unbiased, factual stories, while the web tends to contain a lot more opinions, particularly within the rapidly growing social media space.

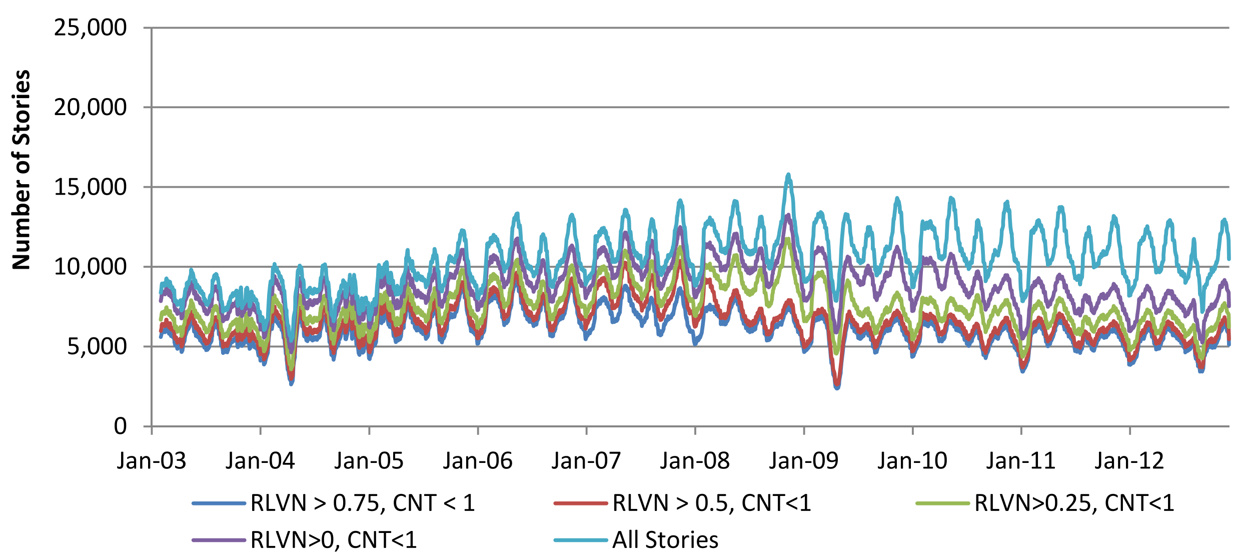
Figure 13: Aggregate web sentiment (rolling 21 days) for various relevance filters



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 14 and Figure 15 show the number of news stories and web mentions, respectively. Two points are worth making. First, as we've seen in our past research, news volume tends to have a very strong cyclical component that lines up with the quarterly earnings cycle in the US. During reporting season there are significantly more news stories compared to other periods. However, in the aggregate web sentiment this pattern is much less pronounced. This is further evidence that the web content is less "financial focused" then professional newswires. Instead of endless stories about quarterly earnings, we are probably more likely to find more "human focused" content like product reviews, customer feedback, etc.

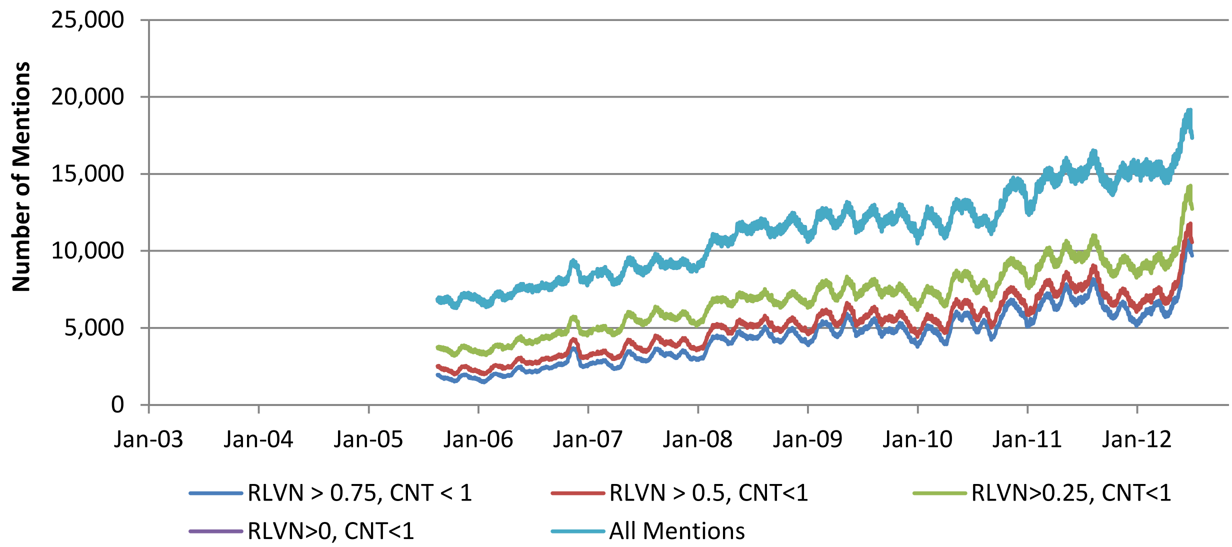
Figure 14: Number of news stories (rolling 21 days) for various relevance filters



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

The second point to highlight is the steady increase in the number of web stories over time (Figure 15). This will come as no surprise to anyone. The explosion in content on the web since 2006 has been nothing short of staggering, and this is reflected in the data set.

Figure 15: Number of web stories (rolling 21 days) for various relevance filters



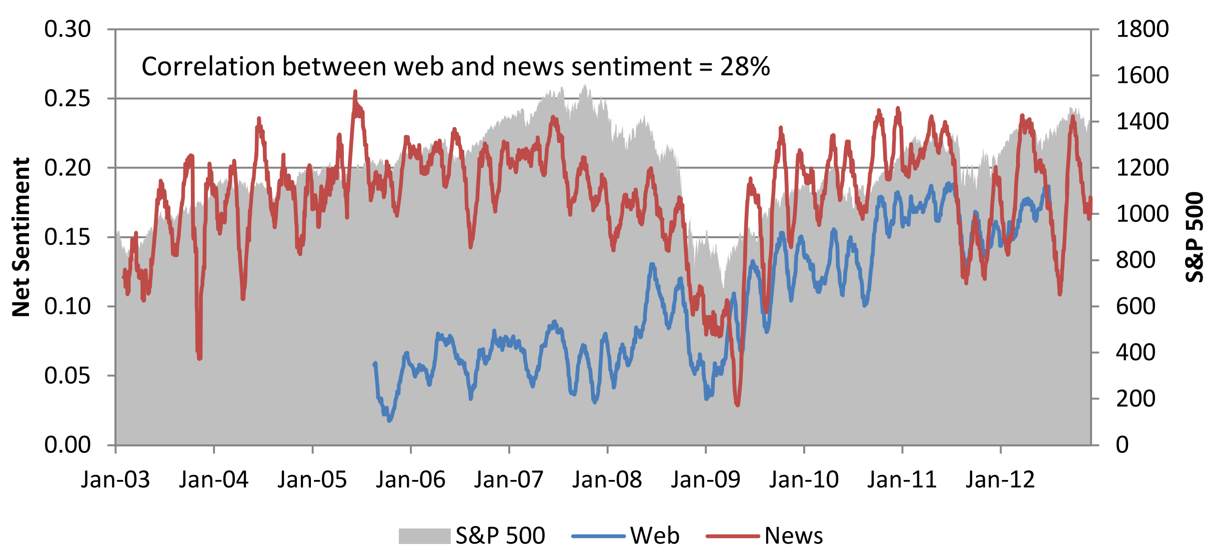
Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Coming back to our previous point about the upwards trend in aggregate sentiment (recall Figure 13), the increase in number of stories does seem to correlate with the rising level of sentiment. We do not have a good explanation for this finding.

Sentiment and the market

Comparing news and web sentiment to the market, we see that news sentiment tends to track the market level more closely than web sentiment does. Is this further evidence that professional financial newswires are more focused on financial outcomes than the web? If so, which source of information has better predictive power?

Figure 16: Net sentiment (rolling 21 days, no filters, no filters) compared to market level



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

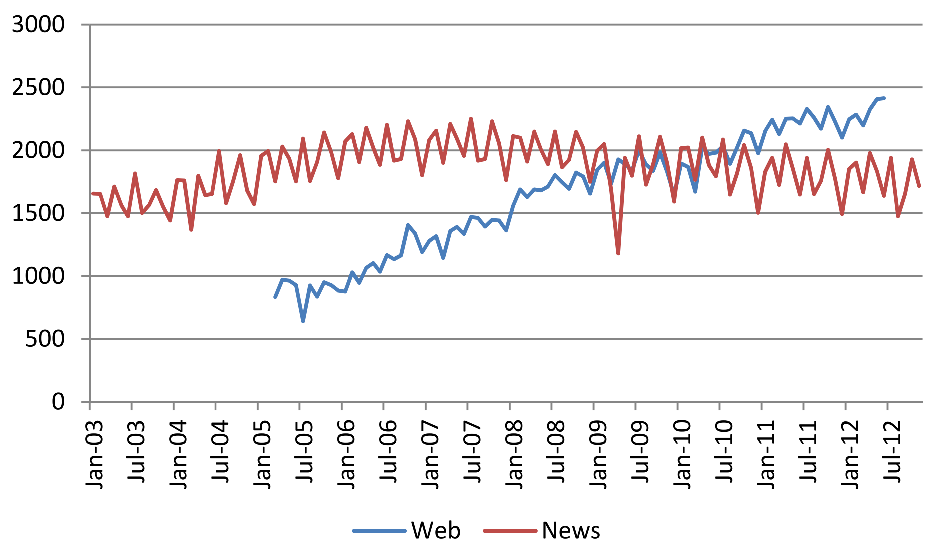
Backtesting analysis

In our preliminary analysis we showed that news and web data are somewhat uncorrelated: cross-sectionally the distribution of sentiment can be quite different, and indeed the overlap between stocks that appear in each data set at a given point in time is quite low. Academically this is all quite interesting, but the real question is: which sentiment source will give us a better signal for stock selection?

Monthly backtesting

We start with the simple case of monthly rebalancing, where we define sentiment as the average net sentiment of all stories about a particular sock in the last 21 days. To focus only on stories that are highly relevant and unique we apply two filters: RLVN > 0.75 and CNT < 1. Figure 17 shows the coverage of this factor for each data set. As we saw before, the coverage for the web data has been climbing steadily, and is now higher than for the news data.[3]

Figure 17: Coverage of Russell 3000, for 21D Web and News Sentiment

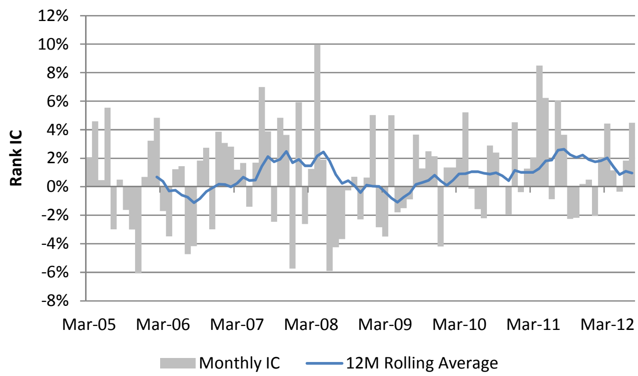


Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

We will make the assumption that on average we want to buy stocks with good news and sell stocks with bad news. Figure 18 and Figure 19 show the monthly rank information coefficients (IC) for the web sentiment and news sentiment factors, respectively.

