Does Unusual News Forecast Market Stress?

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Abstract

We find that an increase in the "unusualness" of news with negative sentiment predicts an increase in stock market volatility. Our analysis is based on over 360,000 articles on 50 large financial companies, mostly banks and insurers, published in 1996–2014. We find that the interaction between measures of unusualness and sentiment forecasts volatility at both the company-specific and aggregate level. These effects persist for several months. The pattern of response of volatility in our aggregate analysis is consistent with a model of rational inattention among investors.

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1 Introduction

Can the content of news articles forecast market stress and, if so, what type of content is predictive? Several studies have documented that news sentiment forecasts market returns. We find that a measure of "unusualness" of news text combined with sentiment forecasts stress, which we proxy by stock market volatility. The effects we find play out over months, whereas in most prior work the stock market's response to news articles dissipates in a few days.

The link between sentiment expressed in public documents and stock market returns has received a great deal of attention. At an aggregate level, Tetlock (2007) finds that negative sentiment in the news depresses returns; Tetlock, Saar-Tsechansky, and Macskassy (2008) study company-specific news stories and responses. Garcia (2008) finds that the influence of news sentiment is concentrated in recessions. Loughran and McDonald (2011) and Jegadeesh and Wu (2013) apply sentiment analysis to 10-K filings. Da, Engelberg, and Gao (2014) measure sentiment in Internet search terms. Our focus differs from prior work because we seek to forecast market stress rather than the direction of the market. We apply new tools to this analysis, going beyond sentiment word counts.

The importance of unusualness is illustrated by the following two phrases, both of which appeared in news articles from September 2008:

> "the collapse of Lehman"
> "cut its price target"

Both phrases contain one negative word and would therefore contribute equally to an overall measure of negative sentiment in a standard word-counting analysis. But we recognize the first phrase as much more unusual than the second, relative to earlier news stories. This difference can be quantified by taking into account the frequency of occurrence of the phrases in prior months. As this simple example suggests, we find that sentiment is important, but it becomes more informative when interacted with our measure of unusualness.

Research in finance and economics has commonly measured sentiment through what is known in the natural language processing literature as a bag-of-words approach: an article is classified as having positive or negative sentiment based on the frequency of positive or negative connotation words that it contains. The papers cited above are examples of this approach. As the example above indicates, this approach misses important information: the unusualness of the first phrase lies not in its use of "collapse" or "Lehman" but in their juxtaposition. We therefore measure

unusualness of consecutive word phrases rather than individual words.

Our analysis uses all news articles in the Thompson-Reuters database between January 1996 and December 2014 about/that mention the top 50 global banks, insurance, and real estate firms by market capitalization as of February 2015. The survivorship bias in this selection of companies works against the effects we find — firms that disappeared during the financial crisis are not in our sample. We run company-specific time series regressions of implied volatility on lagged measures of sentiment and unusualness calculated from the articles. We also extract aggregate measures of unusualness and sentiment and analyze their interaction with implied and realized volatility through vector autoregressions. At both the company-specific and aggregate levels we find that the interaction of unusualness and sentiment measures forecasts volatility and does so better than either measure alone. We also find a statistically significant four-factor alpha in a long-short strategy that sorts the stocks monthly by the interaction measure; sorting on just sentiment or just unusualness does not yield statistically significant average returns.

In most prior work that finds a predictive signal in the text of public documents, the information is incorporated into prices within a few days.[1] In our company-specific regressions, we find evidence that our unusualness-sentiment signal remains predictive at lags as long as six months. Our aggregate analysis uses vector autoregressions; there we find that the response of aggregate volatility (implied or realized) to an impulse in our interacted variables is also significant at six months. In fact, the impulse response is hump-shaped, peaking at around four months. This pattern suggests that the information in the variables we consider is absorbed slowly.

These longer-horizon effects are intuitively plausible. Brewing concerns often generate public discourse well before they materialize as market stress (if they do materialize). For example, Google Trends data shows searches for "subprime" spiking in March 2007, more than three months before the sharp rise in volatility in July 2007. Concerns about a Greek exit from the euro have been in the news for years, yet there is little doubt that the event itself would drive up volatility, despite the anticipation. Arbitraging a predictable rise in volatility is much more difficult than profiting from a predictable stock return: the term structure of implied volatility is typically upward sloping, the roll yield on VIX futures is typically negative, and implied volatility is typically higher than realized volatility, so trades based on options, futures or variance swaps need to overcome these hurdles. The uncertainty around whether a potential stress will materialize (think of betting on Y2K fears) may further dampen risk-adjusted returns based on forecasted volatility.

[1] An exception is Heston and Sinha (2014). By aggregating news weekly, they find evidence of predictability over a three-month horizon.

Rational inattention offers a possible explanation for the patterns we observe. Several studies have found evidence that the limits of human attention affect market prices; see, for example, the survey of Daniel, Hirshleifer, and Teoh (2004). Models of rational inattention, as developed in Sims (2003,2015), attach a cost or constraint on information processing capacity: investors cannot (or prefer not to) spend all their time analyzing the price implications of all available information. We interpret the cost or constraint on information processing broadly. It includes the fact that people cannot read thousands of news articles per day (and having a computer do the analysis involves some investment); but it also reflects limits on the contracts investors can write to hedge market stress, given imperfect information on unobservable macro state variables. Even among professionals, many investors may focus on a narrow set of stocks or industries and may overlook information that becomes relevant only when aggregated over many stocks. Indeed, Jung and Shiller (2005) review empirical evidence supporting what they call Samuelson's dictum, that the stock market is micro efficient but macro inefficient. The allocation of attention between indiosyncratic and aggregate information drives the model of Maćkowiak and Wiederholt (2009b). Investors also need to allocate attention across different time horizons. Dellavigna and Pollet (2007) find that demographic information with long-term implications is poorly reflected in market prices. A related effect may apply in our setting: investors may anticipate the possibility of elevated volatility in the future yet not take actions that eliminate this outcome.

Beyond this qualitative link to rational inattention we develop a precise connection. First, we argue that although investors would like to hedge aggregate risk, information constraints make it impossible to write contracts directly tied to unobservable macro state variables. We interpret the VIX as an example of a resulting imperfect hedge. Next we evaluate the price of an approximate hedge in a formulation consistent with rational inattention, meaning that investors evaluate the conditional expectation of future cash flows based on imperfect information about the past. Building on work of Sims (2003,2015) and Maćkowiak and Wiederholt (2009b), we show that this model predicts that the response of the VIX to an impulse in the macro state variable is hump-shaped, consistent with what we find in our vector autoregressions. In other words, information constraints cause news about macro shocks to be incorporated in the VIX only gradually.

Because the effects we find in the data play out over months, the signals we extract from news articles are potentially useful for monitoring purposes. Along these lines, Baker, Bloom, and Davis (2013) develop an index of economic policy uncertainty based on newspaper articles. Indicators of systemic risk (see Bisias et al. 2012) are generally based on market prices or lagged

economic data; incorporating news analysis offers a potential direction for improved monitoring of stress to the financial system. From a methodological perspective, our work introduces two ideas from the field of natural language processing to text analysis in finance. As already noted, we measure the "unusualness" of language, and we do this through a measure of entropy in word counts. Also, we take consecutive strings of words (called n-grams) rather than individual words as our basic unit of analysis. In particular, we calculate the unusualness (entropy) of consecutive four-word sequences. These ideas are developed in greater detail in Jurafsky and Martin (2009).

The rest of this paper is organized as follows. Section 2 introduces the methodology we use, and Section 3 discusses the empirical implementation. Section 4 presents results based on company-specific volatility, and Section 5 examines aggregative volatility. Section 6 looks at return predictability using unusualness and sentiment. Section 7 develops the connection with rational inattention. Section 8 concludes.

2 Methodology

2.1 Unusualness of language

An important task in modern statistical approaches to natural language processing is word prediction. Jurafsky and Martin (2009), a very thorough reference for the techniques we employ in this paper, gives the following example: What word is likely to follow the phrase *please turn your homework ...*? Possibly it could be *in* or *over*, but a word like *the* is very unlikely. A reasonable language model should give a value for

$$P(in|please\ turn\ your\ homework)$$

that is relatively high, and a value for

$$P(the|please\ turn\ your\ homework)$$

that is close to zero. One way to estimate these probabilities is to count the number of times that *in* or *the* have followed the phrase *please turn your homework* in a large body of relevant text.

To use an example from our data set, up until October 2011, which is around the start of the European sovereign debt crisis, the phrase *negative outlook on* had appeared 688 times, and had always been followed by the word *any*. In October 2011, we observe in our sample 13 occurrences of the phrase *negative outlook on France*. We would like our language model to consider this phrase unusual given the observed history.

An *n-gram* is a sequence of n words or, more precisely, n tokens.[2] Models that compute these types of probabilities are called n-gram models (in this example, $n = 5$) because they give the probability of seeing the fifth word conditional on the first four for a given 5-gram.

Consider the N word corpus $w_1 \dots w_N$. We can write its probability as

$$P(w_1 \dots w_N) = P(w_1)P(w_2|w_1)P(w_3|w_1w_2) \cdots P(w_N|w_1w_2 \dots w_{N-1}). \tag{1}$$

N-gram models are used in this context to approximate conditional probabilities of the form $P(w_k|w_1 \dots w_{k-1})$ when k is so large (practically speaking, for $k \geq 6$) that it becomes difficult to provide a meaningful estimate of the conditional probabilities for most words. In the case of an n-gram model, we would approximate the above with

$$P(w_k|w_1 \dots w_{k-1}) \approx P(w_k|w_{k-(n-1)} \dots w_{k-1}),$$

which allows us to approximate the probability in (1) as

$$P(w_1 \dots w_N) = \prod_{k=n}^{N} P(w_k|w_{k-n+1} \dots w_{k-1}). \tag{2}$$

In (2), we have dropped the probability $P(w_1 \dots w_{n-1})$ of the first $n-1$ words, which should have little effect if $n \approx 4$ and N is in the thousands.

Let us refer to the text whose probability we are trying to determine as the *evaluation corpus*. Since the true text model is not known, the probabilities in (2) will usually have to be estimated from a *training corpus*, $\tilde{w}_1 \dots \tilde{w}_{\tilde{N}}$, where typically $\tilde{N} \gg N$. This idea is to use a large collection of text to estimate the probability that a given word will follow a certain phrase, and then to use these conditional probabilities to determine a probability score for text that we encounter later on.

[2]For example, we treat "chief executive officer" as a single token. When we refer to "words" in the following discussion, we always mean tokens.

N-gram models are often used for tasks like spoken language processing or spelling correction. We propose to use them to gauge the unusualness of a collection of text. Consider an evaluation text $w_1 \dots w_N$ and conditional probabilities $P(w_k|w_{k-n+1} \dots w_{k-1})$ estimated from a training corpus $\tilde{w}_1 \dots \tilde{w}_{\tilde{N}}$.[3] Assuming there are I distinct n-grams in $w_1 \dots w_N$, we can reorganize (2) as

$$P(w_1 \dots w_N) = \prod_{i=1}^{I} P(\omega_n^i|\omega_1^i \cdots \omega_{n-1}^i)^{c_i}, \tag{3}$$

where $\{\omega_1^i \dots \omega_n^i\}$ is the i^{th} n-gram, and c_i is the number of times this n-gram has appeared in the evaluation corpus $w_1 \dots w_N$ (so that $c_1 + \cdots + c_I = N - n + 1$).

For a 4-gram $\{\omega_1\ \omega_2\ \omega_3\ \omega_4\}$, the empirical probability of ω_4^i conditional on $\omega_1\ \omega_2\ \omega_3$ will be denoted by m_i, and is given by

$$m_i(t) = \frac{c(\{\omega_1\ \omega_2\ \omega_3\ \omega_4\})}{c(\{\omega_1\ \omega_2\ \omega_3\})} \tag{4}$$

where $c(\cdot)$ is the count of the given 3- or 4-gram in the training corpus, and where in a slight abuse of notation we write m_i for both the probability and its estimate.

Taking logs in (3) and dividing by the total number of n-grams in the sample, we obtain the per word, negative log probability of the text collection $w_1 \dots w_N$:

$$\begin{aligned} H(w_1 \dots w_N) &\equiv -\frac{1}{N-n+1} \log P(w_1 \dots w_N) = -\frac{1}{N-n+1} \sum_{i=1}^{I} c_i \log m_i \\ &= -\sum_{i=1}^{I} p_i \log m_i, \end{aligned} \tag{5}$$

where p_i is the in-sample probability of observing n-gram i.

Note that the more different the structure of $w_1 \dots w_N$ relative to $\tilde{w}_1 \dots \tilde{w}_{\tilde{N}}$, especially if there are frequently occuring n-grams (i.e. with high c_i, and therefore a high p_i) that have low conditional probabilities m_i based on the training corpus, the lower $P(w_1 \dots w_N)$ will be. We will say that texts with low model probabilities relative to a training corpus are *unusual*.

The quantity in (5) is also the cross-entropy of the model probability for $w_1 \dots w_N$ (i.e. the m's that come from the training corpus) with respect to the true (unobserved) probability of

[3] We will address in Section 3.3 how to handle the situation that the n-gram $\{w_{k-n+1} \dots w_k\}$ was not observed in the training corpus.

having drawn a text $w_1 \dots w_N$ (see Jurafsky and Martin (2009) equation (4.62)). We refer to $H(w_1 \dots w_N)$ as the entropy of the evaluation text. Based on this definition, unusual texts will have high entropy.

Lists of n-grams

We can generalize the definition of entropy in (5) to apply to a list of n-grams as opposed to a corpus $w_1 \dots w_N$. A list j is a set of n-grams and an associated count of how often each n-gram from that list appears in a given month. A list can be represented by the collection $\{c_1^j(t), \dots, c_I^j(t)\}$ which assigns a count to every n-gram in our corpus. For n-gram i that does not appear in list j in month t, $c_i^j(t) = 0$. For example, we may want to consider the list of n-grams that include the word "France," or the list of all n-grams appearing in time t articles. We note that every corpus can be mapped into a list (i.e. a count of how often every n-gram appears in the corpus), but not vice versa.

Given a list of n-grams in month t, the entropy of that list will be defined as

$$H^j(t) \equiv -\sum_i p_i^j(t) \log m_i(t), \tag{6}$$

which is a generalization of (5). Here $p_i^j(t)$ is i's fraction of the total count of n-grams in list j, that is

$$p_i^j(t) = \frac{c_i^j(t)}{\sum_i c_i^j(t)}.$$

Note that m_i is exactly the same as in (4), and in particular does not depend on j.

