News analytics for energy futures

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Abstract

We investigate how crude oil futures markets respond to positive and negative sentiment in news, as measured by the Thomson Reuters News Analytics. We measure the impact of the news sentiment on daily futures returns and on the fundamental factors of the forward curve evolution, such as the forward curve's level and the slope.

We define positive and negative news events as those days when the aggregated daily sentiment is in the top 10% quantiles of the corresponding sentiment distribution. We then relate these events to abnormal futures returns and to significant changes in the forward curve's level and slope.

We find that, for all maturities, positive resp. negative news events are accompanied by long periods of higher resp. lower than normal returns. These abnormal returns are observed already prior to the significant news events, suggesting that news are correlated with price momentum. Furthermore, after a negative news event occurs, returns continue decreasing at least for the subsequent 20 days. This is especially pronounced for nearby maturities, whose returns decrease by more than 3% on average. After a positive news event, returns increase on average by 2-3%. These effects are both statistically and economically significant. We also show a great asymmetry in the market's behavior: although positive and negative events are both 10% of days, the negative events are accompanied by much greater losses than the gains surrounding positive events.

We analyze the complex effect of news on the slope of the forward curve, and show that negative news increase the slope both in backwardation and contango markets. This means that contango deepens and backwardation flattens following a negative news event. Positive news have the opposite, albeit smaller, effect on the forward curve's slope. Generally, the reaction to news is significantly more pronounced in contango than in backwardation market.

The results of the analysis lay foundation for profitable trading strategies, based on taking a long/short position in oil futures of a fixed maturity immediately after a significant positive/negative news event. However, we expect such strategies to be quite risky. The analysis of news effects on the entire forward curve can be used to construct profitable (but much less risky) calendar spread trading strategies.

JEL classification: G14, Q47, G17, G12

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1. Introduction

Traditionally, the analysis of security returns has concentrated on responses to quantitative or *hard* measures such as corporate and economic statistics or, at most, a few ingeniously selected variables intended to proxy for some qualitative characteristic. Over the past decade, the IT revolution has provided us with a wealth of digitized text containing qualitative information and the processing power to apply algorithms that seek to quantify *soft* aspects of this text, such as relevance, sentiment and novelty. Recently, Thomson Reuters has introduced its News Analytics Engine, which is based on powerful linguistic analysis techniques. Computer analysis of thousands of news articles determines whether the news is positive, negative or neutral, and whether an article is relevant to a specific company, index or a commodity.

In the past few years, even before the emergence of computer-aided news analysis such as Thomson Reuters News Analytics, several articles appeared that have analyzed the effects of volume and "tone" of news on equities – specifically stock index and individual stock returns, volumes and volatilities and company earnings. The forerunners of such research are two articles by Tetlock (2007, 2008). The 2007 article studies the relationship between daily DJIA returns and sentiment (measured by Harvard IV-4 Psychosocial Dictionary (HPSD)) in the Wall Street Journal. Tetlock et al (2008) use event studies to investigate the relationship between a sentiment index based on the HPSD and stock returns and earnings of specific S&P500 companies. Broadly, the existing research in this area finds that sentiment can help predict stock returns and fundamentals such as earnings. In the case of forecasting the returns of stock indices, there is indication that news is largely noise: it drives down returns for a few days, but prices subsequently rebound to fundamentals. Recent research by Bollen et al. (2011) found significant relationships between the "mood" of Twitter messages and Dow Jones returns. However, research into the effects of new sentiment on the returns of other assets such as commodities is virtually nonexistent. So in this paper, we provide the first overview of the relationship between news sentiment and energy, specifically crude oil futures.

There are several challenges when dealing with commodities. First of all, in contrast to equities, for which there is a single price that is the focus of attention, commodities trade in the form of futures contracts with monthly maturities that stretch several years into the future. So the object of interest is not just one price, but an entire forward curve, consisting of many futures prices. News sentiment may affect the returns of different maturities differently. Furthermore, it is not immediately clear whether sentiment measures will work as well for commodities as they do for equities, as commodity prices are driven by supply and demand rather than by present value of future cash flows. So while one would presume that just about any article with lots of positive words and a reference to Apple would correlate with upward pressure in its stock price, it is not clear whether an article with lots of positive words and a reference to crude oil would correlate with upward or downward pressure on the oil price. If the headline is "Stability in Middle East and growth in rig counts leads to boom in crude supply", we would expect the price to go down, whereas the sentence "Boom in China and growth in the US makes oil soar" might lead us to expect prices to go up,

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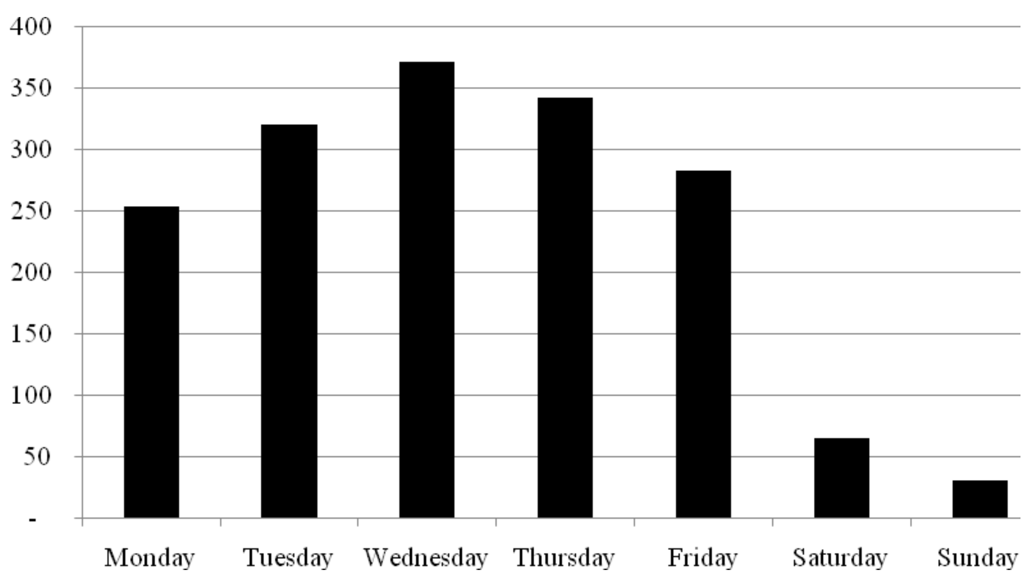
while both articles may be classified as “positive”. Thus, for sentiment measures to work effectively for commodities, they have to differentiate between sentiment with relation to factors that cause, or correlate with, supply and demand. Thomson Reuters News Analytics has been recently extended for commodities, implementing this differentiation by means of complex linguistic and contextual analysis.