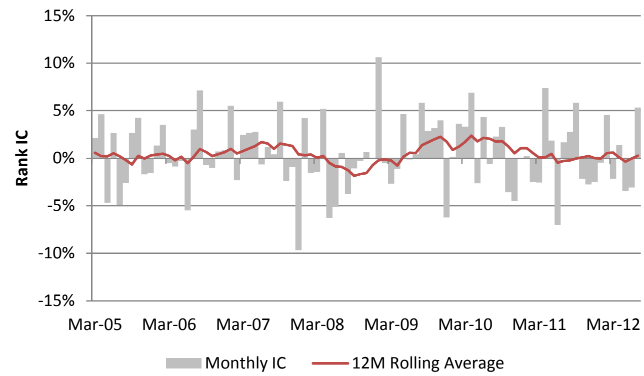
[3] To avoid the risk of lookahead bias, we cut-off all web/news stories at 3.30pm EST. We are making the assumption that we can trade at the close on the last day of each month, so this gives us 30 minutes to compute the sentiment score for each stock before trading on the close on the same day.

Figure 18: Web Sentiment: Monthly rank IC



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

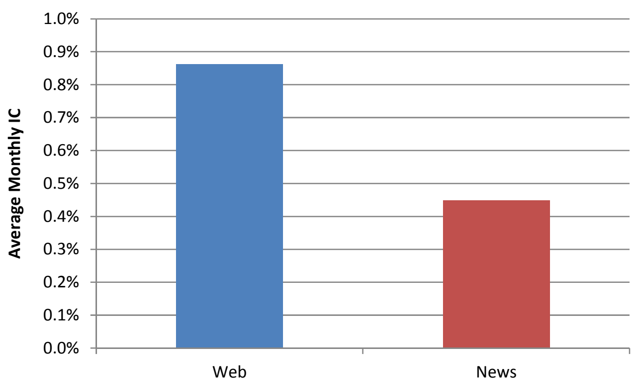
Figure 19: News Sentiment: Monthly Rank IC



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

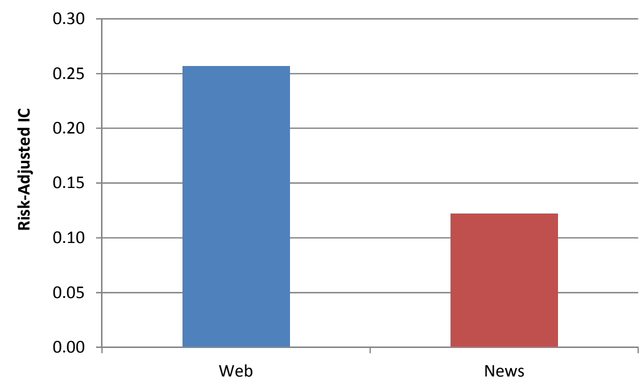
The average web sentiment IC is about 0.85% compared to 0.45% for news, over the period for which both factors have data (Figure 20). The chart in Figure 21 shows that this significant difference in predictive power remains even if we focus on risk-adjusted IC (i.e. average rank IC / standard deviation of rank IC) as a measure of risk-adjusted predictive power.

Figure 20: Average monthly rank IC comparison (over common sample)



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

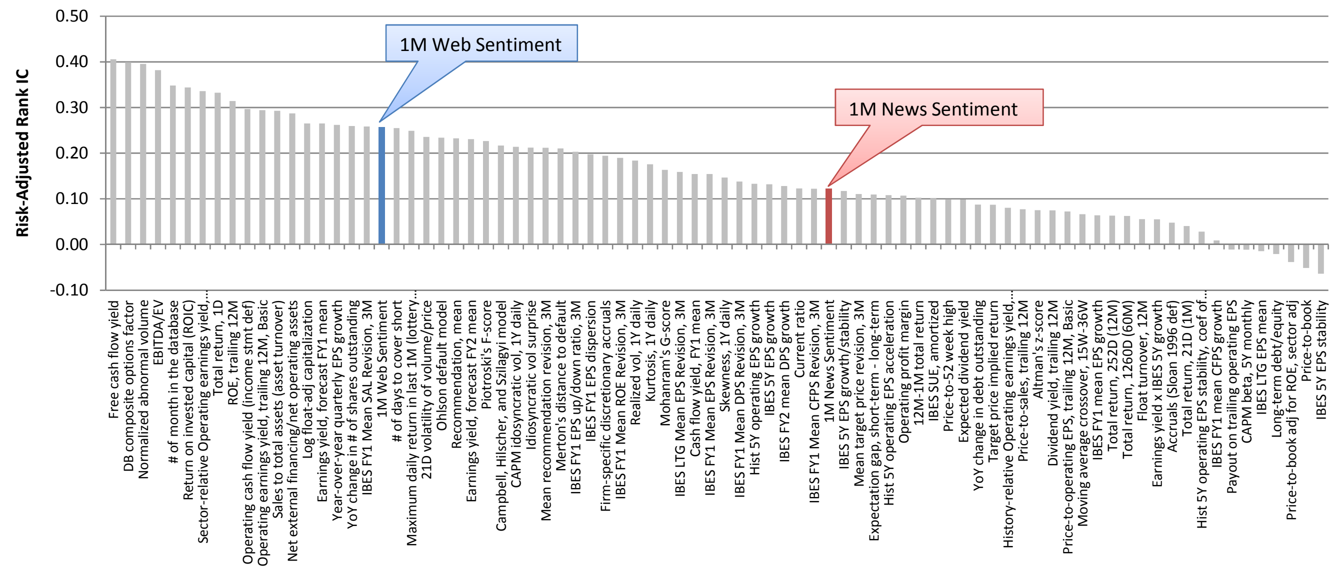
Figure 21: Average monthly risk-adjusted rank IC comparison (over common sample)



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

However, even though the web data has better predictive power, the actual magnitude of the IC (0.85%) does not seem particularly compelling in a world where a 2% IC is often considered the minimum to get excited about. Or does it? Keep in mind this backtesting is over a fairly short history that begins in 2005. To get some context, we compare the risk-adjusted rank IC of these two factors to a wider universe of factors over the same period. Figure 22 shows the results. It turns out that the web sentiment factor actually ranks quite well when compared to other typical quant factors over this period (one which was admittedly quite difficult for quants).

Figure 22: Performance of quant factor library in risk-adjusted IC terms, over common sample (2005-present)



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Rank IC is a good measure of a factor's ability to rank stocks across the universe, but it does not necessarily translate directly into return space. In Figure 23 and Figure 24 we show the performance of a simple decile spread portfolio that goes long an equally-weighted basket of stocks with high sentiment and short an equally-weighted basket of low sentiment. For both sentiment strategies, the performance is weak.

Figure 23: Web Sentiment: Cumulative decile spread performance

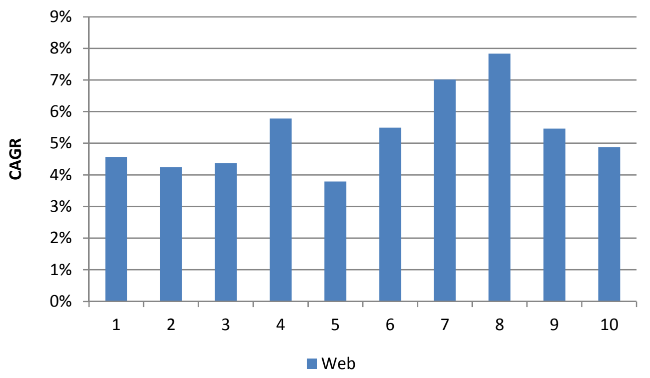
Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 24: News Sentiment: Cumulative decile spread performance

Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

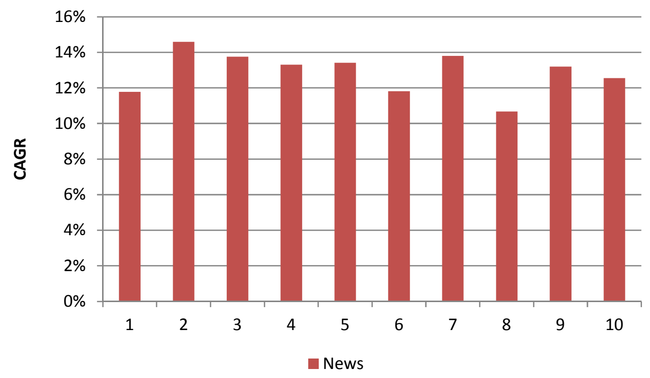
We can see why if we examine the average monthly returns to each decile portfolio (see Figure 25 and Figure 26). In both cases the return profile lacks the monotonic pattern that we want to see in an effective factor. In the case of web sentiment (Figure 25) we see that it is actually stocks with moderately positive sentiment (say deciles 7 and 8) that have done best historically. This is precisely why we argued in Cahan et al. [2010] that it is better to use non-linear models to capture sentiment effects.

Figure 25: Web Sentiment: Annualized returns to decile portfolios



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 26: News Sentiment: Annualized returns to decile portfolios



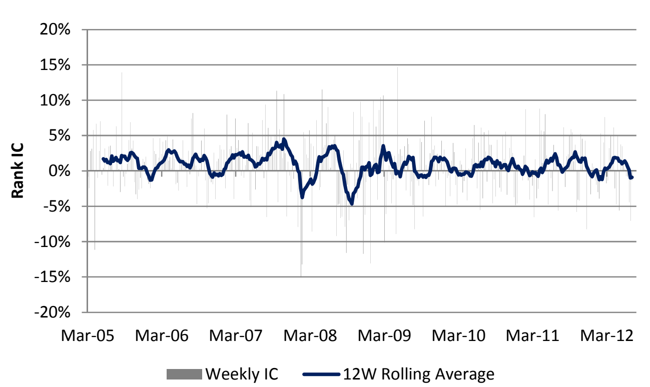
Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Overall, the performance of sentiment is mixed at a monthly frequency. Web sentiment shows the most promise in IC terms, comparing favorably with most other quant factors over the same period.

Weekly backtesting

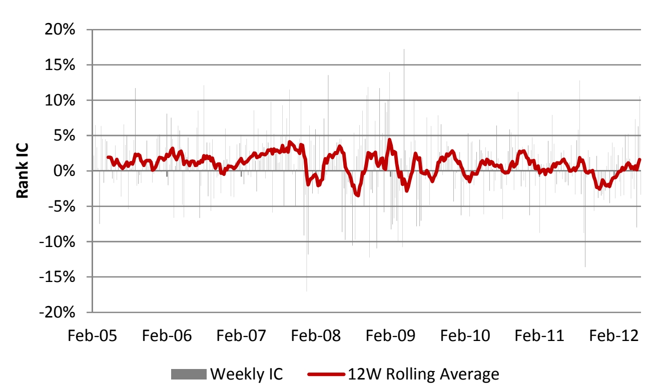
In Cahan et al. [2010] we found that news sentiment was more effective at a weekly horizon, given it is a fairly quick decay signal. In Figure 27 and Figure 28 we show the weekly rank IC for web and news sentiment. Note that here we define the sentiment factor as the average net sentiment for all stories about a particular company in the past five days (compared to 21 days for the monthly sentiment). We also remove the relevance and novelty filters to ensure maximum coverage (since fewer stocks at a given point in time will have been mentioned in the last five days). However, to ensure we still emphasize relevant stories, we weight each story's sentiment by its relevance score.