2.2 Sentiment

The traditional approach for evaluating sentiment has been to calculate the fraction of words in a given document that have negative or positive connotations.[4] To do so, researchers rely on dictionaries that classify words into different sentiment categories. Tetlock (2007) and Tet-

[4]Loughran and McDonald (2011) use a more sophisticated approach that assigns higher weights to negative or positive sentiment words that occur less frequently in a training corpus. Jegadeesh and Wu (2013) empirically assess the importance of words by regressing contemporaneous returns of companies releasing 10K's on the frequency of occurrence of words in those filings.

lock, Saar-Tsechansky, and Macskassy (2008) use the Harvard IV-4 psychosocial dictionary. Recent evidence (Loughran and McDonald (2011) and Heston and Sinha (2014)) shows that the Laughran-McDonald[5] word lists do a better job of sentiment categorization in a financial context than the Harvard dictionary. We use the Laughran-McDonald dictionary in our work.

Because our core unit of analysis is the n-gram, we take a slightly different approach than the traditional literature. Rather than counting the number of positive or negative words in a given article, we classify n-grams as being either positive or negative. An n-gram is classified as positive (negative) if it contains at least one positive (negative) word and no negative (positive) words. We can then measure the tone of (subsets of) news stories by looking at the fraction of n-grams they contain which are classified as either positive or negative.

3 Empirical implementation

Our data set consists of Thomson-Reuters news articles about the top 50 global banks, insurance, and real estate firms by US dollar market capitalization as of February 2015. Almost 90% of the articles are from Reuters itself, with the remainder coming from one of 16 other news services. Table 1 lists the companies in our sample. The raw data set has over 600,000 news articles, from January 1996 to December 2014. Many articles represent multiple rewrites of the same initial story. We filter these by keeping only the first article in a given chain.[6] We also drop any article coming from PR Newswire, as these are corporate press releases. All articles whose headlines start with `REG-` (regulatory filings) or `TABLE-` (data tables) are also excluded. This yields 367,331 unique news stories which we ultimately use in our analysis. Each article is tagged by Thomson-Reuters with the names of the companies mentioned in that article. Many articles mention more than one company. Section A.1 gives more details about our data processing.

Figure 1 shows the time series of article counts in our sample. The per month article count reaches its approximate steady state level of 1500 or so articles in the early 2000's, peaks around the time of the financial crisis, and settles back down to the steady state level towards the end of 2014. The early years of our sample have relatively fewer articles, which may introduce some noise into our analysis.

Our market data comes from Bloomberg. For each of the 50 companies in our sample we construct a US dollar total returns series using Bloomberg price change and dividend yield data.

[5] See `http://www3.nd.edu/~mcdonald/Word_Lists.html`.

[6] All articles in a chain share the same *Reuters ID* code.

Also, for those firms that have traded options, we use 30-day implied volatilities for at-the-money options from the Bloomberg volatility surfaces. Our macro data series are the VIX index and 30-day realized volatility for the S&P 500 index computed from daily returns.[7]

Throughout the paper, our empirical work is at a monthly horizon, both for our news measures and our market and volatility data.

3.1 N-grams

In our empirical work, we use a 4-gram model.[8]

Each article goes through a data cleaning process to yield more meaningful n-grams. For example, all company names (and known variations) are replaced with the string *_company_*. Phrases such as *Goldman Sachs reported quarterly results* and *Morgan Stanley reported quarterly results* are replaced with *_company_ reported quarterly results* thus reducing two distinct 4-grams into a single one that captures the semantic intent of the originals. In this way we reduce the number of n-grams in our sample which will allow us to better estimate conditional probabilities in our training corpus. In another example, we replace *chief executive officer* with *ceo* because we would like the entity referred to as *ceo* to appear in n-grams as a single token, rather than a three word phrase. Section A.1 gives more details about our cleaning procedure.

We collect all 4-grams that appear in cleaned articles.[9] An n-gram must appear entirely within a sentence. Contiguous words that cross sentences do not count as an n-gram.[10] For month t we consider various lists of n-grams, such as the list of all n-grams appearing in time t articles, or the list of n-grams that appear in time t articles that mention a specific company.

For example, in January of 2013, the 4-gram *raises target price to* appeared 491 times in the entire sample (i.e. $c^{All}_{\{raises\ target\ price\ to\}}(\text{January 2013}) = 491$ where *All* is the list of n-grams appearing in all articles). It appeared 34 times in articles that were tagged as mentioning Wells Fargo, 26 times in articles that mentioned JP Morgan, but 0 times in articles that mentioned Bank of America. If we sum across all 50 names in our data set, this 4-gram appeared 1,014 times (more than its total of 491 because many articles mention more than one company).

[7] Month t realized returns are returns realized in that month, whereas the month t VIX level is the close-of-month level.

[8] Jurafsky and Martin (2009, p. 112) discuss why 4-gram models are a good choice for most training corpora.

[9] We use the NLTK package in Python for all text processing applications in the paper (see Section A.1).

[10] Note that this imposes slightly more structure than what is assumed about $w_1 \dots w_N$ in (1).

In each month, we focus on the most frequently occuring 5000 4-grams. In our 19 year data set, we thus analyze $19 \times 12 \times 5000 = 1.14$mm 4-grams. Of these 4-grams, 394,778 are distinct. The first three tokens in the latter represent 302,973 distinct 3-grams.

3.2 Sentiment

We define sentiment of a given subset of articles as the percentage of the total count of all n-grams appearing in those articles that are classified as either positive or negative. For example, we may be interested in those articles mentioning Bank of America, or JP Morgan, or the set of all articles at time t. If we denote by $POS(t)$ ($NEG(t)$) the set of all time t n-grams that are classified as positive (negative), then the positive sentiment of list j is

$$SENTPOS^j(t) = \frac{\sum_{i \in POS(t)} c_i^j(t)}{\sum_i c_i^j(t)}, \tag{7}$$

with the analogous definition for $SENTNEG^j(t)$.

For the list of n-grams from all time t articles, we will simply omit the superscript. For all n-grams coming from articles that mention, say, JP Morgan we will write $SENTPOS^{JPM}(t)$. Figure 2 shows the time series of $SENTPOS$ and $SENTNEG$ in our sample, as well as a scaled version of the VIX. Note that at the aggregate level, negative sentiment appears to be contemporaneously positively correlated with the VIX, whereas positive sentiment is contemporaneously negatively correlated. The correlations are 0.458 and -0.373 respectively. Section 5 will study the dynamics of this relationship in depth.

Table 2 shows the average contemporaneous correlation between the 50 individual implied volatility and sentiment pairs (i.e. between single name implied volatility and the $SENTNEG^j$ and $SENTNEG^j$ series for a given company j), and between the aggregate sentiment series and the VIX. If an individual implied volatility series does not exist, we use the VIX instead. Cross-sectional standard errors are also calculated assuming independence of observations. Averaging across single names reveals that $SENTNEG^j$ ($SENTPOS^j$) is on average positively (negatively) correlated with single name implied volatility, which is consistent with what we observe at the aggregate level.

We thus have fairly strong evidence that our sentiment measures, at the aggregate and single name levels, are responding to the same factors that drive the VIX.

3.3 Entropy

Our entropy measures come from equation (6). We refer to the measure of unusualness of all time t articles as $ENTALL(t)$. The unsualness of only those articles which mention a specific company is $ENTALL^j(t)$, where j is the list of n-grams coming from articles that mention the company in question.

We can also measure the unusualness of subsets of n-grams that do not correspond to all n-grams that come from some set of articles. For example, we can look at the list of n-grams which are classified as having negative (positive) sentiment; we refer to this entropy measure as $ENTNEG(t)$ ($ENTPOS(t)$). Or we can look at the list of n-grams that have negative (positive) sentiment that come from the the subset of articles in month t that mention company j; we refer to these measures as $ENTNEG^j(t)$ ($ENTPOS^j(t)$).

N-grams from month t articles form the evaluation corpus (giving us the p_i^j's) , and n-grams from rolling windows over past articles form the training corpus (giving us the m_i's). The training corpus for month t consists of all 3- and 4-grams in our data set that occured in the two year period from month $t-27$ up to and including month $t-4$. We use a rolling window, as opposed to an expanding window from the start of the sample to $t-4$ in order to keep the information sets for all our entropy calculations of roughly the same size.

It is possible that a given 4-gram that we observe in month t never occured in our sample prior to month t. In this case $m_i(t)$ is either zero (so its log is infinite) or undefined if its associated 3-gram also has never appeared in the training sample. To address this problem, we modify our definition of $m_i(t)$[11] in (4) to be

$$m_i(t) \equiv \frac{c(\{\omega_1\omega_2\omega_3\omega_4\}) + 1}{c(\{\omega_1\omega_2\omega_3\}) + 4}. \tag{8}$$

This means that a 4-gram/3-gram pair that has never appeared in our sample prior to t will be given a probability of 0.25. Our intent is to make a never-seen-before n-gram have a fairly, but not extremely, low conditional probability. The value 0.25 is somewhere between the 25^{th}

[11] We approximate $c(\{\omega_1\omega_2\omega_3\omega_4\})$ in a given training window by only counting the occurrences of those 4-grams which are among the most frequntly occuring 5000 in every month. We therefore underestimate 4-gram counts, especially for less-frequently occuring n-grams, and therefore the m_i's associated with low p_i^ν's are biased downwards. However, because $p \log p$ goes to zero for small p, this is unlikely to have a meaningful impact on our entropy measure. Across the 228 months in our sample, the maximum least-frequently-observed n-gram empirical probability is 0.012%. Rerunning the analysis using the top 4000 n-grams – instead of the top 5000 – in each month leaves our results largely unchanged, suggesting the analysis isn't sensitive to this issue.

percentile and the median $m_i(t)$ among all our training sets. For frequently occuring 4-grams, this modification leaves the value of m_i roughly unchanged. Jurafsky and Martin (2009) discuss many alternative smoothing algorithms for adressing this sparse data problem, but because of the relatively small size of our training corpus, many of these are infeasible.

We exclude the three months prior to month t from the training corpus because sometimes a 4-gram may have occured in our sample for the first time in month $t-1$. Furthermore if the associated 3-gram occured as often in month t as the 4-gram, the training set probability for this n-gram will be 1, and its associated entropy contribution will be zero. However, this n-gram may still be "unusual" in month t if it has only been observed in month $t-1$ and at no other time in our sample. For example the 4-gram *destroyed the world trade* would have a conditional probability of 1 in October 2001, even though it only occured in our sample as of September 2001. Intuitively, this n-gram ought to appear as unusual in October 2001 as well as in September.

Our results are not very sensitive to any of these modeling assumptions (i.e. setting unobserved m_i's to 0.25, having the rolling window be 2 years, and the choice of 3 months for the training window offset).

Contribution to entropy

By sorting n-grams on their contribution to entropy in (6), we can identify for a given month the most and least unusual 4-word phrases. Table 3 shows the three top and bottom phrases[12] by their contribution to entropy in two months in our sample that had major market or geopolitical events: September 2008 (the Lehman bankruptcy) and May 2012 (around the peak of the European sovereign debt crisis). In each case, at least one of the n-grams with the largest entropy contribution reflects the key event of that month – and does so without any semantic context. On the other hand, the n-grams with the smallest entropy contribution are generic, and have no bearing on the event under consideration.

Consider for example the n-gram *nyse order imbalance _mn_* from September of 2008. In our training set, the majority of occurrences of the 3-gram *nyse order imbalance* were followed by *_n_* (a number) rather than *_mn_* (a number in the millions). The frequent occurrence of *nyse order imbalance* followed by a number in the millions, rather than a smaller number, is unusual. This 4-gram has a relatively large p_i, a low m_i (and a high $-\log m_i$), and is the top contributor

[12]Some of the distinct 4-grams come from the same 5-gram.

to negative entropy in this month. On the other hand, the 3-gram *order imbalance* _n_ is almost always followed by the word *shares*, thus giving this 4-gram an m_i of almost 1, and an entropy contribution close to zero. In May 2012, the n-gram *the euro zone crisis* is unusual because in the sample prior to this month the 3-gram *the euro zone* is frequently followed by *'s* or *debt*, but very infrequently by *crisis*. Therefore the relatively frequent occurrence in this month of this otherwise unusual phrase renders it a high negative entropy contributor.

While anecdotal, this evidence suggests that our entropy measure is able to sort phrases in a meaningful, and potentially important, way.

Aggregate entropy

We find that the aggregate entropy measures can be unduly influenced by a single frequently occuring n-gram. For example, if an n-gram i appears only in articles about one company in month t, but appears very often (i.e. has a large p_i) and has a low model probability m_i, this one n-gram can distort the aggregate level entropy measure. A more stable measure of aggregate entropy is the first principal component of the single-name entropy series. For example, $ENTPOS$ can be measured as the first principal component of all the single-name $ENTPOS^j$ series. In the rest of the paper, all aggregate level entropy measures ($ENTALL(t)$, $ENTNEG(t)$, and $ENTPOS(t)$) are computed in this way.[13]

Figure 3 shows the three aggregate entropy series, with a scaled VIX superimposed. All three series are positively correlated with the VIX. $ENTPOS$ has the lowest correlation at 0.15, and $ENTNEG$ has the highest at 0.48. This is in contrast to the sentiment series where the negative and positive has opposited signed VIX correlations. Since entropy reflects unusualness of news, it is perhaps not surprising that all entropy series are positively correlated with the VIX, as all news (neutral, positive, and negative) may be more unusual during times of high market volatility.

Table 2 shows the average single name (and non-principal component aggregate) entropy to VIX correlations. The average single names correlations for ENT and $ENTNEG$ are positive, and the $ENTPOS$ average correlation is marginally negative though very close to zero. The values are smaller in magnitude than the correposnding sentiment ones.

[13]Because of the need to have all data present for computing the principal component, our aggregate entropy measures use only 25 names for $ENTPOS$ and $ENTNEG$, and 31 names for ENT. For names that have observations at the start of sample period, but are missing some intermediate observations, we use the most recently available non-missing value of the associated entropy measure. See Footnote 16 for more details.

The entropy series seem to reflect some of the same factors as the sentiment and VIX series, but also appear to have qualitatively different behavior. This gives hope that entropy contains information complementary to sentiment, a topic we will explore in greater detail in the remainder of the paper.

4 Single name volatility

As we see from Tables 2 and 5, both at the single name and aggregate levels, sentiment and entropy are contemporaneously correlated with single name and market-wide implied volatilites. To explore the ability of these news-based measures to predict stress at the single name level, we regress single name implied volatility (30-day at-the-money) on lagged values of our news measures. The basic regression for name j has the form

$$iVol^j_{1mo}(t) = c + \sum_{l=1}^{6} b1^j_l \; NEWS1^j(t-l) + \cdots + \epsilon^j(t) \tag{9}$$

where $NEWS1^j$ is the news-based indicators under consideration. The j superscript usually indicates that the measure is computed from the list of n-grams coming from articles that mention company j.[14] The regression measures the ability of various news-based measures to predict *future* implied volatility. There are no contemporaneous terms on the right hand side.

We can then average the time series regression coefficients across all names (for which we have implied volatility data) to obtain

$$b1_l = \frac{\sum_j b1^j_l}{\sum_j 1}. \tag{10}$$

We always run the regression above with a lag of 6 months.