2. Data

Thomson Reuters News Analytics historical dataset for commodities is a unique dataset of over 6 million articles from the start of 2003 to the end of 2010, time-flagged to the millisecond. Of these articles, approximately 1 million is classified as relevant to crude oil. For each article we have measures of positive, neutral and negative sentiment, interpreted as probabilities that the article conveys a positive, neutral or negative outlook on that commodity price. There are additional variables, such as the type of a news item, its novelty, its linkage to other news items and so on.

The number of articles varies widely within a week. Fewer articles are published on weekends, as compared to weekdays, as we can see on the graph below. The number of articles peaks on Wednesday, which is not surprising: the most important weekly statistics such as API crude oil inventories and DoE Weekly Petroleum Status Report are published at 10:30 am EST on Wednesdays.

Figure 1: Average number of articles about crude oil per weekday.



On the next page an extract from the historical news analytics dataset is shown. The first two lines hint that the sentiment measure correlates with momentum, in line with Sinha (2009): the leads refer to past price performance, which, if markets are efficient, should be stale information. In the 4th to 6th lines, Iranian comments that OPEC cannot increase output accurately receive positive ratings in 2 cases, but an incorrect negative rating in one. Lines 8 and onward show the repetition of news about a Zambian oil contract, with varying marks. This gives a feel for the kind of news in the database.

While having data at such high frequencies may well be excellent for traders, we choose to aggregate the article sentiment measures into a daily index, in order to relate it to the daily settlement futures prices and returns. We use NYMEX WTI futures, as these are the most liquid oil futures contracts in the world. We focus here on the daily data because the behaviour of returns over longer periods such as a trading day is arguably more economically relevant than that over milliseconds, which is largely due to the market microstructure and not fundamentals such as supply and demand. Moreover, studying the raw news dataset, we found that the sentiment measure is quite noisy: similar articles can be classified very differently. So, hopefully, aggregating over a day should reduce this noise. Finally, working on a longer time scale reduces complications caused by market microstructure, such as the bid-ask bounce and asynchronous trading.

We form the daily index bearing in mind the closing time of the New York Mercantile Exchange (NYMEX) in New York (19:30 GMT or 14:30 EST, which is the same time, given the 5 hour time zone difference). We adjust the timestamps in such a way that each news item is stamped with the date indicating that it was available to traders before the market settlement on that day. The daily aggregated news sentiments are formed by averaging each of the three sentiment scores for all articles on each day and then normalizing the resulting scores so that the daily sentiment scores also add up to one. We take into account only articles whose relevance for crude oil is higher than 0.5.

News is released also during weekends and bank holidays, which means that there are sentiment scores on non-trading days, whereas price data is not available on those days. So we only create daily news sentiment scores for trading days, using the following weighted scheme. First of all, we aggregate news that appeared on non-trading days into the score for the subsequent trading day. It is quite reasonable to assume that people have “short memory”, meaning that, for instance, on Monday they remember news published on Sunday better than those published on Saturday and they remember the Monday’s news the most vividly. So for Monday (and days following bank holidays) scores, we take the exponentially weighted average instead of an arithmetic average, with the weights being 0.9^i, where i is the difference between the day of the news item and the subsequent trading day. For example, a normal Monday is

$$\frac{Score_{Monday} + 0.9 \cdot Score_{Sunday} + 0.9^2 \cdot Score_{Saturday}}{1 + 0.9 + 0.9^2}.$$

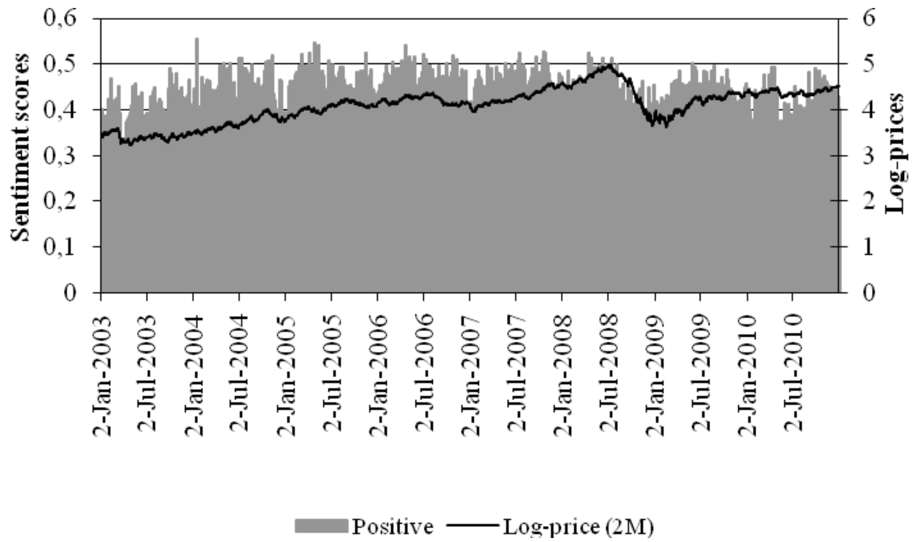
Finally, we also take into account the one-month difference between the beginning of the summer time in UK and US.

Figure 2 shows the resulting positive and negative daily sentiment scores, together with oil log-futures price, for the period 1/1/2003-1/1/2010. Already from these graphs the positive correlation of the price with the positive sentiment score and negative correlation with the negative sentiment score are visible. Also visible is the negative correlation between the positive and negative sentiment scores.

Figure 3 shows the overall empirical distributions of the positive, negative and neutral (defined as

1 - (positive score + negative score)) daily sentiment scores. For an event study (described in the following section) we are interested in those days when the corresponding sentiment score (positive or negative) is in the top 10% of the corresponding daily score distribution. However, for determining this, we will use not the overall distribution shown in Figure 3 (as this would be obviously a forward-looking procedure), but the empirical score distributions obtained from the previous one year of data. Remarkably, there is very little change in these empirical distributions over the considered time frame, with the distributions shown in Figure 3 being quite representative.

