The role of news in commodity markets

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Abstract

In this paper, we give a broad overview of how commodity-related news affects several aspects of commodity markets. We examine the main commodity classes: energy, agriculturals and metals, as well as market responses to news: in terms of prices, returns, volatilities and fine features of prices, such as price jumps. Market responses are analysed for different latencies, ranging from minutes to days and longer horizons. We discuss how these insights can be used in trading strategies, investment decisions and risk management.

In particular, we address the following questions:

- What are the distinguishing features of commodity-related news?
- How commodity prices react to positive and negative sentiment in news?
- How we can combine news signals from several commodity markets into an overall commodity news index? What are the relationships of such a news index with well-known commodity price indices?
- Can we improve volatility forecasts by including news variables in volatility models?
- Which characteristics of commodity price movements – volatility, positive and negative jumps – cause and are caused by news?

Key Words
News sentiment, commodity markets, event studies, commodity indices, volatility modelling.

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 as proxies 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 sentiment, relevance and novelty.

Many studies, starting with the pioneering work by Tetlock (2007, 2008), investigated the effects of either market-wide or company-specific news announcements on stock prices (see e.g., Handbook of News Analytics in Finance (2011), but also Mitra et al. (2009), Gross-Klussman and Hautsch (2011), Sinha (2011), Allen et al. (2013)). Research into the effects of new sentiment on commodity markets is, however, virtually non-existent (with some exceptions, for example an article of Smales (2014) about gold futures). This is surprising for several reasons. First of all, commodity prices are primarily driven by news about supply and demand, such as OPEC or inventory announcements, geopolitical, weather-related news and other external information. So we expect the effect of news on commodity markets to be even more profound than that observed for stock markets. Second, commodities have been in the spotlight of investors' attention for the past decade, as witnessed by a mass of non-traditional, financial players such as hedge, investment and pension funds entering commodity trading. Finally, event-driven trading strategies in commodities and, in particular, energy have attracted a lot of interest recently, particular in the world of hedge funds, but also from large commodity producing and trading firms. So this chapter aims at closing this gap in the literature, by providing an overview of the relationships between commodity-related news sentiment and various characteristics of commodity markets.

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 prices of futures with different maturities. News sentiment may affect futures returns for 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, 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.

Finally, the sheer volume of news for commodities makes any quantitative research challenging. Given the huge amount of news about e.g., crude oil (which is the world's biggest commodity), it is important to separate truly "new" news items, which would potentially move prices, from the so-called *momentum-related news*, where the past price developments are discussed. Consider the following two recent examples. On February 5, 2015, a Bloomberg headline read: "Oil Caps Biggest 2-Week Gain in 17 Years Amid Volatility" (the full explanatory article can be found in Appendix A). This headline was accompanied by the price chart shown in Figure 1.1. The headline obviously referred to the upward price development in the previous two weeks, clearly visible on the chart, and the volatility associated with it. This is typical "momentum" news, as any consequent price developments would reflect the price momentum rather than any new piece of information hitting the markets.

Figure 1.1 Oil price development around Feb 5, 2015

Another illustrative example is the CNBC headline of February 11, 2015, that read: "Capex cuts will determine oil's bottom" (the price chart on that day is shown in Figure 1.2 and again, the associated article can be found in the Appendix A). This, in contrast to the previous example, is a "forward-looking", supply-related piece of news, speculating on how cuts in capital expenditures will affect the declining trend in oil prices. So ideally we would like to separate these two types of news, or at least keep in mind that a large number of news about commodity markets is "momentum" news, i.e., is related to previous price developments.

Figure 1.2 Oil price development around Feb 11, 2015

In this paper we will address various aspects of commodity-related news and its effects on commodity prices. The paper is organized as follows. Section 2 describes the commodity related news data and its aggregate characteristics. Section 3 presents event studies for various commodities and latencies. Section 4 addresses the decomposition of the forward curve into fundamental factors, the effect of news on these factors and in different market conditions. Section 5 presents the construction of commodity news sentiment indices and their relation to the well-known commodity price indices. Section 6 discusses news-augmented volatility models and causality effects between news, volatility and price jumps. Section 7 concludes.

2 Commodity-related news characteristics

2.1 Commodity news volumes

Many commercial and research companies are currently active in the area of news analytics. News analytics providers such as Ravenpack, Bloomberg, Thomson Reuters use sophisticated Natural Language Processing (NLP) techniques in their news analytics engines. These analyse thousands of news articles and determine whether each news item is relevant to a specific company, index or a commodity, and whether the tone of the item is positive, negative or neutral. Most news analytics engines focus specifically on companies (stocks) or general macroeconomic indicators; however, only a handful of news analytics providers also focus on commodities. One such provider is Thomson Reuters, whose News Analytics Engine (TRNA) for commodities and energy we use in our research.

The TRNA news sentiment historical database comprises commodity-related news from various news sources, time-flagged to the millisecond, since 2003 until the present day. As we already mentioned, the volume of commodity-related news is immense: for example, on an average working day we observe between 400 and 500 news items about crude oil, with some days counting up to 800-1000 oil-related items. Compare this to stock-related news, where even for most liquidly traded stocks, we observe on average 40 news items per week.

On average, for all commodities we observe around 800 news items per (working) day; the histogram of the number of commodity-related news items per day is given in Figure 2.1.

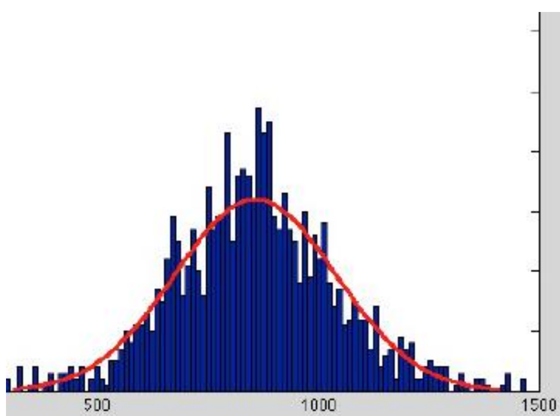


Figure 2.1 Histogram of the number of commodity-related news per working day

Commodity-related news flow has been steadily growing since 2003 until 2008, has stabilized around 2008, and is around 20 000 news items per month.

The commodity-related news flow is relatively evenly spread over working week, as Figure 2.2 shows. For oil, Wednesday is a particularly news-heavy day (lower bars in Figure 4), as weekly API inventory numbers are released at 10:30 am on Wednesdays, generating a lot of news activity around these announcements. For Natural Gas, such inventory numbers are released on Thursdays, making that a particularly news-busy day.

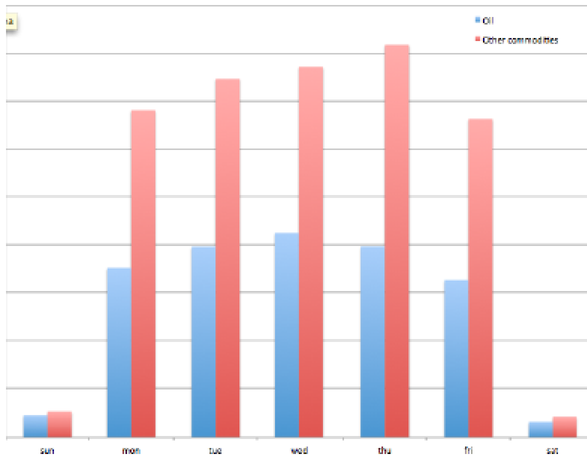


Figure 2.2 Distribution of news volume over weekdays (higher bars: all commodities, lower bars: crude oil).

Figure 2.3 shows the distribution of all energy-related news (oil, gas, oil products, coal, emissions) over a week. Due to oil inventories release, Wednesday still dominates in terms of news volume, with 22% of all energy-related news appearing on Wednesdays.

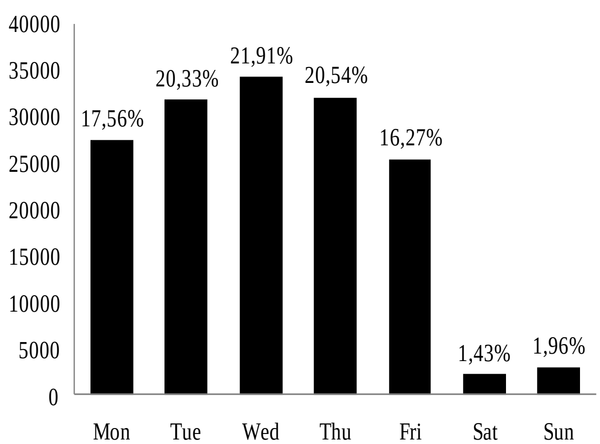


Figure 2.3 Distribution of energy-related news volume over weekdays.

The pattern of news arrival within a working day is shown in Figure 2.4. The peak in news volume corresponds to a few hours when both European and US exchanges are open.

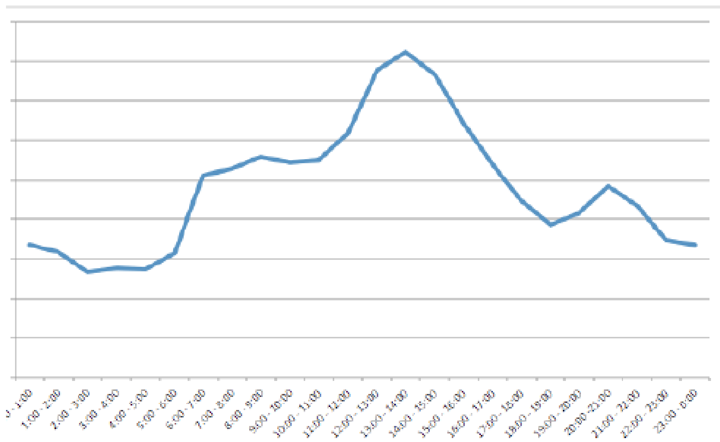


Figure 2.4 Distribution of news volume during a working day

In terms of how much is written about which commodities, we can observe that a single most newsworthy commodity is indeed crude oil, accounting for over 34% of all news volume. Metals, being a large commodity class, account in total for approximately 44% of all news (this excludes gold, which alone accounts for nearly 9% of all news). The volume of news associated with agricultural commodities is rather modest, accounting for just a fraction of all commodity-related news. Table 2.1 presents the percentages of news items associated with several commodities; percentages of positive, negative and neutral news items over the entire historical period are given as well.

Table 2.1 Percentage of all news volume per commodity

	% of total	% pos	% neut	% neg
Crude Oil	34.31%	44.58%	14.27%	41.15%
Metals	44.35%	38.06%	23.03%	38.91%
Natural Gas	11.50%	42.13%	21.51%	36.36%
Gold	8.79%	43.29%	14.7%	42.00%
Corn	0.70%	46.30%	16.45%	37.25%
Soy beans	0.35%	42.97%	15.90%	41.13%

2.2 Quantitative news characteristics

As mentioned above, news analytics engines "read" news items and interpret them using Natural Language Processing algorithms. For commodities, these algorithms are augmented by experts' opinions, arising from consultations with commodity analysts, journalists, editors, as well as traders and other commodity experts. This is because, as said above, for commodity sentiment measures to work properly, positivity and negativity of news must be assessed in relationship to supply and demand, rather than in terms of "human" interpretation of what is positive and negative. The resulting output is a set of quantitative news characteristics for each news item, the main ones being relevance, sentiment and novelty measures.