Figure 27: Web Sentiment: Weekly rank IC



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

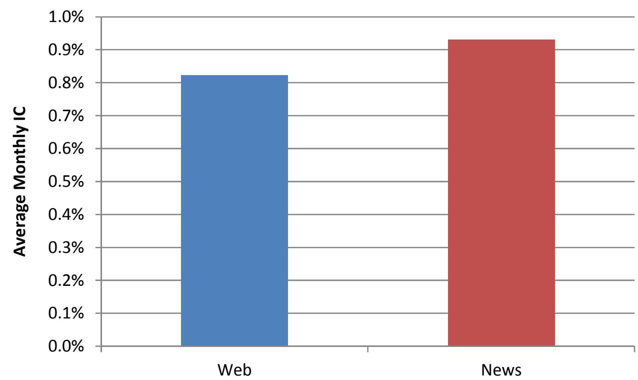
Figure 28: News Sentiment: Weekly rank IC



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

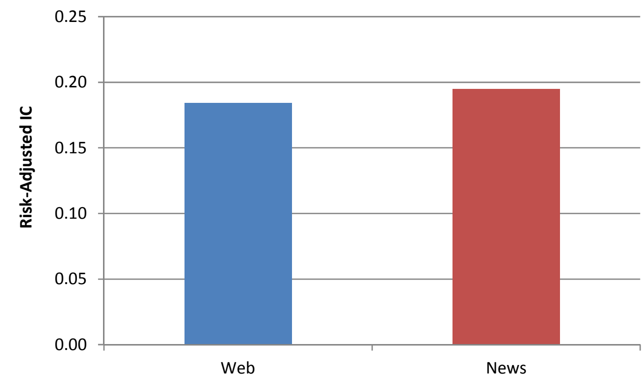
At a weekly horizon the predictive power of web and news sentiment is quite similar, both in average IC (Figure 29) and risk-adjusted IC (Figure 30).

Figure 29: Average weekly rank IC comparison (over common sample)



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 30: Average weekly risk-adjusted rank IC comparison (over common sample)



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Similar to what we saw with the monthly backtesting, the performance of a decile spread portfolio is poor around the financial crisis period. In fact, both strategies show some similarities to momentum in the way that they suffer massive drawdowns around market turning points.

Figure 31: Web Sentiment: Cumulative decile spread performance

Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

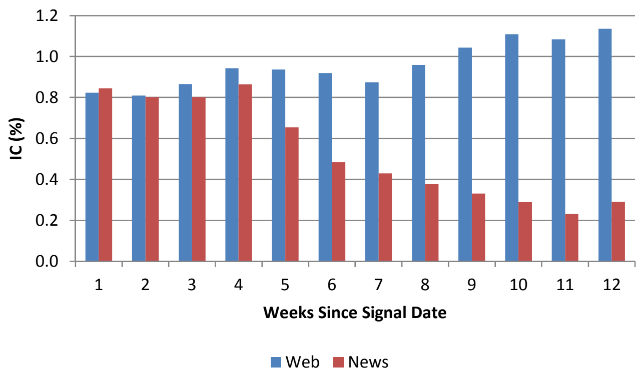
Figure 32: News Sentiment: Cumulative decile spread performance

Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

However, outside of the crisis period, both strategies do show some promise, particularly news sentiment. Recall that this is opposite what we saw at a monthly horizon. Figure 33 shows why. The weekly IC decay of the news signal is much quicker than that for web sentiment. This is also apparent if we look at the turnover of each decile portfolio in Figure 34. While the turnover in most deciles is close to 180%, this comes down more for the extreme deciles of web sentiment (1 and 10) than it does for news sentiment.[4] In other words, there is more persistence in extreme web sentiment than extreme news sentiment.

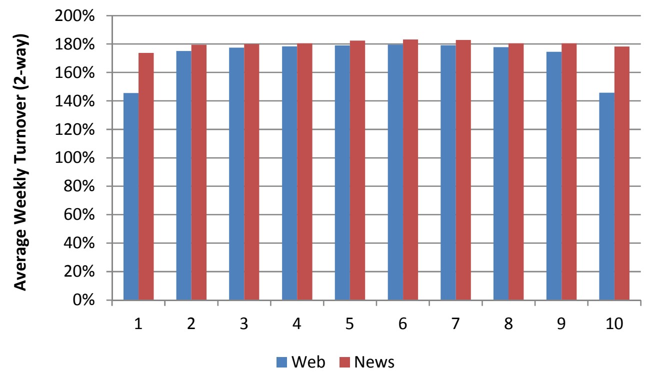
[4] Note this is two-way turnover, so the maximum is 200%, i.e. selling each stock in the portfolio and then buying a new stock to replace each one.

Figure 33: IC decay in 12 weeks after signal date



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

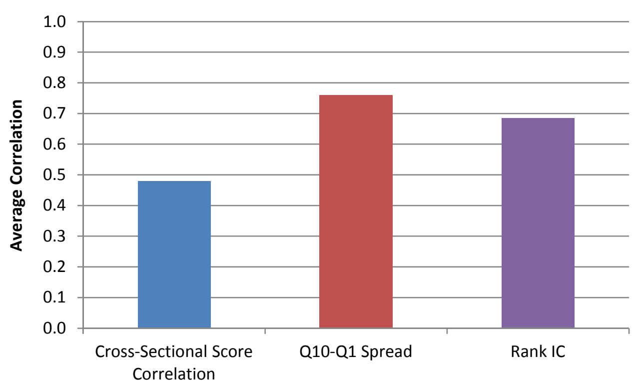
Figure 34: Average weekly turnover by decile, two-way



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

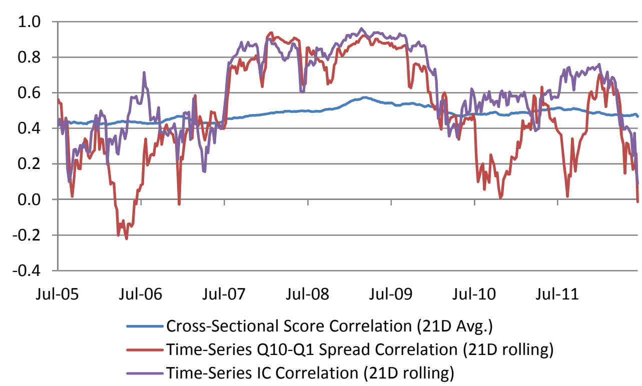
The correlation between the two strategies is moderate in terms of cross-sectional score correlation – which averages around 50% - but higher in performance terms (see Figure 35 and Figure 36).

Figure 35: Average correlations over time



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 36: Time-series of correlations



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Summary of backtesting results

Our results for web and news sentiment are consistent with our previous research where we found that the efficacy of news sentiment as a linear stock selection factor was only moderate at best. Adding web sentiment to the mix does not appear to be a panacea in this regard. While web sentiment shows almost double the predictive power of news sentiment in terms of monthly information coefficient (IC), this predictive power does not translate as cleanly into return space. At a weekly horizon, the two signals are fairly similar in IC terms but news sentiment does better in terms of returns.

No magic bullet

These findings reinforce our belief that using news and web sentiment in quantitative models is not as simple as just buying stocks with high sentiment and avoiding stocks with low sentiment. Indeed, we think one of the reasons sentiment-based factors have not gained popularity quicker than they have is the expectation that somehow sentiment will be a magic bullet that can immediately add uncorrelated alpha when added to a model. As usual in finance, it is not nearly so simple. Our own work suggests that the best way to leverage sentiment is to be smarter about how we use it

– we can do a lot better than just buying positive sentiment and selling negative sentiment. In Cahan et al. [2010] we suggested using non-linear, learning models to convert sentiment into alpha, whereas in Cahan et al. [2011] we proposed a way to enhance momentum by using web connections to define a company's peer group. In the rest of this paper, we will suggest some more ways to use web and news data to create new opportunities for stock selection models.

Case Study 1: News and reversal

Using news and the web to enhance reversal strategies

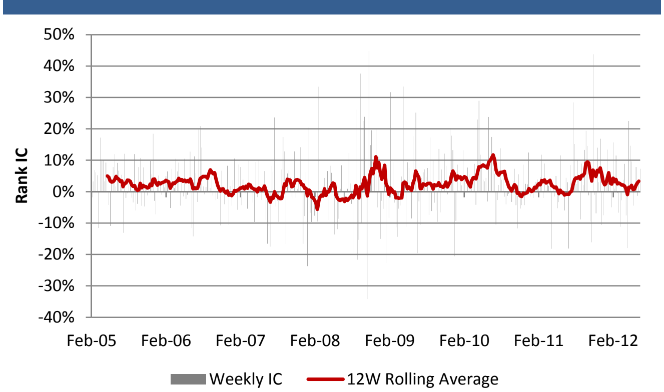
Short-term reversal is a well established phenomenon in stock returns. On shorter time horizons, such as a month or a week, stocks tend to mean revert on average. A stand-alone strategy that buys past short-term losers and sells past winners can generate excess returns over time before costs, and perhaps even after costs. However, because of the high turnover it is more typical to combine reversal with other factors to slow down the turnover, and indeed the factor is a staple ingredient in many multifactor quant models, including our own.

In the context of this paper, we are interested in how reversal and momentum interact with news flow. Academic research has suggested that news can play a role in attenuating the strength of the reversal effect and magnifying the momentum effect. For example, Chan [2003] showed that extreme return stocks with no news tend to show reversal in the subsequent month, whereas those with news showed momentum effects. More recently, Tetlock [2010] found that 10-day reversal in daily returns is 38% weaker in stocks with news, whereas momentum effects often only exist for stocks with news. Both these papers build on the wider finding in most (but certainly not all) academic papers that investors tend to underreact to the information contained in news, which leads to post-news drift in the same direction.

Expanding the definition of "news"

Our unique database of news stories and web stories allows us to build on this academic work by expanding the definition of "news" to encompass mentions in the financial press as well as references to the company on the internet. Given the short history for the web data, we focus on one week (1W) reversal, as that gives us more data points to work with. Figure 37 shows the weekly IC for the 1W reversal strategy, and Figure 38 shows the cumulative performance of a decile spread portfolio. Reversal has been particularly effective as a strategy post the financial crisis, given the choppy risk-on/risk-off market conditions.

Figure 37: 1W Reversal: weekly rank IC



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 38: 1W Reversal: Cumulative decile spread performance

Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

To see whether there is any interaction effect between news and reversal, we conduct an independent double sort using past one week total returns and one week sentiment. The latter variable is the equally weighted average of each stock's news sentiment and web sentiment z-score. In the instance where a stock has a score on only one of the two factors, the missing score is assumed to be zero. Combining the news and web data allows us to get maximum coverage at each point in time. Figure 39 shows the average excess returns (annualized) for each portfolio, and Figure 40 shows the annual information ratio.