Figure 2: Daily sentiment scores and log futures prices



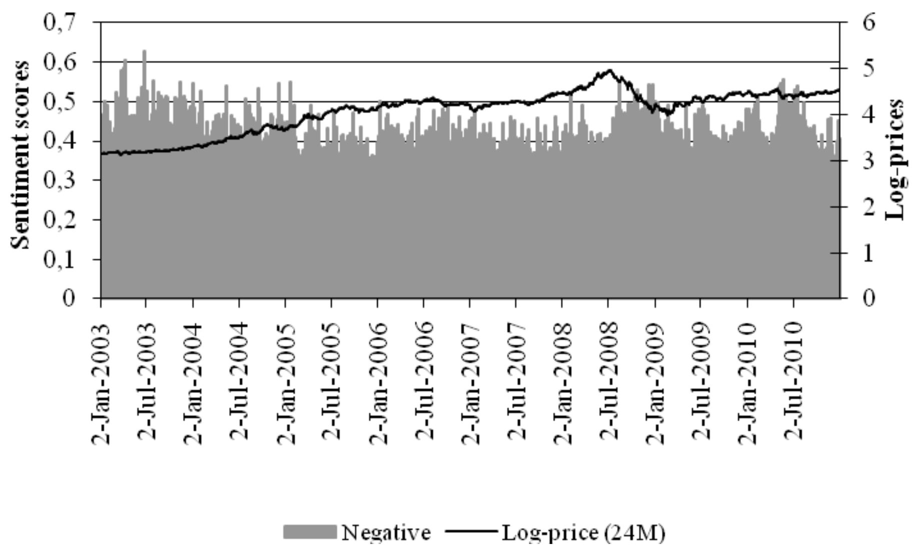
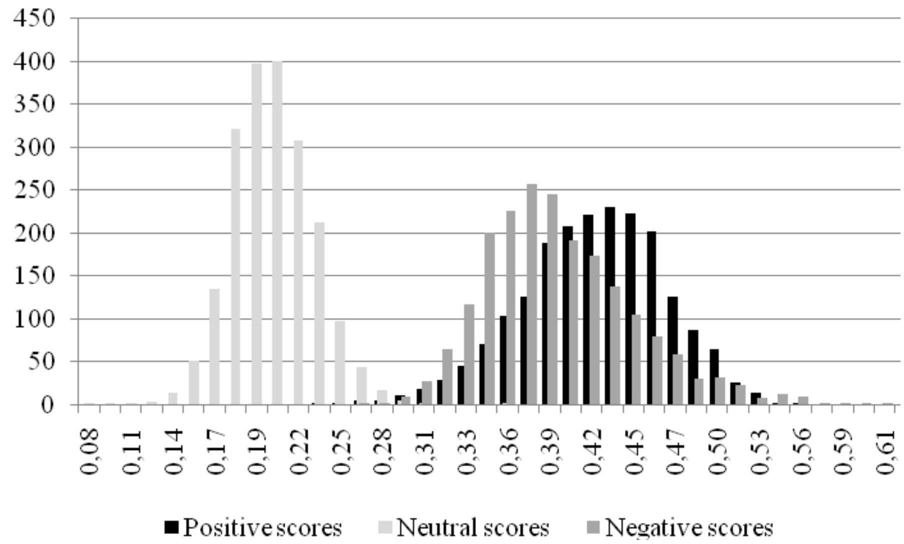


Figure 3: Histograms of the daily sentiment scores.



3. News effects on individual futures returns

We employ event studies as outlined in Kinlay (1997) and used in Tetlock et al (2008). We define an *event* (positive or negative) a day in which positive resp. negative sentiment is in the top 10% of the positive resp. negative sentiment distribution. All other days are considered neutral. On each day, we use the empirical sentiment distributions obtained from the previous one year of data.

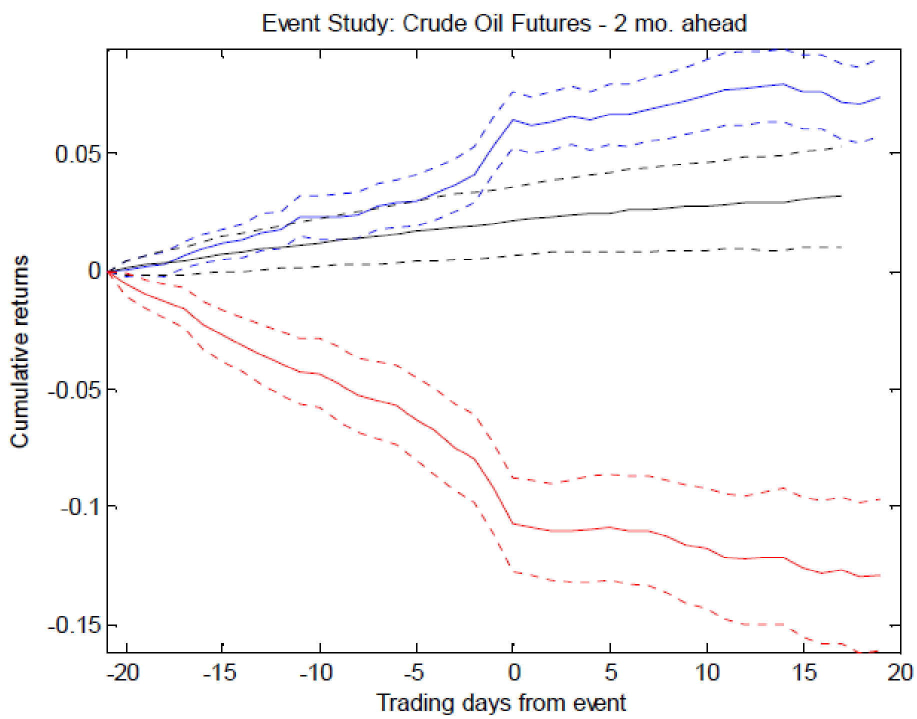
Let March 17, 2003 be the event day (positive or negative). We select the specific maturity (e.g., 2nd nearby, i.e., two months to maturity) and the event window - how many trading days before and after the event we consider (e.g., 10 or 20 trading days). For each event day, we select the specific contract that has the selected maturity. For instance, on March 17, 2003, the 2nd nearby contract is May 2003. We analyze the returns of this specific contract (and not specific time to maturity) during the event window. So in the event study we are considering returns that are actually feasible – we can buy the May contract in February and sell it in March. We calculate the daily returns during the event window for the selected contracts, and then average the returns over the observed events for each day. So for eight years of data, we have approximately 200 positive and 200 negative events. The 95% confidence intervals (represented in all the plots as dashed lines) are based on the sample standard deviation.