Figure 2.5 presents an extract from the Thomson Reuters News Analytic engine output. The first field is the time stamp of the news arrival, followed by the ticker corresponding to a particular commodity, commodity class or a subset, such as grains. The relevance measure, between zero and one, indicates how relevant a news item is for a particular commodity. In contrast to equities, for commodities such a relevance measure is usually equal to one, unless an article addresses several commodities at once (for example, talking about both crude oil and natural gas market developments).

IDN_TIME	STOCK_RIC	RELEVANCE	SENTIMEN	SENT_POS	SENT_NEUT	SENT_NEG	LNKD_CNT1	ITEM_TYPE	BCAST_TEXT
01:58.3	MTAL	1	0	0.191232	0.718185	0.0905829	0	ARTICLE	Hussey copper price Fall to 3.0885 -Decemb
02:54.3	COT	1	-1	0.201419	0.22755	0.571031	0	ARTICLE	NY Cotton No.2 Estimated Volume- 31 Dece
05:12.6	COT	1	0	0.0809842	0.849202	0.0698138	0	ARTICLE	ICE cotton stocks unchanged at 51,142 - De
13:42.4	LIV	0.816497	0	0.0880052	0.779822	0.132173	3	ARTICLE	CME estimated volumes - Dec 31
30:06.3	GRA	1	1	0.785536	0.0735535	0.140911	0	ARTICLE	CBOT rice deliveries - Jan 01
30:07.9	GRA	0.408248	1	0.785306	0.0738494	0.140844	1	ARTICLE	CBOT ethanol deliveries - Jan 01
30:09.1	MEAL	1	1	0.719192	0.128474	0.152334	1	ARTICLE	CBOT soybean deliveries - Jan 01
14:44.3	GOL	1	0	0.318323	0.421302	0.260375	0	ARTICLE	NY COMEX gold and silver delivery notices -
14:51.3	MTAL	1	1	0.416684	0.398823	0.184493	1	ARTICLE	NY COMEX high grade copper delivery notic
46:25.8	CRU	1	1	0.764544	0.0952038	0.140253	0	ARTICLE	S.Korea's Dec crude oil imports up 6.8 pct y/
17:28.4	COC	1	0	0.246601	0.451883	0.301516	0	ARTICLE	NY Cocoa delivery notices - Jan 01
55:52.7	PROD	1	1	0.776333	0.0752391	0.148428	0	ALERT	SAUDI ARAMCO SUSPENDS PLAN TO BUILD
20:23.0	CRU	1	-1	0.0841116	0.125463	0.790426	0	ARTICLE	INTERVIEW-Iran says Saudi Arabia should m
01:50.6	MTAL	1	-1	0.0855812	0.119604	0.794815	0	ARTICLE	Brazil to rework mining code stalled in Cong
53:26.6	CRU	1	1	0.463951	0.258316	0.277733	0	ALERT	U.S. CRUDE <CLc1> UP MORE THAN $1.50 A
53:50.7	CRU	1	-1	0.235173	0.123637	0.641191	1	ARTICLE	NYMEX-US crude up over $54 on stock fall;

Figure 2.5 An extract from TRNA news sentiment database

The next field is the overall sentiment classifier, where 1 stands for positive, -1 for negative and 0 for neutral. This field is calculated from the following three most important quantitative news characteristics, which are the sentiment scores: positive, neutral and negative. These are three numbers between zero and one, adding up to one, which should be interpreted as *probabilities that a news item conveys positive, neutral or negative outlook on this commodity's price*.

Another important indicator is novelty, measured by counting how many times has a particular news item been mentioned before (zero being the first time the news is reported). Furthermore, many other characteristics are reported. Some of them can be quite useful, for example, whether a news item is an article or alert, or which other news items it is related to. The headlines of news items are given as well.

The overall impressions of such a news analytics engine's output are that the data is relatively high-frequency (which could be excellent for intraday traders), and that the sentiment grade is quite noisy: for example, very similar news items (containing essentially the same information) can be classified wildly differently (and hence incorrectly in some cases). This makes it questionable whether all this information is economically relevant.

One way to deal with this noise is to filter out a meaningful signal from noisy observations of sentiment. This can be done with the signal processing technique of Kalman filtering, and will be described shortly. Another way is to aggregate the sentiment scores into daily numbers.

2.3 Sentiment aggregation

Often it is informative to analyse how daily closing prices are related to / respond to news sentiment: 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. Furthermore, working on a longer time scale reduces complications caused by market microstructure, such as the bid-ask bounce and asynchronous trading.

To relate news sentiment to daily closing prices, we should aggregate the sentiment scores into daily numbers. This is also useful for dealing with the noisy signal, as aggregating sentiments over a day should reduce the noise.

To form the daily sentiment index for a particular commodity, we need to filter out all news items relevant for that commodity. Next, we must bear in mind the opening and closing times of the corresponding commodity exchange, where this particular commodity is traded. For the purpose of creating daily sentiment score, we define a "news day" as the time interval close-to-close of the corresponding exchange. For example, if working with WTI crude oil futures, we need to synchronise the time stamp of news to the time of New York Mercantile Exchange (NYMEX) in New York (its closing time would be 19:30 GMT or 14:30 EST, which is the same, given the 5 hour time zone difference). As the news data is usually stamped with GMT or UTC time stamp, we also need to bear in mind the daylight saving time. In other words, we should 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 can be 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. Often one would take into account only news items whose relevance for a particular commodity is higher than a certain threshold, e.g., 0.3 or 0.5. Alternatively, averages weighted by relevance can be taken.

A popular sentiment measure is the so-called *net-positive score*, obtained by subtracting the negative score from the positive one (this measure can be calculated for daily scores or per individual news item).

News is released also during weekends and bank holidays, which means that there are sentiment scores on non-trading days (whereas trading might be not available on those days). So we can create daily news sentiment scores only 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 number of days between the day of the news item and the subsequent trading day. For example, a normal Monday's score is

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

The same scheme can be used for news released during bank holidays. Finally, we can also employ a weighting scheme which weights news received during trading hours heavier than those that appeared outside trading hours.

Figure 2.6 shows the resulting positive and negative daily sentiment scores for crude oil, together with oil log-price, for the period 1/1/2003-1/1/2013. Already from these graphs the positive correlation of the price with the positive sentiment score is visible. It also appears that the daily sentiment series is much more stable (stationary) than either the price or the volatility.

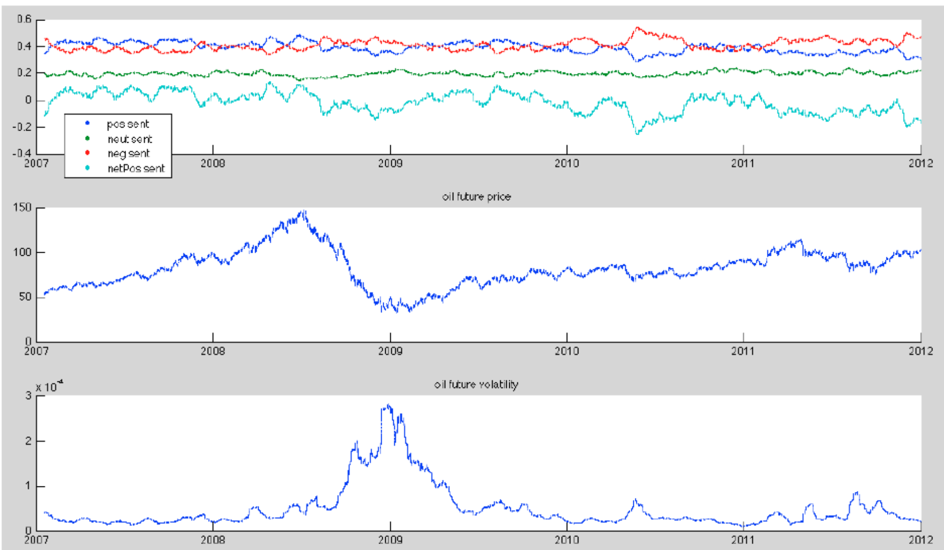


Figure 2.6 Top graph: negative, positive, neutral and net positive daily sentiment scores; middle graph: WTI log-price, bottom graph: daily oil price volatility.

In the next section, we will relate the daily sentiment scores for various commodities to the futures prices by means of event studies. But first we describe how a meaningful sentiment signal can be obtained from the noisy sentiment observations in real time.

2.4 Intraday filtering of the news sentiment signal

Recall that the sentiment of a news item is defined as the triple *(pos,neut,neg)* representing probabilities that the item can be classified as positive, neutral or negative with respect to the relevant commodity price. (Because these three probabilities add up to one, it is sufficient to consider only two of them, e.g., positive and negative). News items arrive at irregular intervals and non-equispaced over time. What is needed for quantitative trading strategies, however, is a running sentiment indicator: a relatively smooth measure of the sentiment for a particular commodity at each point in time.

So we assume that such a sentiment measure exists, but is unobserved. Denote such a measure by S_t – we assume that, at each point in time t, it is a two dimensional vector, containing probabilities that the time-t sentiment is positive or negative. What is observed, is the aggregate of sentiments of all news items prior to t, which we consider a noisy measurement of the true signal S_t.

More precisely, we define the observed sentiment (positive and negative) at time t as

$$s_t^{p,n} = \sum_{t_i < t} w_{t-t_i} s_{X_{t_i}}^{p,n},$$

i.e., it is the weighted average of all news items' sentiments prior to time t. We assume that people have "short memory" and weigh news items by hyperbolically decreasing weights. The weights are chosen in such a way that 90% of all the weight is on the latest 9 articles – the choice that follows from several cognitive studies showing that people remember well on average only 9 last things that happen to them.

Next, we assume a certain dynamics of the unobserved sentiments, for example a random walk, and the observation mechanism, both given by the so-called Local Level model (Durbin and Koopman (2001)):

$$S_{t+1}^{p,n} = S_t^{p,n} + \eta_t^{p,n}, \qquad \eta_t^{p,n} \sim N(0, \sigma_{\eta^{p,n}})$$
$$s_t^{p,n} = S_t^{p,n} + \varepsilon_t^{p,n}, \qquad \varepsilon_t^{p,n} \sim N(0, \sigma_{\varepsilon^{p,n}})$$

The discretization time interval can be chosen e.g., 1 or 5 minutes. The volatility of the signal $\sigma_{\eta^{p,n}}$ is much lower than the volatility of noise $\sigma_{\varepsilon^{p,n}}$, and their ratio is called signal-to-noise ratio. Now the unobserved sentiment series S_t can be filtered out by applying Kalman filter methodology, together with the assessment of the uncertainty (standard error) about this sentiment at each point in time. For technical details on this, we refer the reader to Borovkova and Mahakena (2015).

We applied this procedure to the Natural Gas news sentiment and an example of the resulting sentiment indicator on a 5-minutes grid is shown in Figure 9 (solid red (positive) and green (negative) lines). The extracted signal is much smoother than the actual observed sentiment series for individual news items. It can also deal with no-news periods: in the absence of news, the sentiment stays the same but the uncertainty surrounding it (not shown) increases.

An even smoother signal can be obtained if we use the Kalman smoother instead of the Kalman filter. Such a Kalman smoother utilizes not only information observed prior to time t, but also some of the subsequent information, for example obtained in the next minute or next 5 minutes.. For trading this is not very useful as this is a forward-looking procedure, but for a smooth measurement of the commodity market sentiment, it can be applied. In

Figure 2.7, this Kalman smoothed sentiment indicator is shown in dotted lines, which are indeed even smoother than the filtered signal.