Figure 39: Double sort analysis, annualized relative returns

	Q1 (-ve sent.)	Q2	Q3	Q4	Q5 (+ve sent.)
Q1 (past losers)	5.0%	14.8%	14.5%	15.1%	6.4%
Q2	0.0%	5.5%	1.0%	2.8%	5.0%
Q3	-2.5%	-0.5%	0.3%	2.7%	2.5%
Q4	-2.7%	-1.4%	-1.0%	-1.0%	0.2%
Q5 (past winners)	-1.0%	-6.9%	-4.9%	-7.0%	-1.8%
Spread	**6.1%**	**21.7%**	**19.4%**	**22.2%**	**8.2%**

Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

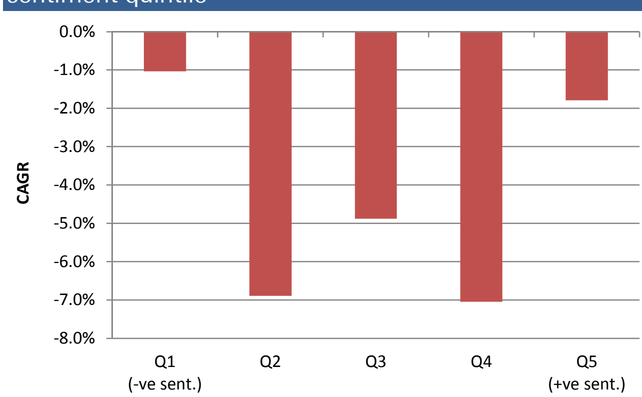
Figure 40: Double sort analysis, annualized information ratio (IR)

	Q1 (-ve sent.)	Q2	Q3	Q4	Q5 (+ve sent.)
Q1 (past losers)	0.40	1.21	1.23	1.44	0.66
Q2	0.00	0.94	0.16	0.47	0.80
Q3	-0.45	-0.11	0.06	0.51	0.41
Q4	-0.36	-0.23	-0.17	-0.16	0.02
Q5 (past winners)	-0.09	-0.69	-0.54	-0.79	-0.21
Spread	**0.32**	**1.16**	**1.08**	**1.33**	**0.53**

Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

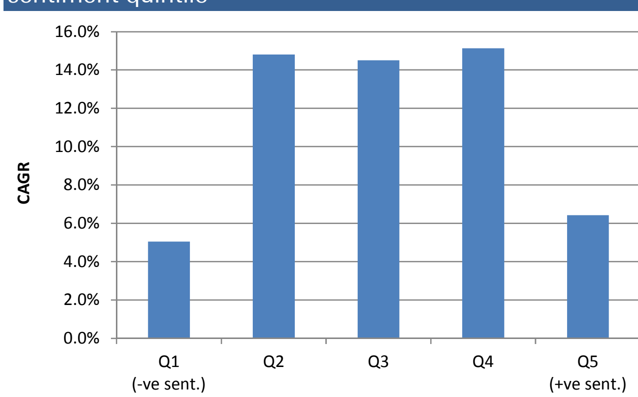
The key result is the bottom row in each table, labeled "Spread". This is the difference between the past losers and past winners, for a given level of sentiment. From both tables it is clear that the reversal effect is muted for stocks with both low and high sentiment. This is easier to see if we look at the results graphically. Figure 41 shows annualized excess returns for past winner stocks within each sentiment quintile, and Figure 42 shows the same for past losers. The left hand chart shows that on average past winner all stocks underperform in the following week, but the reversal is much weaker for the extreme sentiment stocks. Similarly, in the right hand chart, past losers all outperform on average, but again the reversal is moderated in extreme sentiment stocks.

Figure 41: Performance of past winners portfolio, by sentiment quintile



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 42: Performance of past loser portfolio, by sentiment quintile



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

The interesting thing about these results is that the direction of the sentiment matters less than the absolute intensity of the sentiment. In other words, stocks with extreme positive or negative sentiment show similar behavior. To confirm this, in Figure 43 and Figure 44 we repeat the double sorts, except this time we use number of mentions instead of sentiment. Number of mentions is simply a count of the number of times each stock has appeared in either a news article or web posting in the last week. The bottom row now shows that on average reversal is much stronger in stocks with little news, with an annualized spread return of 22.1% compared to 4.5% for stocks with lots of news.

Figure 43: Double sort analysis using number of mentions, annualized relative returns

	Q1 (little news)	Q2	Q3	Q4	Q5 (lots of news)
Q1 (past losers)	16.1%	10.2%	15.2%	6.8%	3.2%
Q2	4.8%	7.6%	2.6%	0.7%	0.7%
Q3	0.7%	3.4%	-3.3%	0.4%	1.1%
Q4	-2.2%	-2.1%	-0.8%	1.0%	-2.4%
Q5 (past winners)	-6.0%	-5.3%	-7.7%	-2.2%	-1.3%
Spread	**22.1%**	**15.5%**	**22.9%**	**9.0%**	**4.5%**

Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 44: Double sort analysis using number of mentions, annualized information ratio (IR)

	Q1 (little news)	Q2	Q3	Q4	Q5 (lots of news)
Q1 (past losers)	1.43	0.75	1.16	0.63	0.27
Q2	0.92	0.87	0.40	0.12	0.10
Q3	0.15	0.52	-0.58	0.08	0.16
Q4	-0.39	-0.25	-0.12	0.15	-0.32
Q5 (past winners)	-0.64	-0.43	-0.75	-0.23	-0.14
Spread	**1.29**	**0.71**	**1.16**	**0.51**	**0.25**

Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Certainly this would appear to suggest that what matters is not so much the direction of news flow, but whether the stock has been in the news at all. However, the number of mentions a stock gets on the web and in the press is of course heavily influenced by the size of the company. So are we just seeing a size (or volatility or liquidity) effect here? To dig deeper we repeat our double sorts with some alternatively factors: market cap, trailing volatility, float turnover, and average daily volume (ADV). The results are shown in Figure 45 through Figure 50 below.

Figure 45: Double sort analysis using market cap, annualized relative returns

	Q1 (small cap)	Q2	Q3	Q4	Q5 (large cap)
Q1 (past losers)	16.1%	8.2%	6.7%	8.5%	11.3%
Q2	4.1%	1.6%	4.6%	1.8%	1.7%
Q3	11.6%	-2.4%	0.7%	0.5%	-4.1%
Q4	8.0%	1.6%	-0.4%	-3.5%	-7.5%
Q5 (past winners)	5.4%	-1.9%	-4.3%	-9.4%	-14.2%
Spread	**10.7%**	**10.1%**	**11.1%**	**17.9%**	**25.6%**

Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 46: Double sort analysis using market cap, annualized information ratio (IR)

	Q1 (small cap)	Q2	Q3	Q4	Q5 (large cap)
Q1 (past losers)	1.17	0.76	0.58	0.72	0.76
Q2	0.45	0.26	0.83	0.26	0.20
Q3	1.32	-0.39	0.14	0.07	-0.46
Q4	0.87	0.26	-0.06	-0.46	-0.75
Q5 (past winners)	0.47	-0.21	-0.46	-0.92	-1.16
Spread	**0.62**	**0.64**	**0.62**	**0.98**	**1.16**

Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 47: Double sort analysis using volatility, annualized relative returns

	Q1 (low vol)	Q2	Q3	Q4	Q5 (high vol)
Q1 (past losers)	0.8%	2.8%	6.6%	10.3%	18.0%
Q2	-0.9%	1.9%	6.1%	4.5%	4.2%
Q3	-4.1%	-1.4%	1.0%	2.5%	9.7%
Q4	-4.3%	-4.9%	-2.2%	1.3%	9.4%
Q5 (past winners)	-5.9%	-7.1%	-4.3%	-3.4%	-2.3%
Spread	**6.7%**	**9.9%**	**10.8%**	**13.7%**	**20.3%**

Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 48: Double sort analysis using volatility, annualized information ratio (IR)

	Q1 (low vol)	Q2	Q3	Q4	Q5 (high vol)
Q1 (past losers)	0.06	0.32	0.82	0.92	0.93
Q2	-0.08	0.30	1.16	0.58	0.27
Q3	-0.35	-0.21	0.20	0.37	0.66
Q4	-0.34	-0.68	-0.37	0.18	0.62
Q5 (past winners)	-0.41	-0.75	-0.56	-0.45	-0.16
Spread	**0.55**	**0.80**	**0.81**	**0.92**	**1.06**

Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 49: Double sort analysis using ADV, annualized relative returns

	Q1 (low ADV)	Q2	Q3	Q4	Q5 (high ADV)
Q1 (past losers)	8.1%	8.7%	8.6%	9.8%	15.3%
Q2	-0.5%	2.6%	1.5%	4.7%	3.9%
Q3	-1.1%	1.9%	0.8%	-1.0%	0.8%
Q4	-1.2%	-0.1%	0.8%	-1.6%	-3.2%
Q5 (past winners)	-4.4%	2.4%	-2.6%	-1.7%	-9.1%
Spread	**12.5%**	**6.3%**	**11.2%**	**11.5%**	**24.4%**

Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

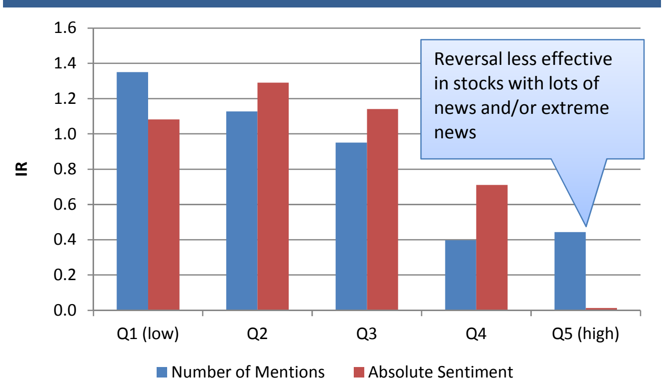
Figure 50: Double sort analysis using ADV, annualized relative returns

	Q1 (low ADV)	Q2	Q3	Q4	Q5 (high ADV)
Q1 (past losers)	0.82	0.86	0.77	0.68	0.93
Q2	-0.07	0.43	0.25	0.65	0.49
Q3	-0.15	0.33	0.15	-0.16	0.11
Q4	-0.16	-0.02	0.12	-0.21	-0.39
Q5 (past winners)	-0.47	0.27	-0.28	-0.16	-0.74
Spread	**0.84**	**0.40**	**0.64**	**0.55**	**1.04**

Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

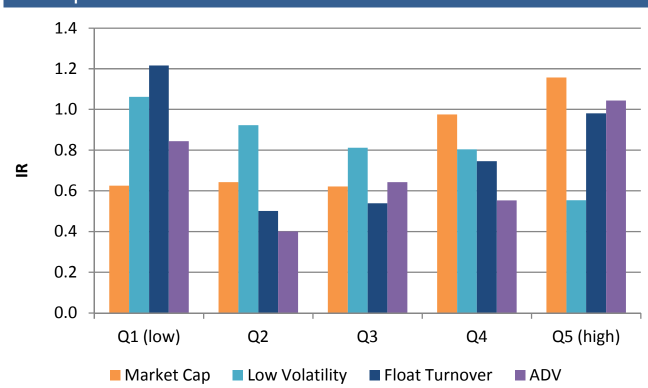
To make things easier to see, we summarize everything in Figure 51 and Figure 52. The left hand chart shows the performance of a reversal strategy by (1) number of mentions and (2) absolute sentiment. We compare this to the right hand chart that shows the same thing by (1) market cap, (2) volatility, (3) float turnover, and (4) ADV.

Figure 51: Information ratio for reversal conditioned by absolute sentiment and number of mentions



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 52: Information ratio for reversal conditioned by other potential factors



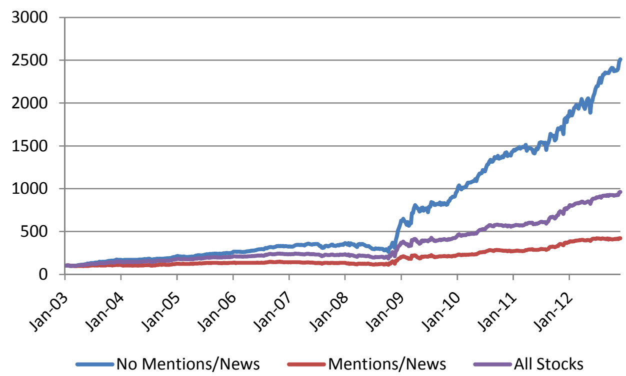
Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

The interesting result jumps out immediately: none of the other factors in Figure 52 attenuate reversal to the same degree that news intensity (measured by absolute sentiment) or number of mentions does. This is despite the sometimes high correlation between news flow and the size of a company. The result is consistent with the hypothesis that investors tend to overreact to price shocks that are not news driven, temporarily overvaluing or undervaluing the security and leading to a reversal thereafter as this mispricing is corrected.

