The Role of Media Coverage in the Information Diffusion Process in the Stock Market

Abstract

In this paper we present results from an event study based on a unique data set of corporate news in the media. The data is provided by Media Tenor, a research institute which collects and rates all corporate news from the most important German daily newspapers and TV news. Our analysis is based on roughly 300,000 corporate news on 125 large- and medium-sized companies in 5 large daily newspapers and 7 TV news shows from Germany between July 1998 and October 2006. Since media analysts rate the news, we have an exogenous measure whether news are good or bad news for a company. Based on this data we can show that the incorporation of information in prices is fairly fast. The main price reaction occurs on the day of the arrival of the new information. This price jump is especially large if the news coverage in the media is accompanied by ad hoc announcements made by the corporation itself. While there is only a very short-term post-event drift after good news, prices tend to drift for several days after bad news. The post-event trading volume is significantly higher than before the news for several days for good as well as bad news. To provide a test of the model of Hong and Stein (1999) we define several proxies for the speed of the information diffusion through different investor groups. We find that for smaller companies with lower abnormal media coverage the information diffusion is indeed slower, as predicted by theory.

Keywords: information diffusion, corporate news, media coverage, post-event price drift

JEL Classification Code: G14

1 Introduction

A central question to researchers and practitioners concerned with asset pricing is how precise and fast new information is reflected in the prices of securities. According to the strong form of market efficiency of Fama (1970), prices should reflect all available information (including insider information) instantaneously. However, even his semi-strong (i.e. prices reflect all public information) and weak (i.e. historical prices have no forecasting power) versions of market efficiency were recently challenged by numerous empirical studies that found autocorrelation patterns in securities prices. While the findings in the mid- and long-term price movements are controversial[1], for short-term reactions (up to 40 trading days) to new information, most researchers agree on the notion that a positive serial correlation (i.e. momentum) exists. But there is a controversial discussion about what causes this serial correlation. Possible explanations from different theories include delayed information diffusion, investors' inattention, and investors' limited capability to process information instantaneously. All of which would lead to underreaction with respect to new information, causing slow incorporation in prices and thus positive serial correlation. In addition, misperception of information due to different personal biases can cause under- and prolonged overreactions with subsequent reversals which also lead to the observed autocorrelation patterns.[2]

This paper contributes to literature by analyzing how stock prices and volume are affected by corporate news. Due to a unique data set, we are able to provide new insights of how different kinds of public information are incorporated into stock prices, and how fast the market reaction is; thus we are able to test the model of Hong and Stein (1999). The analysis is based on data provided by Media Tenor, a commercial media research institute, which collects and analyzes media coverage of companies in Germany. They analyze every report in the leading national daily newspapers and the main TV news, and evaluate whether it is good, neutral or bad news for the respective company. This

[1] By reviewing the empirical literature, Fama (1998), p. 284, argues that in the long-run underreaction is nearly as frequently observable as overreaction, and that the long-term return anomalies are sensitive to the different statistical approaches. His conclusion is that the respective empirical studies are unable to discard the efficiency hypothesis.

[2] Hong and Stein (2007) classify one specific group of heterogenous-agent models as *disagreement models* and subdivide this class of models into those that rely on either *gradual information flow*, *limited attention* or *heterogenous priors* as underlying mechanisms.

gives us an exogenous measure whether news are good or bad news[3], and we are able to simultaneously look at all kinds of news (including rumors and soft facts) that, to the best of our knowledge, have not been investigated before. We find that stock prices strongly react on days that we consider to be defined as news shock days, with ex-ante expected results. Prices rise if a day is identified as a good news day, and fall if there is an abnormal large amount of bad news on that day. The price reactions are particulary large if the news shock is accompanied by an ad hoc announcement. In addition, in accordance with other empirical analyses, we find only a short-term post-event price drift for positive news shocks, but a larger drift after bad news. Trading volume is abnormally high for several days after positive and negative events. Furthermore, we confirm the theoretical prediction that the price drift is stronger for companies where the information diffusion is slower, i.e. for smaller companies and for companies with more abnormal news coverage.

The remainder of this paper is structured as follows: In Section 2 we review the model of Hong and Stein (1999) that we test, along with existing empirical evidence on the short-term post-event price reactions to corporate events, and media coverage of companies. In Section 3, we provide a description of the data we use in our analysis. Section 4 provides stock price and volume reaction results from an event study and for different information diffusion parameters at the market-wide level. Section 5 concludes.

2 Related Literature

There exists a large amount of literature on market reactions to corporate news. For the theoretical as well as the empirical literature we can only provide a short review of some important studies that we regard as influential to the questions addressed in this paper. After giving an overview of theoretical models which can explain post-event drifts of prices and high trading volumes, we provide and comment on a categorization of the empirical literature of stock market reactions to new information. Our main focus is on studies that

[3]Existing analyses of the influence of good and bad news on price drifts endogenously derive whether information is positive or negative from significantly positive or negative returns for the respective company. See Pritamani and Singal (2001) and Chan (2003).

look at short-term reactions, especially those who use media coverage of companies for their analysis.