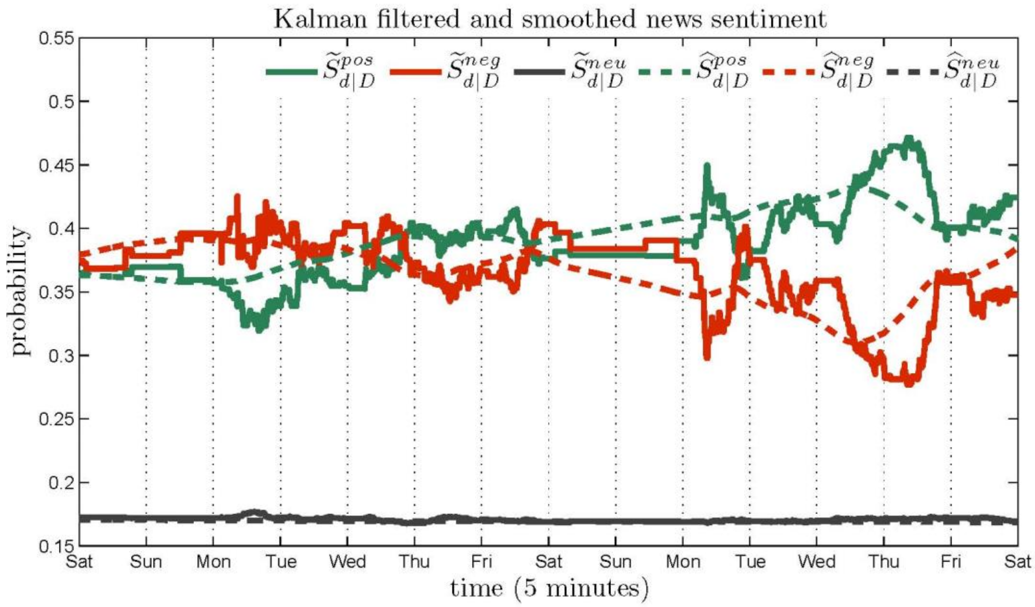


Figure 2.7 Kalman filtered (solid) and smoothed (dashed) news sentiments for Natural Gas

The procedure of filtering out a meaningful sentiment signal from noisy news sentiment observations can be applied to any commodity or a class of commodities. The resulting sentiment indicator can have many applications, for example, in trading or risk monitoring. Such a signal provides an excellent input to quantitative trading strategies, but can also be used for monitoring the overall sentiment of a particular commodity market.

3 Effects of news on returns: Event studies

We employ event studies as outlined in Kinlay (1997) and used in Tetlock et al. (2007, 2008). We define an *event* (positive or negative) as a day in which positive resp. negative sentiment is in the top 10% of the positive resp. negative sentiment distribution. These would be the days that are “overwhelmed” by positive resp. negative news about a particular commodity. All other days are considered neutral. On each day, we use the empirical sentiment distributions obtained from the previous one year of data.

Now we describe the construction of our event studies. Note that commodities predominantly trade in the form of futures contracts with different maturities. So in the event studies presented in this section, we analyse the effects of extreme news days on a particular maturity’s futures returns. The effects of news on the characteristics of the entire forward curve are analysed in the next section.

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, 2015, the 2nd nearby contract is May 2015. We analyse 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, average the returns over all the observed events for each day before or after the event and depict the cumulative returns. The 95% confidence intervals (represented in all the plots as dashed lines) are based on the sample standard deviation of average returns.

Figure 3.1 shows the average cumulative returns of 2-months ahead WTI futures during the event window of 40 days. The top line shows the average cumulative returns for a positive event, the middle line – for neutral days and the bottom line – for a negative event.

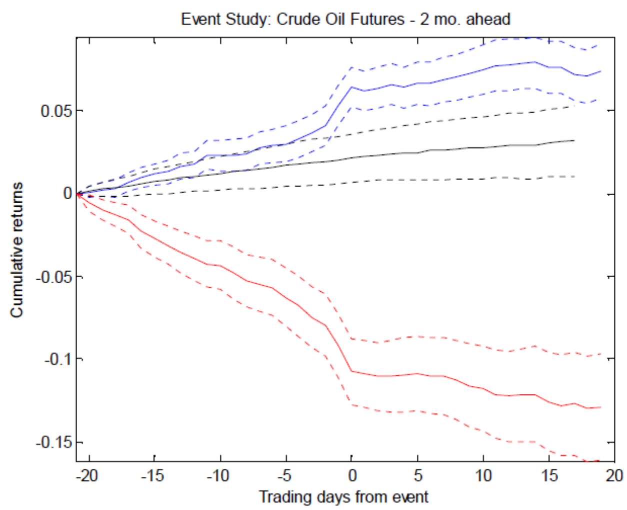


Figure 3.1 Event study for WTI crude oil futures with 2 months to maturity; top: positive, middle: neutral, bottom: negative events

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 during the event day and in the day 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 day immediately prior to the event and in the event day itself. This shows that, either the news is providing stale information which has already been incorporated into the prices, or the news sentiment is correlated with the price momentum: articles about previous returns are likely rated as positive if past returns were high and negative if past returns were low – in this case, returns cause sentiment. In other words, we indeed observe many news stories that are about past price developments, as noted in introduction. However, it is likely that the emerging picture is the result of both stale information and correlation of news sentiment with the price momentum. Unfortunately, at present there is no indicator related to each news item signalling that this item is momentum news, neither there is a possibility of filtering out momentum-related news from the news analytics engine output. Currently our efforts, in collaboration with Thomson Reuters, are focusing on filtering out or flagging such news items and we expect to improve the TRNA output by adding such an indicator to each news item.

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 by 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.

Looking at a more distant 1-year maturity in Figure 3.2, 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.

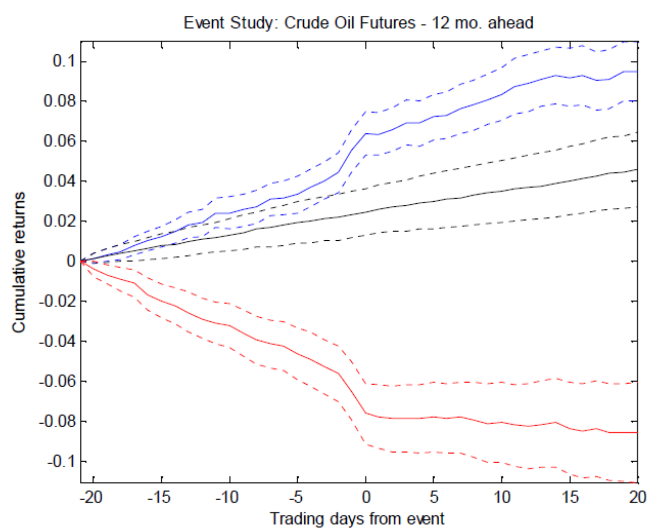


Figure 3.2 Event study for WTI crude oil futures with 12 months to maturity; top: positive, middle: neutral, bottom: negative events

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: 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.

Similar pictures to those for oil are observed for many other commodities. Figure 3.3 shows event studies for NYMEX Natural Gas futures of two month maturity and the event window of 20 days. In this figure we show not only the cumulative returns surrounding top 10% of sentiment days, but also top 30% for comparison. Note that the effects are greater for more extreme sentiment days, as expected. For top 10% sentiment days, the cumulative effect surrounding negative news events is even greater than for crude oil, while for positive events, the price increases prior to and on the event day and then reverts back to the normal level.

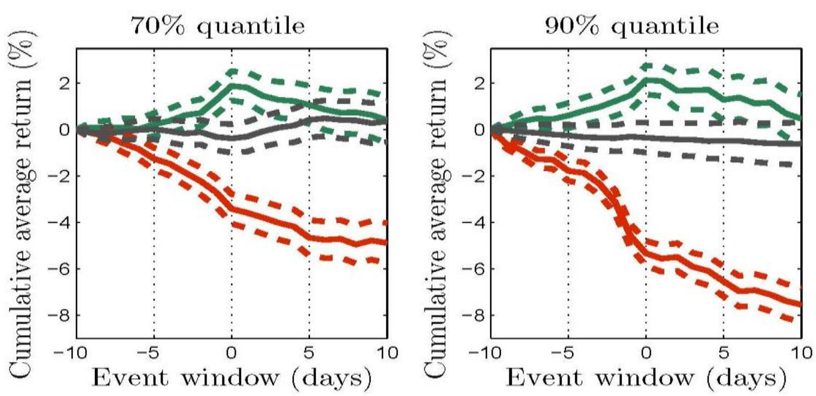


Figure 3.3 Event study for NYMEX Natural Gas futures with 2 months to maturity; top: positive, middle: neutral, bottom: negative events

Figure 3.4 shows the event study for 2-month ahead copper futures, as an example of an industrial metal. All the same features discussed above are again observed, as it is the case for other metals such as aluminium. Figures 3.5 and 3.6 demonstrate the event studies for two agricultural commodities: wheat and soybeans, again with similar features (asymmetry and price momentum).

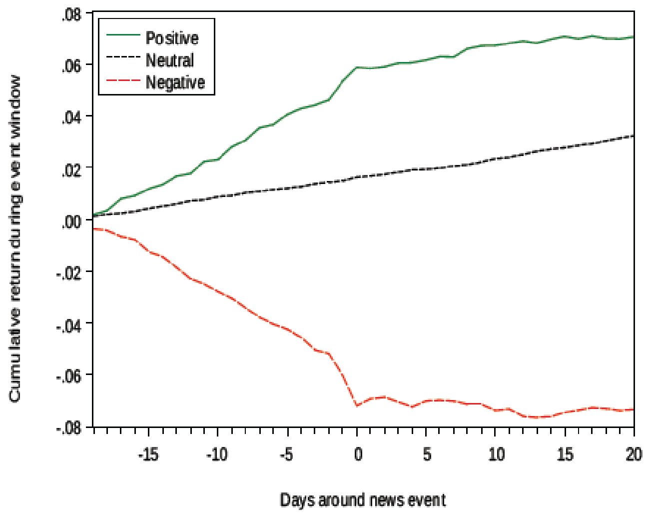


Figure 3.4 Event study for copper futures with 2 months to maturity; top: positive, middle: neutral, bottom: negative events

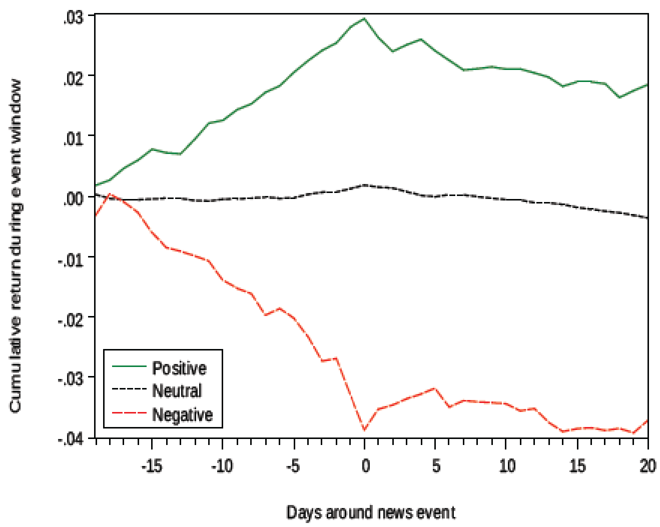


Figure 3.5 Event study for wheat futures with 2 months to maturity; top: positive, middle: neutral, bottom: negative events

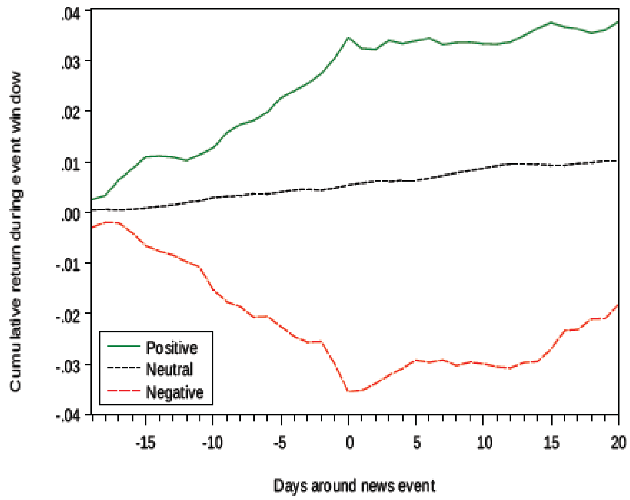


Figure 3.6 Event study for soybean futures with 2 months to maturity; top: positive, middle: neutral, bottom: negative events

One commodity for which surprisingly we observe less asymmetry in the reaction to positive and negative news is gold (the corresponding event study is shown in Figure 3.7) – this is in contrast to what is observed by Smales (2014) for gold futures, which can be due to the chosen historical period. Also, here we did not use futures prices, but the daily gold fixings at London Bullion Exchange.