We compute standard errors for each coefficient $b1_l$ in (10) under the assumption of independence. The $\cdots$ in (9) indicate the possibility that additional news factors will be present in the regression (e.g. 6 lags of $NEWS2$ in addition to $NEWS1$). We normalize all $NEWS$ variables to have unit standard deviation to make interpretation of coefficients easier.

To establish a baseline result for (9) we run the regression with $NEWS1^j$ set to the percent

[14] Only the article count measure doesn't look at n-grams (see $ARTICLE\_PERCTOT^j$ below).

of all month t articles that mention company j, which we call $ARTICLE_PERCTOT^j$s.[15] We use this measure because of our prior belief that it should contain minimal information content for future volatility. Figure 5 shows the results. All coefficients from (9) are not statistically different from zero – which confirms our initial belief that article count by itself is not useful for forecasting future implied volatility.

The bottom chart in Figure (5) shows a plot of the fraction of all unadjusted R^2's of the single name regressions, using $ARTICLE\_PERCTOT$ on the right hand side, that are greater than a given value x, i.e. $f(x) = Pr(R^2 > x)$. Note that the x-axis in the chart starts at 1 and goes to 0. This function is one minus the cumulative distribution function of the R^2's from the single name regressions.

For an idealized zero-value regressor, this graph should be zero at all values of R^2 that are larger than 0, with a spike to probability one at $R^2 = 0$. The area under this curve would be zero. However, spurious correlations in the data induce some single names to have non-zero R^2's even if $ARTICLE\_PERCTOT^j$ truly has not predicitve value, and we have to control for this fact in interpreting the results of other regressors.

Similarly, for the ideal regressor with perfect explanatory power for every single name in our cross-section, the R^2 curve would spike up to 1 at $R^2 = 1$, and remain at 1 for all other potential R^2 values. The area under this curve would be 1. It is easy to show that the area under the $f(x)$ curve (AUC) is equal to the cross-sectional mean of R^2's.

We will use the empirical $f(x)$ for $ARTICLE\_PERCTOT^j$ as the baseline R^2 curve (i.e. the one that obtains for a regressor with no predictive value). Comparing the AUC of the R^2 curves of other news-based variables to this one will tell us the incremental improvement in the cross-sectional average of R^2's that is achieved by a given regressor relative to a regressor with no predictive value. Furthermore, examining the shape of a given news-based R^2 curve relative to the baseline one yields a richer picture of the predictive power of the measure in question relative to only looking at the difference in cross-sectional means of R^2's.

4.1 Predictive ability of news measures for single name volatility

Table 6 shows the difference in AUC's between our news-based measures and $ARTICLE\_PERCTOT$, or, equivalently, the difference in cross-sectional means of R^2's. We include the two sentiment

[15] All results are qualitatively similar if we use the percent of all time t n-gram counts that come from articles that mention name j.

indicators, the three entropy indicators, and a variable that interacts negative sentiment with negative entropy ($ENTSENT\_NEG$).[16]

Consistent with some of the prior findings in the literature (for example, Tetlock (2007)) we find that negative sentiment is a good predictor for future market outcomes – though Tetlock looks at stock returns and here we analyze implied volatility – offering an incremental improvement in average R^2's relative to the no-predictability benchmark of roughly 14%. Negative entropy yields an R^2 improvement of 9.5%.

Interestingly the interacted variable, $ENTSENT\_NEG$ improves average R^2's by nearly 23%, which is about double the improvement of either of the negative news measures separately. Figure 6 shows the results of this regression. The difference in the R^2 curve relative to the no-predictability benchmark is dramatic. All 6 lagged coefficient are statistically significant.

Strinkingly, the coefficient estimates are economically very large. A one unit standard deviation increase in last month's $ENTSENT\_NEG$ will increase this month's one month implied volatitility by 4 volatility points on average. This is a very significant effect.

Perhaps even more surprisingly, the effect remains strong and statistically significant even at a lag of six months. Assuming a news innovation that is completely transitory, a one unit standard deviation move in $ENTSENT\_NEG$ from six months prior to month t still increases month t implied volatility by 2 volatility points. This is an important result – news innovations persist in implied volatility markets even after half a year's time. We will discuss this effect in greater length in Section 7.

4.2 Which matters more?

As table 6 suggests, the three most important variables for determining future single-name implied volatilies are negative sentiment and entropy, and the interaction term. We run the regression in (9) with these three measures included as regressors (lagged from one to six months). As Figure 7 shows, when all three variables are included, negative sentiment and entropy are statistically and economically marginal, while the interacted term $ENTSENT\_NEG$ remains both statistically significant and economically very important. In fact, even including entropy and

[16]In each single name regression, we exclude those months when one of the regressors is not available. For example, in a month where a given name had no n-grams classified as negative, while the negative sentiment measure is zero, the negative entropy measure from (6) is not computable. Replacing all such unobservable entropy scores with zero slightly reduces the magnitude of our results, but does not change any of the qualitative conclusions.

sentiment as controls in the regression, the value of the coefficients on lags of $SENTENG\_NEG$ are largely the same as when this term was the only regressor.

Finally, the incremental improvement in the cross-sectional average of R^2's is 17% where the benchmark R^2 curve comes from the model with regressors given by $ARTICLE\_PERCTOT$, $NGRAM\_PERCTOT$ and $ARTICLE\_PERCTOT \times NGRAM\_PERCTOT$.

To summarize our conclusions from the single-name analysis:

- Current news is reflected in future implied volatility at a time horizon of (at least) 6 months.
- In univariate tests, negative entropy, negative sentiment, and the product of the two were the three best performing regressors for forecasting future single-name implied volatilities.
- Of these three, the interaction term $ENTSENT\_NEG$ was the best predictor, both in univariate tests and in a test that included all three variables as regressors in (9).

Our results strongly suggest that sentiment and entropy are both important measures of news content, and that negative *and* unusual news are the most important for forecasting future stress episodes (as measured by implied volatilities). In the next section, we will investigate the dynamics of these relationships using aggregate data.

5 Aggregate volatility

We now turn from company-specific measures of entropy, sentiment, and volatility to aggregate measures. We document evidence that unusual negative news predicts an increase in volatility as measured either by the VIX or by realized volatility on the S&P 500 index. As discussed in Section 3, each aggregate measure of entropy is the first principal component of the corresponding measures across the financial companies listed in Table 1, whereas aggregate sentiment follows from (7) applied to the set of all n-grams in month t.

We consider the five aggregate news based measures from Figures 2 and 3, as well as the interaction variable $ENTSENT\_NEG(t) = ENTNEG(t) \times SENTNEG(t)$. Table 4 gives some descriptive statistics about these measures, and Table 5 shows the contemporaneous correlations among these six variables, and the VIX index. Figure 4 shows a plot of $ENTSENT\_NEG$ versus the VIX index.

$SENTPOS$ has a negative correlation with the VIX, whereas all the entropy measures have a positive correlation, suggesting that at the aggregate level, news unusualness increases with market volatility. All entropy measures are positively correlated with one another, and negatively correlated with $SENTPOS$.

It is notable that although $ENTNEG$ and $SENTNEG$ have a low correlation of 0.19, their correlations with the VIX are 0.48 and 0.46 respectively. So even though the two do not share much in common, it appears they both explain a meaningful portion of VIX variability. The interaction variable $ENTSENT\_NEG$ has the highest VIX correlation of the news based measures at 0.6. It also has a high correlation with its consituents: 0.86 with $SENTNEG$ and 0.64 with $ENTNEG$.

This correlation result, the visual evidence in Figure 4 and the desriptive statistics in Table 4 all suggest that the interacted variable $ENTSENT\_NEG$ is a closer fit to the VIX (and realized volatility) than either negative sentiment or entropy separately.

In the next two sections, we explore the dynamics of this relationship in greater detail.

5.1 Event studies

For a first look at the data, we examine changes in the VIX around high and low values of our aggregate measures. For each aggregate measure (such as $ENTNEG$ or $SENTNEG$), we sort the 177 months from April 1999 through December 2013 according to the value of the measure and select the months in the top and bottom and quintiles. We think of the months in these quintiles as event dates. For each such month, we record the level of the VIX over the 25 month period starting 12 months before the event and ending 12 months after. We then average the VIX paths across the months in each quintile to see the average behavior of the VIX around one of these events.

As a point of reference, Figure 8 shows the results when the events are high and low values of the VIX itself. The dashed lines are two standard errors above and below the solid average line. As expected, the left panel shows that the VIX increases to a peak and then declines; the right panel confirms that the VIX decreases and then increases around a low value, but the pattern is much less pronounced around a low point than around a high point. In part for this reason, we focus primarily on the quintile associated with high volatility when we sort on other variables.

Figure 9 shows corresponding event studies for various measures, starting with $ENTNEG$

in the first row. Around a high level of $ENTNEG$, we see the VIX first climbing and then staying elevated, in contrast to the sharp mean-reversion we see in Figure 8. Around a low level of $ENTNEG$, the drop and rebound in the VIX is more pronounced than it is around a low level of the VIX itself in Figure 8. High levels of $SENTNEG$ have a similar association with the VIX, but low levels of $SENTNEG$ are associated with a steady decline in the VIX, unlike the pattern around low levels of $ENTNEG$. Around a high level of the interaction variable $ENTSENT\_NEG$ we again see a climb in the VIX but almost no subsequent decline — a high level of the $ENTSENT\_NEG$ variable signals a sustained elevation in volatility.[17] We interpret this as evidence that unusual negative news forecasts market stress. Indeed, the effect is large, with a high level of $ENTSENT\_NEG$ associated with VIX increase of almost 10 points. The effect lasts for months, consistent with the findings in the company-specific regressions of Section 4. As a final point of comparison, the lower-right panel of Figure 8 shows that high levels of overall entropy have no association with changes in the VIX.

We obtain qualitatively similar results using realized volatility (measured as the standard deviation of daily returns within a month) instead of the VIX. For example, the left panel of Figure 10 shows the evolution of realized volatility around top quintile levels of $ENTSENT\_NEG$: as with the VIX, realized volatility climbs to month zero and remains elevated, declining only slowly after the peak. The right panel of Figure 10 shows the behavior of the volatility risk premium, measured as the difference between the VIX and realized volatility. The volatility risk premium declines slightly, indicating that realized volatility increases a bit more than implied volatility around high levels of $ENTSENT\_NEG$ and suggesting that elevated $ENTSENT\_NEG$ is associated with increased market stress and not simply increased risk aversion. The figure uses end-of-month VIX values, but the pattern remains the same if we use beginning-of-month VIX values to calculate the volatility risk premium.

5.2 Impulse Response Functions

We next investigate interactions among the aggregate variables through vector autoregressions (VARs). The event studies of the previous section have the advantage of being nonparametric. A VAR model imposes more assumptions but also provides a more systematic analysis, so the perspectives complement each other.

We estimate a VAR model in six variables, initially ordered as follows: VIX, SPX_RVOL

[17] This behavior for the interacted variable does not automatically follow from similar behavior for $ENTNEG$ and $SENTNEG$ because high levels of these variables need not occur together.

(realized volatility), $SENTNEG$, $ENTSENT\_NEG$, $SENTPOS$, and $ENTSENT\_POS$. The Akaike information criterion selects a model with two lags; we estimate each equation in the VAR separately using ordinary least squares. We analyze the model through its impulse response functions. Each impulse is a one standard deviation shock to the error term for one variable in a Cholesky factorization of the error covariance matrix. A shock to one variable has a direct effect on variables listed later in the order of variables but not on variables listed earlier. Our ordering is thus stacked against finding an influence on either measure of volatility from the entropy and sentiment measures.

The left panel of Figure 11 shows impulse response functions in response to a shock to $ENTSENT\_NEG$, together with bootstrapped 95% confidence intervals.[18] Both the VIX and realized volatility have statistically significant responses to the shock. A one standard deviation increase in $ENTSENT\_NEG$ increases the VIX by 1.5 points and increases realized volatility by two points, so a 2-3 standard deviation shock to $ENTSENT\_NEG$ has a large economic impact on volatility. The right panel shows corresponding results in response to a shock to $SENTNEG$. There, neither VIX nor realized volatility exhibits a statistically significant response.

Next we reverse the order of $ENTSENT\_NEG$ and $SENTNEG$ and recalculate the impulse response functions. The left panel of Figure 12 shows that the VIX and realized volatility now have statistically significant responses to $SENTNEG$, increasing by roughly 1.25 and 1.75 points, respectively. But the right panel shows that they still have marginally significant responses to $ENTSENT\_NEG$ following the order change. Taking Figures 11 and 12 together suggests the following conclusions: An increase in negative sentiment or its interaction with entropy each predicts an increase in volatility; the effect of negative sentiment is captured by the interaction term; but there is an effect from the interaction term that is not captured by negative sentiment alone. This is consistent with our findings in the company-specific regressions of Section 4.

Figures 13 and 14 show that a similar pattern holds for positive sentiment and its interaction with entropy. A shock to the interaction variable $ENTSENT\_POS$ has a statistically significant (negative) effect on both VIX and realized volatility when it is listed before $SENTPOS$ (Figure 13, left panel), whereas $SENTPOS$ does not (Figure 13, right panel). When the order of the variables is interchanged, $SENTPOS$ has a statistically significant effect on VIX (Figure 14, left panel), and $ENTSENT\_POS$ has a marginally significant effect on both VIX and realized volatility (Figure 14, right panel). As one would expect the magnitudes of the responses

[18] We used the **R** package "vars" for the VAR estimation and impulse response functions; see Pfaff (2008).

to the positive signals are smaller than the responses to the negative signals, but the overall pattern is similar. The pattern suggests that both positive sentiment and its interaction with entropy influence volatility, and that the interaction term captures an effect that is not present in the sentiment variable alone.

The time horizon of the impulse responses is also noteworthy. Consider, for example, the two responses in the upper left portion of Figure 11. They show that the effect on volatility of an increase in $ENTSENT\_NEG$ plays out over months, peaking around four months after the shock and dissipating slowly. In Section 4 we found that the corresponding coefficients in the company-specific regressions remain statistically significant at lags of several months. These time scales are markedly different from those in prior work using news sentiment to predict returns (including Da et al. 2014, Jegadeesh and Wu 2014, Tetlock 2007, and Tetlock et al. 2008), where effects play out over days. In other words, directional information is incorporated into prices within days, but signals forecasting elevated volatility can remain relevant for months.

Volatility is of course much more persistent than returns are, but this property is insufficient to explain the volatility responses in Figures 11–14. Including implied and realized volatility in the VARs controls for persistence. Although persistence of volatility could make a predictor of high volatility in the present a predictor of high volatility in the future, the impulses responses of VIX and realized volatility to the news variables are consistently hump-shaped wherever they are statistically significant. The responses at month 4 are therefore not simply lingering effects of a larger response in month 1, as persistence by itself would predict. In Section 7, we will see that the hump-shaped responses are consistent with a simple model of rational inattention of agents who face constraints on the volume of information they can process.