2.1 Models Explaining Underreaction to News

To answer the question whether market efficiency holds from a theoretical point of view, one first has to define what private and public information is and how these concepts relate to the different forms of market efficiency. Grossman and Stiglitz (1980) point out that the strong form of efficiency cannot exist in equilibrium if costs of information acquisition exist, because if the costly information does not help to generate excessive returns which at least offset these costs, nobody has an incentive to acquire information. Thus the models and empirical analyses concentrate on testing the semi-strong and weak form of market efficiency. The difference between the strong and the semi-strong form is whether private information is reflected in the asset prices or not. This leads to the question what private and public information is. The following is a simple example of how difficult it is to answer this question (based on an analysis of Davies and Canes (1978)): A brokerage firm (with insider information) first made recommendations public to their clients, and then published them in the Wall Street Journal a few days later. Davies and Canes (1978) find a significant price reaction on both dates. Did the clients have had private or public information? In that case, most people would classify the information as private. But what if the broker would have published their recommendations in the Wall Street Journal directly? Is the information then private to the readers of the Journal? Or is this public information because everybody potentially could have had this information?

We agree with most authors that information is public as soon as everybody can obtain this information. Whether people are actually aware of this information (and process it correctly) is another question that has to be addressed. If attention to news or the processing capacity is limited for investors, this might lead to a slow information diffusion through different types of investors, and thus cause a delayed price reaction. Brav and Heaton (2002) divide the existing models into *behavioral* and *rational structural uncertainty* theories. Investors in the behavioral models suffer from cognitive biases and therefore cannot rationally process the available information. Comparatively, investors in the rational structural uncertainty models are rational in the sense that they update their beliefs statistically correct (according to Bayes' rule), but they lack knowledge of the fundamental structure of the economy. Yet the authors point out that it is hard to distinguish the two classes of theories, because similarities in the mathematical modelling create very similar return patterns and thus empirically indistinguishable hypotheses.

Kyle (1985) shows that rational investors with insider information have an incentive to gradually spread their information, because they know that their demand influences market prices, and thus can exploit the lack of knowledge of noise traders who trade in a sequential auction market with efficiently price-setting market makers. Hong and Stein (1999) model their information diffusion in a different way. In their behavioral model to explain short-term underreaction (and long-term overreaction), one group of investors with the same constant absolute risk aversion (CARA) utility, the *newswatchers*, obtain a piece of private information on the true value of a single liquidating dividend of a risky asset. They condition the value of the asset on this information, but on the other hand, fail to condition on current or past prices. The newswatchers are subdivided into z groups that are identical, except for the initial piece of information they get. Every of the z groups receives information on one of z independent subinnovations (each with the same variance) of a total dividend innovation. At time t every group of newswatchers have a $1/z$ piece of the total information. In time $t+1$, each group gets a further piece of information that is known to another group since t already. This means that information rotates between the z groups and at time $t+z-1$ the former (partly) private information is public to every group of newswatchers. Thus, the information diffuses linearly, and serial correlation emerges because the restriction of these investors to condition on observed prices prevents a fully revealing equilibrium. The gradual information diffusion could be explained by limited attention to information or limited capacity to process information.[4] Hong and Stein (1999) introduce another type of investor, the *momentum traders*, to their model. These traders also have CARA utility, but, in contrast to the newswatchers[5], they exhibit a finite investment horizon of j periods. The momentum traders do not observe any signals about the true value of the liquidating dividend, but are able to condition their forecasts on past prices. But they are bounded in their forecasting ability and thus

[4]See, for examples, Mankiw and Reis (2002) and Hirshleifer and Teoh (2006) for models with limited investors' attention and Sims (2003) and Peng (2005) for models with limited information processing capacity of investors.

[5]For a remark on the time-inconsistent behavior of the newswatchers, see Hong and Stein (1999), p. 2152.

make univariate forecasts based on price changes from $t-2$ to $t-1$, meaning that they are also unable to rationally extract and accumulate the different pieces of information.

