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Asset returns, news topics, and media effects*

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Abstract

We decompose the textual data in a daily Norwegian business newspaper into news topics and investigate their predictive and causal role for asset prices. Our three main findings are: (1) a one unit innovation in the news topics predict roughly a 1 percentage point increase in close-to-open returns and significant continuation patterns peaking at 4 percentage points after 15 business days, with little sign of reversal; (2) simple zero-cost news-based investment strategies yield significant annualized risk-adjusted returns of up to 20 percent; and (3) during a media shortage, due to an exogenous strike, returns for firms particularly exposed to our news measure experience a substantial fall. Our estimates suggest that between 20 to 40 percent of the news topics' predictive power is due to the causal media effect. Together these findings lend strong support for a rational attention view where the media alleviate information frictions and disseminate fundamental information to a large population of investors.

JEL-codes: C5, C8, G4, G12

Keywords: Stock returns, News, Machine learning, Latent Dirichlet Allocation (LDA)

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1 Introduction

Can news in a business newspaper explain daily returns, and what is the effect of the media itself? To the extent that new information is broadcasted through the media, and interpreted through the lens of classical economic theory, the answer to the first question should be an unambiguously yes. Asset prices should respond to new information. However, as exemplified by Roll (1988), the economic literature has had a hard time finding a robust relationship between stock prices and news. This has led to alternative explanations, like irrational noise trading and the revelation of private information through trading, for understanding stock price movements (see, e.g., Shiller (1981), Campbell (1991), and Tetlock (2007)). Below we suggest an alternative explanation, echoing the one given in Boudoukh et al. (2013), namely that the finance literature simply has been doing a poor job of identifying relevant news. On the other hand, in a world where arbitrage forces were unlimited one could argue that new information should be incorporated into prices as soon as it is made public and before the (mass) media have time to report it. According to this view, evidence of non-predictability is as expected. Still, even though the news reported might not be genuine new information in itself, news broadcasted through the media might matter because it can reach a broad population of investors, alleviate informational frictions, and contribute to gradual diffusion of information (Peress (2014)). However, establishing causal link from the media to financial markets is difficult, because one has to separate the new information component from the effect of the ether.

In this paper we offer new insights regarding the relationship between news, returns, and the media. We informally assume a rational attention view where investors faced with information processing costs, or limited cognitive ability, potentially learn about economic developments important for multiple stocks through the media (Peng and Xiong (2006), Kacperczyk et al. (2009), and Schmidt (2013)). We operationalize this view by decomposing the textual information in a business newspaper into different types of news about economic developments, and analyze market responses to these news items. In particular, we use a Latent Dirichlet Allocation model (Blei et al. (2003)), proven to summarize textual data in much the same manner as humans would do (Chang et al. (2009)), to decompose the textual information in the major business newspaper in Norway into news topics. We then construct series representing how much, and in which tone, each topic is written about in the newspaper across time, where news topics are tone adjusted, i.e., classified as either positive or negative news, using a dictionary-based approach commonly applied in the literature (see, e.g., Tetlock (2007), Loughran and Mcdonald (2011)). Finally, the resulting news topic time series are linked to a large cross section of companies listed on the Oslo Stock Exchange between 1996-2014.

Our hypothesis is simple: To the extent that the newspaper provides a relevant de-

scription of the economy, the more intensive a given topic is represented in the newspaper at a given point in time, the more likely it is that this topic represents something of importance for the economy's current and future needs and developments. As such, it should also move stock prices. For example, we hypothesize that when the newspaper writes extensively about developments in, e.g., the oil sector, and the tone is positive, it reflects that something is happening in this sector that potentially has positive economy-wide effects, and especially for firms related to the oil sector.

The newspaper content is available in the morning, at least two hours prior to the when the market opens. Controlling for lagged returns, time- and firm-fixed effects, and other well known predictors, numerous regressions show that a one unit positive innovation in the news predicts roughly a 1 percentage point increase in close-to-open returns, and 1.5 percentage points increase in close-to-close returns. In the days following the initial news release, the effect accumulates further, suggesting a significant continuation pattern peaking at 4 percentage points after 15 business days, with little sign of reversal. To gauge the robustness and economic significance of these pooled time series regressions we implement simple zero-cost news-based investment strategies yielding significant annualized risk-adjusted returns (*Alpha*) of up to 20 percent.

By exploiting an exogenous strike in the Norwegian newspaper market in 2002 we are, under the assumption that new information is released also during the strike period (although not through the mass media), able to isolate the media component of the news signal from the new information component. Unconditionally, the cross sectional average return falls by roughly 60 basis points during the strike period relative to the periods before and after the strike. Conditioning on how exposed the various firms are to our news measure during the year prior to the strike, we find significant differences in mean returns of the same magnitude: Returns for individual firms with a significant exposure to our news measures fall by 57 basis points during the strike period relative to firms with an insignificant news topic exposure. Thus, the DN news topics seem to be representative for the total causal media effect. Since the average firm in the sample has a positive exposure to news, our results imply that the media component of the news signal accounts for between 20 to 40 percent of the documented overall predictive effect of news topics.

Compared with existing studies in the financial literature using textual data to understand asset prices, the novelty of our approach relates to the usage of news topics and how we relate them to firms. Each topic is a distribution of words, and together the topics summarizes the words and articles in the business newspaper into interpretable factors that we use to capture the continuously evolving narrative about economic conditions. Individual news topics are subsequently linked to companies using their textual description provided by Reuters. For example, a news topic that contains words mostly

associated with the oil market will be linked to an oil company if the textual description of this company contains many of the same words. In contrast, typical textual approaches applied in the asset pricing literature link companies to items in the news using explicit mentioning of their names, abbreviations, or other firm specific characteristics, and conduct event studies to uncover how stock prices respond to news. To us, this seems like an overly restrictive approach inasmuch many news items might be relevant for stock prices without explicitly mentioning, e.g, company names. Consequently, in our setup, all days are news days, but to varying degree, and we avoid "dredging for anomalies", which is Fama's phrase for conducting event studies of different event types until one finds an apparent market inefficiency (Fama (1998, p. 287)).

The validity of our approach for linking news to firms is tested when we randomly assign news topics to firms, and find that no significant predictive power between news and returns can be established in this case. We also show that our results are not driven by well known industry or day-of-the-week effects, and that they are not associated with firm characteristics like book-to-market value, size, or liquidity. When analyzing the news-return relationship across three different sub-samples, we do, however, find that the relationship becomes largely insignificant for the latter part of the sample (2008-2014). Interestingly, this loss of significance is alleviated when we expand the breadth of news sources utilized, suggesting that a broad-based news corpus needs to be applied to capture informative news signals in today's markets.

In sum, our results lend significant support towards classical efficient market based theories where new information should predict subsequent returns. Our results also speak to the growing literature documenting behavioral biases or rational attention, where investors only partially adjust to real information. The fact that we find significant continuation patterns following news innovations, as opposed to reversal, suggests that our methodology correctly parses out fundamental information, and that the media is an important channel for such information diffusion.

Our study contributes to two different strands of the financial literature. First, we relate to a large number of studies using textual information to explain and predict stock price movements. Prominent examples include Antweiler and Frank (2004), Tetlock (2007), and Garcia (2013), while Tetlock (2014), Kearney and Liu (2014), and Loughran and Mcdonald (2016) provide recent literature overviews. While a large share of these studies use textually derived sentiment indicators, finding weak evidence of predictability, evidence saying that only negative news matters, and reversal patterns following news releases, we find relatively strong evidence towards predictability and clear continuation patterns when focusing on news topics. Interestingly, Boudoukh et al. (2013) also find that once news is identified by its type (topic), there is a considerably stronger rela-

tionship between news and returns than what is commonly found. However, while the approach taken in Boudoukh et al. (2013) relies on a substantial number of hard coded rules for classifying the news, our approach utilizes a fully automated machine learning algorithm. As such, our methodology is closer to those implemented in Antweiler and Frank (2006) and Calomiris and Mamaysky (2017), who use a Naïve Bayes classifier and the Louvain method to derive news topics, respectively. We differ in that we do not limit ourself to an event study approach, and by considering individual company returns on a daily frequency.[1]

Second, our study belongs to a smaller group of studies establishing the causal role of the media in financial markets (see, in particular, Engelberg and Parsons (2011), Dougal et al. (2012), and Peress (2014)). In fact, we use the same exogenous strike as identified in Peress (2014) (for the Norwegian market) to disentangle the new information and media effect of the news signal. Novel to our study is that we are able to provide an estimate of the relative importance of the media effect in a given predictive relationship. In terms of interpreting the results and the underlying mechanisms through which the media might be important, Dougal et al. (2012) appeal to a sentiment story, while Peress (2014) provide an information dissemination explanation. The latter is also what we document. However, Peress (2014) argues that the strike likely increased the cost of accessing information and led individual stocks to move more in synch, while our findings suggest that investors also looked for other opportunities when a primary media channel fell out, thus taking aboard the cost of seeking additional and new information. There are clear patterns in the data, although not statistically strong, suggesting that such strike-induced behavior result in more noise trading.

More generally, this study relates to a growing literature in economics where textual, or non-quantitative, information is used to explain economic fluctuations. It is especially noteworthy that when we use the same news topics as here, we find that news predicts quarterly productivity, consumption, and aggregate stock market developments (Larsen and Thorsrud (2015)). Thus, expectations about future cash flows are likely impounded in the news topic signal (Fama (1990)).

The rest of this paper is organized as follows. Section 2 describes the data, the topic model, and how we link news to firms. Section 3 establishes that news topics explain returns, while Section 4 investigates the causal impact of the media. Section 5 concludes.

[1] Calomiris and Mamaysky (2017) use various decompositions of news articles to predict monthly and yearly risk and return developments in 51 aggregate stock markets. Antweiler and Frank (2006) run an event study covering U.S. stocks and *Wall Street Journal* corporate news stories.

2 Data

Our raw data consist of a long sample of the entire newspaper corpus for a daily business newspaper in Norway, and a large panel of daily information for firms listed on the Oslo Stock Exchange. Although the Norwegian stock market is relatively small compared to international markets,[2] we focus on the case of Norway because it allows us to use a long history of the entire publications from the country's most important business newspaper, and we can utilize a well defined exogenous strike in the newspaper market (in 2002) to investigate the causal link from the media to financial markets. Moreover, small economies, like Norway, typically have only one or two business newspapers, making the corpus from one newspaper more representative for the mass media as a whole than in countries where the media landscape is much more diverse. Here, we simply choose the corpus associated with the largest and most read business newspaper, *Dagens Næringsliv* (DN), noting that DN is also the fourth largest newspaper in Norway irrespective of subject matter.

The newspaper corpus used in this paper, the topic model specification, and the way in which news topics are transformed to time series follows Larsen and Thorsrud (2015) closely. We provide a summary of the computations below in Sections 2.1 and 2.2. In the interest of preserving space, technical details are delegated to Appendix B. New to this study is how we associate news topics to firms and returns. This is explained in Section 2.3.

2.1 The news corpus, the LDA and topics

The DN news corpus is generously provided to us by the company Retriever through their "Atekst" database, and covers all articles published in DN from May 2 1988 to December 29 2014. In total this amounts to 459745 articles, well above one billion words, and more than a million unique tokens. This massive amount of data makes statistical computations challenging, but as is customary in the natural language processing literature some steps are taken to clean and reduce the raw dataset before estimation. In particular, we remove stop-words, apply a stemming procedure, and reduce the number of unique words considered based on term frequency - inverse document frequency calculations. A description of how this is done is given in Appendix B.1. We note here that around 250 000 unique tokens are kept after the filtering procedure.

The "cleaned", but still unstructured, DN corpus is decomposed into news topics using a Latent Dirichlet Allocation (LDA) model. The LDA model is an unsupervised topic

[2] See Odegaard (2017b) and Odegaard (2017c) for detailed descriptive statistics and standard asset pricing results for the Norwegian stock market.

model that clusters words into topics, which are distributions over words, while at the same time classifying articles as mixtures of topics. By unsupervised learning algorithm we mean an algorithm that can learn/discover an underlying structure in the data without the algorithm being given any labeled samples to learn from. The term "latent" is used because the words, which are the observed data, are intended to communicate a latent structure, namely the meaning of the article. The term "Dirichlet" is used because the topic mixture is drawn from a conjugate Dirichlet prior. As such, the LDA shares many features with latent (Gaussian) factor models used in conventional econometrics, but with factors (representing topics) constrained to live in the simplex and fed through a multinomial likelihood at the observation equation. A richer description and more technical details of the LDA is provided in Appendix B.2. Here we note that we classify the DN corpus into $K = 80$ different topics using a Gibbs sampling algorithm. Although K might seem somewhat arbitrary chosen, statistical tests conducted in Larsen and Thorsrud (2015) confirm that 80 topics give a good description of the corpus.

The LDA estimation procedure does not give the topics any name or label. To do so, labels are subjectively given to each topic based on the most important words associated with each topic. As shown in Table 7, in Appendix A, which lists all the estimated topics together with the most important words associated with each topic, it is, in most cases, conceptually simple to classify them. The labeling plays no material role in the experiment, it just serves as a convenient way of referring to the different topics instead of using, e.g., topic numbers or long lists of words. What is more interesting, however, is whether the LDA decomposition gives a meaningful and easily interpretable topic classification of the DN newspaper. As illustrated in Figure 4, in Appendix A, it does: The topic decomposition reflects how DN structures its content, with distinct sections for particular themes, and that DN is a Norwegian newspaper writing about news of particular relevance for Norway. We observe, for example, separate topics for Norway's immediate Nordic neighbors (*Nordic countries*); largest trading partners (*EU* and *Europe*); and biggest and second biggest exports (*Oil production* and *Fishing*). A richer discussion about this decomposition is provided in Larsen and Thorsrud (2015).

2.2 News topics as time series

Given knowledge of the topics (and their word distributions), the topic decompositions are translated into time series. This is done in two steps, which are described in greater detail in Appendix B.3 and B.4. In short, we first collapse all the articles in the newspaper for a particular day into one document, and compute, using the estimated word distribution for each topic, the topic frequencies for this newly formed document. This yields a set of K daily time series, where each represent how much (in percent) a given topic is written

about for a given day. Then, for each observation in these time series we identify their sign, i.e., whether or not the news is positive or negative. For each topic, this is done at the article level: For every daily observation, we find the article in the newspaper that is best explained by the topic. The tone of this article is identified using an external word list and simple word counts. The word list used here takes as a starting point the classification of positive/negative words defined by the *Harvard IV-4 Psychological Dictionary*, and then translates the words to Norwegian. The count procedure delivers two statistics, containing the number of positive and negative words. These statistics are then normalized such that each observation reflects the fraction of positive and negative words and subtracted from each other. If the difference is negative (positive), we set the sign equal to -1 (1), and adjust the topic frequencies accordingly.