6 Return predictability

Much of prior work on textual analysis in finance has focused on predicting returns. While the focus of our work has been on forecasting market stress, we want to briefly investigate whether our "unusualness"-based news measures are useful for predicting returns – to place our work into the context of the broader literature. It should be noted that our sample of companies is small (only 50 firms), and all companies are in related industries (finance, insurance, real estate). This lack of company and industry diversification stacks the cards against finding evidence of return predicatability. Furthermore, any results we do find may be unduly influenced by outliers in our small sample of firms. Consequently, the results in this section are only indicative, and should

be interpreted with caution.

We form long-short portfolios of single names in month t based on three different news-based sorts. We choose 10 companies for each of the long and short portfolios. We then look at the returns of that portfolio in month $t+1$, and then form a new portfolio based on month $t+1$ news measures. Sometimes not all month $t+1$ returns are available, in which case our portfolio will have less than 20 names in that month.[19] We use U.S. dollar total returns for all names in our sample, and approximate month t dividends by the last twelve month dividend yield divided by 12.

The three news-based sorts for forming portfolios are:

- $SENTNEG$: Shorts (longs) are the 10 names with the highest (lowest) month t values of $SENTNEG^j$.
- $SENTPOS$ vs $SENTNEG$: Shorts (longs) are the 10 names with the highest values of $SENTNEG^j$ ($SENTPOS^j$) in month t. This is similar to the portfolio scheme from Tetlock, Saar-Tsechansky, and Macskassy (2008).
- $SENTPOS$ vs $SENTNEG$ w/ $ENTALL$: Shorts (longs) are the 10 names with the highest values of $SENTNEG^j \times ENTALL$ ($SENTPOS^j \times ENTALL$) in month t. Ideally, we would like to interact positive and negative sentiment with positive and negative entropy, as we've done elsewhere in the paper. However, as mentioned in Footnote 16, time t negative and positive entropies are frequently not known, and extrapolating from past like-sentiment entropies introduces too much noise. So to maximize the amount of company-months of interacted news measures, we use $ENTALL$, which is almost always available for all names, as the interacting variable.

Figure 15 shows the cumulative returns from all three portfolio schemes. The data starts from April 1998 (the first month for which we calculate news-based measures in our sample) and ends in December 2014. Note that the extremely high returns in November and December of 2014 for the $SENTNEG$ long-short portfolio (14.1% and 26.2% respectively) are correct, and are due to the portfolio's being long Chinese banking stocks, which had incredible rallies in those two months.

Keeping in mind that all of these are zero investment portfolios, the fact that all three news-based sorts generate positive cumulative returns confirms prior findings that there is information

[19] We do not exclude month t names if their month $t+1$ returns aren't available to avoid any type of forward-looking bias.

content in news-based measures for future returns. Note that most prior work has looked at forecastability over daily horizons, and our results are for a monthly holding period. Of the three, the sort that interacts positive and negative sentiment with entropy yields the best overall Sharpe ratio, though not the highest overall returns (which comes from the $SENTNEG$ sort). This result again points out that it is not simply positive or negative news that matters, but positive or negative news that happens to be unusual.

To gain further insight into this result, we regress the monthly returns of the long-short portfolio from each of the three sorts on the Fama-French global factors (market, size, value) and on the global momentum factor.[20] Table 7 shows the results. First we see that all three news-based portfolios have very little overlap with any of the Fama-French factors, with the R^2's of all regressions being effectively zero. There is a slight tendency of all three of our sorts to load on small stocks and short big stocks (even though all stocks in our sample are large) as evidenced by the positive loading on the SMB factor. Using Newey-West standard errors with automatic lag selection, the only alpha that is significant (with a t-statistic of 2.07) among the three news-based portfolios comes from the sentiment-entropy interaction sort.

The results of our return predictability study should be interpreted with caution, as has already been mentioned, because of our small sample size.[21] That said, we confirm that unusual news matter more than news alone, both for forecasting returns, as well as market stress. Furthermore, the positive return of our news-based zero investment portfolios and the low R^2 of our factor regressions (which is similar to the result in Tetlock et al. (2008)) suggests either that: (a) our news-based sorts are picking up a previously undocumented source of priced uncertainty in the market, or (b) the textual analysis literature has identified an exploitable market anomaly that will dissipate over time. Understanding whether (a) or (b) is the best explanation is an interesting area for future research.

7 Rational inattention and information constraints

Several studies have found evidence that the limits of human attention affect market prices. Dellavigna and Pollett (2009) find a less immediate response to earnings announced on Fridays than other days and explain the differences through reduced investor attention. Ehrmann and Jansen (2012) document changes in the comovement of international stock prices during

[20] Data on Fama-French global factors are obtained from Ken French's website using the Quandl API for **R**.
[21] Furthermore, the results are somewhat sensitive to the choice of portfolio size.

World Cup soccer matches during which traders are presumably distracted. Huberman and Regev (2001) document a striking stock market response to "news" that was first made public months earlier. Hirshleifer, Hou, Teoh, and Zhang (2004) explain stock return predictability from accounting data through limited investor attention. Corwin and Coughenour (2008) find that attention allocation by market specialists affects transaction costs. Daniel, Hirshleifer, and Teoh (2002) explain a broad range psychological effects on markets through limited attention.

Limited attention may help explain the patterns we observe in Sections 4 and 5. Searching news articles to extract information about unusualness and sentiment takes time, and investors may perceive that they have better options for gathering data with whatever resources they allocate to making investment decisions. Consistent with Samuelson's dictum (Jung and Shiller 2005), investors may focus on a small set of stocks and pay less attention to macro events.[22] In Dellavigna and Pollett (2007), investors focus on information relevant to near-term returns but are inattentive to information with long-term consequences. A similar effect may apply in our setting, albeit over a shorter horizon. This would be consistent with the impulse response functions for volatility in Section 5.2, in which the response to a signal is greater at intermediate horizons than at the shortest horizons.

We can develop a stronger connection between the impulse response functions and limited attention by building on work of Sims (2003,2015) and Maćkowiak and Wiederholt (2009ab). Sims (2015) presents a theoretical framework, developed in a series of papers starting with Sims (2003), for modeling rational inattention.[23] Agents face constraints or costs on information processing and incorporate these into rational choices. Maćkowiak and Wiederholt (2009ab) build on Sims's framework to model sticky prices for goods; in their setting, a firm allocates limited attention capacity to two types of information, aggregate and idiosyncratic. The qualitative implications of reduced attention our relevant to our setting.

To develop the connection, we will let X_t denote a macro state variable such as the reciprocal of aggregate consumption or its negative logarithm.[24] For simplicity, we suppose that X_t follows a stationary AR(1) process,

$$X_{t+1} = \rho X_t + a u_{t+1}, \tag{11}$$

[22]In the model of Peng and Xiong (2006), investors choose instead to focus on coarser aggregate information and pay less attention to idiosyncratic information. For our purposes, the point is that this is one of the dimensions along which agents need to make an attention allocation decision.

[23]Sims (2003), p.696, makes an explicit connection with the saliency of information in news media.

[24]This formulation makes agents averse to large values of X_t and will simplify the interpretation of the VIX as a hedge for macro risk.

where $\rho \in (0,1)$, and the $\{u_t\}$ are independent, standard normal random errors.

Agents would like to hedge macro risk associated with X_t. However, they face information constraints that prevent them from observing X_t precisely; these constraints reflect intrinsic difficulty in measuring the macro state as well as the limits of agents' attention capacity. As a consequence, agents cannot write contracts with payoffs directly determined by X_t. Instead, they write contracts on an approximation Y_t that solves

$$\min_{b,c} E[(X_t - Y_t)^2]$$

with

$$Y_t = \sum_{\ell=0}^{\infty} b_\ell u_{t-\ell} + \sum_{\ell=0}^{\infty} c_\ell \epsilon_{t-\ell}, \tag{12}$$

subject to an information constraint between the processes $\{Y_t\}$ and $\{X_t\}$. The $\{\epsilon_t\}$ form a sequence of independent, standard normal random errors independent of $\{u_t\}$. Interpret Y_t as the best approximation to the macro state X_t given the information constraint.[25]

Maćkowiak and Wiederholt (2009a) show that the effect of the information constraint is equivalent to having agents observe a noisy signal $S^t = \{\ldots, S_0, S_1, \ldots, S_t\}$ of the past rather than the complete history $\{\ldots, (u_0, \epsilon_0), (u_1, \epsilon_1), \ldots, (u_t, \epsilon_t)\}$. In particular, $Y_t = E[X_t|S^t]$, meaning that the best observable approximation to the macro state is the conditional expectation of the true macro state given the agents' available information.

Next we consider the price at time t of a contract paying Y_{t+1} at time t. We assume a stochastic discount factor of the form[26] $\exp(\lambda u_{t+1} - \lambda^2/2)$, where u_{t+1} is the innovation to the macro state in (11). This factor attaches a greater discount to cash flows that covary negatively with shocks to X_t. Ordinarily, the price at time t would be the time-t conditional expectation of the product of the payoff and the stochastic discount factor. Given agents' limited information

[25] We omit the precise definition of the information constraint because it takes several steps to develop. In the case of scalar (jointly) normal random variables, the constraint reduces to an upper bound on their correlation. The general definition is detailed in Maćkowiak and Wiederholt (2009ab), and relevant background from information theory is reviewed in Sims (2003,2015). The resulting Y_t is optimal among approximations with the moving average representation in (12).

[26] We assume an interest rate of zero for simplicity.

S^t about the past, we model the price as[27]

$$V_t = E\left[e^{\lambda u_{t+1} - \lambda^2/2} Y_{t+1} | S^t\right].$$

The key implication of this formulation (derived in the appendix) is that the impulse response of V_t to a shock to the error in X_t is hump-shaped if agents' information processing constraint is sufficiently tight.

To map this observation to the impulse response functions in Section 5.2, think of the VIX as the price of a contract that imperfectly hedges macro risk: higher levels of the VIX are associated with market stress, so a contract that pays more in these states partly offsets a macro risk. Interpret the aggregate variable $ENTSENT\_NEG$ as a proxy for the macro state. The model we have outlined predicts that when the information constraint between $ENTSENT\_NEG$ and the VIX is tight, the impulse response function should be humped, just as we saw in Section 5.2. The information constraint faced by agents limits how quickly innovations to the macro state get incorporated in the VIX.

A more precise mapping between the model and our application should recognize that $ENTSENT\_NEG$ is itself at best a noisy observation of the macro state, say $ENTSENT(t) = X_t + \sigma_\eta \eta_t$, for some independent error term η_t. Then a one standard deviation shock to $ENTSENT\_NEG$ combines shocks to u_{t+1} and η_{t+1}, but $\{V_t\}$ responds only to the shock to u_{t+1}. In this interpretation, the impulse response functions we observe in Section 5.2 are averages over the responses to random shocks u_{t+1} in the unseen X_t, conditional on the total shock to the error in $ENTSENT\_NEG$ equaling one standard deviation. The average impulse response preserves the hump shape at least if the error variance σ_η^2 is not too large.

8 Conclusion

Using techniques from natural language processing, we develop a methodology for classifying the degree of "unusualness" of news. Applying our measure of unusualness to a large news data set that we obtain from Thomson-Reuters, we show that unusual, negative news forecasts volatility at both the company-specific and aggregate level. News shocks are impounded into volatility over the course of several months. This is a much longer time horizon than previous studies –

[27] Peng and Xiong (2006) develop a theoretical framework for asset pricing in a model with rational inattention. Our pricing formula has the same general structure as their equation (71).

which have focused on returns rather than volatility – have documented.

At the individual company level, we show that negative sentiment and negative entropy are the two best predictors for future implied volatility among our set of news-based measures. However, the interaction of the two turns out to perform better than either indicator alone, as measured by the incremental improvement in the model's R^2 for forecasting future volatility. We show that this result carries over to the aggregate level. Furthermore, at the aggregate level, our news-based measures contain information for forecasting future volatility that is orthogonal to current levels of implied and realized volatility.

As another test of the value of interacting unusualness with sentiment, we construct long-short portfolios based on prior month's news-based sorts. While we find that sentiment based sorts produce positive returns, only sorts based on the sentiment-unusualness interaction term have a positive alpha relative to a four factor model.

At the aggregate level, we find that news shocks are incorporated into realized and implied volatilities in a hump-shaped manner. This response would not obtain simply from the persistence of volatility: in this case a news shock would dissipate monotonically. A hump-shaped response indicates that news is not absorbed by the market instantaneously. We argue that this type of response is consistent with investors who are either unwilling or unable to observe the true state of the world at every moment in time.

Using tools from the rational inattention literature, we develop a simple model of the price of a security which tracks the true macro state of the world subject to an informational flow constraint. When the flow rate is sufficiently restricted, our model generates a hump-shaped price response to macro innovations.

The connection we make between this market friction and an empirical measurement of how market prices incorporate news is novel, and leads to many interesting research questions. Primary among these is how to relate our results to Samuelson's dictum on micro- vs macro-efficiency. We hope to pursue this question in future research.

Finally, because of our finding that news is incorporated into market volatility only gradually, our methodology should prove useful for risk monitoring.

A Appendix

A.1 Data cleaning

This section summarizes our data cleaning methodology. Further details are available from the authors.

Articles whose headlines begin with `REG-` (regulatory filings) and `TABLE-` (data tables) are deleted. The `reuters` tag at the start of an article and in the end-of-article disclaimer is removed, as is any additional post article information identifying the author of the article.

Punctuation characters (`,` or `;` and so on) and quotation marks are deleted, as are prefixes and suffixes that are followed by a period (e.g. `mr`, `corp`, etc.). All known references to any of the fifty companies in our sample are replaced with the string `_company_`.[28] Different references to the same, multi-word entity are replaced with a unique string. For example, all variations of `standard & poor's` are replaced with `snp`, references to `new york stock exchange` are replaced with `nyse`, and so on.

References to years, of the form `19xx-xx` or `20xx-xx` or similar forms, are replaced with `_y_`. We replace all numbers identified as being in the millions (billions) with `_mn_` (`_bn_`). Other numbers or fractions are replaced with `_n_`. The symbols `&` and `$` are deleted. All references to percent (e.g. `%` or `pct` or `pctage` etc.) are replaced with `pct`.

We make an attempt to delete all references to email addresses or web sites, though we do not have a systemic way of doing so.

Following this text processing step, we use the NLTK package from Python to convert the raw text into n-grams. First `sent_tokenize()` segments the text into sentences. Then `word_tokenize()` breaks the sentence into single words. In this step, standard contractions are split (e.g. `don't` becomes `do` and `n't`). Finally `ngrams()` is used to create 3- and 4-grams from the post-processed, tokenized text.

[28] It is likely that we have not identified all possible references to companies in our sample.