Figure 4 shows the average returns on 2-months ahead WTI futures during the event window. The top graph (blue lines) shows the average returns for a positive event, the middle graph (black lines) – for neutral days and the bottom graph (red lines) – for a negative event. We see that, in the 20 days leading to a positive event, the overall average return on 2-month ahead crude oil futures is 6%, of which 2% are in the 2 days immediately prior to the event. In contrast, the overall average return is -11% leading up to a negative event, again with about -2% in the 2 days immediately prior to the event. Thus, either the news are providing stale information which has already been incorporated into prices, or the news sentiment is correlated with the price momentum: articles about previous returns are likely rated as positive if past returns were good and negative if past returns were bad – if this is the case, returns will cause sentiment. In other words, we suspect that many news stories are about the past price development. However, it is likely that the emerging picture is the result of both stale information and correlation of news sentiment with the price momentum.

If there is no dramatic news (neutral days), returns are on average 2% per month; this is in line with the theory that, by buying commodity futures, you are essentially selling insurance (the return on the contract is your premium) to the commodity producer against a drop in price. For an insurance salesman, no news is good news. Equivalently, one can think of this in terms of normal backwardation: if the normal situation is for the price of the future to increase as it approaches maturity, that is what we expect to happen if there is no dramatic news.

Note that, in the 15 days after a positive event, cumulative returns rise further 2-3%, then flatten out. It is unclear whether that is significantly more than the 2% returns observed in the absence of dramatic news. In contrast, cumulative returns drop another 3% after a negative event.

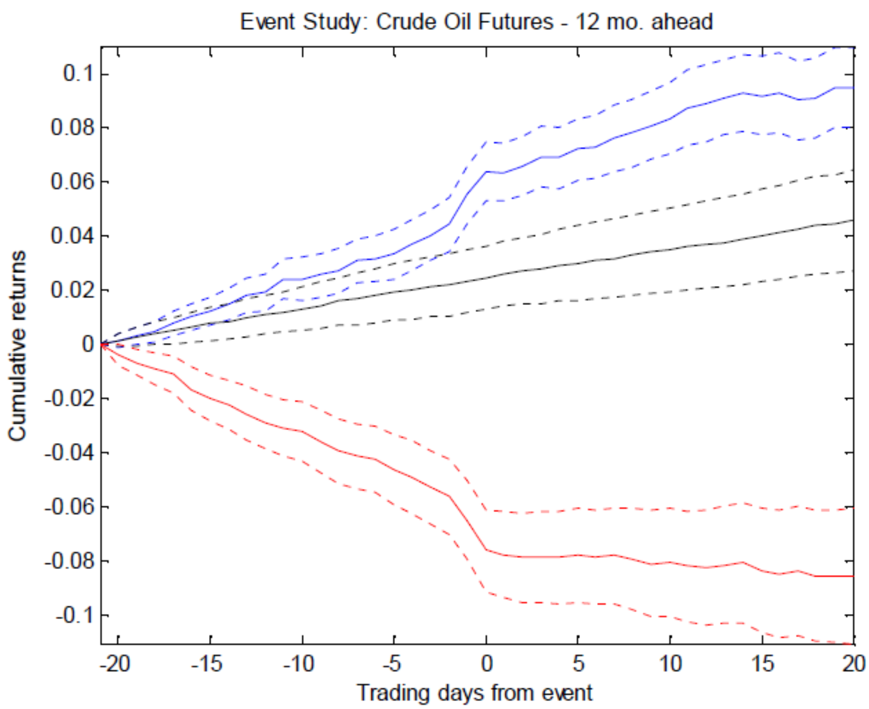
Figure 4:

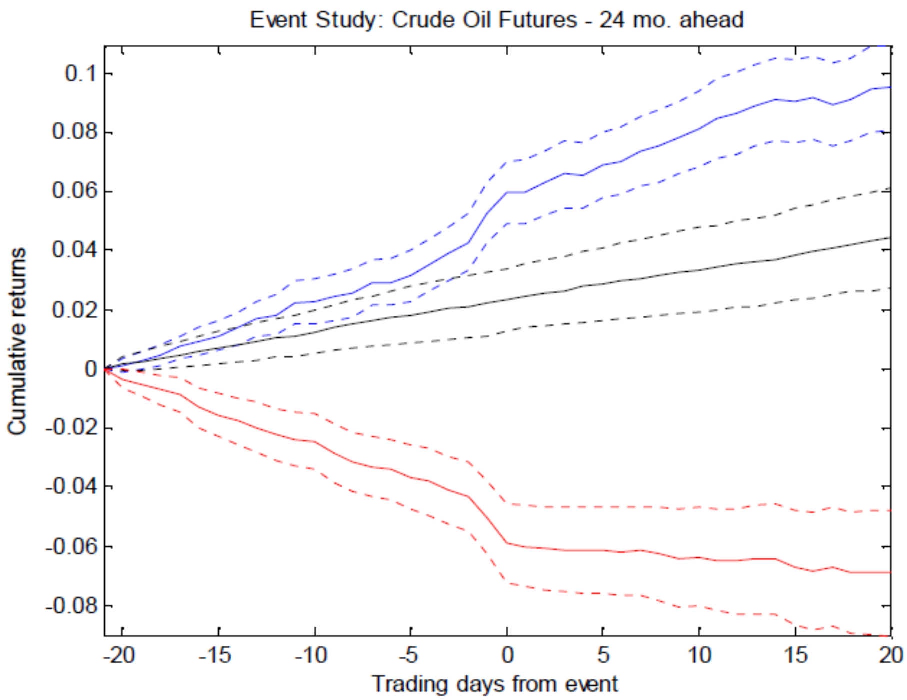


Looking at a more distant 1-year maturity in the upper graph in Figure 5, we see that returns fall only 8% preceding a negative event, and the post-event fall in returns is also smaller than in the 2-month case. In contrast, cumulative returns climb more than 3% after a positive event.

Looking even further down the forward curve, we observe a similar picture. Figure 5 (lower graph) shows the event study for 2-year ahead maturities. The magnitude of negative news effect is lower still, while the positive news has a similar effect.