We note that this procedure explicitly uses the output from the topic model also when defining the sign of the news, and that different topics might get their sign defined from the same article. We have experimented with other ways of identifying the sign of the topic frequencies, finding that the method outlined above seems to work the best in a number of different applications (Thorsrud (2016a), Thorsrud (2016b), and Larsen (2017)).[3]

2.3 Financial data and linking news to firms

We obtain daily data for all firms listed on the Oslo Stock Exchange from Reuters Datastream. For each firm, we collect both open and close prices, and compute (log) close-to-open ($c2o$), open-to-close ($o2c$), and close-to-close ($c2c$) daily returns. We also collect the commonly used predictors (log) book-to-market (B/M), (log) market value (MV), and turnover ($Turn$), where the latter is computed by dividing the total number of shares traded by the number of shares outstanding. In addition we use three measures of observed common time-fixed effects, namely (log) close-to-close returns on the Oslo Stock Exchange Benchmark index (R^{mh}), the close-to-close return on the S&P500 (R^{mi}), and the daily (log) change in the price of oil (R^{oil}).[4] Stocks listed for less than half a year are removed from the sample. To avoid including extreme price observations associated with listing and de-listing of firms, we exclude the first and last week of each firm's return observations. In total we are left with 233 individual firms. The full sample stretches

[3] We have also used the word list suggested by Loughran and Mcdonald (2011) as a starting point for classifying positive/negative words, finding that this does not alter the end result by much. Still, there are undoubtedly more sophisticated methods that can be applied to identify the tone of the news (see, e.g., Pang et al. (2002)).

[4] As roughly 50 percent of Norway's exports are linked to petroleum products and a large share of the companies traded on the Oslo Stock Exchange are directly exposed to the oil sector, controlling for the price of oil in asset pricing equations is often done when working with Norwegian data (see, e.g., Næs et al. (2009)).

from 1996 to 2014, but only a few stocks are traded throughout the whole sample period.

To link companies to news, we use the word distributions estimated from the news corpus and each firm's textual description provided by Reuters. On average, across firms, the textual description is roughly a half-page description of what each company's primary business is. The firms textual description are then classified using a procedure for querying documents outside the set on which the LDA is estimated (Heinrich (2009) and Hansen et al. (2014)). This corresponds to using the LDA model on the firm descriptions, but with the difference that the sampler is run with the estimated word distributions from the newspaper corpus held constant (see Appendix B.3). The end product of this procedure are vectors with topic probabilities for each firm description. From these vectors we map firms with topics using the topic with the highest weight (probability) in describing the firm's core business.

An example helps illustrating our procedure. The first three, out of 10, sentences describing the firm *Frontline* reads:

> Frontline Ltd. is a shipping company. The Company is engaged in the ownership and operation of oil tankers. The Company operates oil tankers of two sizes: very large crude carriers (VLCCs), which are between 200,000 and 320,000 deadweight tons, and Suezmax tankers, which are vessels between 120,000 and 170,000 deadweight tons...

Following the steps described above, the elements with highest value in the vector with topic probabilities for this firm description are *Shipping*, *Airline industry*, and *Foreign*, with weights 0.31, 0.06, and 0.02, respectively. Thus, we associate *Frontline* with the *Shipping* topic. As seen from the word cloud for this topic, Figure 1, the sentences and the word distribution for the topic share many important words. In our setting, the better the mapping is between the word distribution for a given topic and the words used in the description of the firm, the more likely it is that we match this particular firm with this topic.

Summary statistics for our firm and topic mapping are provided in Table 8 and Figure 5 in Appendix A. We highlight four overall impressions. First, of the 80 individual news topics, 33 are successfully mapped to one or more firms. We have informally looked at all estimated firm and topic mappings. It is our impression that the procedure produces intuitive mappings in well over 70 percent of the cases. However, for some firms the topic mapping seems weird. While we could have excluded companies from the sample in such cases, or manually changed the mapping, we have refrained from doing so to keep the analysis as transparent as possible. Second, a large share of topics are mapped to relatively few companies. On the other hand, a large share of the firms are linked to the topics *Oil service*, *Shipping*, and *IT systems*, in particular. Third, there are large

Figure 1. The *Shipping* topic represented as a word cloud. The size of a word reflects the probability of this word occurring in the topic. The word cloud is created based on the 40 most important words in the topic.

variations in average returns, standard deviations, average size and book-to-market values across firms with different topic mappings, but no clear patterns indicating a systematic relationship. Finally, we see from Figure 5 that the number of firms included in the panel data set, and which topic assignments that dominate, changes considerably across time. For example, during the 1990s the breadth of the market was much thiner than during the 2000s, and topics associated with oil, health, and fishery have become more important over the years.

3 News and returns

Let $y_{i,t}$ denote the return series for company i at time t, where we consider both the (log) change in the price from market closing on day $t-1$ to either the opening ($c2o$) or closing price ($c2c$) on day t as return measures. Then, our main statistical tool for analyzing whether or not news explains returns is a general panel data regression of the form:

$$y_{i,t} = \gamma T_{k,t} + \boldsymbol{z}_{i,t}'\boldsymbol{\delta} + \alpha_i + \delta_t + u_{i,t} \tag{1}$$

where $T_{k,t}$ is the news topic, associated with topic k, and γ the parameter of interest. The newspaper, and thus $T_{k,t}$, becomes available after the market closes on day $t-1$, and usually in the morning on day t, at least 2 hours prior to when the market opens. Accordingly, the timing used in (1) ensures that we do not use news that was generated by market movements on day t itself. Additional commonly used predictors are included in the vector $\boldsymbol{z}_{i,t}$, and α_i and δ_t are firm- and time-fixed effects, respectively.

Table 1 highlights our first main result. Regressing $c2o$ returns on the news measure produces positive and highly significant news coefficients. Controlling only for lagged returns ($c2c$) and firm- and time-fixed effects, we see from column I that a one unit

Table 1. Firm specific news topics and day t close-to-open (c2o) and close-to-close returns (c2c). In each regression the key independent variable is $Topic_t$. All regressions control for the firm's lagged close-to-close return (R_{t-p}), for $p = 1, \ldots, 14$. Control variables listed in the table include: close-to-close return on the S&P500 (R^{mi}_{t-1}), close-to-close returns on the OSEBX (R^{mh}_{t-1}), the daily change in the oil price (R^{oil}_{t-1}), the book-to-market value (B/M_{t-1}) the market value (MV_{t-1}), and finally the turnover ($Turn_{t-1}$). All regressions are estimated by OLS. Fixed effects are included as specified in the table. Following Tetlock et al. (2008), we compute clustered standard errors by trading day. Robust t-statistics are in parentheses. The last column reports the unconditional standard deviation of the individual predictors.

	c2o			**c2c**			
	I	**II**	**III**	**I**	**II**	**III**	**Std(X)**
$Topic_t$	0.0107***	0.0135***	0.0090**	0.0153***	0.0272***	0.0208***	0.017
	(0.0022)	(0.0031)	(0.0037)	(0.0031)	(0.0051)	(0.0062)	
R^{mi}_{t-1}		0.3453***	0.3410***		0.2816***	0.2774***	0.013
		(0.0177)	(0.0217)		(0.0285)	(0.0371)	
R^{mh}_{t-1}		-0.0120	-0.0180		-0.0012	-0.0023	0.016
		(0.0133)	(0.0158)		(0.0222)	(0.0275)	
R^{oil}_{t-1}		0.0139**	0.0067		0.0231*	0.0132	0.020
		(0.0067)	(0.0091)		(0.0120)	(0.0169)	
B/M_{t-1}		-0.0007***	-0.0007***		-0.0008***	-0.0007***	0.889
		(0.0001)	(0.0001)		(0.0002)	(0.0002)	
MV_{t-1}		0.0002*	0.0002*		-0.0003*	-0.0003*	1.802
		(0.0001)	(0.0001)		(0.0001)	(0.0002)	
$Turn_{t-1}$			0.0115***			0.0076***	0.047
			(0.0021)			(0.0022)	
R^2	0.0088	0.0298	0.0301	0.0054	0.0128	0.0128	
Obs.	540708	540708	391533	540708	540708	391533	
α_i	yes	yes	yes	yes	yes	yes	
δ_t	yes	no	no	yes	no	no	

(standard deviation) innovation in the news correspond to roughly a 1 (0.02) percent increase in returns. Augmenting the regressions with various other control variables does not alter this finding by much. At most, we obtain an effect size of 1.35 percent, and, when controlling for turnover, in column *III* of the table, the effect size is 0.9 percent. Note here, however, that the number of observations is somewhat reduced as not all firms have recorded turnover for the whole sample period. As is common in this type of regressions, the R^2 is low, indicating that most of the day-to-day variation in individual firm valuations is idiosyncratic. We observe from column *II* and *III*, however, that the returns on the previous day's S&P500 (R^{mi}_{t-1}) has a particularly positive and strong predictive power for the subsequent returns. In unreported results we also confirm that it is this variable that attributes the most to the increase in R^2 across columns *I* and *II*. The U.S. market closes over 6 hours after the Norwegian market, so the R^{mi}_{t-1} variable also contains more timely information than any of the other variables used in the regressions. Still, including

the S&P500 hardly changes the size and significance of the news coefficient. Among the other potential determinants of $c2o$ returns, the (log) change in oil prices (R^{oil}_{t-1}), book-to-market (B/M_{t-1}), market-value (MV_{t-1}), and turnover ($Turn_{t-1}$) all show signs of being significant, confirming well known asset pricing results.[5]

Because of the short window between when the newspaper is released in the morning and the market opens, it is natural to interpret the findings thus far as saying that the news topic variables capture new information that the market responds to. This is not to say that it is the newspaper that generates this news. For example, firm-specific news might be released after the market closes on day $t-1$, and then written about in the newspaper that is published in the morning on day t. Still, although the media might report on already known information, the fact that they actually report on it, and the intensity and manner in which they do so, might have a separate effect on asset pricing valuations. We investigate this further in Section 4. Below, however, we first investigate if the news topics carries fundamental information or noise, report on various robustness checks, including assessments of particular time periods, and implement a simple trading strategy.

3.1 Continuation or reversal?

A classical finding in finance is that investors overreact to noisy information, and underreact to new fundamental information (see, e.g, French and Roll (1986) and Campbell et al. (1993)). This results in significant continuation patters in returns following new information about fundamentals, but a reversal following information that turned out to be noise.

The columns labeled $c2c$ in Table 1 reproduce the regressions discussed above, but now using close-to-close returns as the dependent variable. Accordingly, compared to when using $c2o$ returns, prices have a longer time to respond to the news signal (which is released early in the morning on day t). As seen from the table, the news variable remains highly significant, but the magnitude of the effect is somewhat larger than previously found. Now a one unit positive news innovation translates into a 1.53 percent increase in returns for the specification reported in column I, and up to 2.72 percent for the specifications reported in column II. These numbers are approximately 50 and 130 basis points larger than those obtained when looking at $c2o$ returns, and suggests significant intra-day continuation

[5] Petersen (2009) documents how previous results in the asset pricing literature are highly sensitive to how the standard errors in panel data regressions are computed. In unreported results we show that all of our significant tests are robust to clustering the standard errors on either time, firms, and groups (topics), i.e., t, i, and k using the notation from equation (1). Irrespective of clustering level, the news coefficients are always significant at either the 1 or 5 percent level.

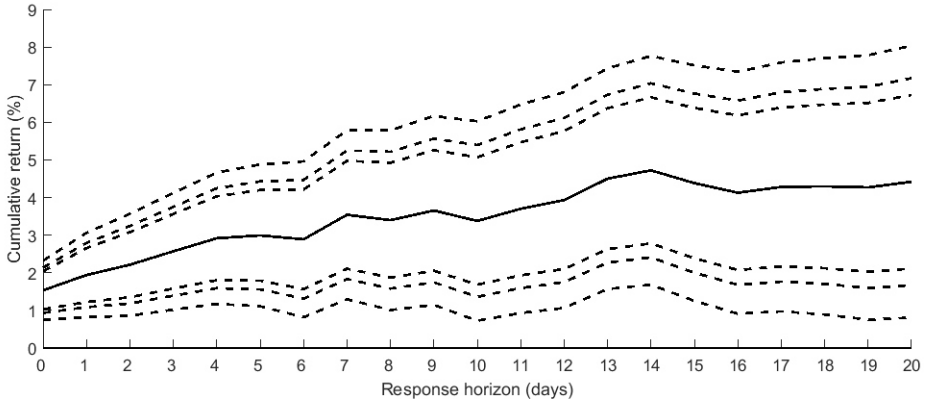

Figure 2. Predicted cumulative close-to-close returns. The solid line is the mean response to a one unit news innovation, and the broken lines represent the 99%, 95%, and 90% confidence intervals, respectively. Standard errors are computed by clustering on trading day.

patterns.[6]

To investigate the degree to which our suggested news measure predicts asset prices beyond the day in which the news is published, we look at how news predicts cumulative close-to-close returns. In particular, let $y_{i,t:t+h}$ denote the cumulative close-to-close return for firm i across horizons t to $t+h$. Then, regression specification I from Table 1, which yielded the smallest short-term effect size, is estimated for each $h = 1, \ldots, 20$, using $y_{i,t:t+h}$ as the dependent variable. Figure 2 reports the mean predictions together with 99%, 95%, and 90% confidence intervals from this experiment. By construction, the impact effect is as reported in Table 1, but the effect of a one unit news innovation also accumulates substantially over time. A maximum effect of roughly 4 percent is obtained after 15 business days, before it levels off. Converting this number into the effect following a one standard deviation news innovation gives an increase in returns of roughly 7 basis points. Without exception, the response path is significant at the 1 percent level.[7]

Many textual studies in finance have given the news-return relationship a behavioral interpretation and documented significant overreaction patterns (Tetlock (2014)). In our results, confer Figure 2, we see little sign of reversal, suggesting that the news topics carries new fundamental information (as opposed to noise). One plausible interpretation of the observed continuation pattern is given by theories of rational attention where information

[6] In Table 11, in Appendix A, we run similar regressions for open-to-close returns ($o2c$), confirming that the intra-day effect of the news is roughly, depending on the exact model specification, between 50 and 130 basis points.

[7] We have also done these experiments by first cleansing the news topic variables for potential autocorrelation and common time fixed effects, giving the regressions an impulse response interpretation as in the local linear projection framework (Òscar Jordà (2005)). Doing so we observe that the impact effect is of the same magnitude as already documented in Table 1, suggesting that the news topic variables are fairly exogenous to past developments in the market and not very persistent. Moreover, in the days following the initial news shock, the effect on returns accumulates as above, with little sign of reversal.

gathering is costly and/or the investors are cognitively constrained. In such a setting, the media matters because it can reach a broad population of investors and potentially alleviate informational frictions by contributing to information diffusion (Peress (2014)). Such an interpretation is also consistent with findings reported in Larsen and Thorsrud (2015). They use the same news data as here, but construct a quarterly news index and show that unexpected innovations to this index are followed by a permanent increase in productivity and consumption. Thus, the news signal apparently generates co-movement between productivity and asset prices, indicating that expectations about future cash flows are impounded in the signal (Fama (1990)).

3.2 Randomization, additional fixed effects and interaction terms

A novelty of our analysis is that we treat every day as a news day by linking news topics to returns using word distributions derived from the business newspaper and the firm's textual descriptions (confer Section 2.3). Panel A of Table 9, in Appendix A, shows that the way we link companies to news is crucial for obtaining significant results. In particular, when we randomly assign news topics to firms, and run exactly the same regressions as described for Table 1, we find that almost no significant predictive power can be established.[8]

One could suspect, however, that the way in which we link firms to news resembles some type of industry classification, and that the results presented thus far capture industry effects (see, e.g., Hou and Robinson (2006)), or that the news topic variables proxy well known weekday effects (see, e.g., Doyle and Chen (2009)). In Panel B, in Table 9, we redo the regressions from Table 1, but now include industry specific dummies and control for the day of the week. As seen from the results, irrespective of which control variables we include, the news topic coefficients are almost identical to those found earlier.