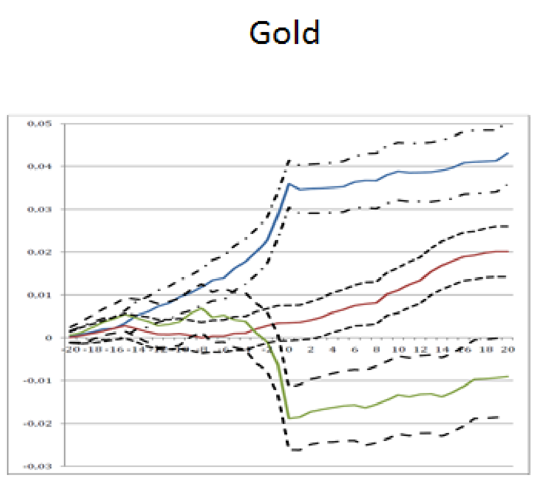


Figure 3.7 Event study for gold prices at LBE; top: positive, middle: neutral, bottom: negative events

So to summarize the findings of the events studies, we can conclude that:

- The largest price move is observed on the event day (and in some cases one day before the event).
- For most commodities, we observe a great asymmetry: negative events are accompanied by much greater losses than gains surrounding positive events (-12% for oil, -8% for NG, of these approximately 2-3% is post-event). Hence, commodity markets seem to give greater credence to negative news.
- News sentiment is correlated with price momentum: so news is either "old", i.e. provides stale information already incorporated into prices, or is about past price developments.

For completeness, Appendix B provides quantitative characteristics of event studies for different commodities, i.e. the tables of average cumulative returns.

For comparison, we present an event study performed on a higher frequency data. We take this time the first nearby WTI futures contract (the most liquid one) and define an event as a one-minute interval with the value of the running sentiment measure, described in the previous section, in the top 10% of the corresponding sentiment distribution (positive or negative). Figure 3.8 shows the cumulative returns for positive (upper) and negative (lower) events during an 8-hour window surrounding such an event. Again, we observe a significant price move prior to the event and price reversal in the subsequent hours. There is again a significant asymmetry in the reaction to positive and negative events: the price move accompanying a negative event is almost twice the size as the move accompanying a positive event.

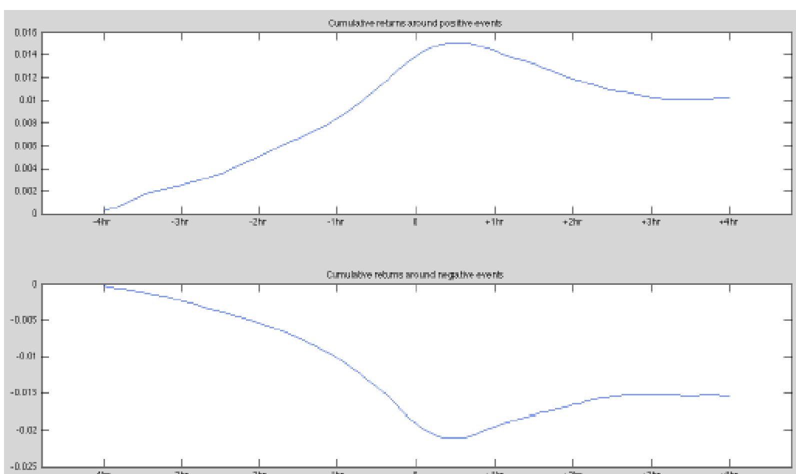
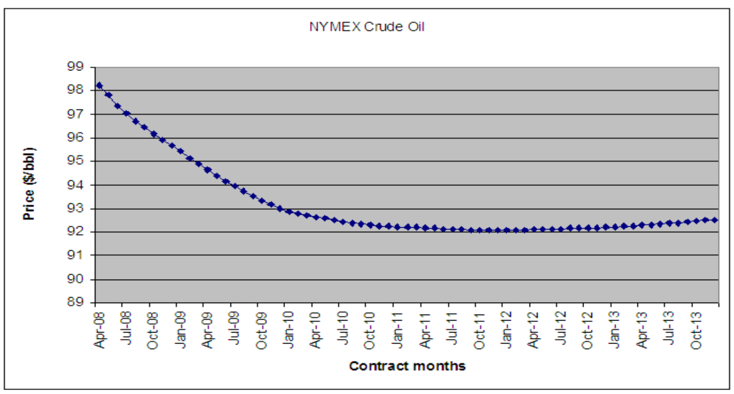


Figure 3.8 An intraday event study for the first month WTI futures, 8 hour window. Top: positive sentiment, bottom: negative sentiment

4 News effects on forward curves

The main object in study of commodity markets is the forward curve: a collection of futures prices for different maturities. Crude oil futures are traded up to 96 monthly maturities into the future, for natural gas, the number of available monthly maturities on NYMEX is 72. Other commodities are also traded for many maturities ahead. While futures for most commodities (energy, metals) expire monthly, agricultural commodity futures have irregular maturities, with more frequent maturities traded during harvest season.

Crude oil futures market can be in two fundamental states: the so-called backwardation, when futures for longer maturities are cheaper than those expiring sooner, and contango, which is the opposite situation. These two states are shown in Figure 4.1. Backwardation is correlated with high oil prices and low inventories and contango – with low prices and high inventories; however, periods of contango with high oil prices and backwardation with low oil prices have been also observed. These two market states are very persistent and can last for months if not years. It takes approximately two weeks for the oil market to transit from one state to another. Many price features and market fundamentals are distinctly different in these two market states. So we expect the effects of news on the forward curve to be also different in these two states.



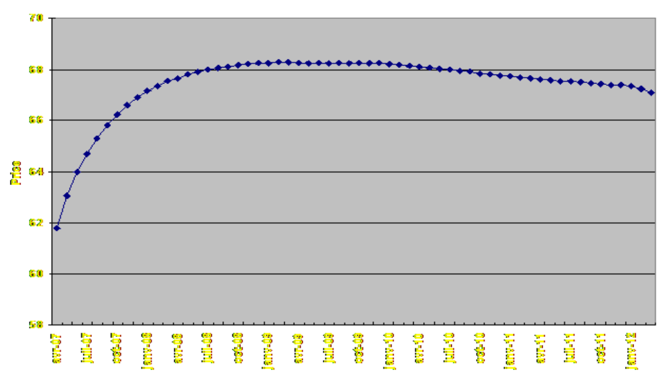
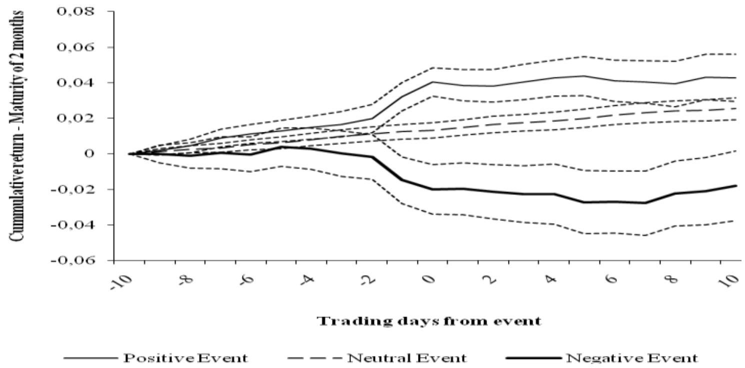


Figure 4.1 Backwardation (upper) and contango (lower) market states

To study this, we separate backwardation and contango market states and analyse the effect of news separately for these two market states. We perform similar event study as in the previous section (for the 2-month ahead WTI crude oil futures) separately for backwardated and contango markets, we observe that positive and, in particular, negative news events are accompanied by larger price moves in contango than in backwardated market (Figure 4.2).



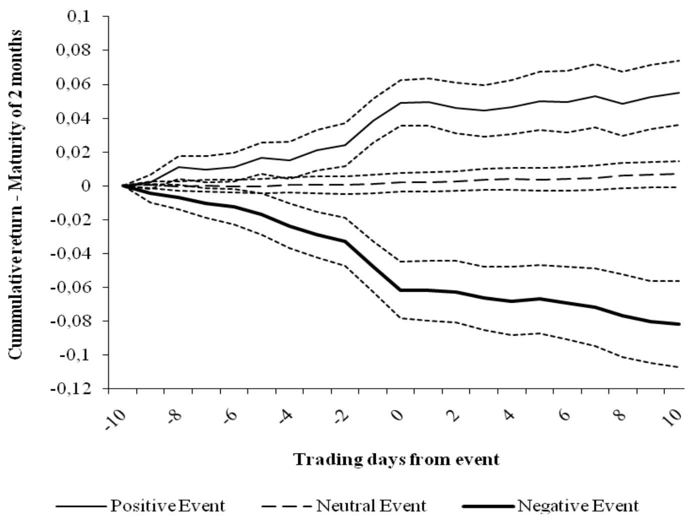


Figure 4.2 Event studies for 2-month ahead WTI futures, backwardation (top) and contango(bottom)

There could be several explanations for this phenomenon. First, in contango market, the expectation of market participants is that the prices will rise. When a negative event occurs, it is in contrast to what majority is expecting. Bearing in mind that the reaction to *negative news* is dominant, it appears that the market reaction to news is higher in contango. Second, and perhaps most plausible explanation is that commodity investors, who invest predominantly in futures, earn money in backwardated market just by rolling their contracts forward. In contango, on the other hand, they lose money by replacing their expiring contracts by the new ones, so any negative event occurring in this situation will exacerbate their losses, causing a stronger reaction to news. Finally, it can also be the case that the later period in our dataset coincided with domination of contango, and also with heightened awareness of commodity-related news, so larger price effects in contango is partially also a coincidence.