A.2 Rational inattention

Proposition 3 of Maćkowiak and Wiederholt (2009a) shows that the optimal Y_t in (12) has

$$b_\ell = a\left(\rho^\ell - \frac{1}{2^{2\kappa}}\left(\frac{\rho}{2^{2\kappa}}\right)^\ell\right), \tag{13}$$

and

$$c_\ell = c_0\left(\frac{\rho}{2^{2\kappa}}\right)^\ell, \tag{14}$$

where κ is the upper bound constraint on the information flow rate between the sequences $\{X_t\}$ and $\{Y_t\}$; see also Section 3.2.2 of Sims (2015). The definition of the information flow rate is detailed in Maćkowiak and Wiederholt (2009ab), and relevant background from information theory is reviewed in Sims (2003,2015). At $\kappa = \infty$, $b_\ell = a\rho^\ell$ and $c_\ell = 0$, so Y_t coincides with the moving-average representation of the AR(1) process X_t. At $\kappa = 0$, we have $b_\ell = 0$, and no information about $\{u_t\}$ is incorporated into Y_t; in fact, Y_t is identically zero in that case because $c_0 = 0$ at $\kappa = 0$.

The innovation u_{t+1} is independent of past values of u_t and ϵ_t, and it remains so conditional on the agents' information S^t. A standard calculation for normal random variables therefore gives

$$E\left[e^{\lambda u_{t+1} - \lambda^2/2} Y_{t+1} | S^t\right] = E[b_0\lambda + Y_{t+1}|S^t].$$

It follows from (13)–(14) (and is shown explicitly in Appendix G of Maćkowiak and Wiederholt 2009a) that

$$Y_{t+1} = \left(\frac{\rho}{2^{2\kappa}}\right) Y_t + \left(1 - \frac{1}{2^{2\kappa}}\right) X_{t+1} + c_0\epsilon_{t+1}.$$

Replacing X_{t+1} with the right side of (11) and using the fact that $E[X_t|S^t] = Y_t$ (proved in Appendix H of Maćkowiak and Wiederholt 2009a) we get

$$E[Y_{t+1}|S^t] = \left(\frac{\rho}{2^{2\kappa}}\right) Y_t + \left(1 - \frac{1}{2^{2\kappa}}\right) \rho E[X_t|S^t] = \rho Y_t$$

and then

$$V_t = b_0\lambda + \rho Y_t.$$

The price premium $b_0\lambda$ increases with κ because b_0 does. In other words, the contract is worth more with looser information constraints because it yields a better hedge in that case.

Given this representation and (13), the response of $V_t, V_{t+1}, \ldots$ to an impulse of $u_t = 1$ is given by $b_0\lambda + \rho b_t$, $t = 0, 1, \ldots$. As illustrated in Figure 16, for small values of κ, this is a hump-shaped function of t, and for large values of κ it decreases monotonically.

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1	Berkshire Hathaway	26	Australia & New Zealand Bank
2	Wells Fargo	27	AIG
3	Ind & Comm Bank of China	28	BNP Paribas
4	JP Morgan Chase	29	National Australia Bank
5	China Construction Bank	30	Morgan Stanley
6	Bank of China	31	Itau Unibanco
7	HSBC Holdings	32	UBS
8	Agricultural Bank of China	33	Bank of Communications
9	Bank of America	34	Royal Bank of Scotland
10	Visa	35	Prudential
11	China Life Insurance	36	Simon Property Group
12	Citigroup	37	Barclays
13	Commonwealth Bank of Australia	38	Bank of Nova Scotia
14	Ping An Insurance	39	Blackrock
15	Mastercard	40	AXA
16	Banco Santander	41	Banco Bilbao Vizcaya Argentaria
17	Westpac Bank	42	China Merchants Bank
18	American Express	43	Metlife
19	Royal Bank of Canada	44	Banco Bradesco
20	Lloyds	45	Nordea Bank
21	Goldman Sachs	46	Zurich Insurance
22	Mitsubishi UFJ	47	Intesa Sanpaolo
23	US Bancorp	48	ING
24	Allianz	49	Sumitomo Mitsui
25	TD Bank	50	Allied Irish Banks

Table 1: Companies included in the Thomson-Reuters news sample.

	ENTNEG	ENTPOS	ENTALL	SENTNEG	SENTPOS
Mean correlation	0.197	-0.003	0.095	0.309	-0.102
S.E.	0.026	0.019	0.024	0.024	0.017

Table 2: Correlation and standard error between different entropy and sentiment measures and 1 month at-the-money implied volatilities for the 50 stocks in our sample, and for the aggregate level sentiment and entropy series. The aggregate entropy series used here are the ones derived from the list of n-grams from all articles in month t, and not from the first principal component of the single name series. So each correlation is an average across 51 observations. If a stock implied volatility series is not present, and for the aggregate measures, the VIX index is used instead of single name implied volatility. Cross-sectional standard errors, which assume independence, are shown.

Month	Year	w1	w2	w3	w4	Total	Rank	p_i	m_i
9	2008	nyse	order	imbalance	_mn_	81	1	0.009	0.020
9	2008	the	collapse	of	lehman	38	2	0.004	0.004
9	2008	filed	for	bankruptcy	protection	138	3	0.016	0.245
9	2008	problem	accessing	the	internet	33	400	0.004	0.961
9	2008	imbalance	_n_	shares	on	299	401	0.034	0.999
9	2008	order	imbalance	_n_	shares	299	402	0.034	0.999
5	2012	_bn_	from	a	failed	28	1	0.008	0.009
5	2012	the	euro	zone	crisis	36	2	0.011	0.087
5	2012	declined	to	comment	on	56	3	0.017	0.258
5	2012	you	experience	problem	accessing	77	208	0.023	0.998
5	2012	experience	problem	accessing	the	77	209	0.023	0.998
5	2012	problem	accessing	the	internet	77	210	0.023	0.998

Table 3: This table shows the top and bottom three 4-grams, as determined by their contribution to $ENTNEG$ in selected months of our sample. The "Total" column shows the number of times the given n-gram has appeated in that month, and the "Rank" column gives its rank by entropy contribution – this is lower than 5000 because we restrict analysis to those n-grams which are classified as having negative sentiment. p_i and m_i are the in-sample probability and the training sample conditional probability for the n-gram (see equation (6)). Note that some of the 4-grams come from the same 5-gram.

	ENTNEG	ENTPOS	ENTALL	SENTNEG	SENTPOS	ENTSENT_NEG	VIX	SPX_rvol
Mean	7.401	6.443	7.446	3.744	2.233	28.156	21.169	17.366
Min	2.140	2.172	4.724	1.484	0.819	7.881	10.420	6.310
Max	11.592	16.747	9.908	8.077	4.958	77.348	59.890	79.190
SD	1.837	2.092	1.066	1.265	0.594	13.948	7.876	9.892

Table 4: This table reports summary statistics for the aggregate news-based measures, as well as the VIX and realize volatility for S&P 500. Start and End refer to the start and end dates of data availability for the variable in question. $SENTNEG$ and $SENTPOS$ are aggregate negative and positive sentiment measures. $ENTALL$, $ENTNEG$ and $ENTPOS$ are the first principal components of single-name level entropy measures applied to all n-grams, and those classified as negative and positive respenctively. $ENTSENT\_NEG$ interacts $SENTNEG$ with $ENTNEG$. All data series are monthly, and run from April 1998 to December 2014.

	SENTNEG	SENTPOS	ENTALL	ENTNEG	ENTPOS	ENTSENT_NEG	VIX
SENTNEG	1.00						
SENTPOS	-0.14	1.00					
ENTALL	-0.18	-0.42	1.00				
ENTNEG	0.19	-0.44	0.71	1.00			
ENTPOS	-0.09	-0.16	0.56	0.34	1.00		
ENTSENT_NEG	0.86	-0.32	0.19	0.64	0.08	1.00	
VIX	0.46	-0.37	0.30	0.48	0.15	0.60	1.00

Table 5: This table reports contemporaneous correlations among monthly levels of our news-based indicators and the VIX index. $SENTNEG$ and $SENTPOS$ are aggregate negative and positive sentiment measures. $ENTALL$, $ENTNEG$ and $ENTPOS$ are the first principal components of single-name level entropy measures applied to all n-grams, and those classified as negative and positive respenctively. $ENTSENT\_NEG$ interacts $SENTNEG$ with $ENTNEG$.

	Change in AUC
ENTSENT_NEG	0.227
SENTNEG	0.139
ENTNEG	0.095
SENTPOS	-0.019
ENTALL	-0.028
ENTPOS	-0.033

Table 6: We regress single-name implied volatility in month t on six lags (months $t-1$ through $t-6$) of each of the news-based variables in this table, measured for j equal to the single name in question (equation (9) from the text). We then repeat the same regression using six lags of $ARTICLE\_PERCTOT$ (percent of articles in a given month that mention company j) as the regressor. We run these regressions for each single-name in our sample, and collect the R^2's across all single-name regressions. We then measure the area under the R^2 curve ($\Pr(R^2 > x)$) for the news-based regressions and for the control regression which uses lags of $ARTICLE\_PERCTOT$ as the right hand side variables. This table reports the differences in the areas under the R^2 curve of the news-based measure relative to $ARTICLE\_PERCTOT$.

Model	Alpha	Mkt_RF	SMB	HML	WML	Adj R2
SENTNEG	0.474	0.070	0.232	0.132	0.053	-0.004
	(1.19)	(0.72)	(1.28)	(0.81)	(0.52)	
SENTPOS vs SENTNEG	0.187	0.032	0.164	0.059	-0.031	-0.012
	(0.97)	(0.55)	(1.39)	(0.27)	(-0.40)	
SENTPOS vs SENTNEG w/ ENTALL	0.4753	0.0114	0.1331	0.0071	-0.0448	-0.012
	(2.07)	(0.14)	(1.28)	(0.05)	(-0.52)	

Table 7: Results of monthly regressions of news-based zero-investment portfolio returns on the Fama-French global three factor model (market, size (SMB), and value (HML)), and a global momentum factor (WML). The portfolio formation criteria are explained in Section 6. Robust t-statistics are shown in parentheses, and are obtained using Newey-West standard errors with automatic lag selection, as implemented in the `sandwich` package in **R**.

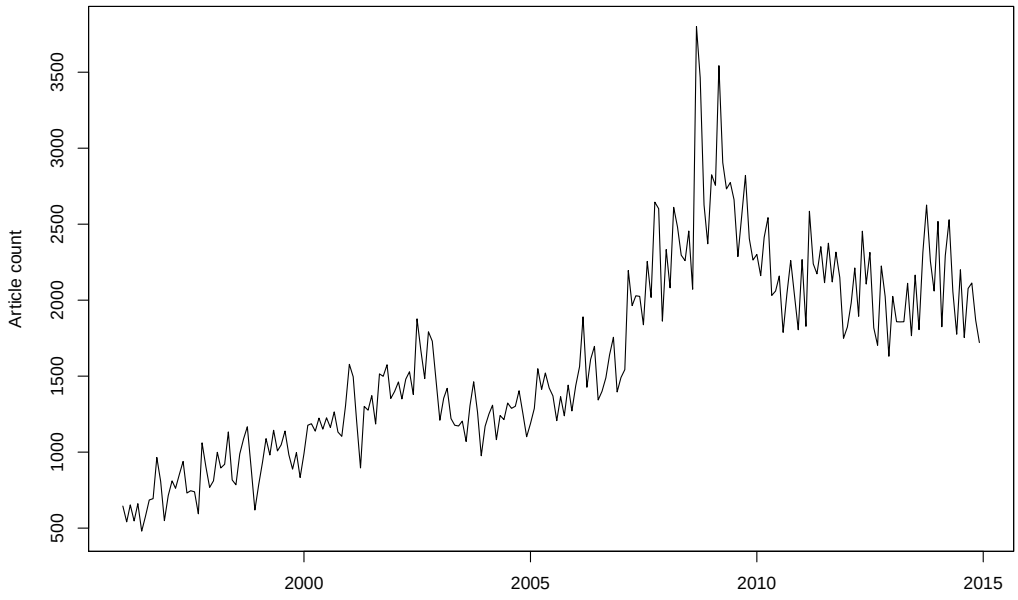

Figure 1: Monthly article count in the Thomson-Reuters news sample.

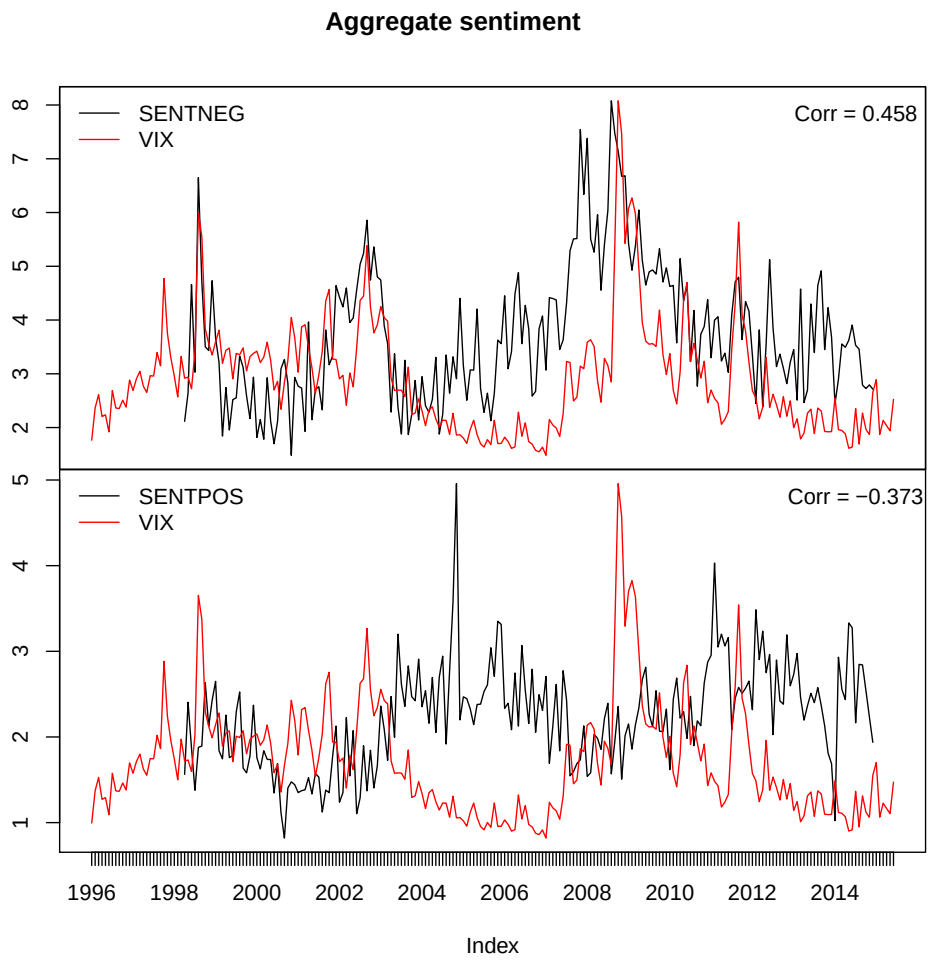

Figure 2: Monthly plots of $SENTNEG(t)$ and $SENTPOS(t)$ as defined in (7). Each series computes the proportion of all n-grams in a given month that are classified as having either positive or negative sentiment. Superimposed on each sentiment series is the scaled VIX index. Correlation between sentiment and VIX is shown in the upper right hand corner of each chart.