What about stocks with no news at all?

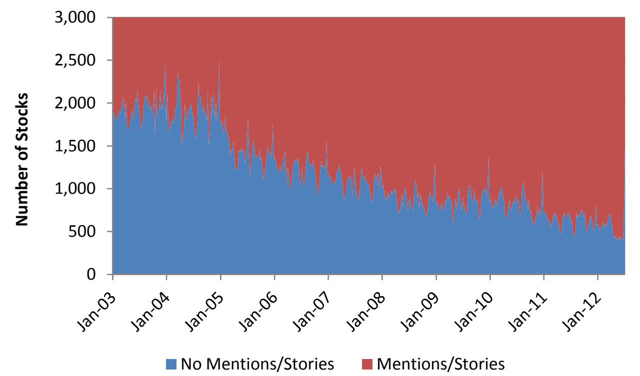
So far in the double sorts we considered only stocks that have at least some news (i.e. decile 1 was stocks with the least news, but still some news). To take things to the extreme, we test how reversal works in stocks with no web mentions or news stories at all in the past week, compared to those with at least one mention. Figure 53 shows the cumulative performance of the weekly reversal strategy in each sub-universe, as well are the overall universe. As expected, reversal is strongest in the stocks with no web or media attention.

Figure 53: Cumulative performance of reversal strategy in stocks with and without web mentions/news stories



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

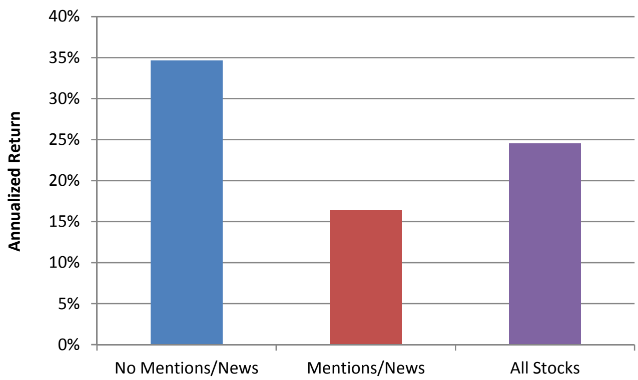
Figure 54: Number of stocks in universe with and without web mentions/news stories



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

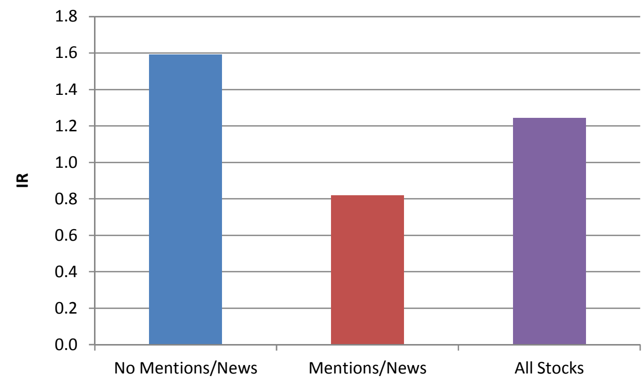
The chart in Figure 54 shows how many stocks comprise this no news universe (the blue portion). Because web and news coverage has steadily increased over time, the no news universe has been shrinking steadily. As a result, it is important to consider risk-adjusted returns since the volatility of the reversal portfolios in the no news universe will be higher due to their smaller size. Figure 56 shows the information ratio for the strategy in each universe, and confirms that even in risk-adjusted terms it works best in the no news universe.

Figure 55: Annual returns of reversal strategy in stocks with and without web mentions/news stories



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

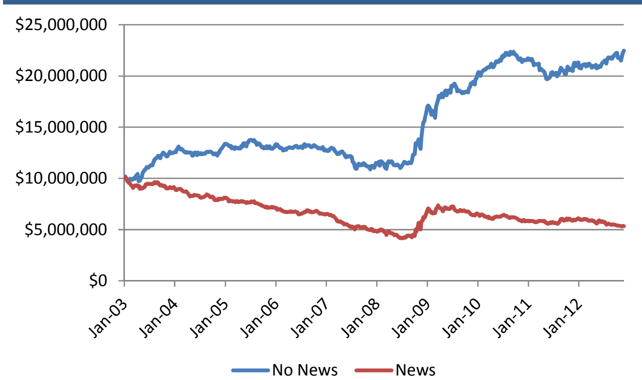
Figure 56: Information ratio of reversal strategy in stocks with and without web mentions/news stories



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

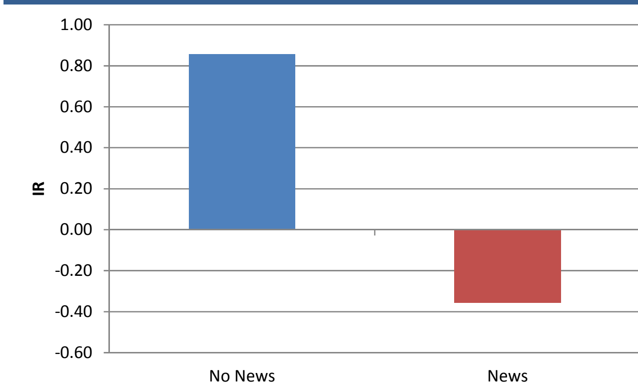
Of course, no news stocks tend to be lower liquidity small cap names that slip below the radar for precisely that reason. So the better performance we see in this universe could reflect the higher limits to arbitrage in this subsection of the universe. As with any backtesting analysis, it is difficult to accurately model the true costs of trading. But we can make an attempt. In Figure 57 and Figure 58 we show the performance of an optimized, market-neutral reversal portfolio in stocks with and without web or news mentions. The portfolio is beta and sector neutral, and we assume transaction costs of 15 bps one-way (i.e. these are charged twice in a rebalance). The portfolio starts out with a size of $10m. Most importantly, we include an ADV constraint to limit trading to less that 20% of ADV; this steers the portfolio away from less liquid stocks within each universe. Despite this, the reversal strategy is still much more effective in the no news universe.

Figure 57: Cumulative performance of weekly reversal in stocks with and without news, after costs



Source: Axioma, Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 58: Information ratio for weekly reversal strategy in stocks with and without news, after costs

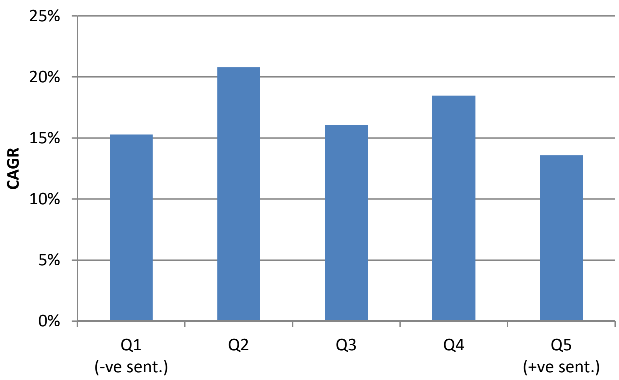


Source: Axioma, Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

S&P 500 analysis

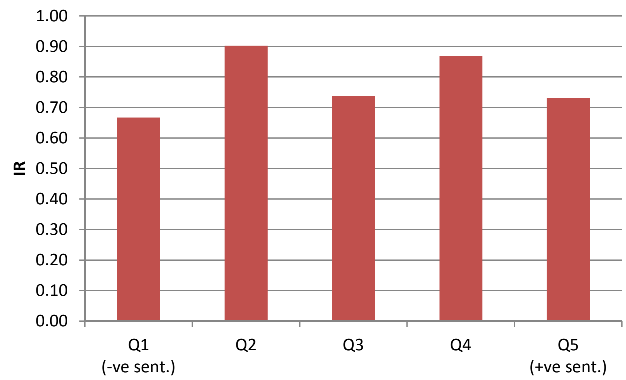
Another way to address the question of trading costs is to repeat the analysis on a larger cap universe. An obvious candidate is the S&P 500, where we can agree that limits to arbitrage will be less pronounced. Figure 59 and Figure 60 show the annualized returns and information ratios for a one week reversal strategy within each sentiment quintile (note since almost all the S&P 500 stocks will typically have at least one mention in a week, we cannot study the performance of reversal in no news stocks). Comparing the chart to the results in the wider Russell 3000 universe, the "inverse U" pattern is weaker although it still shows up in both raw returns as well as risk-adjusted returns.

Figure 59: Annual performance of weekly reversal strategy by sentiment quintile, S&P 500



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 60: Annual information ratio of weekly reversal strategy by sentiment quintile, S&P 500



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

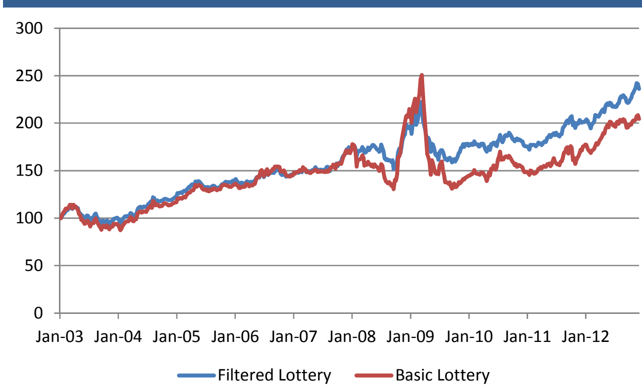
Case Study 2: News and the lottery factor

Enhancing another type of reversal

One of the interesting variations on reversal that we have studied in the past is the so-called "lottery factor". This factor is defined as the maximum daily return in the past month (or last week if doing weekly rebalancing). The idea is to avoid or short stocks with a large one-day jump recently. The argument is behavioral – when a stock has a big jump it tends to attract speculators, who perhaps believe they will get a similar lottery-like payoff in the future. Of course, more often than not this does not happen, and eventually this speculative money exits leading to a strong reversal.[5]

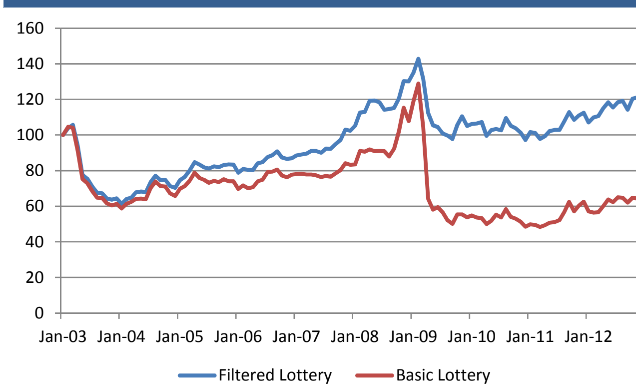
However, there are many cases where a large jump in share price is warranted, for example a positive earnings surprise or the stock being named as a takeover target. In such cases where there is positive firm-specific news, it seems plausible that the usual reversal effect would be mitigated to some extent. Fortunately, with our database of web and news mentions of individual companies we can directly test this hypothesis. We start by backtesting a weekly and monthly version of the lottery factor, as defined previously (i.e. the maximum daily return in the past week or month) – see the red line in Figure 61 and Figure 62. Then we apply a very simple filter when computing the factor scores: we zero out any daily return where there was a company-specific news item or web mention. The performance of this filtered strategy is the blue line in the charts below.