Figure 5:





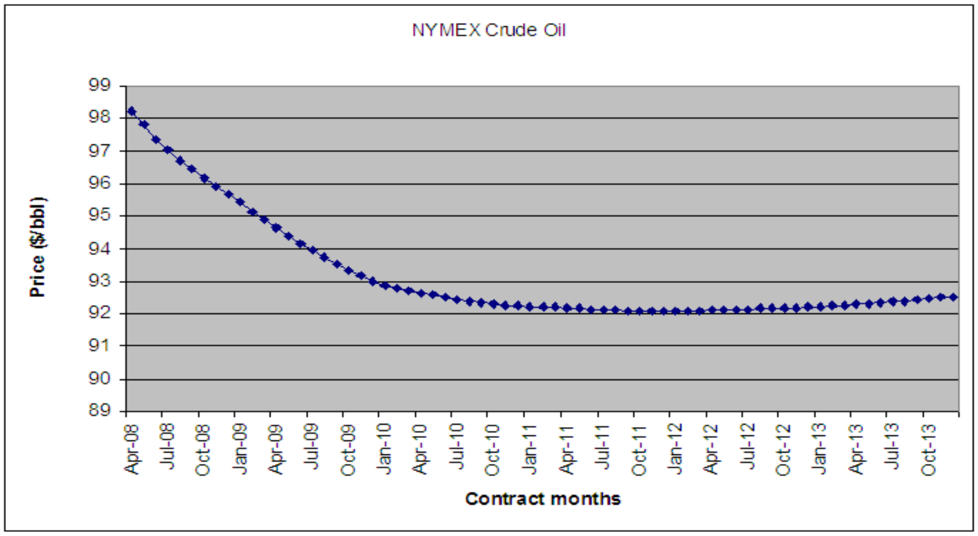
In all of the above graphs, the most distinctive feature is the asymmetry: although positive and negative events are both 10% of days, the negative events are accompanied by much greater losses than the gains surrounding positive events. So it seems that, overall, the oil futures market gives greater credence to negative news: positive news being seen to include self-serving statements for market participants. Another explanation for this asymmetry can be found in behavioural aspects of finance: it has been observed in finance literature that bad earnings announcements have disproportionately large (negative) effect on stock prices (overreaction), compared to good earnings announcement. However, recall that the meaning of positive and negative news is different for crude oil than for stocks: a news that sounds positive, can, in fact, have a negative effect on the price (and hence, will be classified as negative) and vice versa. So one of the interesting conclusions of this study that it is not negativity in terms of traditional human emotion that causes market overreaction, but negativity with respect to the price development of the considered asset or the asset class.

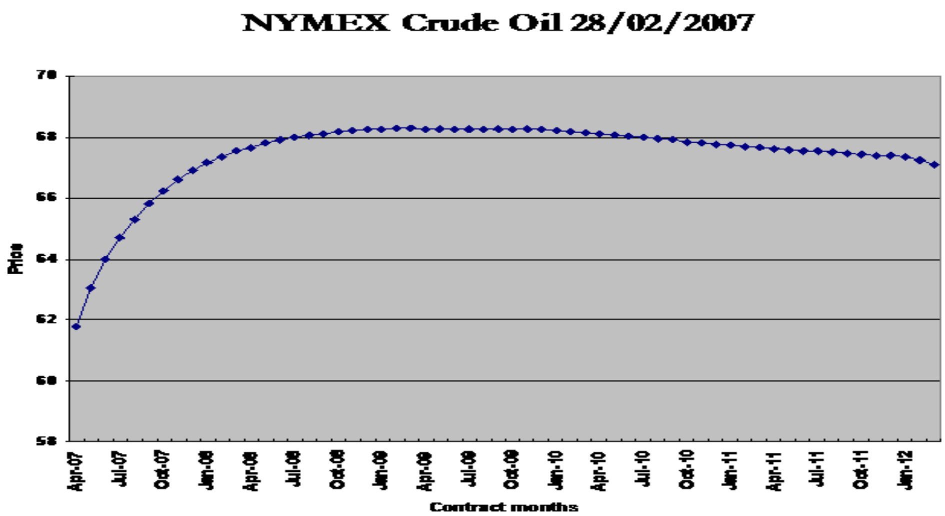
4. Forward curve decomposition and news effects on fundamental factors

Now we analyze the response of the entire crude oil forward curve to significant news events. For that, we extract the fundamental factors driving the forward curve evolution such as the level and the slope, as described in the forward curve model by Borovkova and Geman (2007).

Recall that the oil futures market can be in two fundamental states: backwardation, when the prices of shorter maturity futures are higher than those of longer maturities, and contango, which describes the opposite situation. These two states are illustrated in Figure 6.

Figure 6: Backwardation (upper) and contango (lower) forward curves





The first fundamental factor in Borovkova and Geman (2007) model is *the level of the forward curve*, defined as the geometric average of all available futures prices (possibly, liquidity-weighted). To take into account backwardation/contango shape of the curve, the model is extended with the second fundamental factor: *the forward curve's slope*. It is defined as the slope of the OLS regression line fitted to futures log-prices vs. times to maturity. The model also allows for the stochastic forward premium (the third fundamental factor) and deterministic maturity-related seasonality, essential when modelling natural gas or electricity forward curves. For more detail, we refer to Borovkova and Geman (2007, 2008).

The historical forward curve level and slope is shown in Figure 7. We perform event studies similar to those described in the previous section, with response variables being the daily level's logreturn and the daily change in the forward curve's slope. Here we consider the window of 20 days surrounding an event.

When we analyze the effect of significant news events on the forward curve level, the same picture emerges as in the previous section (Figure 8). This is not surprising, as this effect is the "average" response of all individual maturities to significant positive or negative news.