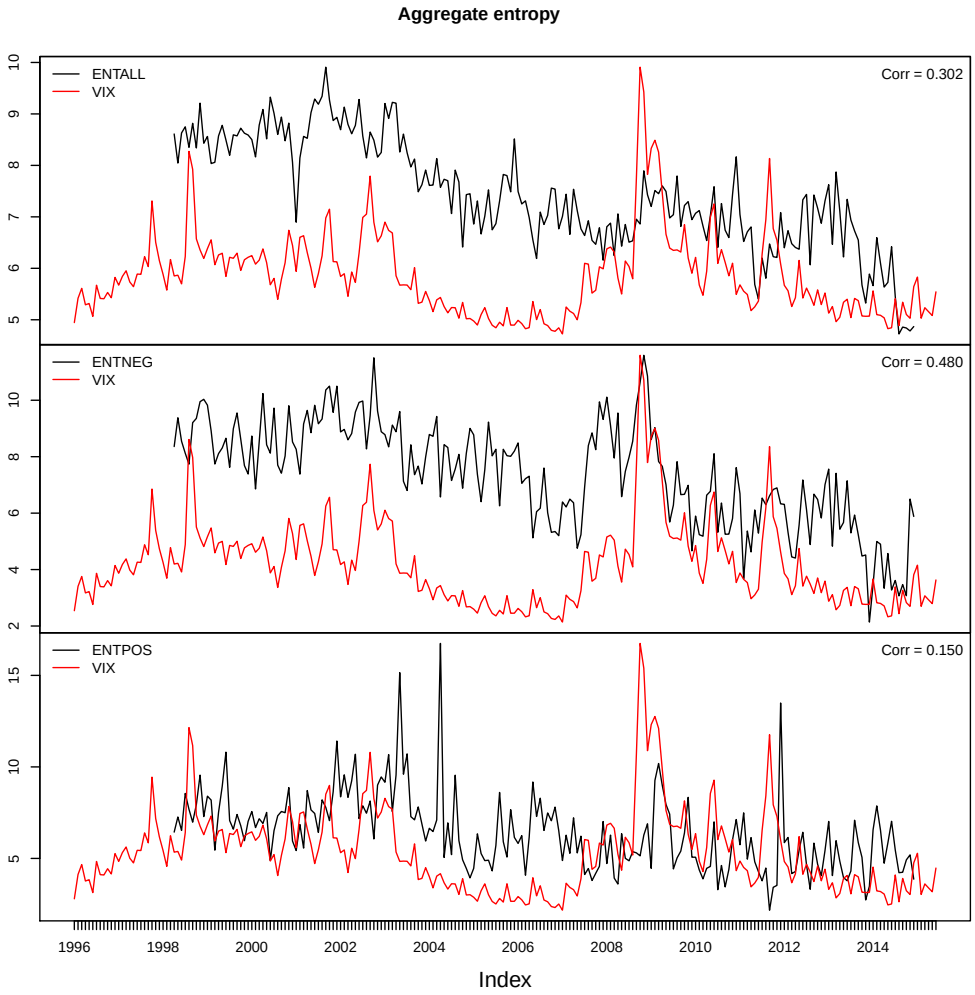

Figure 3: Monthly plots of $ENTALL(t)$, $ENTNEG(t)$ and $ENTPOS(t)$ as defined in Section 3.3. Each series is the first principal component of the associated single name entropy measures, for those names with observations available in all time periods of the sample. Superimposed on each entropy series is the scaled VIX index. Correlation between entropy and VIX is shown in the upper right hand corner of each chart.

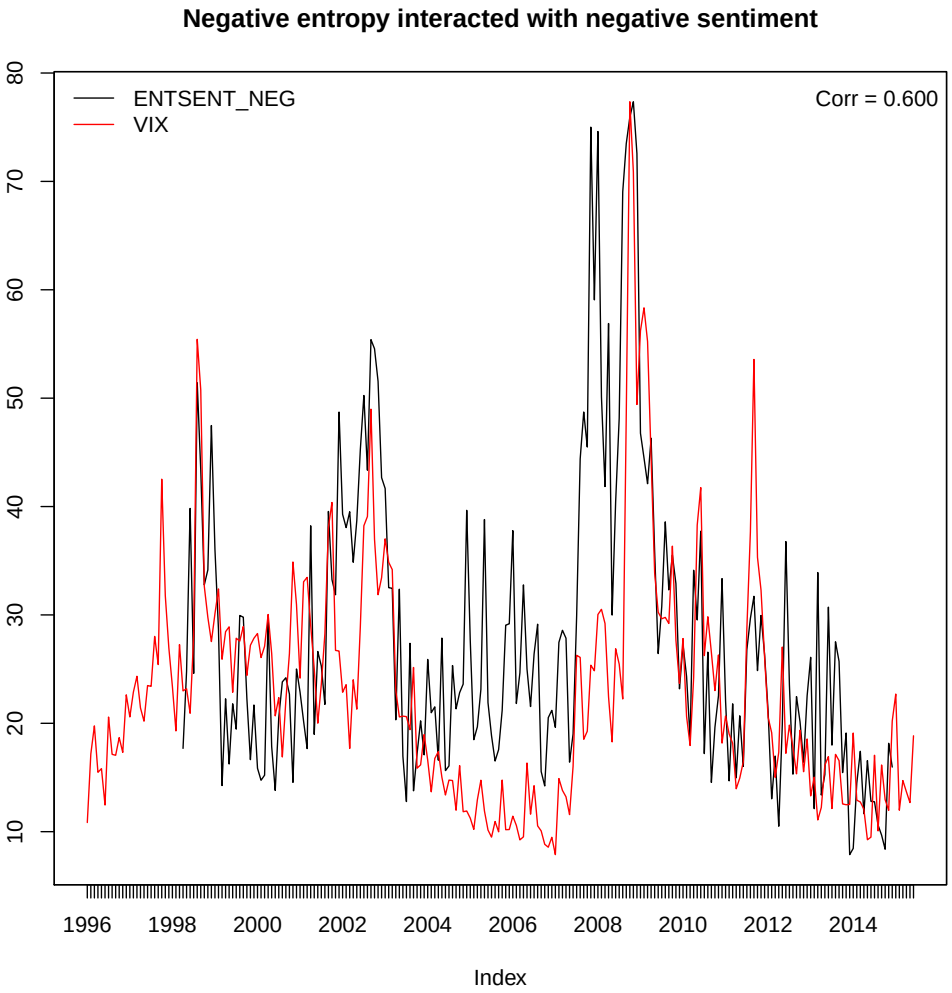

Figure 4: Monthly plot of $ENTSENT\_NEG(t) \equiv ENTNEG(t) \times SENTNEG(t)$. The entropy series is the first principal component of the associated single name entropy measures, for those names with observations available in all time periods of the sample. $SENTNEG$ is defined in (7). Superimposed on $ENTSENT\_NEG$ is the scaled VIX index. The correlation between $ENTSENT\_NEG$ and VIX is shown in the upper right hand corner.

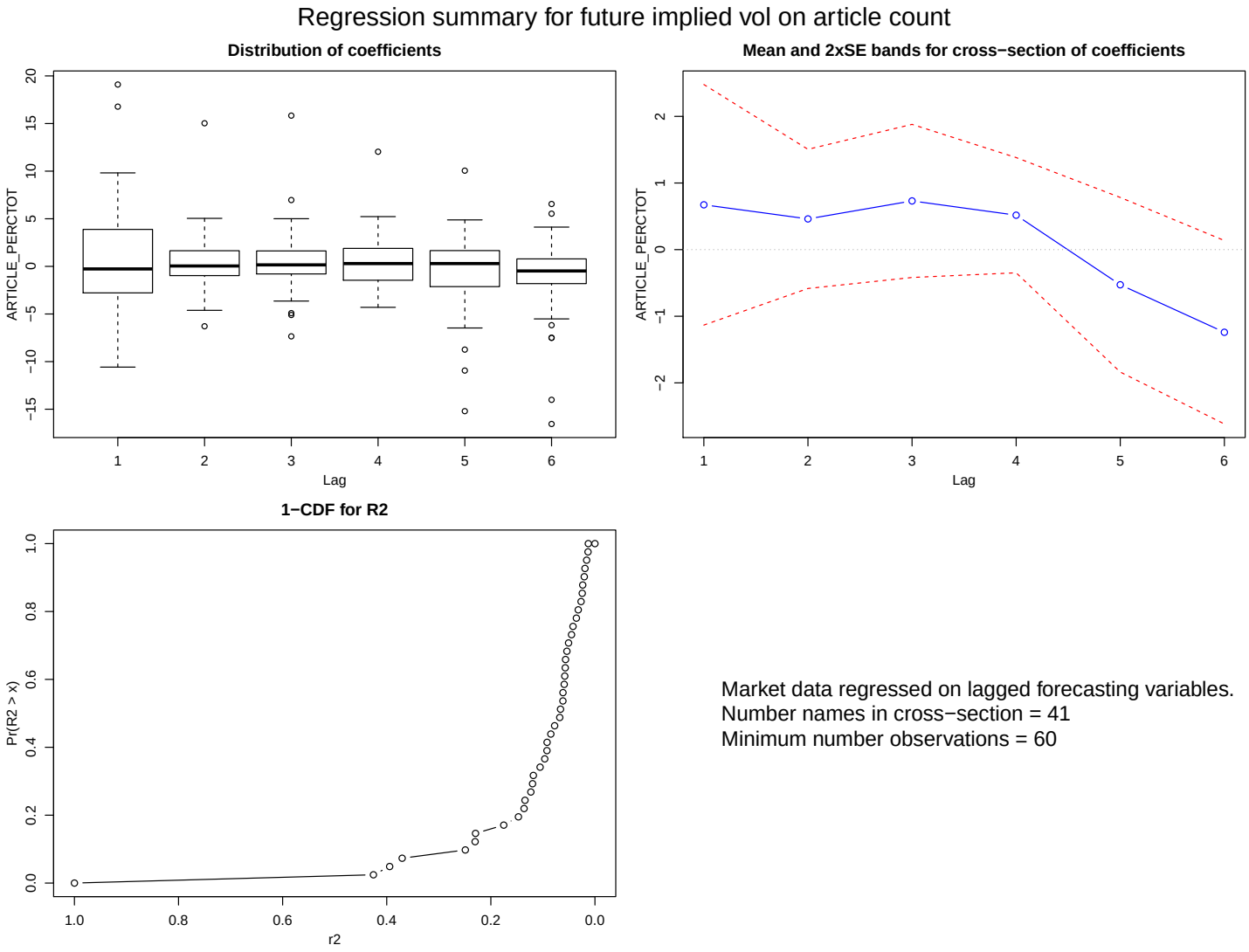

Figure 5: The results of the regression in (9) with $NEWS1^j$ set to the percentage of articles at time t that mention company j. The $ARTICLE\_PERCTOT$ variables are normalized to have unit standard deviation. The top row shows the interquartile ranges, median, and outliers of the 6 lagged coefficients for the news-based measure, and the cross-sectional mean of each coefficient with a two standard error band. The bottom row plots 1 minus the cumulative distribution function of the unadjusted R^2's from the single name regressions, i.e. $f(x) = \Pr(R^2 > x)$.

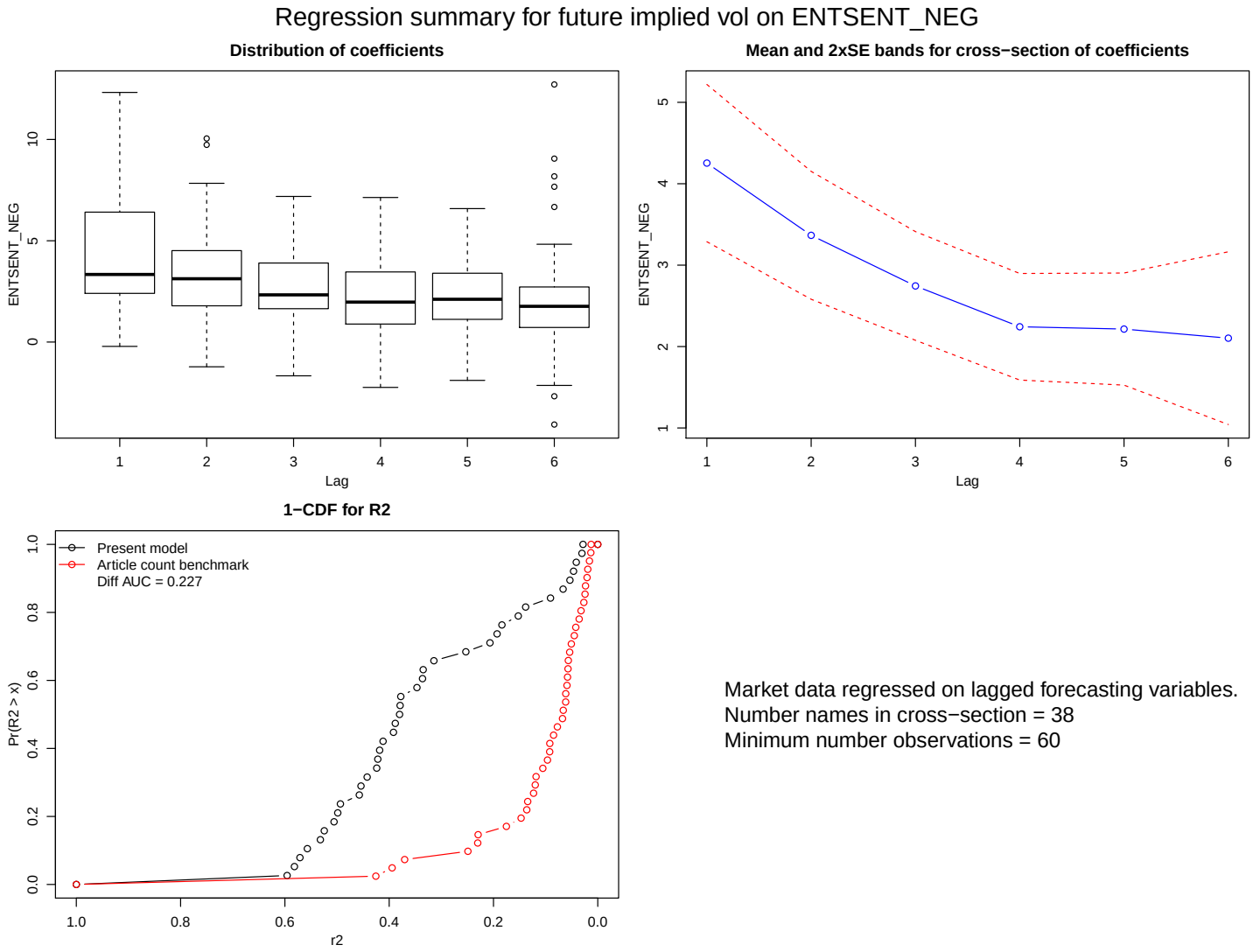

Figure 6: The results of the regression in (9) with $NEWS1^j$ set to the time t interacted value of negative sentiment with negative entropy for company j. The $ENTSENT\_NEG$ variables are normalized to have unit standard deviation. The top row shows the interquartile ranges, median, and outliers of the 6 lagged coefficients for the news-based measure, and the cross-sectional mean of each coefficient with a two standard error band. The bottom row plots 1 minus the cumulative distribution function of the unadjusted R^2's from the single name regressions, i.e. $f(x) = \Pr(R^2 > x)$, as well as the baseline R^2 curve for $ARTICLE\_PERCTOT$.