Another concern could be that the news topic variables are associated with particular firm characteristics such as book-to-market value, size, or liquidity, i.e., well known pricing factors (Fama and French (1993), Carhart (1997), and Pastor and Stambaugh (2003)). In Table 10, in Appendix A, we interact the news variable with book-to-market values ($B/M_{t-1} : Topic_t$), market values ($MV_{t-1} : Topic_t$), and turnover ($Turn_{t-1} : Topic_t$), and include these as additional control variables in the panel regressions. As seen from the results, non of the interaction terms are significant, and, the coefficients associated with the news topic variable remains significant at the 1 or 5 percent level with roughly the same effect size as already presented. Thus, there are no significant patterns indicating that our main results are driven by value, size, or liquidity characteristics.

[8] For close-to-close returns and the regression specification in column *III* of Table 9, the $Topic_t^R$ variable is barely significant at the 10 percent level.

We have also tried sorting firms into quantiles based on their average book-to-market value, size, and turnover, and then, for each quantile and firm characteristic, estimated the effect of news. The findings resemble those described above, namely that for most quantiles and characteristics the news coefficient is positive, significant, and show no pattern of being associated with specific firm characteristics.

In sum, we find that our results are robust to falsification tests (randomizing topic assignments), various additional fixed effects (industry and weekday effects), and is not driven by well known firm characteristics.

3.3 Changing market and media trends

During the last two decades both the media and stock market have undergone substantial changes. First, as noted in Section 2.3, the breadth of the Norwegian stock market has become much bigger over the years, potentially suggesting that also a broader set of media is required to adequately cover it. For example, during the first years of our sample less than 60 firms were listed on the Oslo Stock Exchange. In contrast, in 2014 over 120 companies were listed and included in our data set. Second, while printed news was a primary media channel a decade ago, internet usage and online consumption of newspaper content dominates today (SSB (2017)). In terms of the number of readers of printed news, our primary source DN has been ranked as the fourth largest in Norway, irrespective of subject matter, throughout the whole sample. In terms of online readers, however, DN has faced substantially tougher competition. For example, DN's share of the total number of online readers declined by 25 percent around 2008 due to the establishment of competing news media (Medianorway (2017)). Together these trends suggest that DN's role as an information diffusion channel might be weakened across time, and that the relationship between the (DN) news topics and returns accordingly.

The results reported in Table 2 addresses this issue. Here we have divided the sample (1996 - 2014) into three equally sized sub-samples, and redone the estimation from the columns labeled I in Table 1. As seen from the table, the predictive effects are positive and significant for all sub-samples and for both close-to-open and close-to-close returns, but the strength of the effect tend to diminish over time. The graph to the left in Figure 3 shows that this general pattern carries through also for longer term predictions. During the period 1996-2002 we find a positive, highly persistent, and significant predictive relationship between news and returns. For the period 2002-2008, this relationship weakens somewhat, but remains significant. The really dramatic change is for the last sub-sample, 2008-2014, where the predictive relationship between news topics and returns becomes insignificant after only one day.

In line with the discussion above, one interpretation of these findings is that DN,

Table 2. Firm specific news topics and day t close-to-open (c2o) and close-to-close returns (c2c) across sub-samples. For each return variable, regression specification I from Table 1 is used. All regressions are estimated by OLS. Fixed effects are included as specified in the table. Following Tetlock et al. (2008), we compute clustered standard errors by trading day. Robust t-statistics are in parentheses.

	c2o			**c2c**		
	1996-2002	**2002-2008**	**2008-2014**	**1996-2002**	**2002-2008**	**2008-2014**
$Topic_t$	0.0169***	0.0084***	0.0086**	0.0267***	0.0135***	0.0099*
	(0.0047)	(0.0031)	(0.0039)	(0.0065)	(0.0042)	(0.0055)
R^2	0.0056	0.0100	0.0107	0.0045	0.0069	0.0062
Obs.	130332	197231	213412	130332	197231	213412
α_i	yes	yes	yes	yes	yes	yes
δ_t	yes	yes	yes	yes	yes	yes

from which we derive our news signal, has become less important for understanding the news-return relationship. On the other hand, the results might also indicate that financial markets have become more efficient over time, and that information frictions that were present during the 1990s and early 2000s are no longer binding.

To cast further light on these two competing explanations, our textual data provider Retriever has provided us with a broad-based sample of news articles from the biggest players in the Norwegian (business) newspaper market. This extra set of data covers the period 2008-2014, and includes news from four additional sources.[9] We utilize this extra data in four steps. First, we clean the textual data, as described in Section 2.1. Then, in a second step, we apply a procedure for querying documents outside the set on which the LDA is estimated, as described in Section 2.3. That is, we keep the topic definitions estimated from the DN corpus, and classify the augmented corpus based on these existing word distributions. The advantage with this approach is that we ensure that the topics, in terms of word distributions, stay the same across the extended data set (multiple sources) and the original one (DN only).[10] Third, we compute new topic time series, for the period 2008-2014, based on the tone and frequency associated with each topic from the aggregated corpus (DN and additional sources), as in Section 2.2. As such, the extra data allows us to capture a much broader news base than when using DN

[9]The sources are *Aftenposten*, *Finansavisen*, *Bergens Tidende*, and *E24*. The latter media is an online media channel only. To avoid using news content that are generated as a response to market movements on day t, we define the online news corpus for a given day t as containing news articles from eight in the morning on day $t-1$ to eight in the morning on day t, i.e., before the market opens on day t.

[10]Because of lack of identifiability in the LDA, the estimates of the topic and word distributions can not be combined across samples for an analysis that relies on the content of specific topics. A disadvantage of this approach is that by definition it does not take into account the possibility that the additional news sources write about other news topics than those defined by DN.

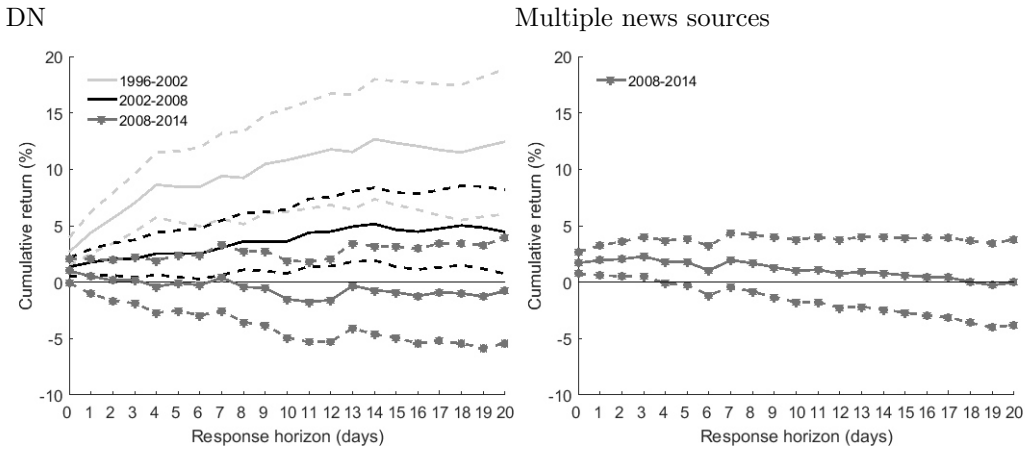

Figure 3. Predicted cumulative close-to-close returns across sub-samples. The solid line is the mean response to a one unit news innovation, and the broken lines represent the 95% confidence intervals, where standard errors are computed by clustered on trading day. In the graph to the left, DN is the only newspaper source. In the graph to the right, we include a broader set of news sources (available for the latest sample period only).

alone. Finally, we redo the predictive regressions discussed above.

The results reported in the right graph in Figure 3 are striking. When the broad based news topic variables are used, they predict significant continuation, peaking after three business days and remaining significant for up to one business week. For longer horizons the effect becomes insignificant, and slowly reverts to zero. This stands in stark contrast to the comparable result in the graph to the left in Figure 3, where the predictive relationship between news and returns during the 2008-2014 period was basically insignificant after day 0. Still, compared to a decade ago, the persistence of the news-return predictive relationship is reduced substantially.

We conclude from these results that financial market might have become more efficient, but that the media still have significant predictive power. However, as the size of the stock market itself has grown, and the variety of news sources delivering business relevant news has proliferated, our results suggest that a broad-based news corpus now needs to be applied to capture informative news signals.

3.4 A news based trading strategy

The analysis thus far has focused on average effects across all firms. To gauge the degree to which the news affects individual firms valuations, we run a zero-cost investment strategy similar to those implemented in, e.g., Tetlock et al. (2008) and Boudoukh et al. (2013). The strategy is implemented as follows: For each trading day we go 1 dollar long in all stocks that receive positive news in the morning, and 1 dollar short in all stocks that receive negative news. For a trade to take place we require that we have at least 5 stocks

on each side. Based on the continuation patterns shown in Figure 3, the stocks are held for up to 5 trading days. At the end of each day we compute the total daily (close-to-close) return from both the long and short portfolios we have at that point in time, controlling for the fact that stocks are bought on opening prices and sold on close prices. The total daily return from the strategy is the difference between the daily return from the long and short portfolios.

Columns labeled I in Table 12, in Appendix A, summarize the yearly returns and Sharp Ratios generated by the benchmark zero-cost portfolio using DN and multiple media as news sources (from 2008), respectively. For the strategy utilizing only DN as a news source, negative returns are observed for 5 our of 18 years; 1997, 2006, 2007, 2009, and 2011. On average, across all the years, the annualized daily return is 16.8 percent, with a Sharp Ratio of about 0.89. For comparison, this return is almost four times that of the market as a whole, see Figure 6 in Appendix A, which has a Sharp Ratio of 0.33. Although good, these numbers improve substantially when the news signal traded upon utilizes multiple sources. It that case, negative portfolio returns are only observed in three out of 18 years, and the annualized average return is 29.1 percent with a Sharp Ratio of 1.56. However, as also seen from the table, the average numbers of daily trades conducted to form the long and short portfolios are substantial. In a real world setting, this would have implied substantial trading costs which would likely have subtracted away a large part of the aggregate returns.

To reduce the number of trades conducted, we also run an alternative trading strategy. This strategy is similar to that above, but with the difference that news is only traded upon if the news signal is over or below one standard deviation of the respective news topic time series. Here, the computations of the standard deviations are recursively updated throughout the trading experiment, using the past 252 observations to calculate the standard deviations. As seen from the columns labeled II in Table 12, this more restrictive trading strategy reduces the average returns on the portfolios somewhat. Still, the annualized average daily returns are 11.7 and 21.3 percent, with Sharp Ratios of 0.60 and 1.1, for the DN only and multiple sources strategies, respectively. More importantly, however, the alternative strategies generates these return by far fewer trades than above.

Do the two zero-cost investment strategies generate risk-adjusted returns as well? In Table 3 we use the daily return series generated by the two strategies, subtract the risk-free rate, and run regressions controlling for the standard risk factors (Fama and French (1993), Jegadeesh and Titman (1993), Carhart (1997), and Pastor and Stambaugh (2003)): the market (MR) size (SMB), book-to-market (HML), momentum (UMD), and liquidity (LIQ).[11] Only for the alternative trading strategy, and when using DN as the only news

[11]Professor Bernt Arne Ødegaard, at the University in Stavanger, constructs these risk factors for the

Table 3. Risk-adjusted return for zero-cost investment strategies. Either *DN*, or multiple sources *Multiple news sources* are used to derive the news signal. Given the news source, in the columns labeled *I*, all news signals are potentially traded on. In the columns labeled *II*, only news signals over or above one standard deviation is traded on. The dependent variable is the strategy generated return less the risk-free rate. The independent variables include contemporaneous factors for: the market (MR), size (SMB), book-to-market (HML), momentum (UMD), and liquidity (LIQ). We compute all coefficient standard errors using heteroskedasticity-consistent standard errors (White (1980)). Robust t-statistics are in parentheses.

	DN		**Multiple news sources**	
	I	**II**	**I**	**II**
MR	-0.0445***	-0.0154	-0.0448***	-0.0110
	(0.0165)	(0.0149)	(0.0168)	(0.0156)
SMB	0.0557**	0.0060	0.0107	-0.0361
	(0.0250)	(0.0278)	(0.0257)	(0.0254)
HML	0.0584***	-0.0041	0.0516***	-0.0056
	(0.0194)	(0.0200)	(0.0189)	(0.0215)
UMD	0.0538***	0.0085	0.0373*	0.0037
	(0.0195)	(0.0188)	(0.0206)	(0.0205)
LIQ	0.1362***	0.0227	0.1312***	0.0420*
	(0.0217)	(0.0220)	(0.0225)	(0.0216)
Alpha	0.0333**	0.0267	0.0851***	0.0643***
	(0.0167)	(0.0178)	(0.0165)	(0.0178)
R^2	0.0601	0.0014	0.0409	0.0014
Obs.	4667	4667	4688	4688

source, can we not reject the null hypothesis of a zero *Alpha*. When using multiple news sources, for example, the point estimate is between 0.06 and 0.08, implying an annualized risk-adjusted daily return of between roughly 15 and 20 percent. Although comparisons across markets and time periods might be misleading, we note that these numbers are comparable in magnitude to those found in both Tetlock et al. (2008) and Boudoukh et al. (2013) for the U.S. market. Interestingly, the news-based trading strategies tend to be negatively correlated with the market, and positively correlated with momentum and liquidity, but the significance of these correlations varies substantially.

We emphasize that the trading experiments conducted here are deliberately kept simple. More than providing examples of realistic trading opportunities, they cast light on the robustness of the pooled time series regressions presented in the previous sections.[12] We conclude that the significant news-return relationship is not driven by the panel data approach, and also has the potential for being economically important.

Norwegian market and makes them publicly available (see Odegaard (2017a) and Odegaard (2017b)).

[12] As such, it is perhaps interesting to know which news is actually traded on across time. This is illustrated in Figure 7, in Appendix A, using a heatmap.

4 The causal media effect

The news signal potentially contains (at least) two different components. First, news in the business newspaper can be genuine new information. Second, the media might itself affect markets by how they report news stories and by disseminating information to a broad population of investors. As genuine new information is more likely to be generated exogenous to the media (and reported in the media with a time lag), it is the second component that reflects media's potential causal role in predicting returns. To separate between these two components, however, is difficult, because we only observe the signal, and not its two underlying components.

To address this issue we exploit a strike in the Norwegian newspaper market in 2002, which started on May 30 and ended on June 7, i.e., lasting for seven business days. The same event was used in Peress (2014) to investigate the causal effect media has on trading and price formation. But, in contrast to his cross-country event study, we focus on the case of Norway, changes in returns, and condition our analysis on the news topic variables. Although this might seem like a more narrow analysis, it allows us to obtain a novel estimate of the media effect in a given predictive relationship. Simply put, we ask how much of the increases in returns documented in the preceding sections can be attributed to the causal (DN) news topics media effect.