When studying the evolution of the forward curve, it is not efficient to consider futures prices for different maturities separately, as these prices move, for a large part, together. Instead, we should define fundamental factors describing the forward curve's evolution and relate all futures prices to those factors. One such choice of the fundamental factors is described in Borovkova and Geman (2007, 2008) and it is inspired by the technique of Principal Component Analysis and study of interest rates yield curve. In Borovkova and Geman model, the first fundamental factor is the *level* of the curve, defined as the geometric average of futures prices of all maturities (possibly liquidity-weighted). Another factor, describing the backwardation or contango shape of the curve, is its *slope*, defined as the coefficient of the ordinary least squares regression of log-futures prices vs. time 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, electricity or agricultural forward curves. For seasonal commodities such as Natural Gas it is possible to extract maturity-related seasonalities by the procedure described in Borovkova and Geman (2007) and describe the evolution of the forward curve by the level and the slope, defined in the same way as above.

Almost all possible movements of the forward curve (90-95% of those) can be explained by movements of these two fundamental factors. So in this section we will investigate the effects of news sentiment on the movements of these two fundamental factors: the level and the slope.

Here we shall demonstrate the effects of news on forward curves on the example of crude oil; for oil products and metal commodities effects are similar. When dealing with natural gas or agricultural commodities, particular attention should be given to seasonal (either harvest- or heating season-related) nature of futures prices, resulting in complex maturity-related seasonalities. A typical Natural Gas forward curve is shown in Figure 4.3; note significantly higher futures prices during winter months. This occurs due to the fact that natural gas is only partially storable and hard to transport, so these seasonal peaks are not completely smoothed out by transporting gas from warmer to colder regions, or by injection during summer months and extraction during winter months.

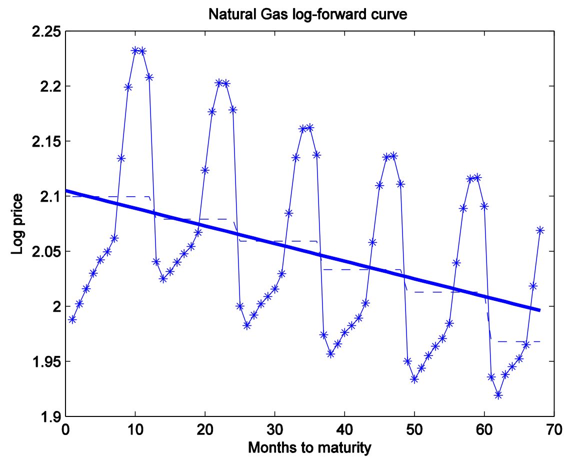


Figure 4.3 Natural gas log-forward curve with the fitted regression line

We perform event studies similar to those described in the previous section, with response variables being daily log-returns of the forward curve's level and daily changes in the forward curve's slope.

When we observe the effect of positive and negative news events on the forward curve's level, the same picture emerges as in the previous section (Figure 4.4). This is not surprising, as this effect is the "average" response of all individual maturities to significant positive or negative news.

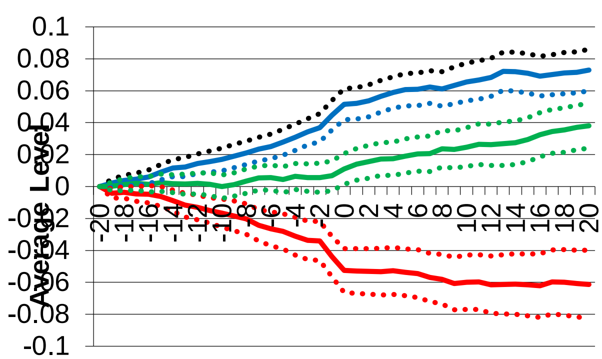


Figure 4.4 The event study for the crude oil forward curve's level;
top: positive, middle: neutral, bottom: negative events

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 4.5. 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.

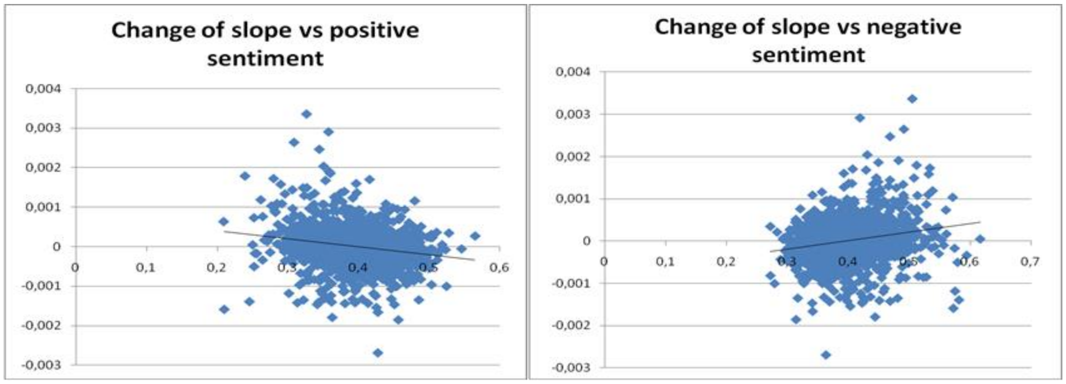


Figure 4.5 Linear regression of slope changes vs sentiment

To investigate the cumulative effect of news on the slope through time, we again perform an event study. Figure 4.6 shows the event study results for the aggregated change in slope during 20 days surrounding a significant news event.

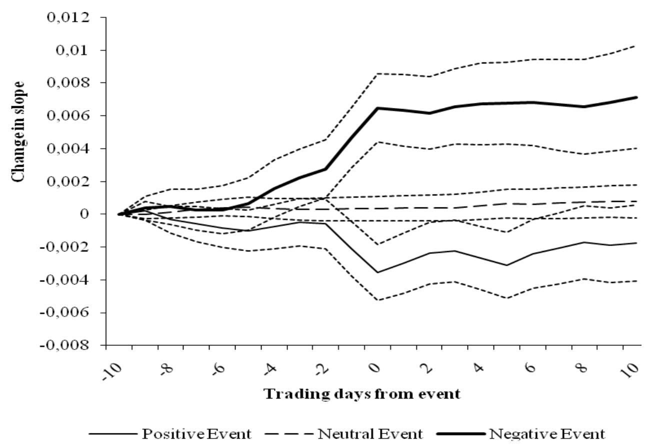


Figure 4.6 The event study for the crude oil forward curve's slope; top (solid) line: negative event, bottom (thin solid) line: positive event, dashed line: neutral

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, e.g., around a negative news event, prices for all maturities fall, but nearby futures fall in price more than distant maturities – the illustration of this effect is given in Figure 4.7. This observation gives rise to a relatively low-risk trading strategy: at negative event, one can enter short position in short term futures and a corresponding long position in long maturity futures (and do the opposite at a positive event). By this, one can benefit from the subsequent price move, but at low risk, as such a short-long strategy is well hedged.

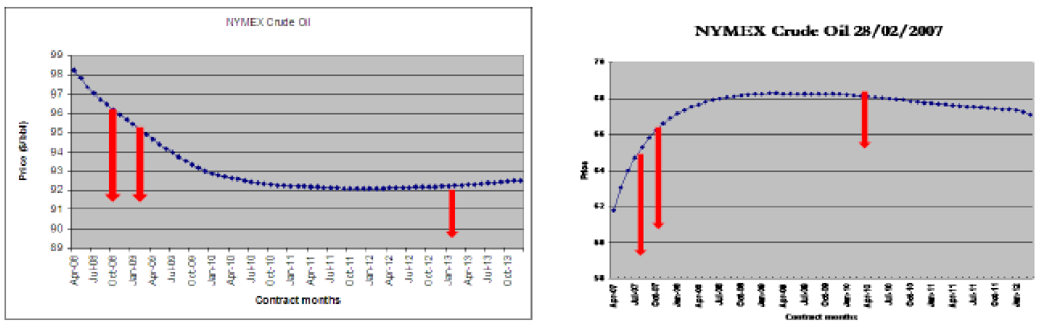


Figure 4.7 Illustration of the negative event's effect on the crude oil forward curve's slope

So to summarize the results of this section, we can note that the effects of news sentiment on commodity forward curves are complex and not obvious. Moreover, these effects depend on the overall state of the market. Analysing the effects of news sentiment on the fundamental factors of the forward curve can give rise to profitable and low-risk trading strategies, as trading in calendar spreads is much less risky than taking outright futures positions. For seasonal commodities, such as natural gas or agricultural commodities, maturity related seasonalities should be taken into account.

5 Commodity news sentiment indices

In the first decade of 2000, surging interest in commodities has led institutional and private investors to entering commodity markets. Such non-traditional, financial players invest in commodities predominantly by means of *commodity indices*, which are baskets of commodity futures. The three most popular indices are DJ-UBS, S&P Goldman Sachs (GSCI) and Reuters/Jefferies CRB commodity indices. Each index has its advantages and disadvantages. For example, GSCI is the most tracked index in the market — it has the most funds following, or tracking, its performance. However, the most closely *watched* index is the Reuters/Jefferies CRB Index. The CRB Index is a global benchmark for what the commodities markets are doing. The composition of the indices is also quite different, for example GSCI gives a relatively large weight (over 70%) to energy commodities. On the other hand, DJ-UBS commodity index is more diversified, as no single commodity may constitute less than 2% and no related group of commodities (e.g., energy, precious metals, livestock or grains) may constitute more than 33% of this index.

Commodity-related news sentiment is measured in e.g., Thomson Reuters News Analytics (TRNA) for many specific commodities or commodity classes. However, if we want to investigate the sentiment of the commodity market as a whole and to relate it to commodity price indices such as GSCI, we need to construct a market-wide commodity news sentiment index. Such a news index can be constructed on the basis of any price index, or even independently of it, in the following way.

First, we need to determine the weights of each commodity, commodity class or a group in such a news index. If the goal is to relate it to a price index such as DJ-UBS or GSCI, then the weights in the price index can be used for this purpose. For example, the weights of commodities in DJ-UBS commodity index (as of 2012) are given in Appendix C. Note that the sentiment measures are not available for all commodities in the price index. For example, there is no separate ticker in the news sentiment database for commodities such as live cattle, individual industrial or precious metals or for different grades of oil and oil products. So we assign the weights to those commodity groups equal to the aggregate DJ-UBS weights of the corresponding commodities in that group, also shown in Appendix C.

The market-wide commodity news sentiment index can be constructed on the daily basis, using daily sentiment scores for individual commodities or commodity classes, or for higher frequencies, using commodity-specific running sentiments, whose construction we described in Section 1.2. Let $S_{k,t}$ be sentiment for commodity (or commodity group) k at time/day t, and let w_k be the commodity-k weight in the index. The overall commodity news sentiment index at time t is then the weighted average of the commodity-specific sentiments:

$$S_t^{Index} = \sum_{k=1}^{K} w_k S_{k,t},$$

where K is the number of commodities in the index and $\sum_{k=1}^{K} w_k = 1$.

If for a certain day or time t there are no news about a particular commodity i (which can happen for smaller commodities such as some agricultural commodities), then we need to re-normalize the weights in the index so that the absolute weights remain the same but relative weights still add up to one: $\widetilde{w_k} = \frac{w_k}{\sum_{j \neq i} w_j}$. For example, let the commodity news sentiment index consist of three commodities: oil (with the weight 0.6), gold (with the weight 0.3) and wheat (with the weight 0.1). If, on the day t, there is no news about wheat, then the sentiment index on that day is calculated as

$$S_t^{Index} = \frac{0.6}{0.6+0.3} S_{oil,t} + \frac{0.3}{0.6+0.3} S_{gold,t}.$$

If we wish to construct commodity news sentiment index not related to any price index, we can define the weights being equal to the proportion of the average news volume about each commodity or commodity group provided by the news analytics engine. For example, for TRNA, such weights (for some commodities) are given in Table 1 (second column). Note that, for such a choice, agricultural commodities would be rather underrepresented, while energy and metals would receive quite a large weight, so such a news sentiment index would rather closely resemble that obtained on the basis of GSCI.