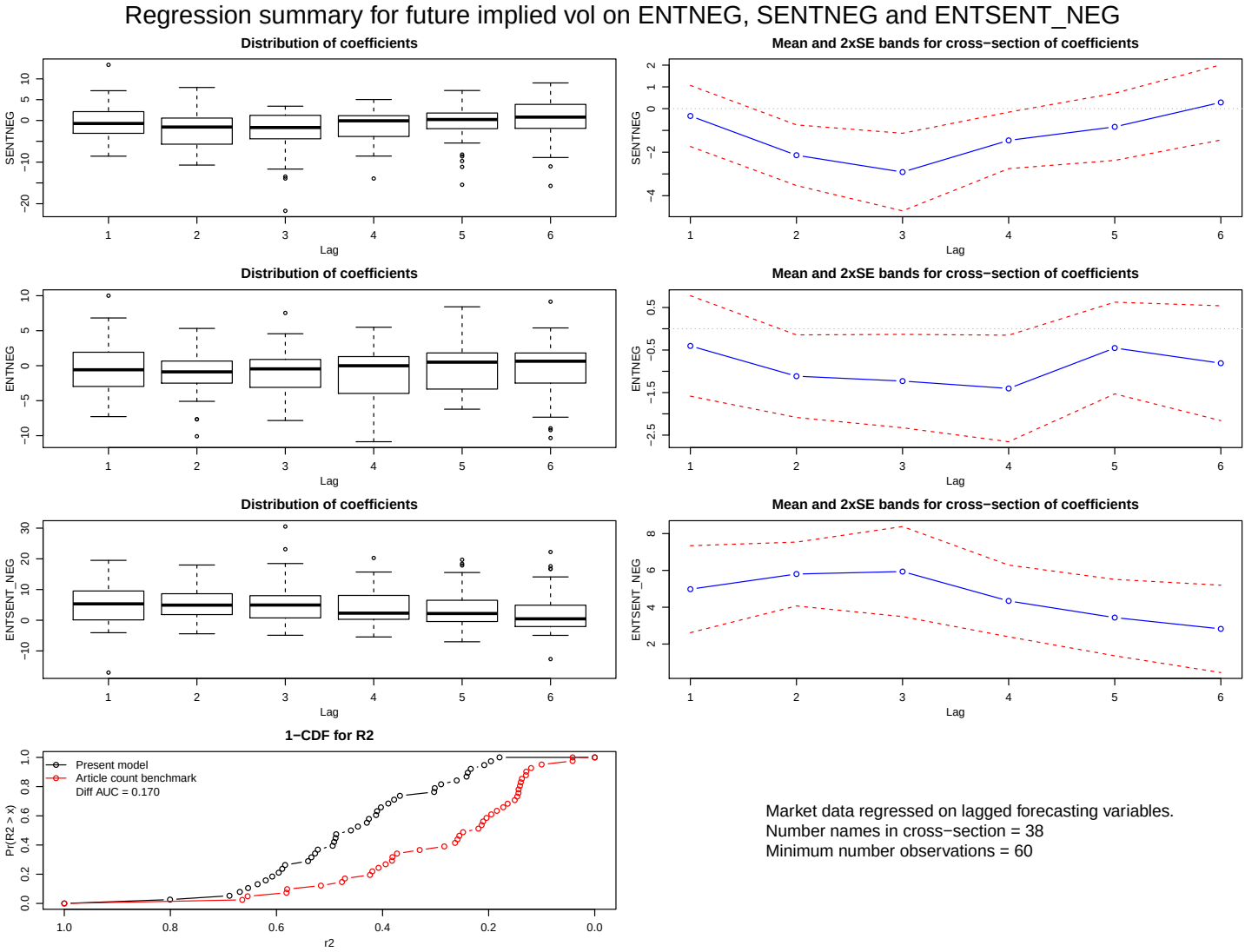

Figure 7: The results of the regression in (9) with three news-based variables: $SENT\_NEG$, ENT_NEG and $ENTSENT\_NEG$, all of which are normalized to have unit standard deviation. The rows show the interquartile ranges, median, and outliers of the 6 lagged coefficients for each news measure, and the cross-sectional mean of each coefficient with a two standard error band. The bottom row plots 1 minus the cumulative distribution function of the unadjusted R^2's from the single name regressions, i.e. $f(x) = \Pr(R^2 > x)$, as well as the baseline R^2 curve using $ARTICLE\_PERCTOT$, $NGRAM\_PERCTOT$ and the interaction term $ARTICLE\_PERCTOT \times NGRAM\_PERCTOT$ as regressors.

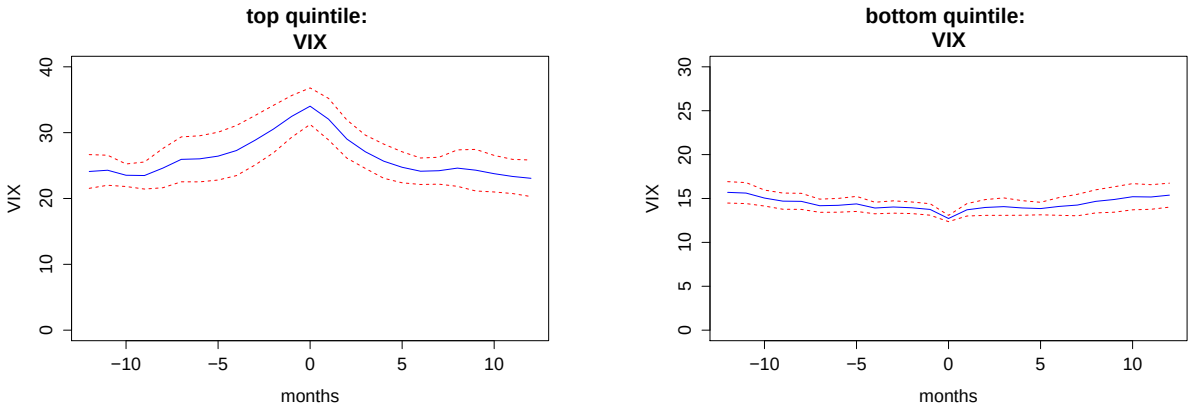

Figure 8: Average level of the VIX 12 months before and after high (left) and low (right) values of the VIX. High and low values are defined by the top and bottom quintiles. Dashed lines show plus and minus two standard errors.

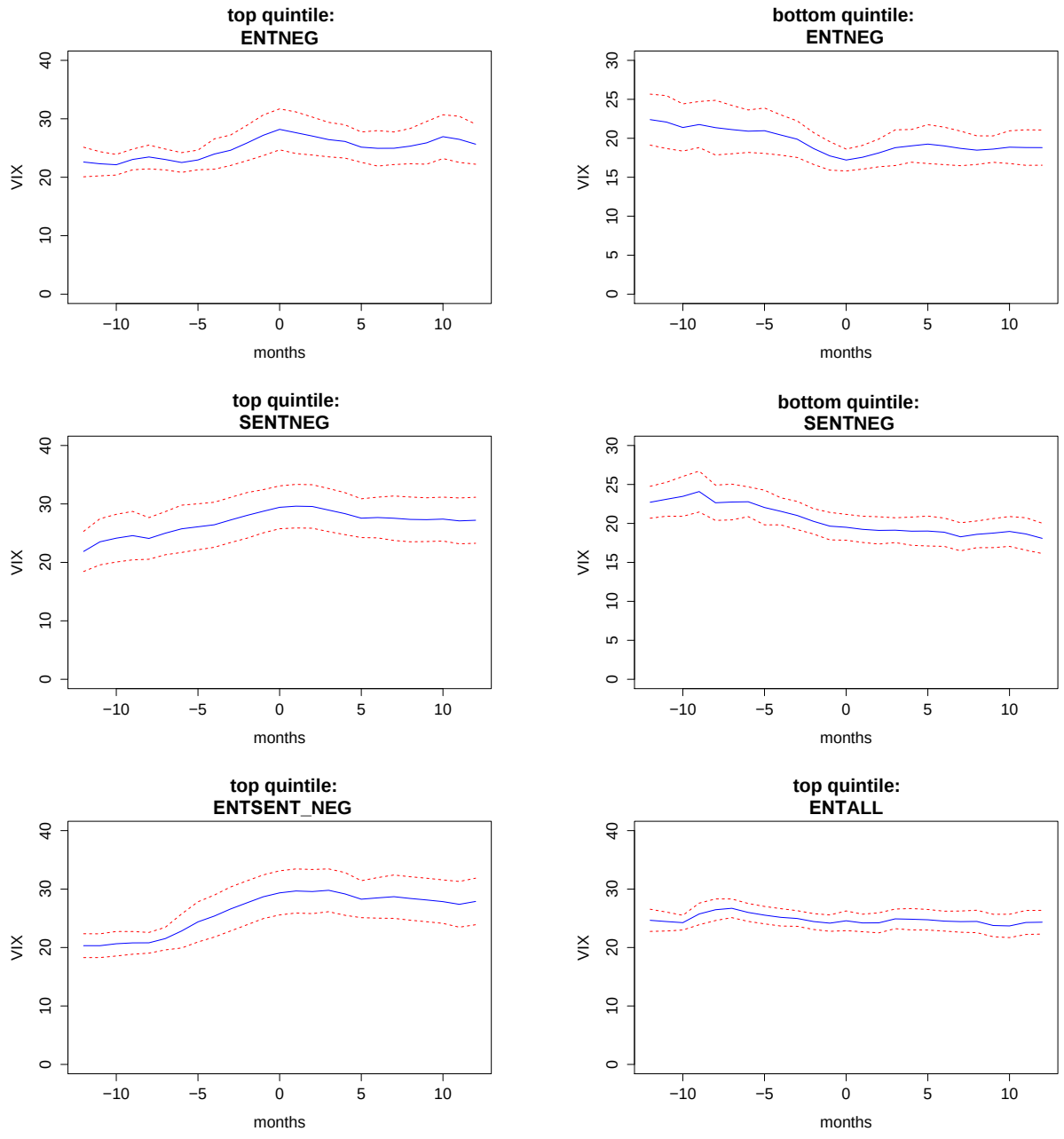

Figure 9: Average level of the VIX 12 months before and after high (left) and low (right) values of various entropy and sentiment measures. High and low values are defined by the top and bottom quintiles for each measure. Dashed lines show plus and minus two standard errors.

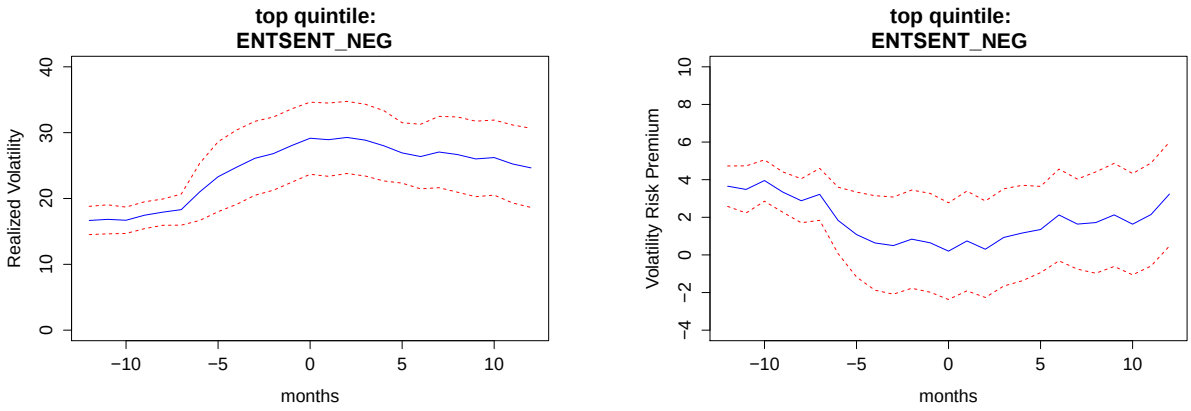

Figure 10: Average level of realized volatility (left) and the volatility risk premium (right) 12 months before and after top quintile values values of $ENTSENT\_NEG$. Dashed lines show plus and minus two standard errors.

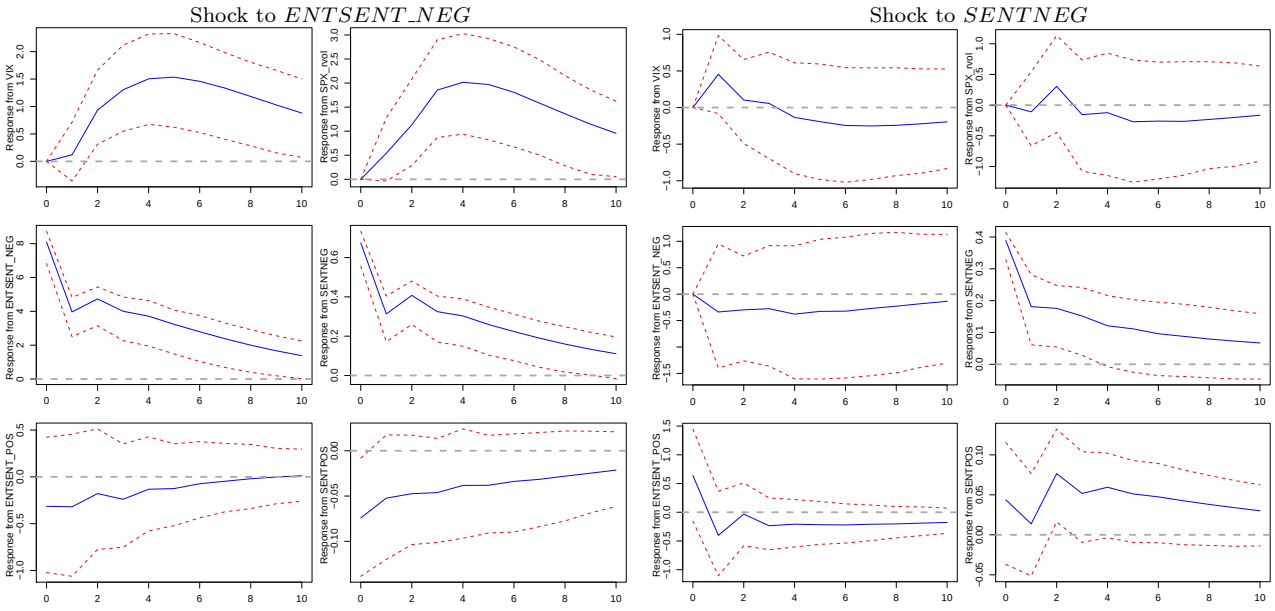

Figure 11: Impulse response functions for a shock to $ENTSENT\_NEG$ (left) and $SENTNEG$ (right). The order of the variables in the VAR model matches the order of the figures in each block of six, reading left to right, then top to bottom. Dashed lines show 95% bootstrap confidence intervals. The horizontal time axis is in months.