According to Peress (2014), the newspaper strike affected the press on a national scale, involved the media sector only, and occurred on days on which the stock market was open. Moreover, the strike was called by the media profession itself due to their working conditions, and it was not driven by stock market movements on the day of the strike or the preceding days. Thus, we can safely assume that it was truly exogenous to market developments.[13]

Conditional on the strike being truly exogenous, the central premise for being able to quantify the media effect of news is that news in terms of new information was released also during the strike period, although not through the mass media. As such, we follow an event study approach where in total 103 stocks enter our sample in the year(s) prior to, during and after the strike. We focus on both their close-to-open and close-to-close returns, and use N days prior to and N days after the strike to compute the non-strike affected returns. In the following, we denote the change in returns $\Delta r_{i,d-ba} = \hat{r}_{i,d} - \hat{r}_{i,ba}$, where $\hat{r}$ is the average return for company i, during the strike period ($\hat{r}_{i,d}$) and before and after ($\hat{r}_{i,ba}$), respectively. By adjusting N, we can down-weight observations right

[13] See Peress (2014) for a richer discussion about these issues. It should be noted, however, that he also includes a Norwegian newspaper strike in 2004. During this journalist strike the DN newspaper was in fact published, and the event can not be used here. We further note that, given the timing of the strike event in 2002, the explosion of digital media seen the last decade had hardly begun.

Table 4. Summary statistics of news and returns, before and during and after the strike. In the rows labeled Δr_{d-ba}, each table entry is a function of $\Delta r_{i,d-ba} = \hat{r}_{i,d} - \hat{r}_{i,ba}$, where $\hat{r}$ is the average return for company i, during the strike period ($\hat{r}_{i,d}$) and before and after ($\hat{r}_{i,ba}$), respectively. The length of the strike period ($\hat{r}_{i,d}$) is constant and equal to seven business days. The total length of the window used during and before and after the strike equals 51 days. In the interest of readability, the numbers reported in the columns $E(X)$, $VAR(X)$, $min(X)$, and $max(X)$ are scaled by 100. The table row labeled $t(\beta)$ provides summary statistics for $t_i(\beta)$, a standardized firm specific news loading, estimated on a classification sample prior to the strike period.

	E(X)	**VAR(X)**	**Skew(X)**	**Kurtosis(X)**	**min(X)**	**max(X)**	**N**
Δr^{c2o}_{d-ba}	-0.3918	1.1684	0.0028	4.6416	-3.8829	3.0488	103
Δr^{c2c}_{d-ba}	-0.6171	1.5688	-0.2377	4.6911	-4.5117	3.9407	103
$t(\beta)$	2.3016	3.9414	0.6000	3.3606	-1.3632	8.8093	103

before and right after the strike, as these might be driven by anticipation effects (about the forthcoming strike) and adjustments following the end of the strike period. We denote the total length of the before, during, and after strike sample by W. In the main results presented below $W = 51$, but we show that our results are robust to both shorter and longer windows.

4.1 Unconditional and conditional effects

The first row in Table 4 documents that, on average across firms, the average returns during the strike period fell by between 40 to 60 basis points relative to the average returns prior to and after the strike. The dispersion across firms is however large, with minimum and maximum values reaching -3.88 and 3.04 percent, and -4.51 and 3.94 percent, for $c2o$ and $c2c$ returns, respectively. Still, the skewness and kurtosis statistics suggest that the distribution is not far from normal, albeit with some outliers. For both types of returns, the mean effects are significantly different from zero on the 1 percent significance level, suggesting that the media has a positive causal role in explaining short-term return patterns.[14]

A valid objection to the simple calculations done above is that they do not necessarily tell us something about how the media shortage affected returns. The fall might simply be due to the effect the strike itself, or other not controlled for common events, had on markets. Accordingly, we would ideally need two different groups of firms and returns. One where the media shortage should matter, and one where it should not. Unfortunately, such classifications are not observed. Moreover, although the numbers might reflect the

[14] A direct comparison of our results to those in Peress (2014) would have been interesting, but not feasible. He focuses on pooled cross-country averages, trading volume, and volatility, and does not report raw return statistics for the Norwegian newspaper strike in 2002.

causal media effect, they do not necessarily relate to the news topic variables used in this study, i.e., those obtained from the DN newspaper.

To accommodate the concern, and to relate the media shortage to the DN news topic variables, we run a difference-in-difference type of experiment, with some modifications. As above, we first compute the difference between returns during the strike and those before and after the strike. Then, conditioning on how sensitive the respective stocks were to the news topic variables in the year prior to the strike, we construct a treatment and control group, and run simple regressions to quantify the media effect due to the shortfall of the DN news topics. Intuitively, all stocks might be affected by the strike, but those firms that had a particularly high sensitivity to news topics prior to the strike should also respond stronger to their shortfall during the strike.[15]

More formally, we consider the model:

$$\hat{r}_{i,e} = \alpha_i + \delta D_e + \tau w_{i,e} + u_{i,e} \tag{2}$$

where the event indicator $e = \{ba, d\}$ indicates the periods before and after (ba) and during (d) the strike, α_i is a firm-fixed effect constant across e, $D_e = 1$ if $e = d$ and zero otherwise, and $u_{i,e}$ are idiosyncratic errors. The parameter of interest is τ, measuring the effect of $w_{i,e}$, a binary indicator of the treatment. Before and after the strike $w_{i,ba} = 0$ for all i. During the strike, however, $w_{i,d} = 1$ if firm i is in the treatment group, i.e., particularly sensitive to the DN news topics, and zero otherwise. A simple estimation procedure of the two-period model in (2) is to first difference to remove α_i:

$$\Delta r_{i,d-ba} = \hat{r}_{i,d} - \hat{r}_{i,ba} = \delta + \tau \Delta w_i + \Delta u_i \tag{3}$$

with $\Delta w_i = w_{i,d}$ (since $w_{i,ba} = 0$ for all firms i in period $e = ba$).

While (3) is a standard difference-in-difference model (Meyer (1995) and Angrist and Krueger (1999)), the crux here is to construct $w_{i,d}$, which depends on the firm's news topic sensitivity. We construct $w_{i,d}$ in two steps. First, we estimate news topic sensitivity, denoted by $t_i(\beta)$, from time series regressions of each individuals firm's close-to-open return ($y_{i,t}$) on news topics ($T_{k,t}$) during the year preceding the strike:

$$y_{i,t} = \beta_i T_{k,t} + \boldsymbol{z}'_{i,t}\boldsymbol{\delta} + u_{i,t} \tag{4}$$

where $t_i(\beta)$ is the t-statistic associated with β_i.[16] The third row of Table 4 reports how

[15] Estimating the average media shortage effect only for returns in the treatment group would not permit us to exclude the general effect the strike itself might have on returns. Of course, if the general strike effect affects firms in the two groups differently, our experiment design will not be able to efficiently isolate the strike effect from the (DN) media shortage effect.

[16] We focus on $t(\beta)$, rather than β, to control for differences in precision due to differences in residual variance. To reduce potential biases in the regressions, we also include additional controls, $\boldsymbol{z}_{i,t}$, including R^{mi}_{t-1}, $B/M_{i,t-1}$, $MV_{i,t-1}$, and lagged close-to-close returns for stock i, i.e., the significant regressors in the panel regressions run in Section 3.

Table 5. Estimated media effects from $\Delta r_{i,d-ba} = \delta + \tau \Delta w_i + \Delta u_i$, where $\Delta r_{i,d-ba} = \hat{r}_{i,d} - \hat{r}_{i,ba}$, and $\hat{r}$ is the average return for company i, during the strike period ($\hat{r}_{i,d}$) and before and after ($\hat{r}_{i,ba}$), respectively. The total window length is $W = 51$. Δw_i is a binary variable with $\Delta w_i = 1$ if $t_i(\beta) > co$, and zero otherwise. $co = 2$, and $t_i(\beta)$ is a standardized firm specific news loading, estimated on a classification sample prior to the strike period. The *Size* and *Power* columns report the fraction of test statistics with a p-value<0.05 in a simulation experiment on time periods without an actual strike. See the text for details. We compute all coefficient standard errors using heteroskedasticity-consistent standard errors (White (1980)). Robust t-statistics are in parentheses.

	I			**Size**	**Power**
Return	δ	τ	$R^2 adj$	τ	τ
$\Delta r^{c2o}_{i,d-ba}$	-0.0026*	-0.0027	0.0055	0.0000	0.3478
	(0.0014)	(0.0021)			
$\Delta r^{c2c}_{i,d-ba}$	-0.0033**	-0.0057**	0.0423	0.0870	0.5217
	(0.0013)	(0.0024)			

$t(\beta)$ is distributed across the 103 firms in the sample. Clearly, the t-statistic is large (and significant) on average. Still, many companies also have a negative exposure towards the news variable, although not significantly so. Second, given the distribution of $t(\beta)$, we define a cut-off co, and set $w_{i,d} = 1$ if $t_i(\beta) > co$ and $w_{i,d} = 0$ otherwise. Here, the natural cut-off is $co = 2$, i.e., approximately the 5 percent significance level, dividing the sample in roughly two equally sized groups. We show below, however, that our results are robust to a range of other plausible cut-off values (more or less significant).

Column I in Table 5 reports the results from estimating equation (3) using $w_{i,d}$ and two different dependent variables, $\Delta r^{c2o}_{i,d-ba}$ and $\Delta r^{c2c}_{i,d-ba}$. For close-to-open returns, we find no significant differences in means across the two groups of firms. For close-to-close returns however, there is a clear and significant difference. Firms where the news topic variables were important prior to the strike period experience 57 basis points lower returns during the media shortage relative to those firms where the news topic variables were not important.

It seems very unlikely that the patterns documented above are obtained by chance, reflect differences in trends, or are present regardless of the media shortage. We show this by sampling 23 non-overlapping periods of returns with $W = 51$, computing $\Delta r_{i,d-ba} = \hat{r}_{i,d} - \hat{r}_{i,ba}$ as if $r_{i,d}$ contained a strike event (while it in reality did not) , and redo regression (3) for each draw.[17] On average, when no actual strike is present, we are only able to reject

[17]The first period drawn starts in early 2000, and the last period drawn ends in late 2005. The window with the actual strike period in 2002 is excluded. Increasing the number of non-overlapping periods, by drawing non-overlapping periods from a larger time span, means that many firms that were included in the sample in 2002 will fall out (they are either not listed on the Oslo Stock Exchange, or delisted). In unreported results we show that the size and power statistics are robust to using a shorter window, i.e.,

the null-hypothesis of no significant effects at the 5 percent level in at most 8.7 percent of the cases (see column *Size* of Table 5). Conversely, if we impose the media effect estimated above on each of the $\hat{r}_{i,d}$ periods sampled, we see from the column labeled *Power* that we obtain a significant relationship in 52 percent of the cases ($c2c$), and a substantially lower number for the effect that was not significant in the first place ($c2o$). Naturally, if we increase the effect size imposed on the non-overlapping periods, the power increases, and vice versa (not shown). Moreover, qualitatively, non of the results reported in column I in Table 5 are affected by varying the cut-off value (co) between 1.6 to 3 (from weakly significant to highly significant) when constructing $w_{i,d}$, or by using a different window length to construct $\hat{r}_{i,ba}$ (see Tables 13 and 14, in Appendix A).

Together, these results provide strong evidence towards a causal (DN specific) news topic media effect. For close-to-close returns, the difference in mean between the synthetic control and treatment groups is even of the same magnitude as the total strike effect documented in Table 4, i.e., 60 basis points. To put these numbers into context, a conservative estimate implies that roughly 20 percent of the close-to-close returns predicted by news topics are due to the media effect alone, while a more positive estimate suggests as much as 37 percent.[18] Thus, seen through the lens of rational attention theories where investors face information processing costs, or have limited cognitive ability (Peng and Xiong (2006), Kacperczyk et al. (2009), and Schmidt (2013)), the media serves an important independent role in alleviating informational frictions.

4.2 Accounting for treatment intensity and asymmetries

A weakness with the approach just taken is that it does not account for the basic intuition that, all else equal, firms' news topic sensitivity might affect the intensity at which the media shortage affects returns. For example, firms with a particularly high (low) and (in)significant sensitivity to news prior to the strike period might also be more negatively (positively) affected than the other firms during the media shortage.

To investigate this hypothesis we extend the regression model in (2) by taking into account potential differences in how the media shortage affects returns within and between the treatment and control group. In particular, we consider the model:

$$\hat{r}_{i,e} = \alpha_i + \delta D_e + \tau^t \tilde{w}_{i,e} t_i(\beta)^t + \tau^c \tilde{w}_{i,e} t_i(\beta)^c + \tau \tilde{w}_{i,e} + \ b_2 t_i(\beta)^t + b_3 t_i(\beta)^c + u_{i,e} \qquad (5)$$

where α_i, δD_e, and $u_{i,e}$ have the same interpretations as before. Now, however, $\tilde{w}_{i,e}$ is a binary strike indicator, where $\tilde{w}_{i,e} = 1$ if $e = d$ and zero otherwise for all firms i. This

with $W = 31$ and a larger number of non-overlapping periods.

[18] According to the estimates in Table 5, the DN news topic effect is 57 basis point, while the maximum (minimum) predictive effect from the pooled time series regression reported earlier in Table 1 is 272 (153) basis points i.e., $57/272 = 0.21$ ($57/153 = 0.37$).

strike event indicator is then interacted with the terms $t_i(\beta)^t$ and $t_i(\beta)^c$. $t_i(\beta)^t = t_i(\beta)$ if $t_i(\beta) > co$ and 0 otherwise, and $t_i(\beta)^c = t_i(\beta)$ if $t_i(\beta) <= co$ and 0 otherwise. As such, in response to the media shortage, τ^t and τ^c capture the potential asymmetries between firms with a significant and non-significant sensitivity to the news topics. For estimation, we first difference (5), yielding the following model:

$$\Delta\hat{r}_{i,d-ba} = \tilde{\delta} + \tau^t t_i(\beta)^t + \tau^c t_i(\beta)^c + \Delta u_i \tag{6}$$

where $\tilde{\delta} = \delta + \tau$, and apply ordinary least squares.

Column I of Table 6 reports the regression output. Starting with the results in the $c2c$ row, we see that the $t_i(\beta)^t$ term is highly significant, and, based on the argument above, have the correct negative sign. On the other hand, close-to-close returns for firms in the control group are unaffected by the media shortage. As such, these results are consistent with the results presented in the previous section. Moreover, as the average t-statistic in Table 4 is well above 2, the effect of the media shortage, in percent of the total predictive effect, is in the same ballpark as previously reported, i.e., 20-40 percent. Interestingly, this pattern is reversed when we look at close-to-open returns, where only the $t_i(\beta)^c$ term is significant and positive. Thus, following the media shortage, firms in the treatment group experience an extra underreaction, while the firms in the control group experience an initial overreaction and subsequent intra-day reversal.

Size tests, conducted as described in the previous section, but now applied to the model in 6, show that these results are highly unlikely to occur in time periods without a strike, see the column labeled *Size* in Table 6. Therefore, and perhaps somewhat surprising, because intra-day reversal is not something we easily observe for firms in the control group in periods without a media shortage, the asymmetries documented in Table 6 suggest that the media shortage led to more noise trading. Or, in other words, that the media actually reduces noise (trading). However, as seen from Tables 13 and 14, in Appendix A, the significant overreaction obtained for the control group during the strike is fairly robust to the window size (W) used, but not robust to other cut-off values than 2. That is, for all cut-off values considered, the sign of the $t_i(\beta)^c$ coefficient is estimated to be positive, but only for $co = 2$ do we obtain a significant $t_i(\beta)^c$ coefficient for close-to-open returns.