Figure 7: Historical level and slope of WTI forward curve

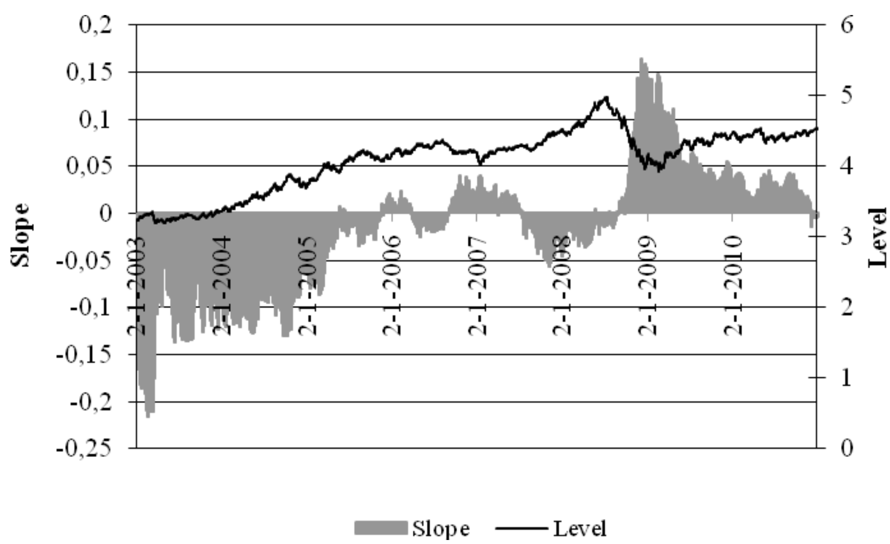
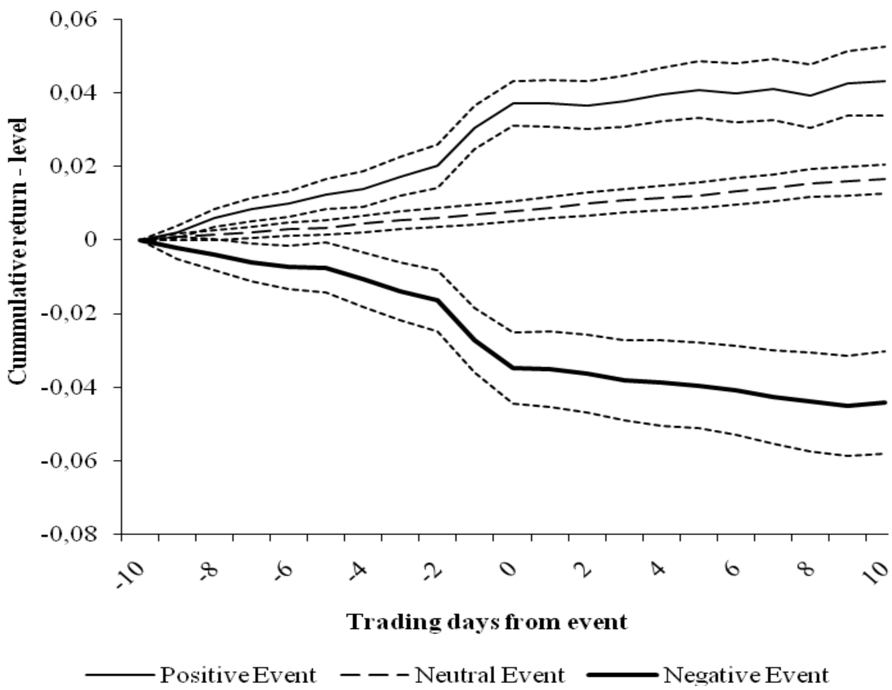
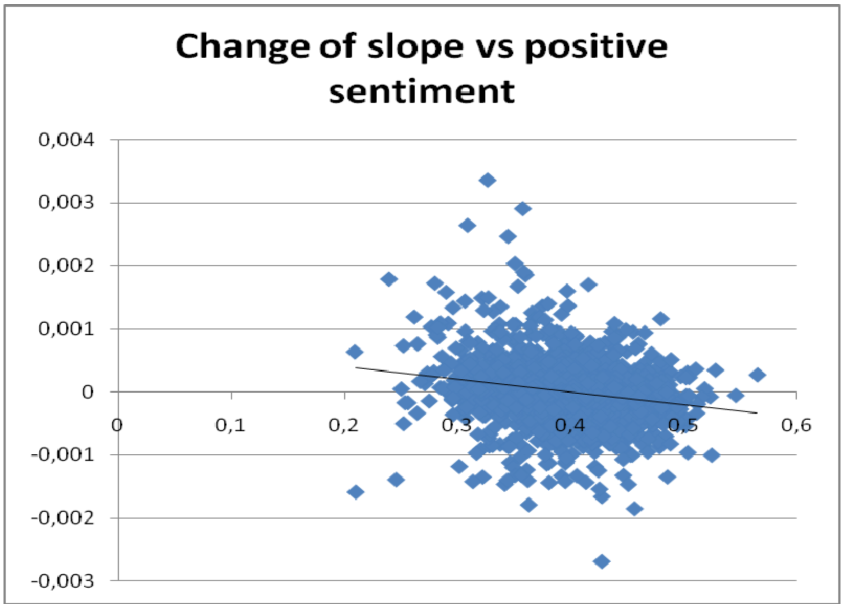


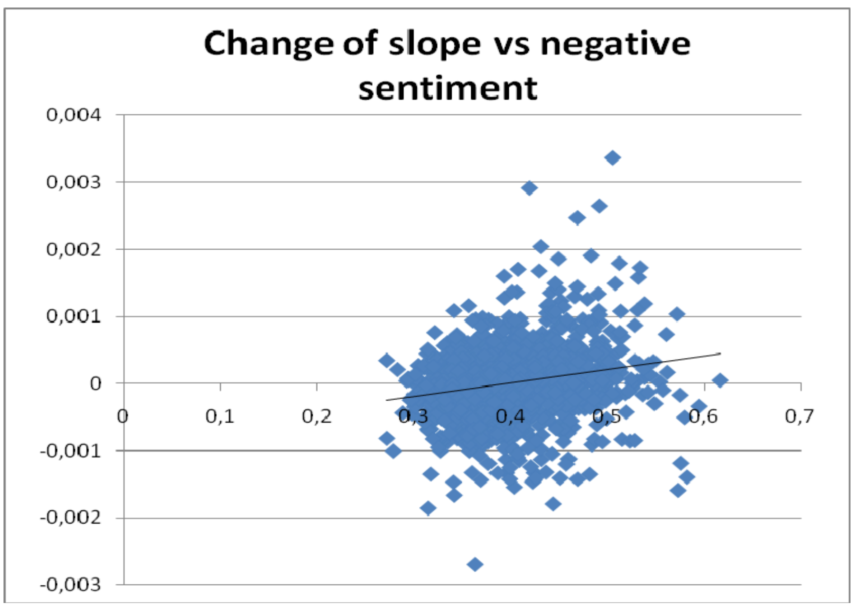
Figure 8: Event study for the level of the forward curve



The effect of news on the forward curve's slope, i.e., on the degree of backwardation or contango in the oil futures market, is not intuitively obvious. To assess this effect, we first fit a linear regression to the daily change in slope vs. daily sentiment, shown in Figure 9. This figure shows that, on average, positive sentiment decreases the slope, while negative sentiment does the opposite and increases the forward curve's slope (all linear regression coefficients are all significant at 5% level). This is somewhat surprising, as it is the opposite from the effect of news on the level and on individual maturities' returns.