Having constructed an aggregated commodity news sentiment series, we can employ again event studies and vector autoregression (VAR) models, to relate it to the corresponding commodity price index's returns and volatility. Furthermore, we can use the Granger Causality test to determine whether the market-wide news sentiment is driving the index returns and volatility or vice versa. Finally, we can employ cointegration analysis to test for long-term relationships between the commodity news sentiment and price indices. In this section, we report such findings for the example of Goldman Sachs Commodity Index (GSCI), for daily closing prices and returns; the relationship between the news sentiment and the volatility will be dealt with in the next section.

First, we look at the relations between the returns and sentiment. We calculated the historical correlation between the daily returns of the commodity price indices and the daily changes in the corresponding news sentiment index. These are presented in Table 5.1.

Table 5.1 Correlations between index returns and news sentiment daily changes

GSCI	**DJ-UBS**	**CRB**
0.0946	0.1243	0.2139

The event studies for commodity price indices at the daily frequency provide results that are very similar to the event studies presented in Section 1.3, as such an event study is just a weighted average of event studies for individual commodities. Hence, we do not present daily event study plots for commodity indices here, but only for price responses at a higher frequency. Figure 5.1 shows such an event study for event window of +/- 4 hours for CRB index, the time grid is 1 minute. Note again the same features as observed before: a significant price move prior to an event, but also a significant price move for an hour after an event (positive or negative), as well as asymmetry between the reaction to positive and negative news event.

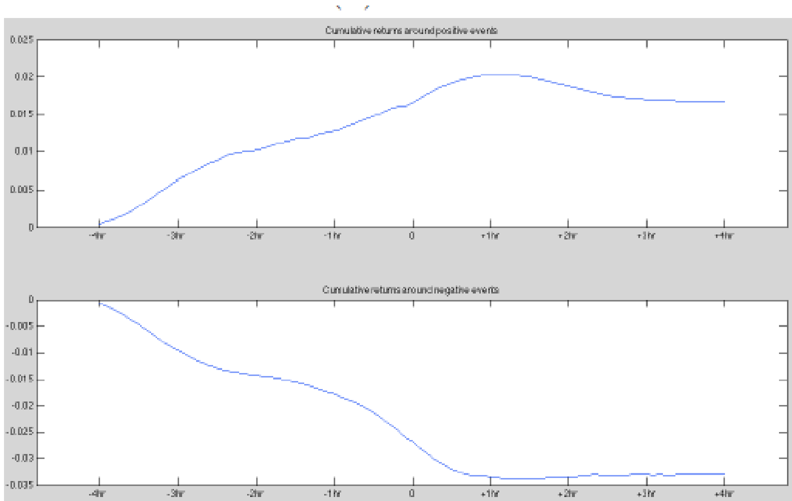


Figure 5.1 Intraday event study for CRB, event window 8 hours. Top: positive sentiment, bottom: negative sentiment

We applied Vector Autoregression (VAR) to GSCI lagged returns and daily changes in the related net-positive sentiment index. From this analysis we observe a clear autocorrelation structure in the sentiment index, lasting up to four days. We also observe a slightly significant (at 10%) and positive effect of net positive sentiment on the next day's return. On the other hand, we also find a very significant (at 1%) effect of previous day return on the next day's sentiment. This means that if there is a positive return on the price index today, it increases the net positive sentiment tomorrow. This is again a manifestation of momentum-related news, i.e., news stories about previous returns.

If we separate the historical period on periods of bullish and bearish market (for example, the period August 2007 - February 2009 is a clear example of a bearish, i.e., declining market) and apply VAR again, we observe that the effect of news sentiment on returns is higher when commodity markets fall, i.e., in bearish market, and almost insignificant in bullish market. The regression coefficient measuring the influence of net positive sentiment on the next day's return is almost three times higher during bearish market than for the entire sample, while the adjusted R-squared for the regression is more than doubled. This indicates that investors pay more attention and trade more on the basis of news when markets are falling, and are rather ignorant to news when commodity markets rise – the fact confirmed by many other behavioural finance studies. Furthermore, the reduction of the selected autoregression order from 4 to 1 during bearish market indicates that investors need less time to incorporate news during bear periods.

The Granger causality test, applied to the same variables, shows results consistent with the VAR analysis: the news sentiment index Granger-causes the next day return (this is illustrated in Figure 5.2 by means of Impulse Response Function), and vice versa, i.e., the return causes sentiment. These causality relationships are again much stronger in bear than in bull markets. We also observe significant causality relationships between sentiment and volatility, which we will elaborate on in the next section.

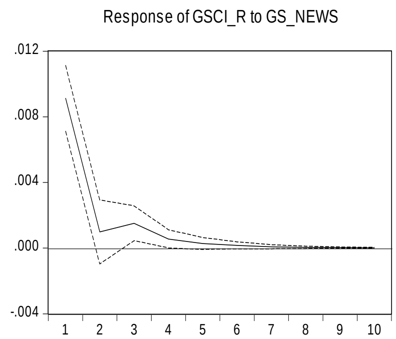


Figure 5.2 Impulse response function of GSCI return to net positive news sentiment (response to 1 S.D.)

Finally, we investigate long-term relationships between news sentiment and price indices. The daily sentiment score is a short-term measure, which is confirmed by the absence of any unit root in the daily sentiment series. So to measure long-term sentiment, we form moving average versions of the sentiment series, averaging the daily sentiment over a month, quarter or half a year. These series, together with the GSCI commodity index, are show in Figure 5.3.

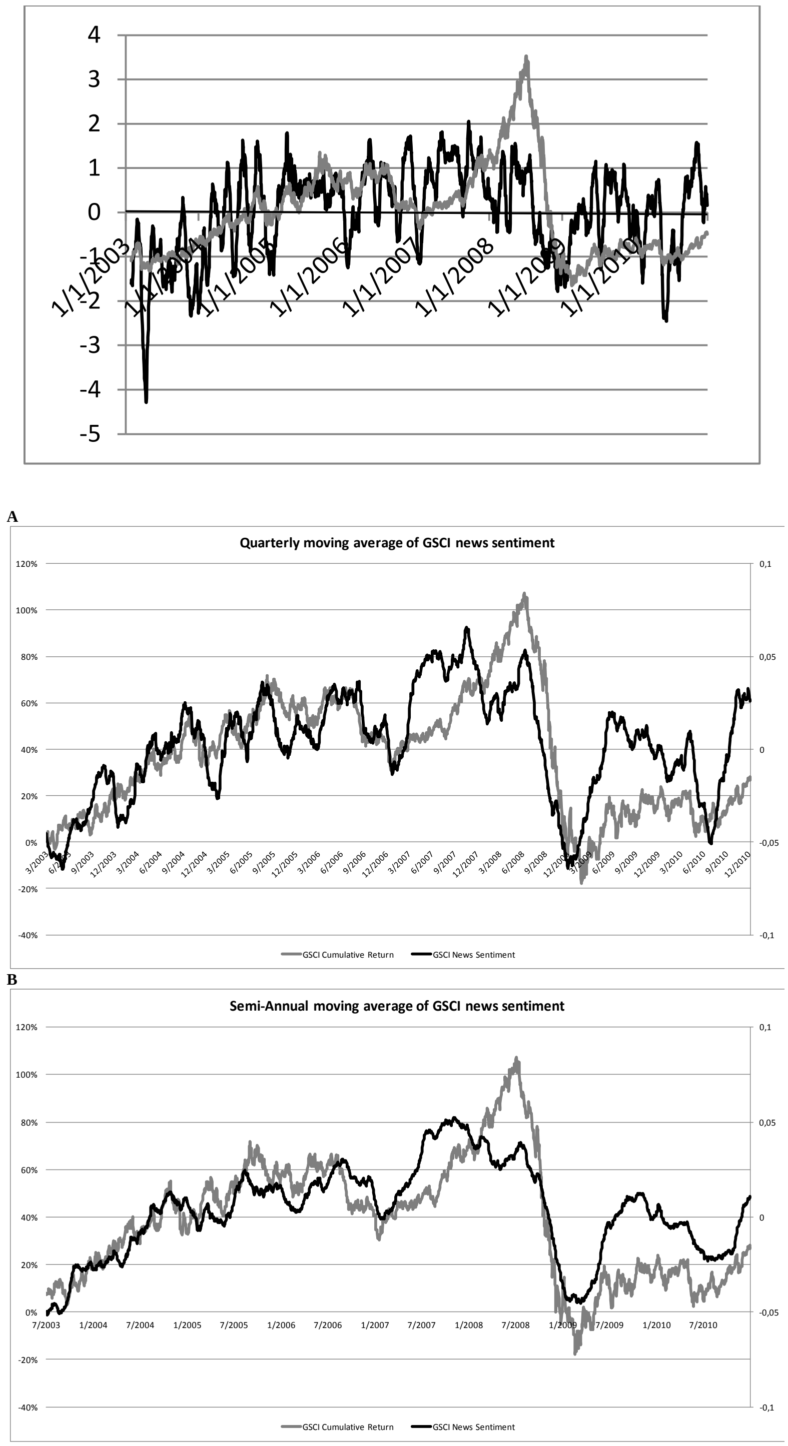


Figure 5.3 Monthly (top), quarterly (middle) and semi-annual (bottom) moving average news sentiment index (black) vs. GSCI (grey)

From the above figures it is clear that the series of long-term sentiment index and the GSCI closely follow each other in terms of long trends. The cointegration test of Johansen confirms strong cointegrating relationships between the long-term sentiment and commodity price index.

To summarize, the commodity market-wide sentiment indices, constructed on the basis of the corresponding price indices, provide both short-term forecasting power as well as reveal long-term relationships between sentiment and prices. They can be used for constructing trading and investment strategies (both short- and long-term) and for monitoring the overall state of commodity markets. In the next section, we will show how including sentiment indices into volatility models can help improve volatility forecasts and hence be used in risk management applications.

6 Volatility and jumps vs. news

6.1 News-augmented volatility models

For equities, significant relationships between volatility and news have been observed in the literature (see e.g., Mitra et al. (2009)). For commodities, we also expect to find significant relationships between news and its sentiment and volatility: when the volume of (particularly negative) news is high, the volatility should rise, reflecting e.g., risk-aversion and other behavioural characteristics of market participants.

Time-changing volatility (also in commodity markets) is routinely modelled by GARCH models of the form:

$$\sigma_t^2 = \omega V_L + \alpha r_{t-1}^2 + \beta \sigma_{t-1}^2$$

where σ_t^2 is the conditional variance on day t, r_{t-1}^2 is the previous day's squared logreturn, V_L is the long-term variance and the positive model coefficients must add up to one to ensure stationarity of the resulting process: $\omega + \alpha + \beta = 1$.

Volatility responds asymmetrically to positive and negative returns, so the so-called leverage effect is often added:

$$\sigma_t^2 = \omega V_L + (\alpha + \gamma I(r_{t-1} < 0)) r_{t-1}^2 + \beta \sigma_{t-1}^2,$$

where the sign of the leverage coefficient γ indicates the so-called normal (γ >0) or inverse (γ <0) leverage effect.