In sum, the results presented here and in Section 4.1 give media an important causal role for understanding asset price fluctuations. Positive evidence of media's causal role in financial markets has also been documented in Engelberg and Parsons (2011), Dougal et al. (2012) and (not surprisingly) Peress (2014). Of the three, however, only the two latter analyses returns.[19] Still, our interpretation of the media effect differs somewhat

[19] Engelberg and Parsons (2011) analyses trading volumes, and show that trades by individual investors located in different locations respond to local newspaper coverage.

Table 6. Estimated media effects from $\Delta\hat{r}_{i,d-ba} = \tilde{\delta} + \tau^t t_i(\beta)^t + \tau^c t_i(\beta)^c + \Delta u_i$, where $\Delta r_{i,d-ba} = \hat{r}_{i,d} - \hat{r}_{i,ba}$, and $\hat{r}$ is the average return for company i, during the strike period ($\hat{r}_{i,d}$) and before and after ($\hat{r}_{i,ba}$), respectively. The total window length is $W = 51$. $t_i(\beta)$ is a standardized firm specific news loading, estimated on a classification sample prior to the strike period. $t_i(\beta)^t = t_i(\beta)$ if $t_i(\beta) > co$ and 0 otherwise. $t_i(\beta)^c = t_i(\beta)$ if $t_i(\beta) <= co$ and 0 otherwise. In both cases $co = 2$. The *Size* and *Power* columns report the fraction of test statistics with a p-value<0.05 in a simulation experiment on time periods without an actual strike. See the text for details. We compute all coefficient standard errors using heteroskedasticity-consistent standard errors (White (1980)). Robust t-statistics are in parentheses.

	I				**Size**		**Power**	
Return	$\tilde{\delta}$	τ^t	τ^c	R^2adj	τ^t	τ^c	τ^t	τ^c
$\Delta r^{c2o}_{i,d-ba}$	-0.0041**	-0.0004	0.0028*	0.0372	0.1304	0.0435	0.1304	0.4348
	(0.0018)	(0.0005)	(0.0017)					
$\Delta r^{c2c}_{i,d-ba}$	-0.0026	-0.0018***	-0.0003	0.0752	0.435	0.0435	0.5652	0.0435
	(0.0022)	(0.0006)	(0.0020)					

from what is provided in these studies. In particular, Dougal et al. (2012) use exogenous variation in the identity of *Wall Street Journal* columnists, and show that this is a good predictor of the next-day return on the Dow Jones Industrial Average. While they appeal to a sentiment story whereby the bullish or bearish sentiment conveyed by columnists influence investors, we provide evidence more in line with an informational dissemination explanation where the media is an important channel for broadcasting fundamental information. This interpretation is also closer to the one given in Peress (2014), who demonstrates that media strikes affect stocks' trading intensity, dispersion, intraday volatility, and autocorrelation. When newspaper strikes are (plausibly) interpreted as events that raise the cost of receiving news, his analysis suggests that constrained investors continue to learn about shocks common to many stocks but choose to ignore firm-specific shocks. Our findings, however, suggest that investors also look for other opportunities when a primary media channel becomes unavailable, thus taking aboard the cost of seeking additional and new information.[20] There are clear patterns in the data, although not statistically strong, suggesting that such strike induced behavior result in more noise trading.

[20]Informal evidence supports such an interpretation. During the Norwegian media strike in 2002, a then small alternative business newspaper (Finansavisen), did not go on strike, and experienced a substantial increase in readers buying their newspaper. In fact, the loss in market shares experienced by DN in 2002 was one of the reasons the editors of DN continued to publish the newspaper even though their journalists went on strike also in 2004.

5 Conclusion

News in the business newspaper predicts daily returns, and the media has an important causal role in this predictive relationship. We reach these conclusions after decomposing the corpus in the main Norwegian business newspaper into daily news topics and linking them to firms and returns.

Although the news topics are available in the morning, well before the market opens, we document significant underreaction in market prices to news and clear patterns of continuation in the days following the initial news release. These results hold both in pooled time series regression, simple zero-cost news-based trading strategies, and are robust when controlling for numerous commonly used predictors. Interestingly, however, the degree of predictability and persistence weakens over time, and towards the latter parts of the sample a broader news corpus, including online media, is needed to achieve significant continuation patterns.

Further, by exploiting an exogenous strike in the Norwegian newspaper market, in 2002, we are able to isolate the media component of the news signal from the new information component. Returns for individual firms with a significant exposure to our news measures fall by 57 basis points during the strike period relative to firms with an insignificant news topic exposure. Since the average firm in the sample has a positive exposure to news, our results imply that the media component of the news signal accounts for between 20 to 40 percent of the documented overall predictive effect of news topics.

In sum, our analysis support a rational attention view where the media alleviate information frictions and disseminate information to a large population of investors. In that respect it is interesting to note that when using the same news topics as here, we find that news topics also predicts quarterly productivity, consumption, and aggregate stock market developments (Larsen and Thorsrud (2015)). Thus, decomposing news published through a business newspaper into news topics puts unstructured textual data into a format that seems fundamental for both macroeconomic developments and asset prices.

Although the methodology used to reach these conclusions is general, the empirical findings are restricted to the Norwegian market. Exciting avenues for future research includes expanding the scope of the analysis to more countries and larger markets, and to investigate in greater detail how market responses to online versus printed news might differ.

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Appendices

Appendix A Additional results

Table 7. Estimated topics and labeling. The topics are labeled based on the meaning of the most important words, while the words are translated from Norwegian to English using Google Translate. See the text for details.

Topic	Label	First words
Topic 0	Calendar	january, march, october, september, november, february
Topic 1	Family business	family, foundation, name, dad, son, fortune, brothers
Topic 2	Institutional investing	fund, investments, investor, return, risk, capital
Topic 3	Justice	lawyer, judge, appeal, damages, claim, supreme court
Topic 4	Surroundings	city, water, meter, man, mountain, old, outside, nature
Topic 5	Housing	housing, property, properties, apartment, square meter
Topic 6	Movies/Theater	movie, cinema, series, game, producer, prize, audience
Topic 7	Argumentation	word, besides, interesting, i.e., in fact, sure, otherwise
Topic 8	Unknown	road, top, easy, hard, lift, faith, outside, struggle,fast
Topic 9	Agriculture	industry, support, farmers, export, production, agriculture
Topic 10	Automobiles	car, model, engine, drive, volvo, ford, møller, toyota
Topic 11	USA	new york, dollar, wall street, president, usa, obama, bush
Topic 12	Banking	dnb nor, savings bank, loss, brokerage firm, kreditkassen
Topic 13	Leadership	position, chairman, ceo, president, elected, board member
Topic 14	Negotiation	solution, negotiation, agreement, alternative, part, process
Topic 15	Newspapers	newspaper, media, schibsted, dagbladet, journalist, vg
Topic 16	Health care	hospital, doctor, health, patient, treatment, medication
Topic 17	IT systems	it, system, data, defense, siem, contract, tandberg, deliver
Topic 18	Stock market	stock exchange, fell, increased, quote, stock market
Topic 19	Macroeconomics	economy, budget, low, unemployment, high, increase
Topic 20	Oil production	statoil, oil, field, gas, oil company, hydro, shelf, stavanger
Topic 21	Wage payments	income, circa, cost, earn, yearly, cover, paid, salary
Topic 22	Regions	trondheim, llc, north, stavanger, tromsø, local, municipality
Topic 23	Family	woman, child, people, young, man, parents, home, family
Topic 24	Taxation	tax, charge, revenue, proposal, remove, wealth tax, scheme
Topic 25	EU	eu, eea, commission, european, brussel, membership, no
Topic 26	Industry	hydro, forest, factory, production, elkem, industry, produce
Topic 27	Unknown	man, he, friend, smile, clock, evening, head, never, office
Topic 28	Mergers and acquisitions	orkla, storebrand, merger, bid, shareholder, acquisitions
Topic 29	UK	british, london, great britain, the, of, pound, england
Topic 30	Narrative	took, did, later, never, gave, stand, happened, him, began

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Table 7 – continued from previous page

Topic	Label	First words
Topic 31	Shipping	ship, shipping, dollar, shipowner, wilhelmsen, fleet, proud
Topic 32	Projects	project, nsb, development, fornebu, entrepreneurship
Topic 33	Oil price	dollar, oil price, barrel, oil, demand, level, opec, high
Topic 34	Sports	olympics, club, football, match, play, lillehammer, sponsor
Topic 35	Organizations	leader, create, organization, challenge, contribute, expertise
Topic 36	Drinks	wine, italy, taste, drinks, italian, fresh, fruit, beer, bottle
Topic 37	Nordic countries	swedish, sweden, danish, denmark, nordic, stockholm
Topic 38	Airline industry	sas, fly, airline, norwegian, braathens, airport, travel
Topic 39	Entitlements	municipality, public, private, sector, pension, scheme
Topic 40	Employment	cut, workplace, measures, salary, labor, working, employ
Topic 41	Politics	conservatives, party, ap, labor party, stoltenberg, frp
Topic 42	Funding	loan, competition, creditor, loss, bankruptcy, leverage
Topic 43	Literature	book, books, read, publisher, read, author, novel, wrote
Topic 44	Statistics	count, increase, investigate, share, average, decrease
Topic 45	Watercraft	ship, boat, harbor, strait, shipowner, on board, color
Topic 46	Results	quarter, surplus, deficit, tax, group, operating profit, third
Topic 47	TV	tv, nrk, channel, radio, digital, program, media
Topic 48	International conflicts	war, africa, irak, south, un, army, conflict, troops, attack
Topic 49	Elections	election, party, power, politics, vote, politician, support
Topic 50	Music	the, music, record, of, in, artist, and, play, cd, band, song
Topic 51	Oil service	rig, dollar, contract, option, offshore, drilling, seadrill
Topic 52	Tourism	hotel, room, travel, visit, stordalen, tourist, guest Â
Topic 53	Unknown	no, thing, think, good, always, pretty, actually, never
Topic 54	Engineering	aker, kværner, røkke, contract, shipyard, maritime
Topic 55	Fishery	fish, salmon, seafood, norway, tons, nourishment, marine
Topic 56	Europe	german, russia, germany, russian, west, east, french, france
Topic 57	Law and order	police, finance guards, aiming, illegal, investigation
Topic 58	Weekdays	week, financial, previous, friday, wednesday, tdn, monday
Topic 59	Supervision	report, information, financial supervision, enlightenment
Topic 60	Retail	shop, brand, steen, rema, reitan, as, group, ica, coop
Topic 61	Startups	bet, cooperation, establish, product, party, group
Topic 62	Food	food, restaurant, salt, nok, pepper, eat, table, waiter
Topic 63	Stock listings	shareholder, issue, investor, holding, stock exchange listing
Topic 64	Asia	china, asia, chinese, india, hong kong, south, authorities
Topic 65	Art	picture, art, exhibition, gallery, artist, museum, munch
Topic 66	Disagreement	criticism, express, asserting, fault, react, should, alleging
Topic 67	Debate	degree, debate, context, unequal, actually, analysis
Topic 68	Life	man, history, dead, him, one, live, church, words, strokes
Topic 69	Goods and services	customer, post, product, offers, service, industry, firm
Topic 70	Telecommunication	telenor, mobile, netcom, hermansen, telia, nokia, ericsson

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Table 7 – continued from previous page

Topic	Label	First words
Topic 71	IT technology	internet, net, pc, microsoft, technology, services, apple
Topic 72	Monetary policy	interest rate, central bank, euro, german, inflation, point
Topic 73	Education	school, university, student, research, professor, education
Topic 74	Regulations	rules, authorities, competition, regulations, bans
Topic 75	Trade organizations	lo, nho, members, forbund, strike, organization, payroll
Topic 76	Fear	fear, emergency, hit, severe, financial crisis, scared
Topic 77	Fiscal policy	suggestions, parliamentary, ministry, selection, minister
Topic 78	Energy	energy, emissions, statkraft, industry, environment
Topic 79	Foreign	foreign, abroad, japan, japanese, immigration, games

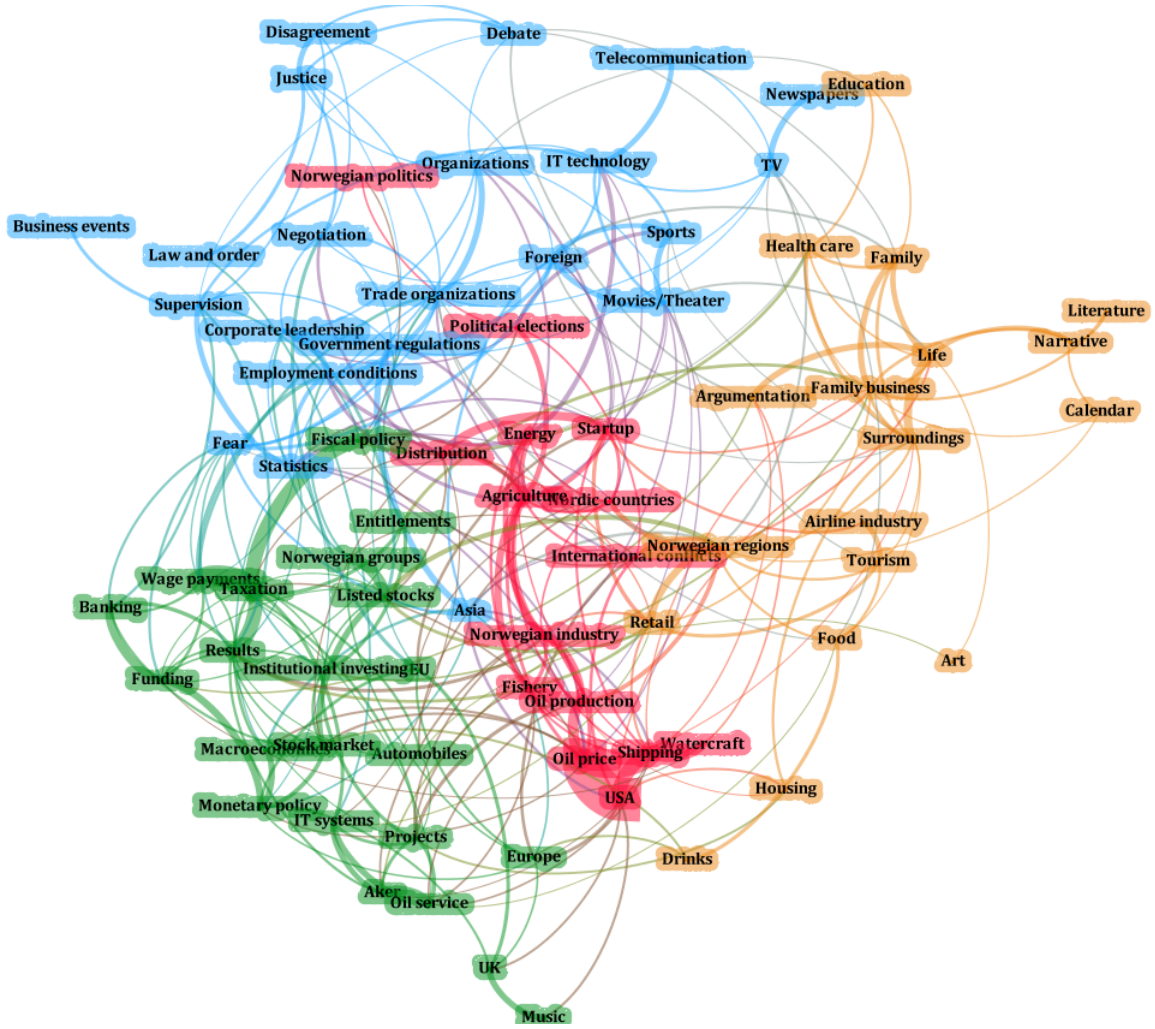


Figure 4. A Network representation of the estimated news topics. The nodes in the graph represent the identified topics. All the edges represent words that are common to the topics they connect. The thickness of the edges represents the importance of the word that connect the topics, calculated as edge weight = 1/ (ranking of word in second topic + ranking of word in first topic). The topics with the same color are clustered together using a community detection algorithm called Louvain modularity. Topics for which labeling is *Unknown*, confer Table 7, are removed from the graph in the interest of visual clarity.