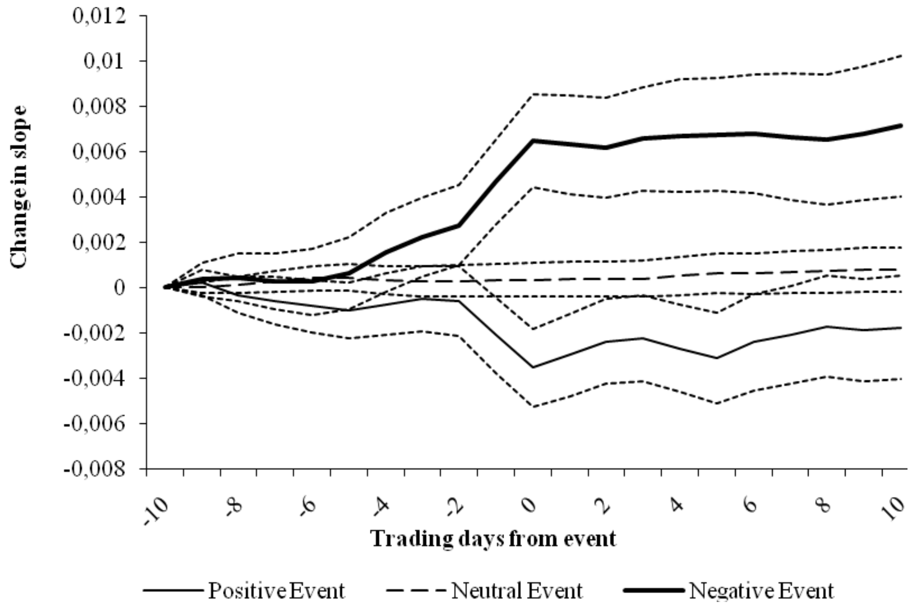
Figure 9: Change of slope vs. positive and negative daily news sentiment





To investigate the cumulative effect of news on the slope through time, we again perform an event study. Figure 10 shows the event study results for the aggregated change in slope during 20 days surrounding a significant news event.

Figure 10: Event study for the slope of the forward curve

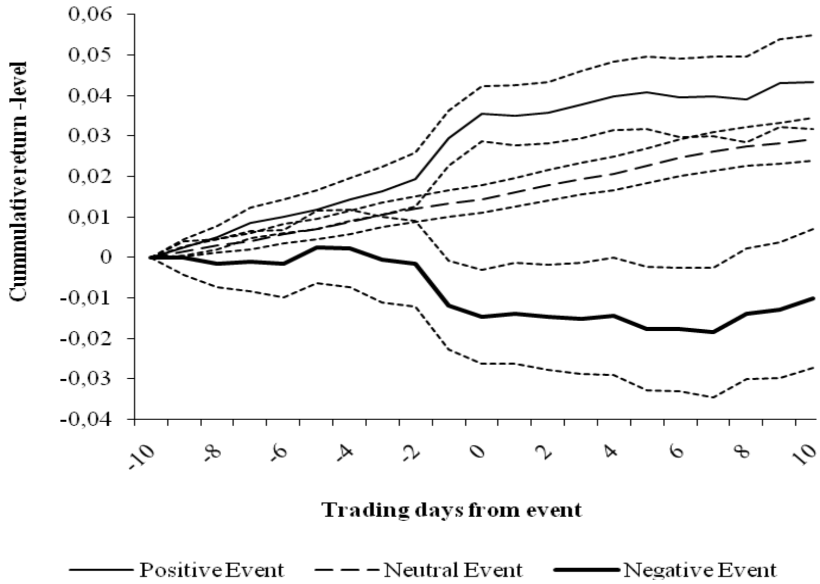


Note that the above picture is indeed the reverse of those seen so far: remarkably, negative news are accompanied by a significant *increase* in forward curve's slope (accumulated increase of approximately 10% of the average slope), while positive news follow a sharp *decrease* in the slope two days before the event, with little change afterwards (in neutral case, the curve's slope stays, on average, the same). Again, asymmetry is clearly present: negative news events are accompanied by a greater change in forward curve's slope than positive news events. This implies that contango deepens and backwardation flattens in the days surrounding negative news event. The reason for this is the fact that, around a negative news event, prices for all maturities fall, but nearby futures fall in price more than distant maturities.

It is interesting to investigate whether the oil market reacts to news differently in backwardation from contango. For that, we separate backwardation and contango markets and analyse the effect of news separately for these two market states. Both linear regression and event study analysis show that that the effect of news is remarkably larger in contango market. Figure 11 shows the event study for the level, separately for backwardation and contango market states. Observe different character of the news effect and remarkably greater magnitude of it in contango market, especially for negative news event.

The forward curve's slope reaction to news is also very different in contango and in backwardation market states (Figure 12). Note that the average development of the slope (neutral line) is flattening of both backwardation and contango. The effect of news on the slope in contango is much greater and more persistent than in backwardation. Bearing in mind that the reaction to *negative news* is dominant, we can explain this by the following observation: contango market implies that market participants expect prices to increase in the future. Then, if significant negative news comes along, it is against overall market sentiment, and hence, has much bigger effect than the positive news, which simply confirms what everyone is already expecting.

Figure 11: Event study for forward curve's level: backwardation (upper) and contango (lower)