For equities, normal leverage effect is usually present. It has been a subject of a long debate in the literature whether the inverse or normal leverage effect is present in commodities. Many studies point out that the inverse leverage effect is persistent in agricultural commodities, as there rising prices are often perceived as being bad for the economy and mankind. For metals and energy, however, evidence is mixed. Prior to the financial crisis of 2007-2008, the inverse leverage effect has been also documented for energy. Recently, however, more and more evidence emerges in the academic as well as in professional literature, pointing out towards disappearance of the inverse leverage effect and even the reversal towards the normal leverage for energy and metals. However, it is still important to include leverage term in volatility models to take into account the possibility of asymmetric volatility.

To study the effects of news sentiment on volatility, we apply the so-called GARCH-X models, where we augment the variance equation with an external sentiment variable:

$$\sigma_t^2 = \omega V_L + (\alpha + \gamma I(r_{t-1} < 0))r_{t-1}^2 + \beta\sigma_{t-1}^2 + \theta sent_{t-1}.$$

We can include different sentiment variables into the GARCH model: positive and/or negative sentiment scores, or the net positive sentiment: $pos_{net} = sent_{pos} - sent_{neg}$. However, it might also be that high (in absolute value) sentiment (regardless whether it is positive or negative) causes volatility, so another choice of a sentiment variable would be the absolute net sentiment: $|sent_{pos} - sent_{neg}|$. It turns out that a slightly modified version of the absolute sentiment is also useful in volatility models: what we will call Absolute Sentiment:

$$AS = \left|sent_{pos} - sent_{neg}\right|/(1 - sent_{neut}).$$

It measures not just the strength of sentiment, but also "agreement" about today's sentiment (note that we can define (1-AS) as "disagreement" about the sentiment). We can illustrate this on the following simple example. Suppose we observed the following sentiment values on several days:

	pos	neut	neg	AS	net pos
Day 1:	0.5	0.4	0.1	2/3	0.4
Day 2:	0.5	0.1	0.4	1/9	0.1
Day 3:	0.8	0	0.2	0.6	0.6
Day 4:	0.6	0.4	0	1	0.6
Day 5:	0.9	0.1	0.3	2/3	0.6

The difference between Day 1 and Day 2 is that, although the positive sentiments are the same, the positive sentiment signal (as well as the overall agreement about this sentiment) is stronger on Day 1, which is captured by both net positive and absolute sentiment. However, if we consider Days 3, 4 and 5, we see that the Absolute Sentiment (AS) gives Day 4 the strongest score, as there is no negative sentiment at all on that day and hence, there is the highest "agreement" about the sentiment. So the Absolute Sentiment can be also included in the models, on itself or possibly combined with the net positive sentiment (e.g., weighting the net positive sentiment by AS).

We have fitted news-augmented asymmetric GARCH models to crude oil and natural gas futures (NYMEX first nearby contracts). The estimation results are presented in the next tables. All reported parameters are significant at 5% (not significant parameters are not reported).

Table 6.1 Parameter estimates, asymmetric GARCH-X, crude oil

Par.	GARCH	Sent_neg	Net pos	|pos-neg|	AS
Constant	0.0000	0.0000	0.0000	0.0000	0.0000
α	0.0198	0.0264	0.0205	0.0224	0.0206
β	0.9265	0.9111	0.9108	0.9258	0.9258
γ	0.0656	0.0631	0.0644	0.0640	0.0646
Θ	--	0.0002	-0.0002		
LogLik	5336.124	5338.691	5339.397	5337.257	5336.978

Table 6.2 Parameter estimates, GARCH-X, natural gas

Par.	GARCH	Sent_pos	Sent_neg	Net pos	|pos-neg|	AS
Constant	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
α	0.0285	0.0377	0.0263	0.0199	0.0008	0.0006
β	0.9617	0.9498	0.9666	0.9741	0.9817	0.9865
Θ	--	-0.0001	0.0001	0.0003	0.0002	0.0003
LogLik	1581.418	1582.171	1582.265	1583.094	1590.190	1589.175

From these tables we see that the best performance for crude oil is observed for the models that include negative sentiment, alone or in combination with positive sentiment (net positive). The coefficient of negative sentiment is highly significant and positive, indicating that high negative sentiment increases volatility, as expected. Significant normal leverage effect is observed for oil futures. For natural gas, the results are different: there is no significant leverage effect (hence, the results for the regular GARCH-X are reported) and the best models are the ones that include either absolute sentiment or AS. This shows that natural gas volatility increases when absolute sentiment is high, regardless whether it is positive or negative. Hence, the choice of the explanatory sentiment variables depends crucially on the commodity in question.

We also investigated the influence of news sentiment on commodity indices' volatility. As expected, negative sentiment significantly increases the next day's index volatility. This is illustrated by the impulse-response function of volatility to net positive sentiment, shown in Figure 6.1.

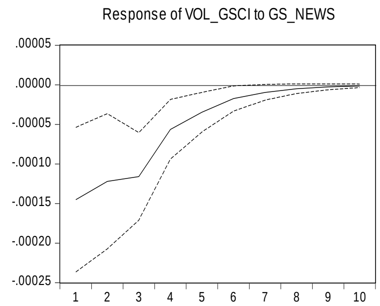


Figure 6.1 Impulse response function of GSCI volatility to absolute positive news sentiment (response to 1 S.D.)

We fitted a news sentiment-augmented asymmetric GARCH model to GSCI returns. The best explanatory power is obtained when including net positive sentiment into the model. The next table shows the estimated coefficients for such a model.

Table 6.3 Estimated coefficients of asymmetric GARCH-X model fitted to GSCI returns

	Coefficient
Constant	0.0000
α	0.0246*
β	0.6242***
γ	0.4005***
Θ (net pos)	-0.0004***

The above table shows that GSCI exhibits the regular leverage effect, which is not surprising, as this index is mostly used by long-only investors. Furthermore, the coefficient corresponding to the net positive sentiment is highly significant and negative, indicating that high positive sentiment decreases and high negative sentiment increases volatility.

In all, we find that sentiment measures are useful for improved volatility forecasting. Including carefully chosen sentiment variables into volatility forecasting models significantly improves model fit and leads to superior forecasts.

6.2 Causality relationships between news, volatility and price jumps

Many commodity prices exhibit jumps, the extreme example of this being electricity prices. These price jumps occur due to unexpected supply interruptions, geopolitical and other external events, which are exactly the kind of information which appears in the news. So if we were able to identify price jumps, we could relate them to the arrival and the sentiment of news. The technique of bi-power variation of Barndorff-Nielsen and Sheppard (2004) allows us to do just that.

Suppose that the log-price process can be well described by the so-called *jump-diffusion*, that is, a stochastic process that consists of a diffusive component (typically modelled by the Brownian motion W_t with a drift) and a jump component J_t (usually taken to be a compound Poisson process):

$$dY_t = a_t dt + \sigma dW_t + dJ_t.$$

If, for each day *t*, we observe high frequency returns $r_{t,i}$, we can estimate the quadratic variation of this process on day *t* by the realized variance:

$$RV_t = \sum_{i=1}^{I} r_{t,i}^2$$

or by its alternative, the so-called *realized kernel RK*, which is an estimator more robust to microstructure noise (see e.g., Barndorff-Nielsen et al. (2008)). If jumps are present, then these estimates will contain both the diffusive component's variance and the jump variance. Can we separate these two components?

It turns out that it is possible, by calculating the so-called *bi-power variation*, which is a variant of the realized variance, robust to jumps (for details, we refer the reader to Barndorff-Nielsen and Shephard (2004)). Together, the jump variance and the jump-robust estimator of the diffusive component's variance (which is exactly the bi-power variation) must add up to the realized variance:

$$RV_t = BPV_t + JV_t.$$

Hence, we can use this equation to calculate the day-*t* estimate of the jump variance JV_t and to separate jumps from the diffusive price moves. Moreover, it is possible to separate up and down jumps, as well as up- and downside semi-variances, i.e., variances corresponding to the positive and negative price moves.

We applied the above procedure to the Natural Gas first nearby futures prices from NYMEX. The reason we chose Natural Gas is that this commodity clearly exhibits price jumps (unlike crude oil, where the presence of jumps has not been established with certainty), and for which there is enough news flow to relate these news to jumps in prices (unlike, e.g., electricity, for which there is no significant amount of news).

The Figure XX shows an extract from the historical dataset, with daily realized variance/realized kernel and jump variation extracted from it by means of the bi-power variation. It turns out that approximately 20% of all daily natural gas price moves can be classified as jumps, of which there are slightly more negative than positive jumps.

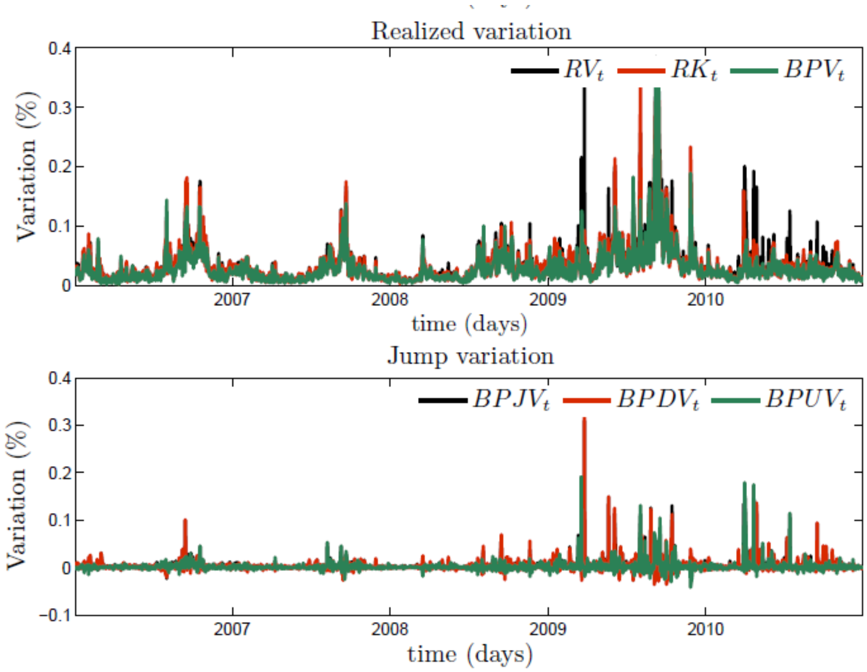


Figure 6.2 Realized variation (top graph) and jump variation (bottom graph) for NG futures

Next, we applied the Granger causality test, to establish whether the realized variance and its components (positive/negative jumps and semi-variances) cause and are caused by news. For news sentiment series, we use the running NG-related news sentiment series, whose construction we described in the Section 2. The two tables below summarize the most important causality relationships. We adopt a convention that columns cause rows, "+" stands for significant at 10%, "++" significant at 5% and "+++" significant at 1% causality relationships.

Table 6.4 Causality relationships between variance and sentiment measures

	RV/RK	NegVar	PosVar	SentPos	SentNeg	SentAbs
RV/RK				++	+++	
NegVar				+	+	
PosVar				++	+++	
SentPos	+++	+	++			
SentNeg	+++	+	+++			
SentAbs		++				

Table 6.5 Causality relationships between price jumps and sentiment measures

	BPV	JV	NegJumpV	PosJumpV	SentPos	SentNeg	SentAbs
BPV					+	++	
JV					+++	+++	+++
NegJumpV					+++	+++	+++
PosJumpV					+++	+++	+++
SentPos			+++	++			
SentNeg			+++	++			
SentAbs		++	++				

The above tables show cross causality relationships between positive and negative news sentiment, the realized variance and both semi-variances. We also see that negative sentiment causes the realized variance (as we have already observed in the previous subsection), but also that the variance measures cause news sentiment.