Table 8. Descriptive statistics. The *Topic name* column reports the topic name and numeric identifier used to relate the firm(s) in column 2 to a specific news topic. The *Number of* column reports both number of firms associated with a news topic and the total number of observations (time plus cross section) for this mapping. Likewise, the *Mean* and *Std.* columns report the mean and standard deviation of close-to-open returns across time and firms. *Size* is measured as market value relative to the (column) total. *BM* is the average book-to-market value for firms within each topic identifier. The sample contains a total of 540708 observations for 233 firms associated with 33 distinct news topics.

Topic name	**Number of**		**Mean**	**Std.**	**Size**	**BM**
	Firms	**Obs.**				
Drinks (36)	1	461	-1.34	6.80	0.67	2.45
Wage payments/Bonuses (21)	2	3184	-0.42	5.04	1.41	3.53
USA (11)	2	4865	-0.39	4.18	0.88	3.37
Asia (64)	1	1096	-0.34	2.80	0.43	0.82
Law and order (57)	1	1953	-0.31	4.67	0.25	1.58
Automobiles (10)	2	2720	-0.22	3.25	0.69	1.91
Oil service (51)	32	59979	-0.20	3.61	3.25	2.08
Airline industry (38)	1	2710	-0.17	2.88	1.53	2.98
Corporate leadership (13)	2	4064	-0.15	4.48	0.51	3.79
Institutional investing (2)	1	3311	-0.14	3.98	0.87	4.11
Watercraft (45)	2	7560	-0.13	4.65	0.30	1.91
Nordic countries (37)	3	10023	-0.10	2.80	1.78	2.32
Norwegian industry (26)	13	32016	-0.08	2.96	11.12	2.14
Fishery (55)	16	30231	-0.07	3.58	1.87	1.40
Oil production (20)	16	38862	-0.06	3.62	15.92	2.70
Health care (16)	10	23849	-0.05	4.01	0.45	5.48
Aker (54)	9	21074	-0.03	3.15	3.81	1.96
Shipping (31)	34	74716	0.00	3.10	1.46	1.34
Listed stocks (63)	7	20328	0.01	3.34	1.66	1.61
Norwegian groups (28)	4	8668	0.01	2.36	6.24	1.54
Housing (5)	5	8894	0.03	2.49	1.69	1.23
Banking (12)	8	32174	0.03	1.78	5.85	1.19
IT technology (71)	14	27514	0.04	4.00	0.63	19.78
Norwegian regions (22)	3	13821	0.04	1.29	0.38	0.97
TV (47)	5	13474	0.04	2.69	16.03	4.11
Projects (32)	3	4836	0.05	3.57	2.23	2.99
Retail (60)	4	9466	0.05	2.06	10.63	1.83
Telecommunication (70)	5	5865	0.06	2.98	0.65	11.64
IT systems (17)	19	46580	0.08	3.61	0.64	2.66
Energy (78)	3	14085	0.11	3.00	1.65	1.67
Funding (42)	3	9796	0.12	1.84	2.03	2.51
Unknown (8)	1	2184	0.15	2.79	0.10	1.55
Entitlements (39)	1	349	0.25	1.57	2.44	3.72

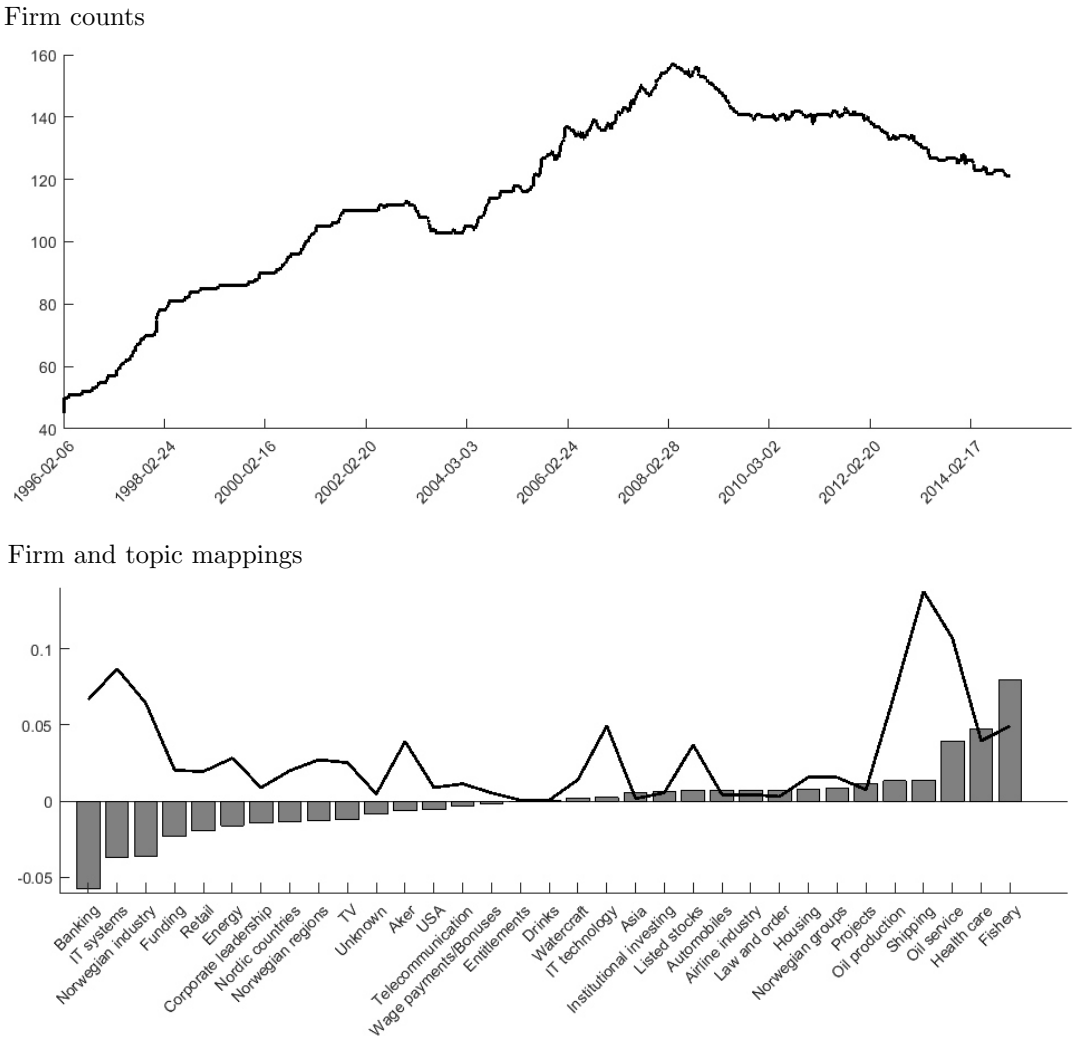


Figure 5. The upper graph reports the number of unique firms in the dataset at each point in time. The line in the lower graph reports how many firms (in percent) each topic is associated with on average across time. The bars report the change (in percentage point) in how many firms each topic is associated with when splitting the sample into two equally sized parts and computing the difference (second sample - first sample).

Table 9. News topics and day t close-to-open (c2o) and close-to-close returns (c2c) with random topic assignments (Panel A) and day and industry effects (Panel B). The second row refers to the model specification, i.e., which control variables that are included in the regressions apart from the variables listed, confer the descriptions and headers used in Table 1. Fixed effects are included as specified in the table. Following Tetlock et al. (2008), we compute clustered standard errors by trading day. Robust t-statistics are in parentheses.

	c2o			**c2c**		
	I	**II**	**III**	**I**	**II**	**III**
Panel A						
$Topic_t^R$	0.0008	0.0018	0.0000	0.0000	0.0060	0.0101*
	(0.0021)	(0.0029)	(0.0033)	(0.0029)	(0.0047)	(0.0056)
R^2	0.0087	0.0297	0.0301	0.0054	0.0126	0.0127
Obs.	540708	540708	391533	540708	540708	391533
α_i	yes	yes	yes	yes	yes	yes
δ_t	yes	no	no	yes	no	no
Panel B						
$Topic_t$	0.0153***	0.0134***	0.0090**	0.0285***	0.0267***	0.0205***
	(0.0036)	(0.0031)	(0.0037)	(0.0053)	(0.0051)	(0.0062)
R^2	0.0063	0.0304	0.0310	0.0037	0.0130	0.0129
Obs.	540708	540708	391533	540708	540708	391533
α_i	yes	yes	yes	yes	yes	yes
δ_t	no	no	no	no	no	no
$Weekday_t$	yes	yes	yes	yes	yes	yes
$Industry_g$	yes	yes	yes	yes	yes	yes

Table 10. Firm specific news topics and day t close-to-open (c2o) and close-to-close returns (c2c) controlling for interaction terms. All regressions include control variables for the firm's lagged close-to-close return (R_{t-p}), for $p = 1, \ldots, 14$. Control variables listed in the table include: the book-to-market value (B/M_{t-1}) the book-to-market value interacted with the news topic ($B/M_{t-1} : Topic_t$) the market value (MV_{t-1}), the market value interacted with the news topic ($MV_{t-1} : Topic_t$), the turnover ($Turn_{t-1}$), and finally the turnover interacted with the news topic ($Turn_{t-1} : Topic_t$). Fixed effects are included as specified in the table. If fixed effects are not included, the set of controls also includes: close-to-close return on the S&P500 (R^{mi}_{t-1}), close-to-close returns on the OSEBX (R^{mh}_{t-1}), and the daily change in the oil price (R^{oil}_{t-1}). Following Tetlock et al. (2008), we compute clustered standard errors by trading day. Robust t-statistics are in parentheses.

	c2o			**c2c**		
	I	**II**	**III**	**I**	**II**	**III**
$Topic_t$	0.0131***	0.0106***	0.0073***	0.0284***	0.0164***	0.0098**
	(0.0033)	(0.0024)	(0.0028)	(0.0053)	(0.0033)	(0.0038)
B/M_{t-1}	-0.0007***	-0.0005***	-0.0006***	-0.0008***	-0.0009***	-0.0009***
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0002)
$B/M_{t-1} : Topic_t$	0.0038	0.0011	-0.0024	-0.0084	-0.0047	-0.0059
	(0.0051)	(0.0047)	(0.0063)	(0.0077)	(0.0066)	(0.0090)
MV_{t-1}	0.0002*	0.0002***	0.0004***	-0.0003**	-0.0001	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$MV_{t-1} : Topic_t$	0.0012	0.0022	0.0076	-0.0076	-0.0042	-0.0028
	(0.0044)	(0.0040)	(0.0062)	(0.0061)	(0.0054)	(0.0076)
$Turn_{t-1}$			0.0106***			0.0060***
			(0.0019)			(0.0019)
$Turn_{t-1} : Topic_t$			0.1323			0.1073
			(0.1102)			(0.1057)
R^2	0.0298	0.0089	0.0103	0.0128	0.0057	0.0063
Obs.	540708	540708	391533	540708	540708	391533
α_i	yes	yes	yes	yes	yes	yes
δ_t	no	yes	yes	no	yes	yes

Table 11. Firm specific news topics and day t open-to-close (o2c) returns. In total seven regressions are reported. The key independent variable is $Topic_t$. All regressions include control variables for the firm's lagged close-to-close return (R_{t-p}), for $p = 1, \ldots, 14$. Control variables listed in the table include: close-to-close return on the S&P500 (R^{mi}_{t-1}), close-to-close returns on the OSEBX (R^{mh}_{t-1}), the daily change in the oil price (R^{oil}_{t-1}), the book-to-market value (B/M_{t-1}) the market value (MV_{t-1}), and finally the turnover ($Turn_{t-1}$). All regressions are estimated by OLS. Fixed effects are included as specified in the table. Following Tetlock et al. (2008), we compute clustered standard errors by trading day. Robust t-statistics are in parentheses.

	I	**II**	**III**	**IV**	**V**	**VI**	**VII**
$Topic_t$	0.0046*	0.0140***	0.0135***	0.0135***	0.0137***	0.0138***	0.0119**
	(0.0026)	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0049)
R^{mi}_{t-1}		-0.0552***	-0.0627***	-0.0636***	-0.0637***	-0.0637***	-0.0635**
		(0.0199)	(0.0214)	(0.0212)	(0.0213)	(0.0213)	(0.0283)
R^{mh}_{t-1}			0.0149	0.0111	0.0110	0.0109	0.0157
			(0.0160)	(0.0163)	(0.0163)	(0.0163)	(0.0205)
R^{oil}_{t-1}				0.0092	0.0093	0.0093	0.0065
				(0.0085)	(0.0084)	(0.0084)	(0.0118)
B/M_{t-1}					-0.0004***	-0.0001	-0.0000
					(0.0002)	(0.0001)	(0.0002)
MV_{t-1}						-0.0005***	-0.0005***
						(0.0001)	(0.0002)
$Turn_{t-1}$							-0.0039**
							(0.0016)
R^2	0.0004	0.0012	0.0012	0.0012	0.0013	0.0014	0.0015
Obs.	540708	540708	540708	540708	540708	540708	391533
α_i	yes	yes	yes	yes	yes	yes	yes
δ_t	yes	no	no	no	no	no	no

Table 12. Annualized yearly mean returns (Mean) and Sharp Ratios (SR) for zero-cost news-based investment strategies. Either *DN*, or *Multiple news sources* are used to derive the news signal. For the period 1997 - 2007, the two are equal. Given the news source, in the columns labeled *I*, all news signals are potentially traded on. In the columns labeled *II*, only news signals over or above one standard deviation is traded on. The three last rows report the average statistic across the whole sample as well as the average daily number of long and short positions implied by the strategies.