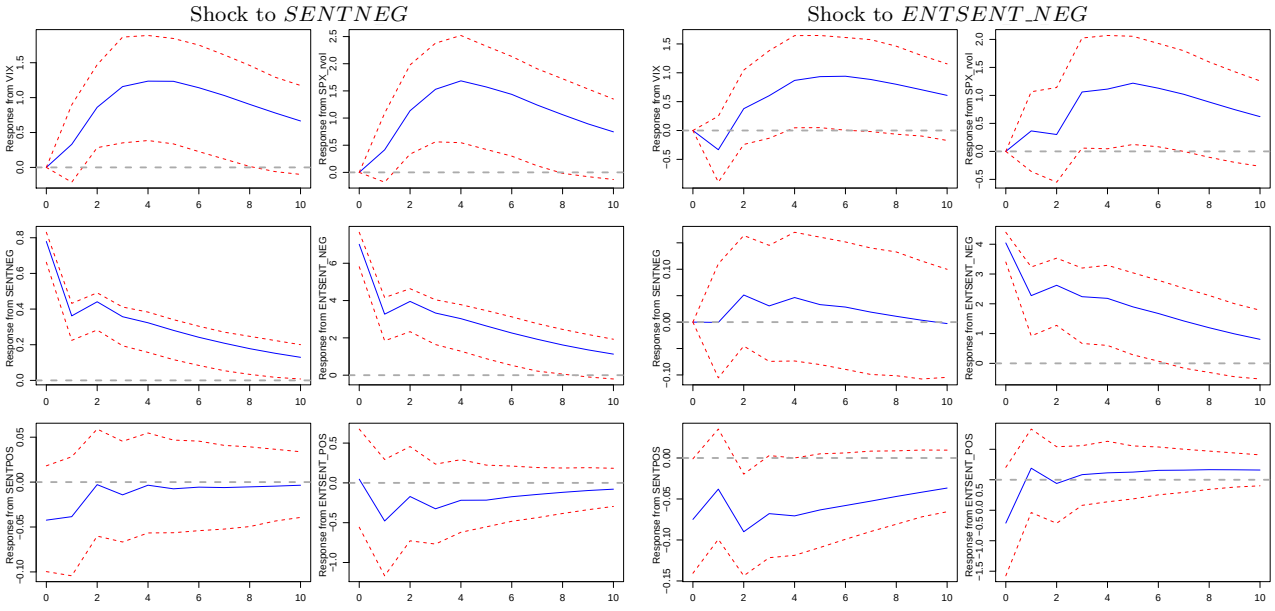

Figure 12: Impulse response functions for a shock to $SENTNEG$ (left) and $ENTSENT\_NEG$ (right). The order of the variables in the VAR model matches the order of the figures in each block of six, reading left to right, then top to bottom. Dashed lines show 95% bootstrap confidence intervals. The horizontal time axis is in months.

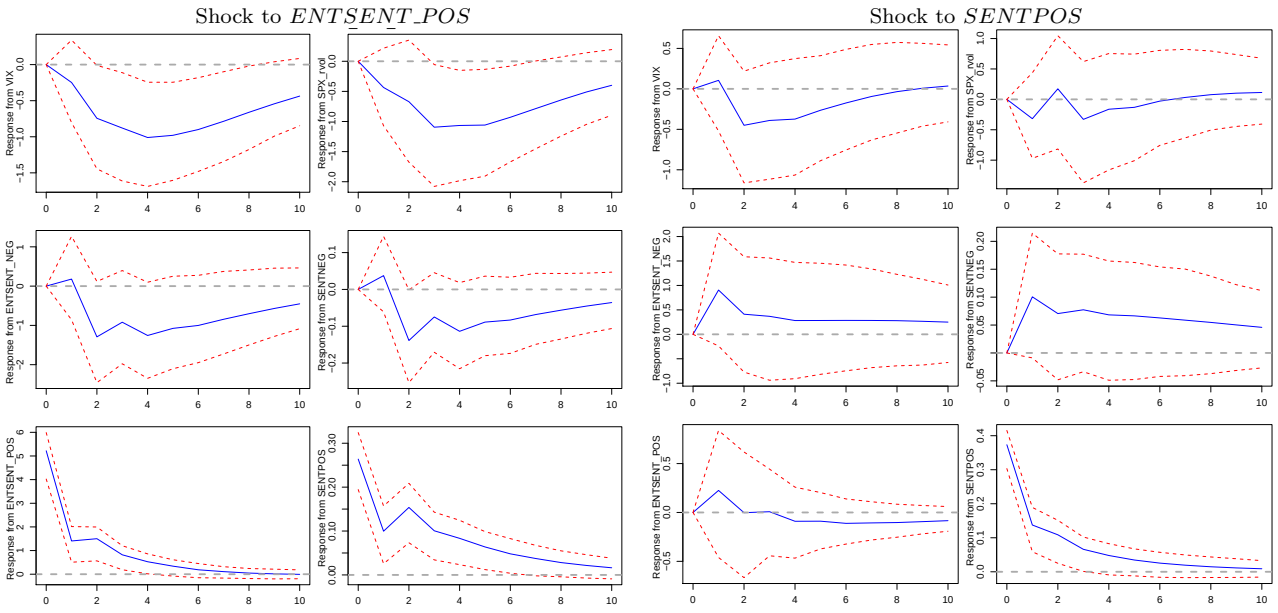

Figure 13: Impulse response functions for a shock to $ENTSENT\_POS$ (left) and $SENTPOS$ (right). The order of the variables in the VAR model matches the order of the figures in each block of six, reading left to right, then top to bottom. Dashed lines show 95% bootstrap confidence intervals. The horizontal time axis is in months.

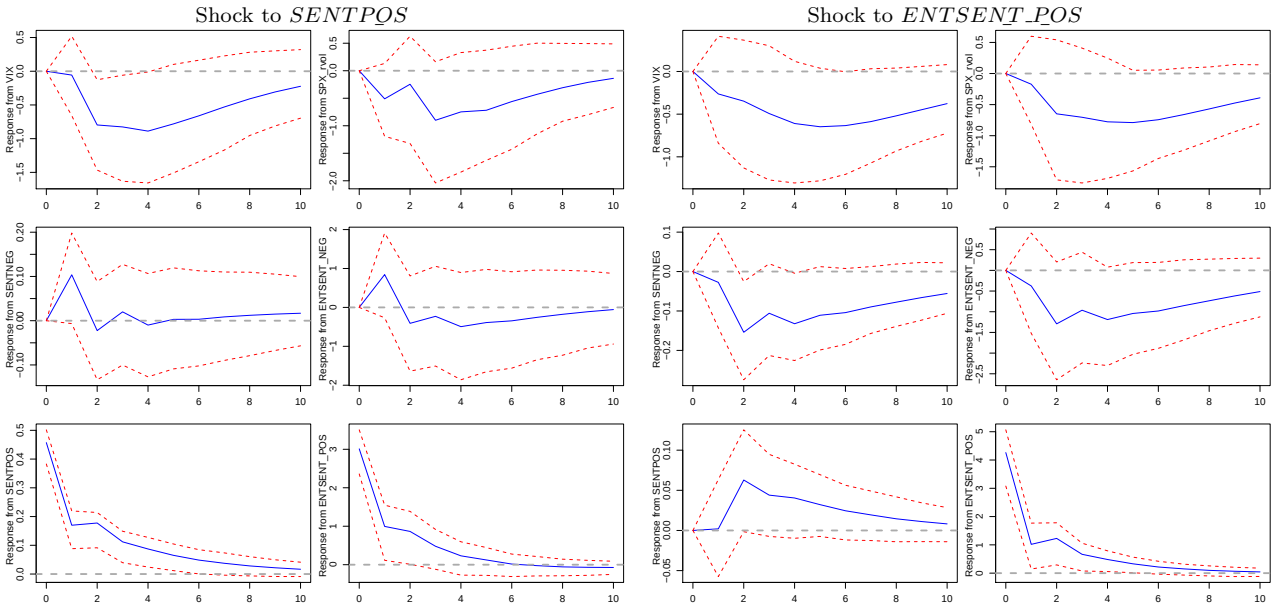

Figure 14: Impulse response functions for a shock to $SENTPOS$ (left) and $ENTSENT\_POS$ (right). The order of the variables in the VAR model matches the order of the figures in each block of six, reading left to right, then top to bottom. Dashed lines show 95% bootstrap confidence intervals. The horizontal time axis is in months.

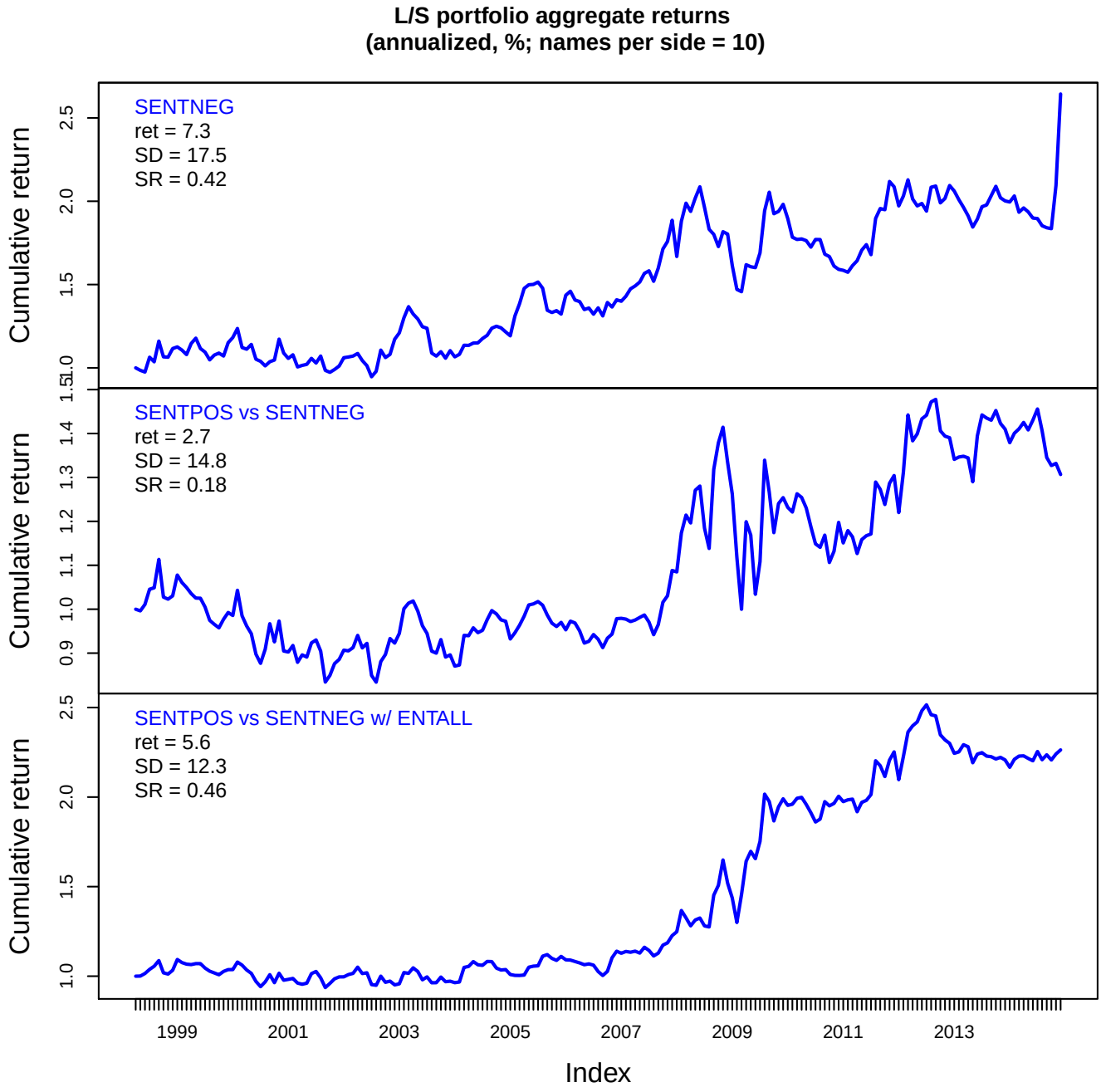

Figure 15: This figure shows the cumulative return of long-short portfolios formed using different prior month news-based sorts. The long and short side of each portfolio contain ten names. In some months the returns of some names may not be available, and the portfolio may contain fewer than twenty names in that month. Data are monthly. Also shown are the arithmetic average monthly return on an annualized basis, as well as annualized return volatility (assuming uncorrelated monthly returns), and the annualized Sharpe ratio of each strategy. The three sorts are described in Section 6.

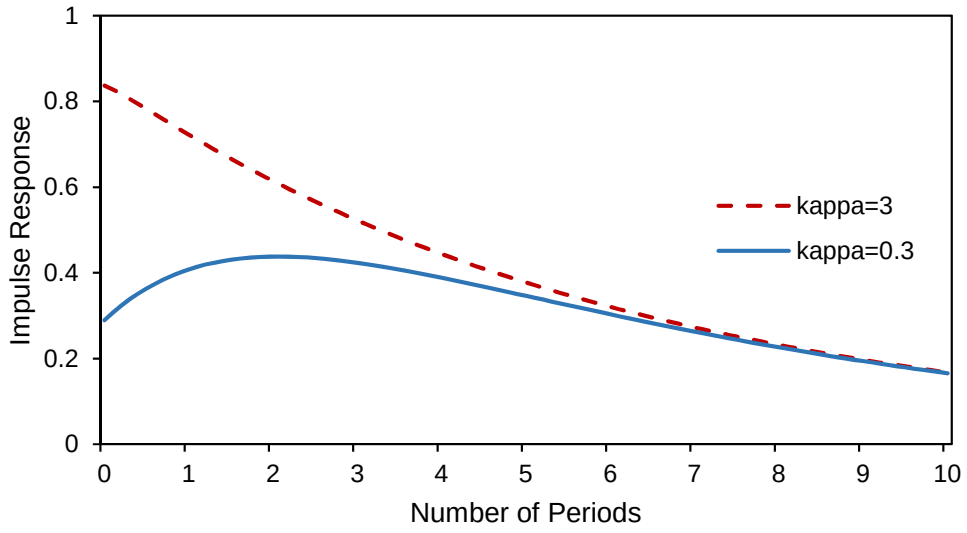

Figure 16: This figure shows impulse response functions in the model of Section 7. The response is hump-shaped for small κ (a tight information constraint) and monotonically decreasing for large κ. The other parameters are $\rho = 0.85$, $\lambda = 0$, and $a = 1$.