Figure 61: Performance of weekly lottery factor, with and without the filter



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 62: Performance of monthly lottery factor, with and without the filter

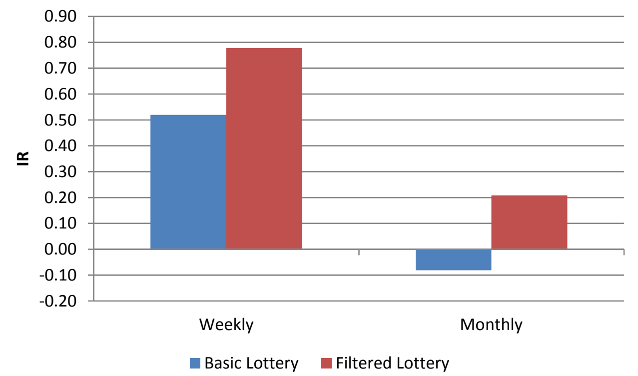


Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

For both the weekly and monthly versions of the lottery factor, this simple overlay actually improves performance, not just in terms of cumulative performance, but also in risk-adjusted terms (sees Figure 63 and Figure 64).

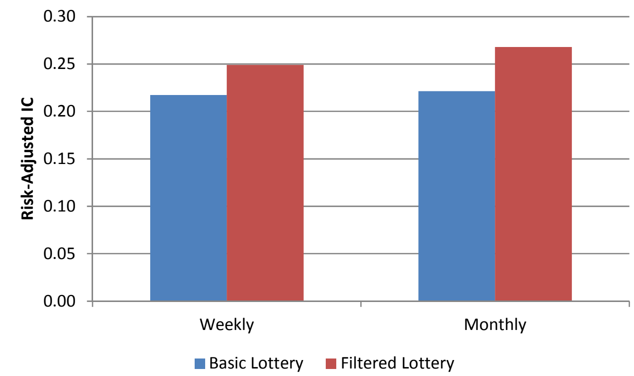
[5] For a more academic discussion of this phenomenon, see Bali, Cakici, and Whitelaw [2011].

Figure 63: IR for lottery factor with and without filter



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 64: Risk-adjusted IC for lottery factor with and without filter



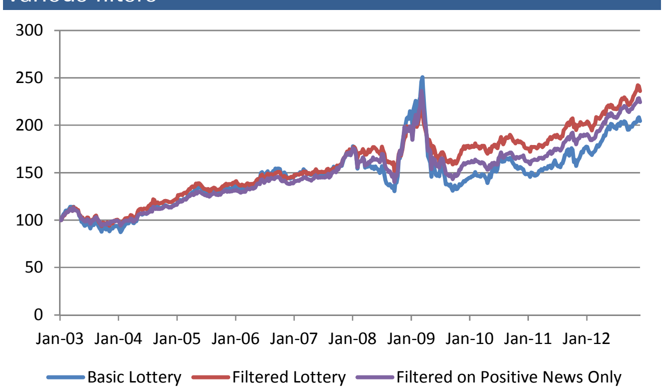
Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Filtering out positive news events only

The next logical step is to only filter out positive news stories. After all, we are focusing on big one-day jumps, so it makes sense to only rule out jumps that are warranted because of positive news, rather just any news.

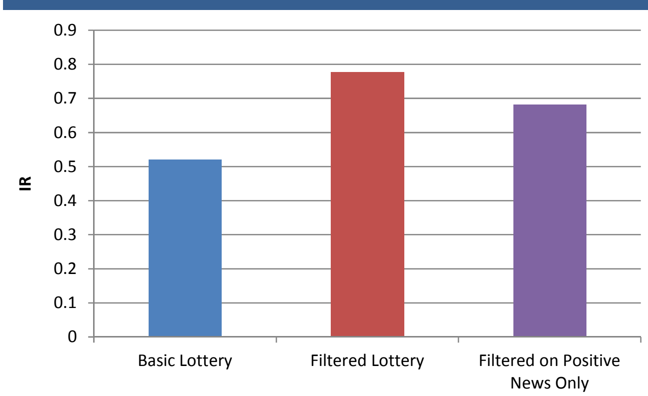
Figure 65 and Figure 66 show the performance of this new strategy (in purple). The somewhat surprising result is that this does not improve performance over the basic filter. However, on reflection this is perhaps not as surprising as it seems. Keep in mind that the sentiment score for each story is designed to measure the *linguistic* sentiment of the text and words in the story. A story could be linguistically very negative (i.e. include a lot of doom and gloom words and so on) but if it is "less bad" than what the market was expecting then the stock could well move up. So filtering out large returns only on positive news days is less effective then filtering out jumps on all news. In a sense, this is further confirmation of our findings in the first section and in our past research, where we argued that trading sentiment as a simple, linear factor without considering the market response to that sentiment is suboptimal.

Figure 65: Performance of weekly lottery factor with various filters



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 66: IR for lottery factor with various filters



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

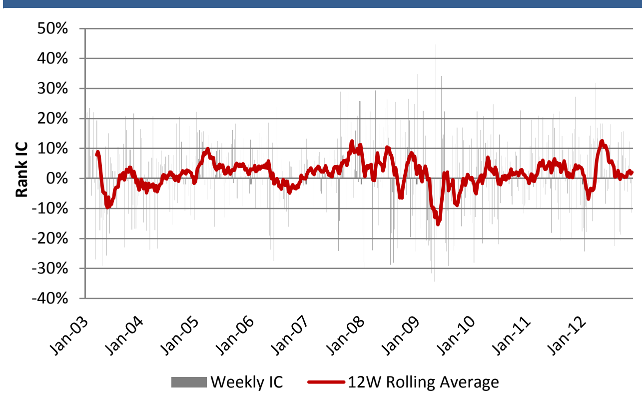
Case Study 3: News and momentum

Can news flow enhance momentum too?

So far we have focused our attention on reversal strategies, but as mentioned academic evidence suggests news has implications for momentum strategies too. In fact, one of the arguments for why momentum exists in the first place is the slow diffusion of news into prices. Both Chan [2003] and Tetlock [2010] found that the efficacy of momentum is enhanced in stocks with news flow.

As with reversal, we will consider a weekly rebalanced momentum strategy to give us more data points to work with. The momentum signal we will focus on is the ubiquitous 12-month minus 1-month momentum. The weekly rank IC of this signal is shown in Figure 67 and cumulative returns to a decile spread portfolio in Figure 68. Of course, the second chart shows one of the devastating properties of momentum, namely the left tail risk around turning points (in this case most dramatically illustrated by the massive drawdown in the March 2009 risk rally). In this paper our focus is not to "fix" momentum per se – we've written plenty about that in the past – rather we are interested in whether momentum does better (or over this period perhaps more accurately less worse) when conditioned by news flow.[6]

Figure 67: 12M-1M Momentum: weekly rank IC



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

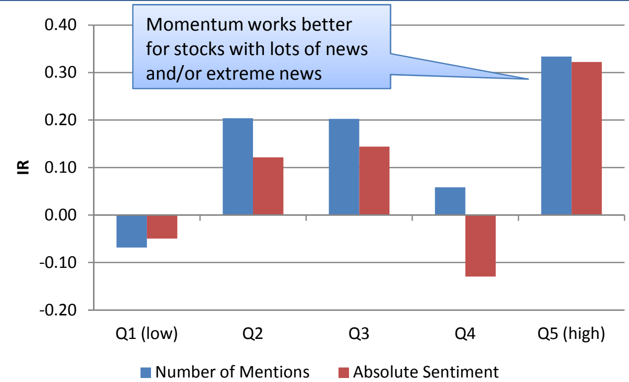
Figure 68: 12M-1M Momentum: Cumulative decile spread performance

Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 69 shows the information ratio for momentum by quintiles of number of mentions and absolute sentiment. In Figure 70 we repeat the chart we saw previously with the same analysis for reversal. The difference is quite stark: momentum certainly appears to do better in the subset of stocks with either lots of news or extreme sentiment. This is exactly opposite what we saw for reversal, and consistent with the academic evidence.

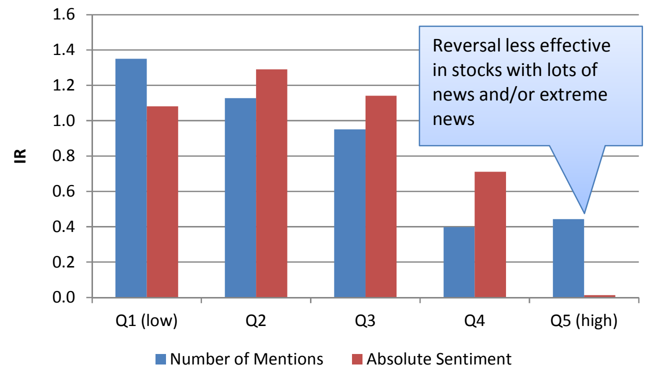
[6] For our other work on momentum, see for example Alvarez et al. [2011] where we propose a neutralization strategy, or Jussa et al. [2012] where we suggest diversifying momentum across asset classes.

Figure 69: Information ratio for momentum conditioned by absolute sentiment and number of mentions (excluding post-crisis risk rally, Mar-May 2009)



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

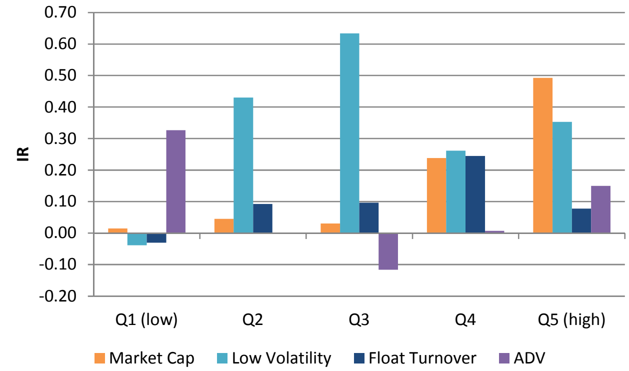
Figure 70: Information ratio for reversal conditioned by absolute sentiment and number of mentions



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

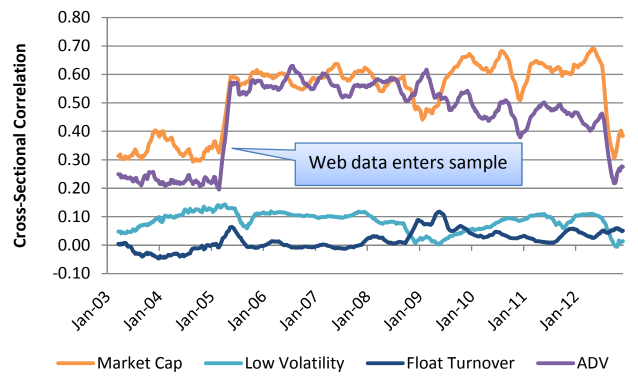
But as with reversal, it is important to consider the correlation that news volume has with other variables like size and liquidity. This is particularly important because academic research (see Lee and Swaminathan [2000] for example) has shown that momentum tends to work better is high volume stocks. We show the same analysis that we used for reversal in Figure 71. This time market capitalization appears to be the most monotonic conditioning variable, with momentum performing best in large cap names. Therefore, in the case of momentum at least, market cap is potentially a useful proxy to condition on if one does not have access to news volume data. Figure 72 shows that the correlation between market cap and number of mentions is relatively high on average over time (so is ADV for that matter, but as shown in the left hand chart this factor is less useful as a conditioning variable).