	DN				**Multiple news sources**			
	I		**II**		**I**		**II**	
	Mean	**SR**	**Mean**	**SR**	**Mean**	**SR**	**Mean**	**SR**
1997	-0.0041	-0.0281	-0.2093	-1.5361				
1998	0.2201	1.2821	-0.0402	-0.2058				
1999	0.1217	0.6976	0.4085	2.1186				
2000	0.1757	0.7391	0.1563	0.5490				
2001	0.5761	2.5282	0.6931	3.2523				
2002	0.3772	1.5547	0.3442	1.3928				
2003	0.0082	0.0409	-0.0740	-0.3787				
2004	0.0533	0.3267	-0.0942	-0.5578				
2005	0.1674	1.3010	0.0605	0.4327				
2006	-0.0612	-0.3790	-0.0214	-0.1484				
2007	-0.0748	-0.6244	0.1741	1.3045				
2008	0.7301	2.5021	-0.0483	-0.1770	1.2581	4.2631	0.6530	2.5132
2009	-0.0023	-0.0120	0.4894	2.4840	0.1985	0.9640	-0.2322	-1.0380
2010	0.0088	0.0495	-0.0585	-0.3351	0.3241	1.8168	0.1866	0.9442
2011	-0.0397	-0.1933	-0.0130	-0.0614	0.4055	2.0592	0.4488	1.9659
2012	0.1501	0.9627	0.3812	2.0636	0.3283	2.0459	0.2130	1.0762
2013	0.3068	2.1912	0.0581	0.3726	0.2389	1.6977	0.1610	1.2627
2014	0.2515	1.8978	-0.1360	-0.8909	0.2846	2.2381	0.0523	0.3035
Whole sample	0.1680	0.8902	0.1174	0.5986	0.2914	1.5571	0.2138	1.0816
N longs	46.30		13.98		47.00		15.26	
N shorts	68.70		10.27		69.36		10.14	

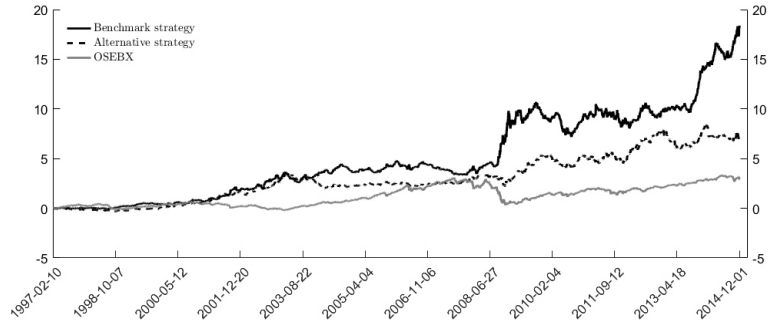
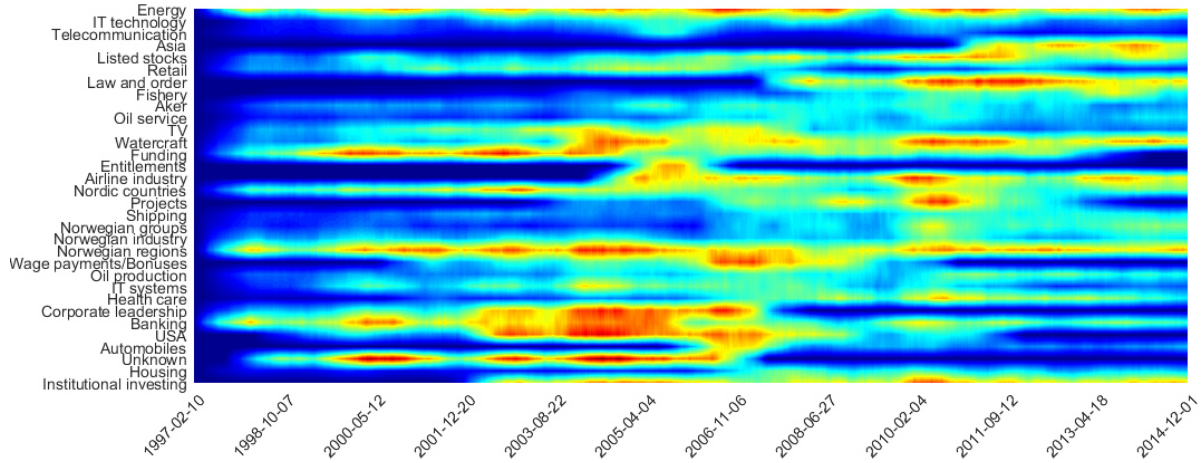


Figure 6. Cumulative returns. The benchmark strategy implements the trading strategy whenever the news signal is different from zero. The alternative strategy implements the trading strategy whenever the news signal is above (below) one standard deviation. OSEBX is the Oslo Stock Exchange benchmark index.

Long positions



Short positions

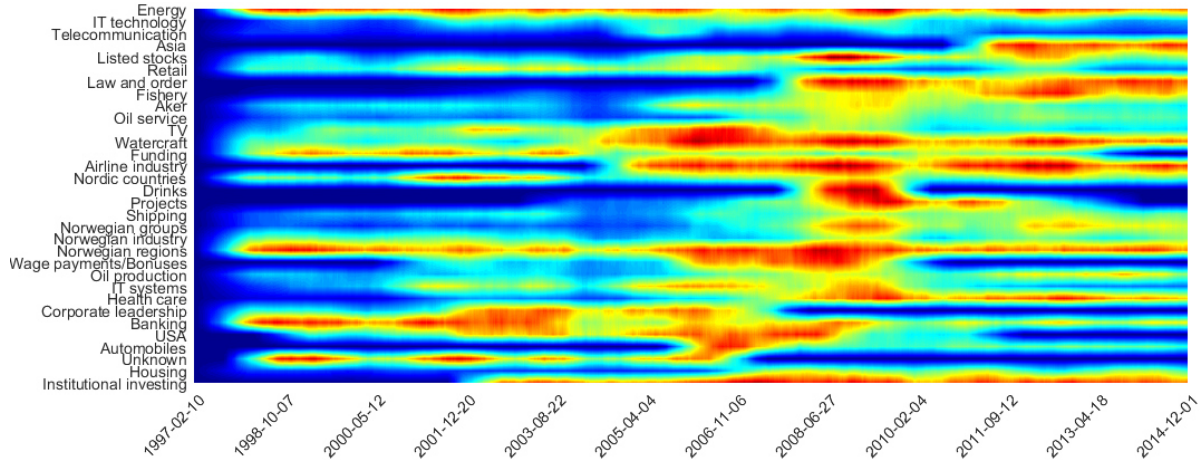


Figure 7. The figure illustrates the news topics that drive the trading activity for the long and short positions of the benchmark strategy. Colors towards the red (blue) end of the color spectrum indicates many (few) trades. More trades will naturally be conducted on the basis of news topics associated with many firms (confer Table 8). Therefore, for each day, the number of trades associated with a given news topic is normalized by the share of firms associated with this topic. In the interest of visual clarity, the resulting numbers are smoothed by a 252-day (backward-looking) moving average filter.

Table 13. Estimated media effects from $\Delta r_{i,d-ba} = \delta + \tau \Delta w_i + \Delta u_i$ (column I) and $\Delta \hat{r}_{i,d-ba} = \tilde{\delta} + \tau^t t_i(\beta)^t + \tau^c t_i(\beta)^c + \Delta u_i$ (column II) for different cut-off values. $\Delta r_{i,d-ba} = \hat{r}_{i,d} - \hat{r}_{i,ba}$, where $\hat{r}$ is the average return for company i, during the strike period ($\hat{r}_{i,d}$) and before and after ($\hat{r}_{i,ba}$), respectively. The total number of firms is 103, and the window length is $W = 51$. In column I, Δw_i is a binary variable with $\Delta w_i = 1$ if $t_i(\beta) > co$, and zero otherwise. Four different values for co are used, as indicated by the first column (together with the number of firms counted below the cut-off). $t_i(\beta)$ is a standardized firm specific news loading, estimated on a classification sample prior to the strike period. In column II $t_i(\beta)^t = t_i(\beta)$ if $t_i(\beta) > co$ and 0 otherwise. Conversely $t_i(\beta)^c = t_i(\beta)$ if $t_i(\beta) <= co$ and 0 otherwise. In Panel A (Panel B) of the table the dependent variable is close-to-open returns (close-to-close). We compute all coefficient standard errors using heteroskedasticity-consistent standard errors (White (1980)). Robust t-statistics are in parentheses.

	I			**II**				
Cut-off/#	δ	τ	R^2adj	$\tilde{\delta}$	τ^t	τ^c	Fstat	R^2adj
Panel A: $\Delta r^{c2o}_{i,d-ba}$								
1.6/38	-0.0034**	-0.0008	-0.0085	-0.0033*	-0.0005	0.0031	0.09	0.0160
	(0.0015)	(0.0021)		(0.0017)	(0.0005)	(0.0024)		
2.0/50	-0.0026*	-0.0027	0.0055	-0.0041**	-0.0004	0.0028*	0.04	0.0372
	(0.0014)	(0.0021)		(0.0018)	(0.0005)	(0.0017)		
2.6/59	-0.0027*	-0.0030	0.0089	-0.0042**	-0.0004	0.0018	0.13	0.0245
	(0.0014)	(0.0021)		(0.0018)	(0.0005)	(0.0016)		
3.0/72	-0.0031**	-0.0026	0.0024	-0.0037*	-0.0005	0.0006	0.28	0.0028
	(0.0013)	(0.0023)		(0.0019)	(0.0005)	(0.0012)		
Panel B: $\Delta r^{c2c}_{i,d-ba}$								
1.6/38	-0.0027*	-0.0054**	0.0350	-0.0024	-0.0018***	0.0012	0.09	0.0815
	(0.0016)	(0.0023)		(0.0019)	(0.0006)	(0.0029)		
2.0/50	-0.0033**	-0.0057**	0.0423	-0.0026	-0.0018***	-0.0003	0.04	0.0752
	(0.0013)	(0.0024)		(0.0022)	(0.0006)	(0.0020)		
2.6/59	-0.0028*	-0.0079***	0.0882	-0.0034	-0.0018***	0.0005	0.13	0.0944
	(0.0014)	(0.0024)		(0.0021)	(0.0006)	(0.0019)		
3.0/72	-0.0034***	-0.0091***	0.1036	-0.0034	-0.0019***	-0.0002	0.28	0.0912
	(0.0013)	(0.0028)		(0.0021)	(0.0006)	(0.0013)		

Table 14. Estimated media effects from $\Delta r_{i,d-ba} = \delta + \tau \Delta w_i + \Delta u_i$ (column I) and $\Delta \hat{r}_{i,d-ba} = \tilde{\delta} + \tau^t t_i(\beta)^t + \tau^c t_i(\beta)^c + \Delta u_i$ (column II) for different window sizes. $\Delta r_{i,d-ba} = \hat{r}_{i,d} - \hat{r}_{i,ba}$, where $\hat{r}$ is the average return for company i, during the strike period ($\hat{r}_{i,d}$) and before and after ($\hat{r}_{i,ba}$), respectively. The total number of firms is 103. The length of the strike period ($\hat{r}_{i,d}$) is constant and equal to seven business days. The length of the window used to estimate $\hat{r}_{i,ba}$ is indicated by the first column of the table. In column I, Δw_i is a binary variable with $\Delta w_i = 1$ if $t_i(\beta) > co$, and zero otherwise. $t_i(\beta)$ is a standardized firm specific news loading, estimated on a classification sample prior to the strike period, and $co = 2$. In column II $t_i(\beta)^t = t_i(\beta)$ if $t_i(\beta) > co$ and 0 otherwise. Conversely $t_i(\beta)^c = t_i(\beta)$ if $t_i(\beta) <= co$ and 0 otherwise. In Panel A (Panel B) of the table the dependent variable is close-to-open returns (close-to-close). We compute all coefficient standard errors using heteroskedasticity-consistent standard errors (White (1980)). Robust t-statistics are in parentheses.

	I			**II**				
Window	c	Δw_i	R^2adj	c	$t_i(\beta)^t$	$t_i(\beta)^c$	Fstat	R^2adj
Panel A: $\Delta r^{c2o}_{i,d-ba}$								
151	-0.0034**	-0.0024	0.0056	-0.0047***	-0.0004	0.0025*	0.04	0.0416
	(0.0014)	(0.0019)		(0.0016)	(0.0004)	(0.0015)		
131	-0.0034**	-0.0025	0.0060	-0.0047***	-0.0004	0.0026*	0.03	0.0426
	(0.0014)	(0.0019)		(0.0016)	(0.0004)	(0.0015)		
111	-0.0032**	-0.0022	0.0029	-0.0045***	-0.0004	0.0026*	0.04	0.0410
	(0.0013)	(0.0020)		(0.0015)	(0.0004)	(0.0015)		
91	-0.0031**	-0.0019	-0.0008	-0.0042**	-0.0004	0.0022	0.08	0.0240
	(0.0013)	(0.0020)		(0.0016)	(0.0004)	(0.0015)		
71	-0.0027**	-0.0021	0.0011	-0.0041**	-0.0003	0.0027*	0.03	0.0388
	(0.0013)	(0.0020)		(0.0017)	(0.0005)	(0.0015)		
51	-0.0026*	-0.0027	0.0055	-0.0041**	-0.0004	0.0028*	0.04	0.0372
	(0.0014)	(0.0021)		(0.0018)	(0.0005)	(0.0017)		
31	-0.0019	-0.0032	0.0076	-0.0041**	-0.0004	0.0036*	0.05	0.0451
	(0.0017)	(0.0024)		(0.0019)	(0.0005)	(0.0021)		
Panel B: $\Delta r^{c2c}_{i,d-ba}$								
151	-0.0038***	-0.0050**	0.0325	-0.0029	-0.0017***	-0.0004	0.00	0.0664
	(0.0013)	(0.0023)		(0.0020)	(0.0006)	(0.0019)		
131	-0.0037***	-0.0049**	0.0326	-0.0028	-0.0017***	-0.0004	0.00	0.0665
	(0.0013)	(0.0023)		(0.0020)	(0.0006)	(0.0019)		
111	-0.0035***	-0.0043*	0.0216	-0.0025	-0.0016***	-0.0005	0.01	0.0550
	(0.0013)	(0.0023)		(0.0021)	(0.0006)	(0.0020)		
91	-0.0036***	-0.0042*	0.0194	-0.0026	-0.0015**	-0.0005	0.01	0.0499
	(0.0013)	(0.0024)		(0.0021)	(0.0006)	(0.0019)		
71	-0.0032**	-0.0048**	0.0295	-0.0026	-0.0016***	-0.0001	0.00	0.0597
	(0.0013)	(0.0024)		(0.0022)	(0.0006)	(0.0020)		
51	-0.0033**	-0.0057**	0.0423	-0.0026	-0.0018***	-0.0003	0.00	0.0752
	(0.0013)	(0.0024)		(0.0022)	(0.0006)	(0.0020)		
31	-0.0013	-0.0041*	0.0177	-0.0010	-0.0013**	0.0004	0.01	0.0346
	(0.0014)	(0.0024)		(0.0023)	(0.0006)	(0.0020)		

Appendix B The textual data and the LDA

B.1 Filtering the news corpus

To clean the raw textual dataset a stop-word list is first employed. This is a list of common words not expected to have any information relating to the subject of an article. Examples of such words are *the*, *is*, *are*, and *this*. The most common Norwegian surnames and given names are also removed. In total the stop-word list together with the list of common surnames and given names removed roughly 1800 unique tokens from the corpus. Next, an algorithm known as stemming is run. The objective of this algorithm is to reduce all words to their respective word stems. A word stem is the part of a word that is common to all of its inflections. An example is the word *effective* whose stem is *effect*. Finally, a measure called *tf-idf*, which stands for term frequency - inverse document frequency, is calculated. This measures how important all the words in the complete corpus are in explaining single articles. The more often a word occurs in an article, the higher the *tf-idf* score of that word. On the other hand, if the word is common to all articles, meaning the word has a high frequency in the whole corpus, the lower that word's *tf-idf* score will be. Around 250 000 of the stems with the highest *tf-idf* score are kept, and used as the final corpus.