From the second table it is clear that jumps (and especially negative jumps) cause absolute as well as positive and negative sentiment – so the sentiment is more sensitive to negative than to positive jumps. Most importantly, all news sentiment measures severely cause jumps. This confirms our hypothesis that jumps are predominantly caused by external information that arrives to the market in the form of news. As a result, market participants take futures positions (long or short) when news sentiment (either positive or negative) is high, causing large price moves that are identified as jumps.

To conclude this section, we argue that the findings of this section – volatility models augmented with sentiment measures, the causality relationships between news sentiment and up/down price moves – can help devising better risk forecasting models for risk management and monitoring purposes.

7 Conclusions

In this paper we gave an overview of news analytics for commodities. We outlined some of the issues such as characteristics of commodity-related news, their effects on returns, volatilities and price jumps, as well as the construction of various news sentiment indices (commodity-specific and market-wide). However, this overview is by no means exhaustive, and commodity news sentiment applications are undoubtedly more numerous than those mentioned here.

The overall conclusion of this paper is that the responses of commodity markets to sentiment in news are complex, depend on the state of the market and on characteristics of a specific commodity. The exciting research area of commodity news analytics is relatively new, fresh and underdeveloped. Any significant advances in the quantitative trading, investment and risk management on the basis of commodity news are still much needed. In particular, investigating high frequency reaction of prices to news sentiment and devising and testing corresponding trading strategies is an interesting research direction.

The main improvement in sentiment analysis for commodities would come from correctly identifying and filtering of momentum-related news (i.e., those news discussing past price developments). Providing other characteristics of news such as whether a news item is supply- or demand-related would also greatly enhance any quantitative trading strategies, risk management or investment applications.

Acknowledgments

The author would like to thank Alan Lammiman, Erszebet Toth, Nikki Be and Nawied Sawari for their invaluable input to the project. The hospitality and excellent working conditions at Institute of Pure and Applied Mathematics at UCLA are also gratefully acknowledged.

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Appendix A News articles

“Oil Caps Biggest 2-Week Gain in 17 Years Amid Volatility” (Bloomberg, February 5, 2015).

Crude oil capped the biggest two-week rally in 17 years on speculation a falling rig count will curb U.S. production growth. Price volatility rose to the highest in almost six years. Brent crude jumped 18 percent in the past 10 trading days, the most since March 1998. A volatility index gauging price fluctuations in West Texas Intermediate crude rose this week to to the highest since 2009.
Oil has rebounded as companies including Statoil ASA, BP Plc and Royal Dutch Shell Plc have reduced investments in response to the market’s collapse. U.S. drillers pulled more rigs off oil fields, according to data from Baker Hughes Inc. Friday. Saudi Arabia cut prices for March exports to Asia to the lowest in at least 14 years, signaling OPEC’s largest producer may continue to fight for market share
“We are establishing a bottom,” said Bill O’Grady, chief market strategist at Confluence Investment Management in St. Louis, which oversees $2.4 billion. “In the long run, probably $60 is going to be your pivot point. Usually you have high volatility when there is a disagreement on where the price should be.”
Brent for March settlement increased $1.23, or 2.2 percent, to $57.80 a barrel on the London-based ICE Futures Europe exchange, up 9.1 percent this week. Even after the recent rally, Brent has still fallen about 50 percent from its June 19 high of $115.71.

“Capex cuts will determine oil’s bottom” (CNBC News, February 11, 2015).

Despite the most-recent rally, oil prices will keep on dropping until capital expenditure cuts filter through the market, RBC Capital's head of commodities research said Wednesday.
"You had rig count reductions and people said this is a turn, but the problem is you're battling with very-high inventory levels, and the [capital expenditures] cuts are probably not going to filter through [until] the back half of the year," Helima Croft told CNBC's "Squawk on the Street."
Croft added other factors could also cause oil prices to bottom. "[Those] are not based on actual production," she said. "Those are more geopolitical factors." Croft also said some of these external geopolitical factors have yet to filter through the oil market.
"There's not a concern in the market right now about Nigeria," she said. "Their election was supposed to take place this weekend; it's been postponed. Historically, we've seen significant volumes of crude come off the market around Nigerian elections. In the 2003 elections ... we lost 850,000 barrels of production because of unrest around oil facilities."
Croft also said she expects oil to make a comeback as soon as early 2016, as long as capex cuts take effect. "This really should filter through 2016 and demand should recover," she said. "We should be looking at a much higher demand picture in 2016."
Nevertheless, Croft added that there will be a selloff on Wednesday if the rig count comes in higher than expected. U.S. crude inventories rose to 4.86 million barrels last week, topping analysts' estimates of 3.7 million. In early afternoon trading Wednesday, WTI was down 1.1 percent to about $49.50 per barrel, while Brent crude dropped 2.4 percent to $55.10 per barrel

Appendix B Cumulative excess returns for event studies

Commodity	Sentiment	Cumulative excess return during days -60 to -6	-5 to 0	1 to 5	6 to 60	-60 to 60
Energy						
Natural Gas (US)	Positive	2,84%	1,84%	0,29%	-0,22%	4,75%
	Negative	-5,78%	-1,81%	0,13%	-8,14%	-15,60%
Natural Gas (Europe)	Positive	2,92%	1,09%	-0,13%	-1,12%	2,76%
	Negative	-3,49%	-1,79%	-0,22%	-6,02%	-11,52%
Agriculture						
Corn	Positive	2,13%	0,54%	-0,35%	0,06%	2,38%
	Negative	-5,56%	-1,36%	0,21%	-0,42%	-7,14%
Oats	Positive	4,59%	1,14%	0,41%	3,35%	9,50%
	Negative	-10,12%	-2,07%	-0,14%	-4,06%	-16,40%
Soybeans	Positive	1,88%	1,25%	-0,28%	1,50%	4,34%
	Negative	-6,28%	-1,65%	0,15%	-0,24%	-8,02%
Metals						
Copper	Positive	6,22%	1,68%	0,13%	-0,53%	7,50%
	Negative	-15,37%	-3,52%	-0,18%	-2,35%	-21,42%
Gold	Positive	-1,24%	0,92%	0,02%	-1,38%	-1,68%
	Negative	-0,74%	-1,29%	0,32%	0,81%	-0,90%
Silver	Positive	-0,01%	1,71%	-0,20%	-3,48%	-1,98%
	Negative	-5,28%	-3,01%	0,20%	1,42%	-6,67%

Commodity	Sentiment	Cumulative excess return during days -20 to -6	-5 to 0	1 to 5	6 to 20	-20 to 20
Energy						
Natural Gas (US)	Positive	0,02%	2,01%	0,16%	2,43%	4,63%
	Negative	-1,35%	-2,15%	1,31%	1,05%	-1,14%
Natural Gas (Europe)	Positive	3,22%	1,04%	1,56%	1,46%	7,28%
	Negative	-0,29%	-0,96%	0,25%	0,05%	-0,95%
Agriculture						
Cocoa	Positive	0,13%	0,65%	0,28%	-0,93%	0,13%
	Negative	-0,38%	-1,53%	0,42%	0,48%	-1,00%
Coffee	Positive	0,58%	0,43%	-0,87%	-0,73%	-0,59%
	Negative	-0,57%	-0,95%	-0,07%	0,97%	-0,62%
Corn	Positive	0,91%	0,21%	-0,68%	-1,24%	-0,80%
	Negative	-1,46%	-2,07%	0,79%	0,16%	-2,57%
Cotton	Positive	0,12%	0,47%	-0,82%	-1,36%	-1,58%
	Negative	-0,80%	-1,94%	-0,22%	0,20%	-2,76%
Oats	Positive	2,85%	1,01%	0,04%	-1,11%	2,80%
	Negative	-3,49%	-2,13%	-0,20%	0,39%	-5,43%
Rough Rice	Positive	0,61%	0,14%	0,17%	0,33%	1,25%
	Negative	-2,78%	-1,92%	0,51%	-0,87%	-5,06%
Soybeans	Positive	1,62%	1,31%	-0,16%	-0,01%	2,76%
	Negative	-2,43%	-1,66%	0,53%	0,71%	-2,85%
Sugar	Positive	0,23%	0,20%	-0,94%	-1,89%	-2,40%
	Negative	-2,57%	-1,79%	0,76%	2,37%	-1,24%
Wheat Chicago	Positive	1,50%	0,84%	-0,28%	-0,03%	2,04%
	Negative	-1,77%	-2,36%	1,27%	-0,15%	-3,00%
Wheat Kansas	Positive	1,86%	0,89%	-0,34%	-0,21%	2,21%
	Negative	-1,83%	-2,23%	0,88%	-0,18%	-3,35%
Livestock						
Feeder Cattle	Positive	0,12%	0,06%	0,36%	0,51%	1,04%
	Negative	-0,66%	-0,50%	-0,03%	-0,14%	-1,34%
Live Cattle	Positive	0,07%	-0,37%	-0,13%	0,08%	-0,35%
	Negative	-0,41%	-0,64%	-0,25%	-0,58%	-1,88%
Metals						
Copper	Positive	2,51%	1,74%	-0,02%	-0,40%	3,83%
	Negative	-5,20%	-3,62%	-0,11%	-1,62%	-10,56%
Gold	Positive	0,59%	0,94%	0,05%	-0,39%	1,19%
	Negative	-0,38%	-1,25%	0,25%	-0,13%	-1,51%
Palladium	Positive	0,09%	0,13%	0,31%	-0,20%	0,33%
	Negative	-1,45%	-3,47%	-0,70%	-1,36%	-6,98%
Platinum	Positive	-0,39%	0,64%	0,47%	1,08%	1,80%
	Negative	-2,65%	-2,30%	-0,51%	-3,00%	-8,46%
Silver	Positive	1,30%	1,66%	-0,25%	-0,66%	2,05%
	Negative	-2,15%	-3,01%	0,22%	-0,30%	-5,23%

Appendix C Composition of DJ-UBS index (2012) and the corresponding news sentiment index

Commodity	**Original weight**	News data	**Weight for analysis**	RIC code
Natural gas	10.77	**Natural gas**	10.77	
WTI Crude oil	9.69	**Crude oil**	18.41	CRU
Brent Crude oil	5.31			
Unleaded/RBOB Gasoline	3.41			
Heating oil	3.46	**Heating oil**	3.46	HOIL
Live Cattle	3.63	**Livestock**	5.74	LIV
Lean hogs	2.11			
Wheat	4.96	**Grains**	4.96	GRA
Corn	6.67	**Corn**	6.67	COR
Soybeans	7.08	**Oils**	10.45	OILS
Soyabean oil	3.37			
Aluminium	5.88	**Metals**	18.64	Met
Copper	7.06			
Zinc	3.12			
Nickel	2.58			
Lead	0			
Tin	0			
Gold	9.79	**Gold**	12.56	GOL
Silver	2.77			
Platinum	0			
Sugar	3.76	**Sugar**	3.76	SUG
Cotton	2	**Cotton**	2	COT
Coffee	2.57	**Coffee**	2.57	COF