Figure 71: Information ratio for momentum conditioned by other potential factors (excluding post-crisis risk rally, Mar-May 2009)



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 72: Cross-sectional correlation between number of web mentions/news stories and other factors



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

News-aware reversal and momentum

Building better reversal and momentum signals

Our research in this paper suggests that reversal tends to work better in stocks with little news whereas momentum is more effective in stocks with lots of news. This reconciles with academic evidence, but more importantly is intuitive. Momentum is partly the result of the market's slow pricing of new information, so it stands to reason that momentum would be less effective for stocks with little new information. On the other hand, in the absence of news investors overreact to price shocks which leads to subsequent reversals.

How can we harness these findings in a unified framework? We propose a very simple idea: weight a stock's momentum score by the number of mentions a stock has seen on the web and in the news, and weight a stock's reversal score by the inverse of that number. More formally, define weighted momentum as

$$WMOM_{i,t} = (1 + N_{W+N})MOM_{i,t}$$

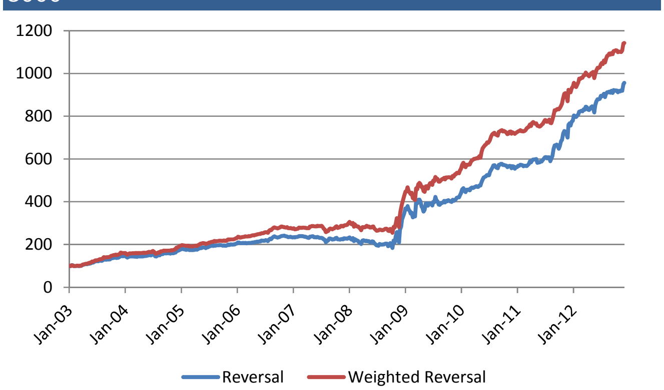
and weighted reversal as

$$WREV_{i,t} = REV_{i,t} / (1 + N_{W+N})$$

where $MOM_{i,t}$ is the 12M-1M momentum score (z-score) for stock i at time t, $REV_{i,t}$ is the reversal score, and N_{W+N} is the number of web mentions plus news mentions in the past five days. Now for two stocks with the same momentum, the one with more news articles will rank better, while for two stocks with the same reversal score the one with less news will be emphasized.

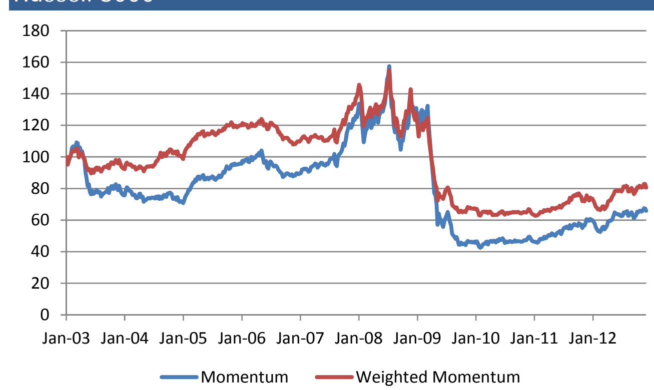
Figure 73 and Figure 74 compare the weekly performance of momentum and reversal with and without the weighting scheme. In both cases, performance is improved.

Figure 73: Performance of reversal strategies in Russell 3000



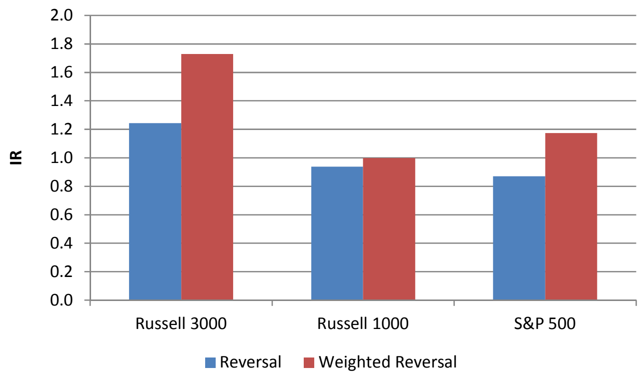
Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 74: Performance of momentum strategies in Russell 3000



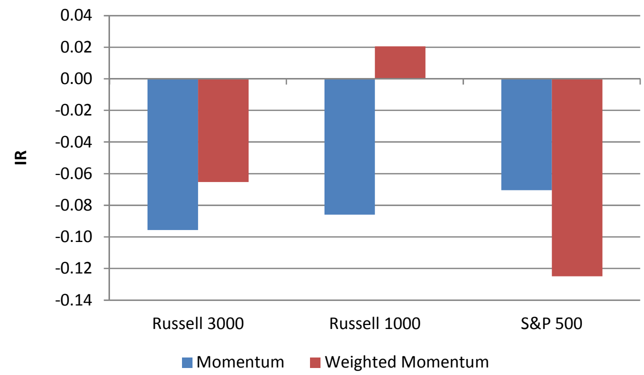
Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 75: Difference in IR for reversal strategies, in various universes



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 76: Difference in IR for momentum strategies, in various universes

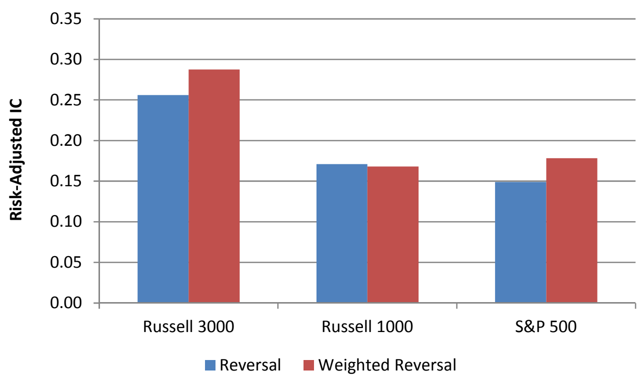


Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

The improvement in reversal performance – as measured by IR – applies even if we focus on larger cap universes like the Russell 1000 and S&P 500 (Figure 75), whereas the gains to momentum are limited to the Russell 3000 and Russell 1000 universes (Figure 76).

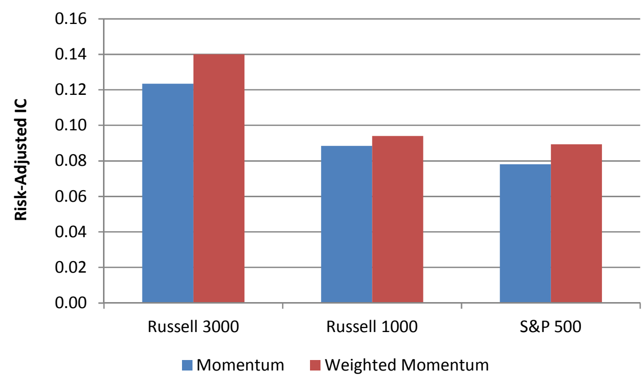
In risk-adjusted IC terms, reversal and momentum are improved in five out of six cases, with the exception being reversal in the Russell 1000 universe where both normal and weighted reversal perform roughly in line (Figure 77 and Figure 78).

Figure 77: Difference in risk-adjusted IC for reversal strategies, in various universes



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 78: Difference in risk-adjusted IC for momentum strategies, in various universes



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

All publicity is good publicity?

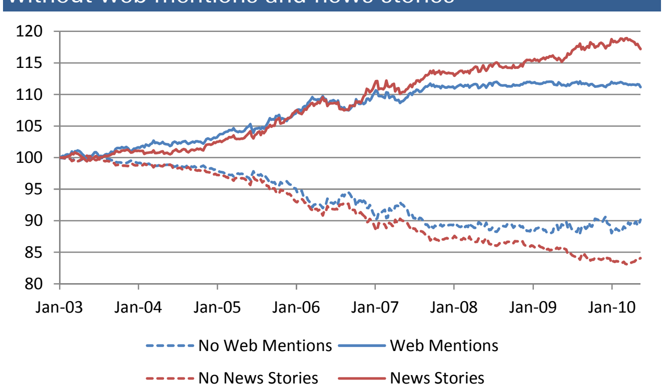
Up to this point we have been comparing the performance of different strategies within the universe of stocks with or without web and news mentions. But what about these two types of stocks themselves? Do stocks with news outperform those with no news or vice versa?

Academic evidence on this front is, as is so often the case, a bit mixed. Fang and Peress [2009] for example found that stocks with no media coverage (measured as coverage in four major US newspapers – the WSJ, NY Times, USA Today, and Washington Post) outperform those stocks with coverage by about 3% per year. They hypothesize that this is because news coverage helps reduce the information costs of investors, hence they do not demand as high returns to hold well-covered stocks.

On the other hand, Barber and Odean [2007] show that individual investors tend to be net buyers of attention-grabbing stocks, i.e. those with high media coverage. They argue this is because of limited attention; a retail investor does not have time to sift through thousands of stocks, so they tend to focus on those that are well publicized in the media. While the authors do not directly test whether this leads to higher or lower returns for high news stocks, they do suggest that due to the short-sale constraint many investors face, the impact of this attention-induced trading will be asymmetrical. Any investor can buy a stock that is in the news, but you can only sell a stock you read about if it is already in your portfolio (assuming you are not able to short). Therefore, one might argue that these high attention stocks become overvalued as investors focus on them too heavily relative to lower profile names. If this is the case, the performance of high news stocks will depend on whether this overvaluation reverses, or whether it has momentum-like behavior.

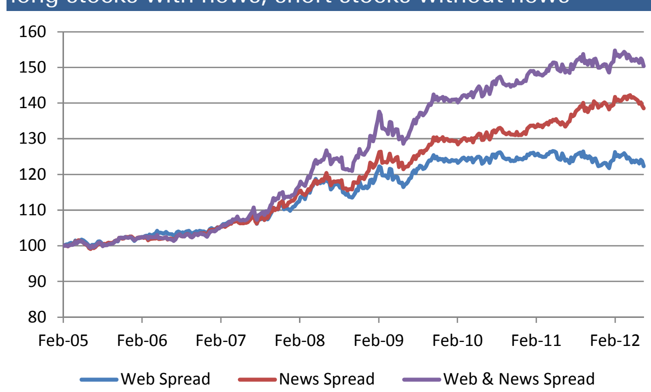
Empirically, we find that over our sample (which is admittedly fairly short) stocks with news outperform those without news fairly consistently. Figure 79 shows the cumulative returns to baskets of stocks with and without (1) web mentions in the last week, and (2) news mentions in the last week.