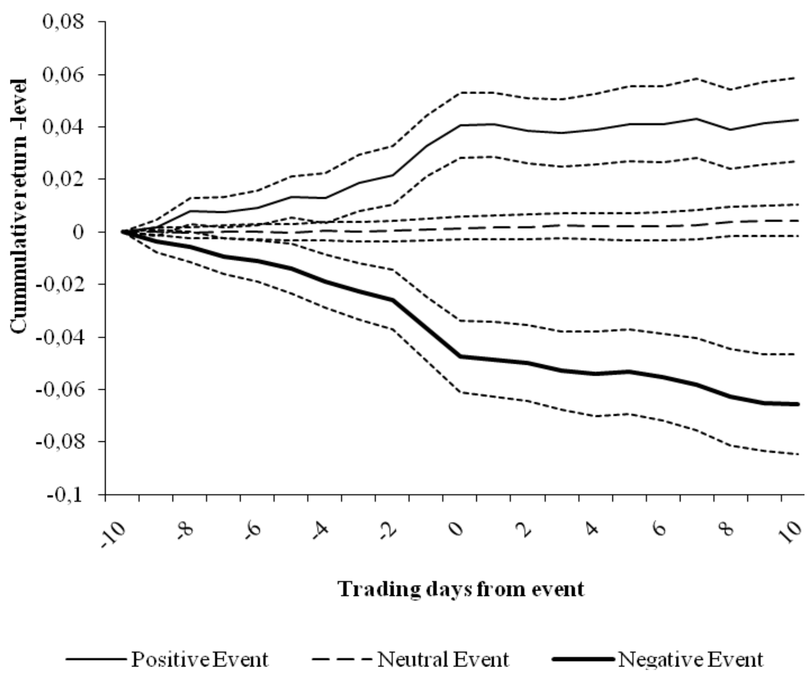
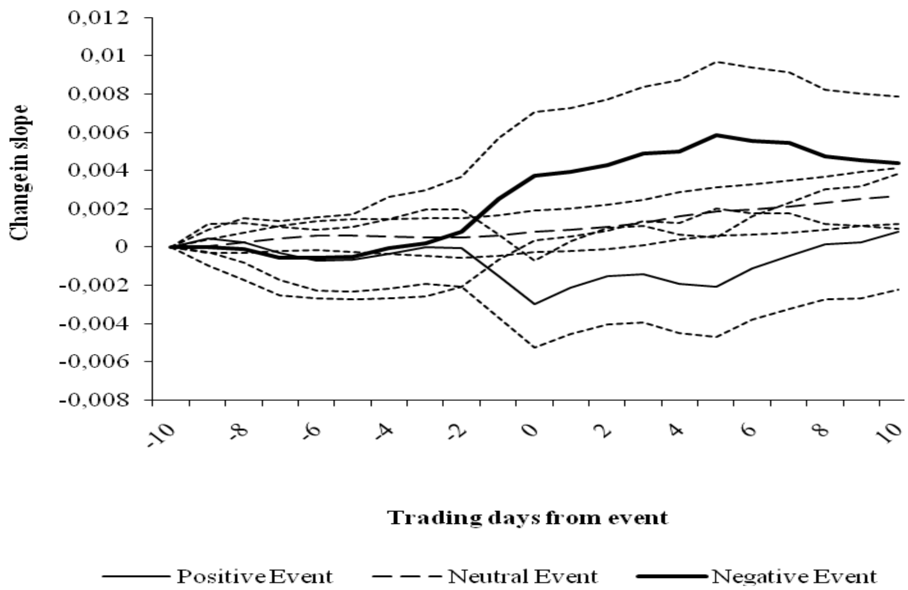
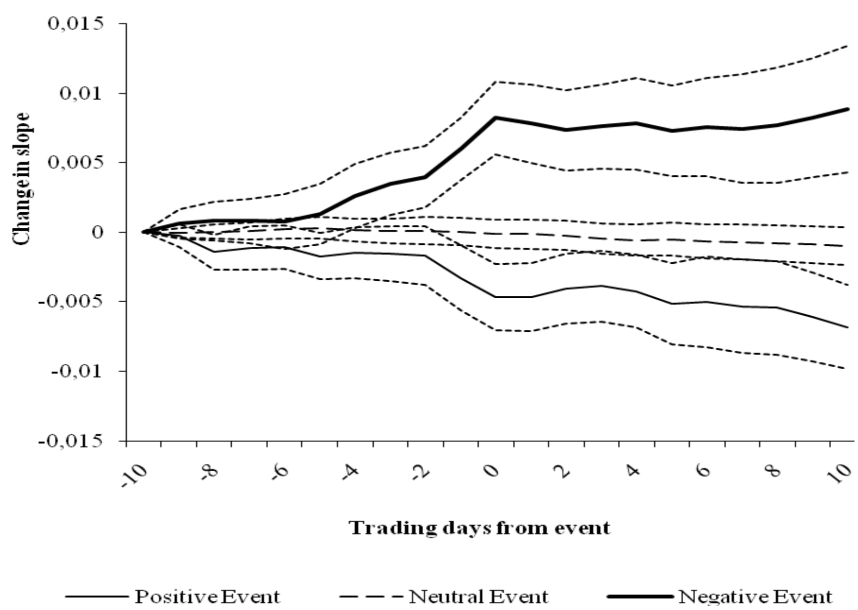


Figure 12: Event study for forward curve's slope: backwardation (upper) and contango (lower)





5. Conclusions and further research

We analyzed how oil futures prices react to significantly positive or negative news sentiment, as measured by Thomson Reuters News Analytics. We found that the days dominated by significantly positive resp. negative news are accompanied by increasing resp. decreasing prices, especially immediately prior to such days. Following negative news day, the returns continue to decrease on average by 3% for next 10 to 20 days. Positive news has the opposite but smaller effect on futures prices.

Forward curve's reaction to negative news can be characterized by deepening of contango and flattening of backwardation; the opposite (and again, smaller) effect is observed for positive news. Remarkable is the difference between the reaction to news in backwardation and in contango market states: all news effects are significantly amplified in contango market. Behavioural aspects of finance can help us in explaining this phenomenon.

The results of the analysis lay foundation for profitable trading strategies. An example of a trading strategy would be to take a long resp. short position in oil futures of a fixed maturity immediately after a significant positive resp. negative news event. The size of the position can be twice bigger for negative than for positive news event, to reflect larger magnitude of the price move. Furthermore, the position can be further increased in contango than in backwardation market. However, we expect such outright trading strategies to be quite risky. The analysis of news effects on the entire forward curve can be used to construct profitable calendar spread trading strategies, whereby a long/short position in futures of shorter maturities would be accompanied by an opposite position in longer maturities. Such strategy could still be profit-generating, but, being nearly market-neutral, would be much less risky than an outright strategy.

This paper is the first attempt at analyzing the effect of news on commodity prices. Current and future research in this area is very broad: from relating news to futures volatility and trading volume to analyzing the relationships between real-time news alerts and high-frequency price quotes to extending the analysis to other energy commodities, metals and agriculturals.

References

Johan Bollen, Huina Mao, Xiao-Jun Zeng. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, 2(1), March 2011, 1-8

Borovkova, Svetlana and Hélyette Geman. (2007). Seasonal and stochastic effects in commodity forward curves. *Reviews of Derivatives Research*, Vol. 9, 167-186.

Borovkova, Svetlana and Hélyette Geman. (2008). Forward Curve Modelling in Commodity Markets, *Risk Management in Commodity Markets: from shipping to agriculturals and energy* (Wiley Finance, London).

MacKinlay, Craig. (1997). Event Studies in Economics and Finance, *Journal of Economic Literature*, 35, 13-39.

Sinha, Nitish. (2009), News Articles and Momentum, Working Paper, University of Maryland.

Tetlock, Paul C. (2007). Giving content to investor sentiment: The role of media in the stock market, *Journal of Finance* 62, 1139–1168.

Tetlock, Paul C, Maytal Saar-Tsechansky and Sofus MacSkassy (2008). More than words: quantifying language to measure firm's fundamentals, *Journal of Finance* 63, 1437-1467.