B.2 LDA intuition, estimation and specification

The LDA model was developed in Blei et al. (2003). Here the estimation algorithm described in Griffiths and Steyvers (2004) is implemented.

Figure 8 illustrates the LDA model graphically. The outer box, or plate, represent the whole corpus as M distinct documents (articles). $N = \sum_{m=1}^{M} N_m$ is the total number of words in all documents, and K is the total number of latent topics. Letting bold-font variables denote the vector version of the variables, the distribution of topics for a document is given by $\boldsymbol{\theta}_m$, while the distribution of words for each topic is determined by $\boldsymbol{\varphi}_k$. Both $\boldsymbol{\theta}_m$ and $\boldsymbol{\varphi}_k$ are assumed to have conjugate Dirichlet distributions with (hyper) parameter (vectors) α and β, respectively. Each document consists of a repeated choice of topics $Z_{m,n}$ and words $W_{m,n}$, drawn from the Multinomial distribution using $\boldsymbol{\theta}_m$ and $\boldsymbol{\varphi}_k$. The circle associated with $W_{m,n}$ is gray colored, indicating that these are the only observable variables in the model.

At an intuitive level, the best way to understand the LDA model is likely to make a thought experiment of how the articles in the newspaper (the corpus) were generated.

1. Pick the overall theme of articles by randomly giving them a distribution over topics, i.e.: Choose $\boldsymbol{\theta}_m \sim \text{Dir}(\alpha)$, where $m \in \{1, \ldots, M\}$.

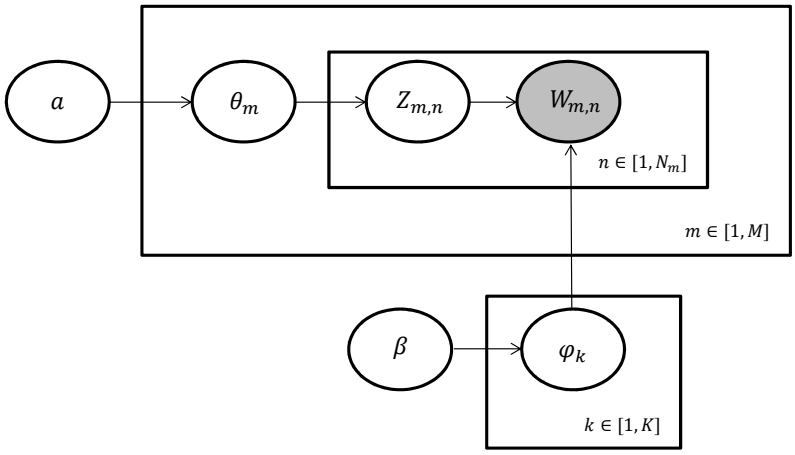


Figure 8. The LDA model visualized using plate notation.

2. Pick the word distribution for each topic by giving them a distribution over words, i.e.: Choose $\boldsymbol{\varphi}_k \sim \text{Dir}(\beta)$, where $k \in \{1, \ldots, K\}$.
3. For each of the word positions m, n, where $n \in \{1, \ldots, N_m\}$, and $m \in \{1, \ldots, M\}$
   3.1. From the topic distribution chosen in 1., randomly pick one topic, i.e.: Choose a topic $Z_{m,n} \sim \text{Multinomial}(\boldsymbol{\theta}_m)$.
   3.2. Given that topic, randomly choose a word from this topic, i.e.: Choose a word $W_{m,n} \sim \text{Multinomial}(\boldsymbol{\varphi}_{z_{m,n}})$.

More formally, the goal of the LDA estimation algorithm is to approximate the distribution:

$$P(\boldsymbol{Z}|\boldsymbol{W}; \alpha, \beta) = \frac{P(\boldsymbol{W}, \boldsymbol{Z}; \alpha, \beta)}{P(\boldsymbol{W}; \alpha, \beta)} \tag{7}$$

using Gibbs simulations, where α and β are the (hyper) parameters controlling the prior conjugate Dirichlet distributions for $\boldsymbol{\theta}_m$ and $\boldsymbol{\varphi}_k$, respectively. A very good explanation for how this method works is found in Heinrich (2009). The description below provides a brief summary only.

First, let V denote the size of the vocabulary, and t a term in V. Then, denote $P(t|z = k)$ as the mixture component, one for each topic, by $\boldsymbol{\Phi} = \{\boldsymbol{\varphi}_k\}_{k=1}^K$, and let $P(z|d = m)$ define the topic mixture proportion for document m, with one proportion for each document $\Theta = \{\boldsymbol{\theta}_m\}_{m=1}^M$. The total probability of the model can then be written as:

$$P(\boldsymbol{W}, \boldsymbol{Z}, \boldsymbol{\Theta}, \boldsymbol{\Phi}; \alpha, \beta) = \prod_{k=1}^{K} P(\boldsymbol{\varphi}_i; \beta) \prod_{m=1}^{M} P(\boldsymbol{\theta}_m; \alpha) \prod_{t=1}^{N} P(z_{m,t}|\boldsymbol{\theta}_m) P(w_{m,t}|\boldsymbol{\varphi}_{z_{m,t}}) \tag{8}$$

Integrating out the parameters φ and θ:

$$\begin{aligned} P(\boldsymbol{Z}, \boldsymbol{W}; \alpha, \beta) &= \int_{\boldsymbol{\Theta}} \int_{\boldsymbol{\Phi}} P(\boldsymbol{W}, \boldsymbol{Z}, \boldsymbol{\Theta}, \boldsymbol{\Phi}; \alpha, \beta)\, d\boldsymbol{\Phi}\, d\boldsymbol{\Theta} \\ &= \int_{\boldsymbol{\Phi}} \prod_{k=1}^{K} P(\boldsymbol{\varphi}_k; \beta) \prod_{m=1}^{M} \prod_{t=1}^{N} P(w_{m,t}|\boldsymbol{\varphi}_{z_{m,t}})\, d\boldsymbol{\Phi} \int_{\boldsymbol{\Theta}} \prod_{m=1}^{M} P(\boldsymbol{\theta}_m; \alpha) \prod_{t=1}^{N} P(z_{m,t}|\boldsymbol{\theta}_m)\, d\boldsymbol{\Theta} \end{aligned} \tag{9}$$

In (9), the terms inside the first integral do not include a θ term, and the terms inside the second integral do not include a φ term. Accordingly, the two terms can be solved separately. Exploiting the properties of the conjugate Dirichlet distribution it can be shown that:

$$\int_{\boldsymbol{\Theta}} \prod_{m=1}^{M} P(\boldsymbol{\theta}_m;\alpha) \prod_{t=1}^{N} P(z_{m,t}|\boldsymbol{\theta}_m)\, d\boldsymbol{\Theta} = \frac{\Gamma\left(\sum_{k=1}^{K}\alpha_k\right)}{\prod_{k=1}^{K}\Gamma(\alpha_k)} \frac{\prod_{k=1}^{K}\Gamma(n_m^{(k)}+\alpha_k)}{\Gamma\left(\sum_{k=1}^{K} n_m^{(k)}+\alpha_k\right)} \tag{10}$$

and

$$\int_{\boldsymbol{\Phi}} \prod_{k=1}^{K} P(\boldsymbol{\varphi}_k;\beta) \prod_{m=1}^{M}\prod_{t=1}^{N} P(w_{m,t}|\boldsymbol{\varphi}_{z_{m,t}})\, d\boldsymbol{\Phi} = \prod_{k=1}^{K} \frac{\Gamma\left(\sum_{t=1}^{V}\beta_t\right)}{\prod_{t=1}^{V}\Gamma(\beta_t)} \frac{\prod_{t=1}^{V}\Gamma(n_k^{(t)}+\beta_t)}{\Gamma\left(\sum_{t=1}^{V} n_k^{(t)}+\beta_t\right)} \tag{11}$$

where $n_m^{(k)}$ denotes the number of word tokens in the m^{th} document assigned to the k^{th} topic, and $n_k^{(t)}$ is the number of times the t^{th} term in the vocabulary has been assigned to the k^{th} topic.

Since $P(\boldsymbol{W};\alpha,\beta)$, in (7), is invariable for any of Z, the conditional distribution $P(\boldsymbol{Z}|\boldsymbol{W};\alpha,\beta)$ can be derived from $P(\boldsymbol{W},\boldsymbol{Z};\alpha,\beta)$ directly using Gibbs simulation and the conditional probability:

$$P(Z_{(m,n)} \mid \boldsymbol{Z}_{-(m,n)}, \boldsymbol{W};\alpha,\beta) = \frac{P(Z_{(m,n)}, \boldsymbol{Z}_{-(m,n)}, \boldsymbol{W};\alpha,\beta)}{P(\boldsymbol{Z}_{-(m,n)}, \boldsymbol{W};\alpha,\beta)} \tag{12}$$

where $Z_{(m,n)}$ denotes the hidden variable of the n^{th} word token in the m^{th} document, and $Z_{-(m,n)}$ denotes all Zs but $Z_{(m,n)}$. Denoting the index of a word token by $i = (m,n)$, and using the expressions in (10) and (11), cancellation of terms (and some extra manipulations exploiting the properties of the gamma function) yields:

$$P(Z_i = k \mid \boldsymbol{Z}_{-(i)}, \boldsymbol{W};\alpha,\beta) \propto (n_{m,-i}^{(k)}+\alpha_k) \frac{n_{k,-i}^{(t)}+\beta_t}{\sum_{t=1}^{V} n_{k,-i}^{(t)}+\beta_t} \tag{13}$$

where the counts $n_{\cdot,-i}^{(\cdot)}$ indicate that token i is excluded from the corresponding document or topic. Thus, sampling topic indexes using equation (13) for each word in a document and across documents until convergence allows us to approximate the posterior distribution given by (7). As noted in Heinrich (2009), the procedure itself uses only five larger data structures; the count variables $n_m^{(k)}$ and $n_k^{(t)}$, which have dimension $M \times K$ and $K \times V$, respectively, their row sums n_m and n_k, as well as the state variable $z_{m,n}$ with dimension W.

With one simulated sample of the posterior distribution for $P(\boldsymbol{Z}|\boldsymbol{W};\alpha,\beta)$, φ and θ can be estimated from:

$$\hat{\varphi}_{k,t} = \frac{n_k^{(t)}+\beta_t}{\sum_{t=1}^{V} n_k^{(t)}+\beta_r} \tag{14}$$

and

$$\hat{\theta}_{m,k} = \frac{n_m^{(k)} + \alpha_k}{\sum_{k=1}^{K} n_m^{(k)} + \alpha_k} \tag{15}$$

In the analysis of the main paper the average of the estimated $\hat{\theta}$ and $\hat{\varphi}$ from the 10 last samples of the stored Gibbs simulations are used to construct the daily news topic frequencies.[21] In unreported experiments, the topic extraction results reported in Section 2.1 do not change much when choosing other samples for inference, for example using the last sample only.

Before estimation three parameters need to be predefined: the number of topics and the two parameter vectors of the Dirichlet priors, α and β. Here, symmetric Dirichlet priors, with α and β each having a single value, are used. In turn, these are defined as a function of the number of topics and unique words:

$$\alpha = \frac{50}{K}, \quad \text{and} \quad \beta = \frac{200}{N}$$

The choice of K is discussed in Section 2.1. In general, lower (higher) values for α and β will result in more (less) decisive topic associations. The values for the Dirichlet hyper-parameters also reflect a clear compromise between having few topics per document and having few words per topic. In essence, the prior specification used here is the same as the one advocated by Griffiths and Steyvers (2004).

B.3 Estimating daily topic frequencies

Using the posterior estimates from the LDA model, the frequency with which each topic is represented in the newspaper for a specific day is computed. This is done by first collapsing all the articles in the newspaper for one specific day into one document. Following Heinrich (2009) and Hansen et al. (2014), a procedure for querying documents outside the set on which the LDA is estimated is then implemented. In short, this corresponds to using the same Gibbs simulations as described above, but with the difference that the sampler is run with the estimated parameters $\mathbf{\Phi} = \{\boldsymbol{\varphi}_k\}_{k=1}^{K}$ and hyper-parameter α held constant.

Denote by $\tilde{W}$ the vector of words in the newly formed document. Topic assignments, $\tilde{Z}$, for this document can then be estimated by first initializing the algorithm by randomly assigning topics to words and then performing a number of Gibbs iterations using:

$$P(\tilde{Z}_i = k \mid \tilde{\boldsymbol{Z}}_{-(i)}, \tilde{\boldsymbol{W}}; \alpha, \beta) \propto (n_{\tilde{m},-i}^{(k)} + \alpha_k)\hat{\varphi}_{k,t} \tag{16}$$

Since $\hat{\varphi}_{k,t}$ does not need to be estimated when sampling from (16), fewer iterations are needed to form the topic assignment index for the new document than when learning

[21] Because of lack of identifiability, the estimates of $\hat{\theta}$ and $\hat{\varphi}$ can not be combined across samples for an analysis that relies on the content of specific topics. However, statistics insensitive to permutation of the underlying topics can be computed by aggregating across samples (see Griffiths and Steyvers (2004)).

both the topic and word distributions. Here 2000 iterations are performed, and only the average of every 10th draw is used for the final inference. After sampling, the topic distribution can be estimated as before:

$$\hat{\tilde{\theta}}_{\tilde{m},k} = \frac{n_{\tilde{m}}^{(k)} + \alpha_k}{\sum_{k=1}^{K} n_{\tilde{m}}^{(k)} + \alpha_k} \tag{17}$$

We note that the same procedure for querying documents outside the set on which the LDA is estimated is implemented when we classify the firms' textual description, confer Section 2.3.

B.4 Sign adjustment

Given knowledge of the topics and the daily topic frequencies, we identify their sign using a dictionary based approach. In particular, for each day, all newspaper articles that day, and each of the K news topics, the article that news topic k describes the best is found. Given knowledge of this topic article mapping, positive/negative words in the articles are identified using an external word list and simple word counts. The word list used here takes as a starting point the classification of positive/negative words defined by the *Harvard IV-4 Psychological Dictionary*. As this dictionary contains English words only, the set of words must be translated into Norwegian. The translated set of words consists of 40 positive and 39 negative Norwegian words, which is somewhat different from the *Harvard IV-4 Psychological Dictionary* both in terms of numbers and exact meaning. The translated word list may be obtained upon request.

The count procedure delivers two statistics for each article, containing the number of positive and negative words. These statistics are then normalized such that each article observation reflects the fraction of positive and negative words, i.e.:

$$Pos_{t,n^a} = \frac{\#positivewords}{\#totalwords} \quad Neg_{t,n^a} = \frac{\#negativewords}{\#totalwords} \tag{18}$$

The overall tone of article n^a, for $n^a = 1, \ldots, N_t^a$ at day t, is defined as:

$$S_{t,n^a} = Pos_{t,n^a} - Neg_{t,n^a} \tag{19}$$

Letting $S_{t,n^a,k}$ denote the sign statistic associated with topic k and $\widetilde{Topic}_{t,k}$ the daily topic frequency, the sign of topic k is adjusted simply as:

$$Topic_{k,t} = \widetilde{Topic}_{k,t} \text{ if } S_{t,n^a,k} >= 0 \text{ and } Topic_{k,t} = -\widetilde{Topic}_{k,t} \text{ if } S_{t,n^a,k} < 0$$