Figure 79: Cumulative excess returns for stocks with and without web mentions and news stories



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

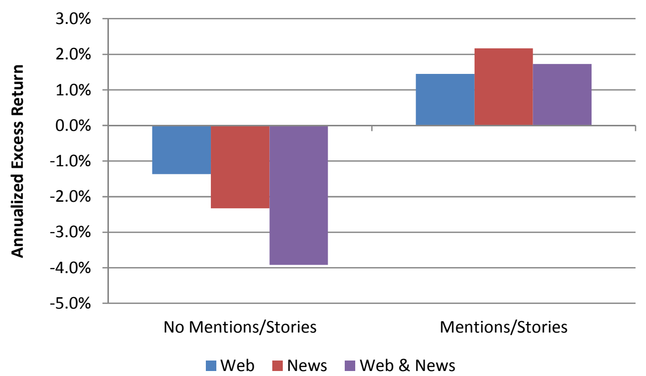
Figure 80: Cumulative performance for spread portfolio: long stocks with news, short stocks without news



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

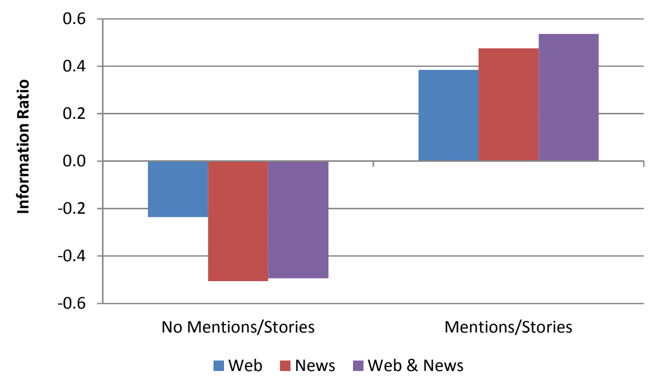
In Figure 80 we show the spread performance from going long high-attention stocks and short low-attention stocks, where attention is again measured by whether a stock had web mentions or news stories in the last week. We also show the results for a combined strategy that goes long stocks that have been mentioned somewhere on the web or in the news in the last week, and short those that have not. This strategy performs best of all, in both raw returns (Figure 81) as well as risk-adjusted returns (Figure 82).

Figure 81: Annualized excess returns



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 82: Information ratio versus equally-weighted benchmark



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

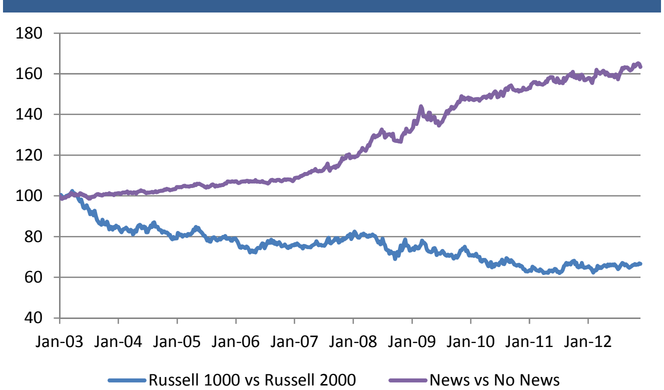
Is this just a size bias?

As we've already seen, the volume of news about a company is closely tied to its size and liquidity. To study whether these exposures are driving our results, we overlay the performance of the news versus no news portfolio with a range of other strategies.

For example, in Figure 83 we see that the outperformance of no news stocks is certainly not being driven by a size bias. In fact, over our backtest period large caps have actually underperformed small caps; so high news stocks have managed to outperform despite the drag from their tilt towards large cap names.

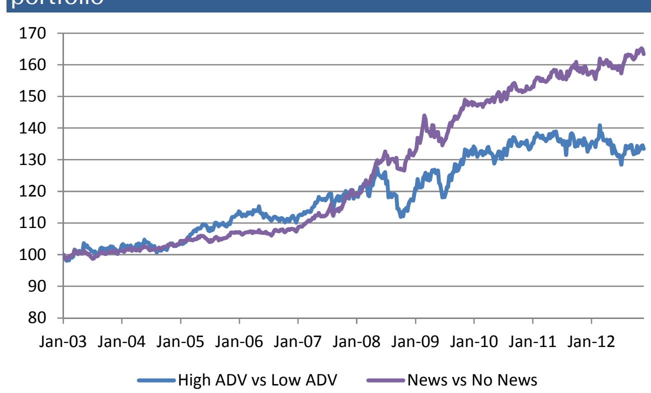
A better match is ADV, as shown in Figure 84. Our results for ADV for this period are opposite much of the academic literature (e.g. Chen, Ibbotson, and Hu [2010]) that typically finds that illiquid names yield a risk premium. In contrast, we find that high ADV names have outperformed, although keep in mind a big part of our sample is dominated by the credit crisis, during which there was a flight to more liquid names.

Figure 83: Comparison to large minus small cap portfolio



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

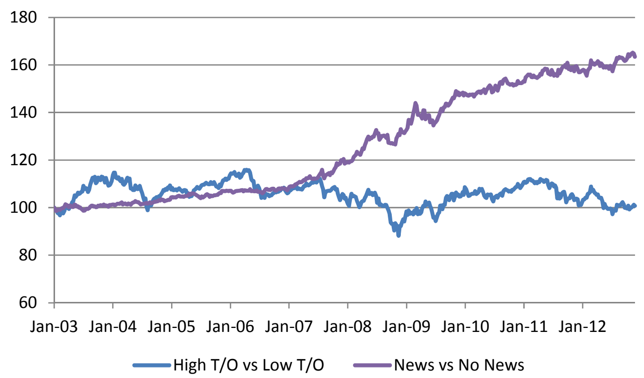
Figure 84: Comparison to high ADV minus low ADV portfolio



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

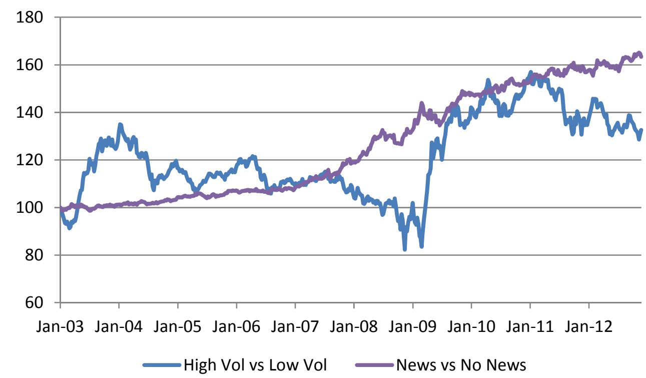
If we look at some other metrics like float turnover (Figure 85) and volatility (Figure 86), we do not see as strong a correlation as what we got with ADV. With ADV there is a bit of a chicken-and-egg scenario, because while it is clear that the strategies are somewhat related, it is not obvious which comes first: does high ADV lead to more news coverage, or does news coverage drive higher ADV? This is a question we will leave for future research. For now, suffice it to say that ADV is potentially a useful proxy for capturing the news versus no news effect.

Figure 85: Comparison to high float turnover minus low float turnover portfolio



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 86: Comparison to high volatility minus low volatility portfolio



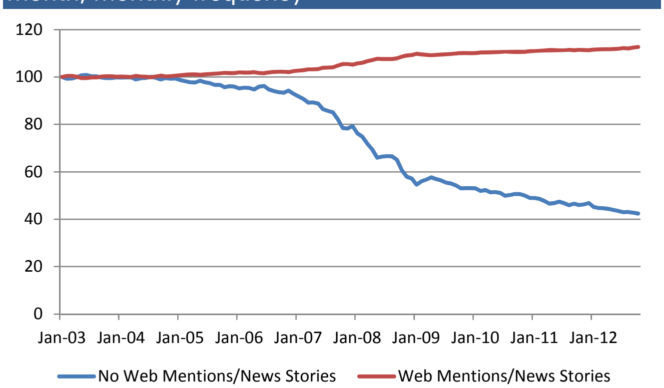
Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

What about longer holding periods?

In the previous results, we have measured the performance of news and no news stocks at a weekly frequency. This is quite a high turnover strategy because each week the set of stocks with news and no news will change, and hence our portfolio will change. Suppose we rebalance monthly instead, using a 1-month lookback to determine news coverage? Figure 87 shows that the results look very similar to the weekly results. In fact, the magnitude of the outperformance for no news is larger.

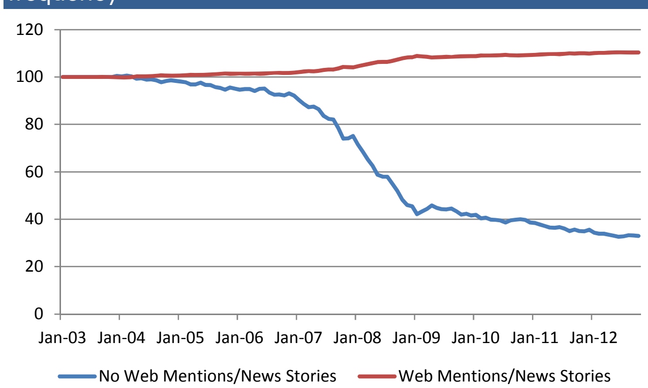
We also repeat the exercise one more time, except this time while we still rebalance monthly, we use a 1-year lookback to determine news coverage (Figure 88).

Figure 87: Cumulative excess returns for stocks with and without web mentions and news stories in the past month, monthly frequency



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 88: Cumulative excess returns with and without web mentions and news stories in the past year, monthly frequency



Source: Bloomberg Finance LP, Compustat, IBES, Moreover, Russell, S&P, Thomson Reuters, Deutsche Bank

So now the blue line represents those stocks that have not had any web or news mentions in the past year. Clearly this is a much smaller portfolio, since in the Russell 3000 it is quite hard not to be mentioned at least once somewhere on the web or in the news during the year. However, the results are still consistent – the no news names underperform significantly.

Conclusion

In this report we have suggested some simple conditioning techniques that can help enhance price-based strategies like reversal, momentum, and the lottery factor. To reiterate our comments at the start of this paper, we think that the real value in news and web data lies beyond simple long positive sentiment/short negative sentiment strategies. Hopefully this report, along with our past research, has provided some ideas on this front.

We also found interesting evidence that web sentiment is slower decay than news sentiment, which is consistent with our hypothesis that the information in professional newswires like Reuters, Dow Jones, and Bloomberg is priced in quicker than less scrutinized web data. Therefore, for longer-term investors web data could be particularly useful in helping to capture a slower decay sentiment signal.

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Appendix 1

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Deutsche Bank Securities Inc.

North American Locations

Deutsche Bank Securities Inc.
60 Wall Street
New York, NY 10005
Tel: (212) 250 2500

Deutsche Bank Securities Inc.
One International Place
12th Floor
Boston, MA 02110
United States of America
Tel: (1) 617 217 6100

Deutsche Bank Securities Inc.
222 South Riverside Plaza
30th Floor
Chicago, IL 60606
Tel: (312) 537-3758

Deutsche Bank Securities Inc.
1735 Market Street
24th Floor
Philadelphia, PA 19103
Tel: (215) 854 1546

Deutsche Bank Securities Inc.
101 California Street
46th Floor
San Francisco, CA 94111
Tel: (415) 617 2800

Deutsche Bank Securities Inc.
700 Louisiana Street
Houston, TX 77002
Tel: (832) 239-4600

International Locations

Deutsche Bank Securities Inc.
60 Wall Street
New York, NY 10005
United States of America
Tel: (1) 212 250 2500

Deutsche Bank AG London
1 Great Winchester Street
London EC2N 2EQ
United Kingdom
Tel: (44) 20 7545 8000

Deutsche Bank AG
Große Gallusstraße 10-14
60272 Frankfurt am Main
Germany
Tel: (49) 69 910 00

Deutsche Bank AG
Deutsche Bank Place
Level 16
Corner of Hunter & Phillip Streets
Sydney, NSW 2000
Australia
Tel: (61) 2 8258 1234

Deutsche Bank AG
Filiale Hongkong
International Commerce Centre,
1 Austin Road West,Kowloon,
Hong Kong
Tel: (852) 2203 8888

Deutsche Securities Inc.
2-11-1 Nagatacho
Sanno Park Tower
Chiyoda-ku, Tokyo 100-6171
Japan
Tel: (81) 3 5156 6770

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