The gradual diffusion of information to the newswatchers leads to positive short-term serial correlation that influences the forecasts of the momentum traders. As a result, this trend is amplified, leading to an overreaction with a convergence to the fundamental value, and thus to negative serial correlation afterwards. Comparative statistics show that the higher the information diffusion parameter z is, i.e. the longer the information needs to rotate before all newswatchers are aware of it, and the higher the risk tolerance of the momentum investors is, the longer is the time of positive serial correlation and the stronger is the overreaction. In addition, the model predicts lower initial price reactions for the first case, while they are the same in the second case. For longer momentum investors' investment horizons, the trend also lasts longer, but overreaction peaks at mid-term investment horizons.[6]

Similar to Hong and Stein (1999), DeLong, Shleifer, Summers, and Waldmann (1990) and Balsara, Zheng, Vidozzi, and Vidozzi (2006) use momentum traders to show how the empirically observed price patterns could be explained. For the same purpose, Daniel, Hirshleifer, and Subrahmanyam (1998), Odean (1998), Gervais and Odean (2001), and Peng and Xiong (2006) include overconfident investors in their models. Barberis, Shleifer, and Vishny (1998) use investors prone to conservatism and the representative heuristic, while Grinblatt and Han (2002) show that disposition effect traders can cause positive serial correlations in stock returns.

2.2 Empirical Literature on Market Reactions to News

To review the literature on price reactions to corporate news, one should define what those news are. Typically, news is regarded as the release of new information to the market (e.g. earnings announcements). But in the focus of researchers are also events that do not carry information itself, but may be able to draw attention to the stock of the respective company (e.g. stock splits). In the absence of short-selling opportunities, this attention

[6] The introduction of constrained contrarian investors, rational arbitrageurs with finite risk tolerance, and the possibility for investors to endogenously choose to be momentum or contrarian investor dampens but does not qualitatively change the results.

might simplify the search problem when one needs to decide which of the thousands of available stocks to buy.[7] The pure attention would lead to buying pressure in a stock. These two hypotheses, the *information based* and the *buying pressure based* stock price drifts can occur simultaneously; as in the model of Hong and Stein (1999). There also exist events (e.g. analysts' recommendations) where it is ex-ante unclear whether they reveal information or just create attention. To disentangle the price effects, researchers attribute the price change that is reversed after some time to the price pressure hypothesis, while the afterwards remaining price change is the stock price justified by the new information.

In our analysis, we focus on the media coverage of corporate news and not the initial news. This type of news was named *second-hand information* by Davies and Canes (1978). It is not clear whether this type of news reveals new information, or whether the media coverage spreads the information to more investors, or whether it just creates attention. That is why we provide an overview over empirical evidence on the influence of corporate news in the media in the later section. First of all, we show empirical analyses concerned with price patterns following special corporate events.

2.2.1 Corporate News

Earnings announcements are probably the most reviewed corporate events. Among many others, Bernard and Thomas (1989, 1990) report short-term post-earnings announcement drifts (PEAD) in the direction of the standardized unexpected earnings (SUE). Positive surprises are followed by positive abnormal returns, while negative returns occur subsequent to negative surprises. The PEAD is stronger for good news and for smaller firms. The authors point out that the drift is unlikely due to a misspecification of the underlying model risk but consistent with a delayed price response. Abarbanell and Bernard (1992) show that it is not only the market, but also security analysts who underreact to earnings announcements. DellaVigna and Pollet (2004) report that short-term price and volume reactions to earnings announcements on Fridays are smaller and tend to drift more. They attribute this effect to lower investor attention on Fridays. Similar results are found for earnings releases before the market start or after its close (as opposed to the trading hours) by Bagnoli, Clement, and Watts (2006). In accordance with the atten-

[7] See Barber and Odean (2007).

tion hypothesis, Hirshleifer, Lim, and Teoh (2006) show that the initial price and volume changes subsequent to earnings announcements are weaker and PEAD is stronger if more firms simultaneously report their earnings. Davis, Piger, and Sedor (2006) analyze the wording of earnings press releases from companies with a textual-analysis program and find a positive (negative) relation between optimistic (pessimistic) language usage and future firm performance. Further evidence for positive serial correlation of stock prices after corporate events comes from the initiation and omission of dividend payments[8] and from open market share repurchases[9]. Nofsinger and Sias (1999) find a positive correlation between changes in the institutional ownership and returns of stocks.

As an alleged case of pure attention events, Fama, Fisher, Jensen, and Roll (1969) and Ikenberry and Ramnath (2002) investigate stock price reactions to stock splits. Both studies find a positive drift after stock splits, but also point out that stock splits are followed by increased dividends/earnings and thus might signal to market participants. The drift then arises from the underreaction of investors and analysts to the new information. For analysts' recommendations, it is unclear whether they reveal insider information, or whether they spread aggregated but already published information through more groups of investors. Stickel (1995), Womack (1996), and Jegadeesh and Kim (2005) show that analysts' recommendations do in fact have an investment value, because upgraded stocks tend to outperform downgraded ones. In an empirical test of the Hong and Stein (1999) model, Hong, Lim, and Stein (2000) analyze (holding the company sized fixed) whether higher analyst coverage leads to a faster incorporation of information into stock prices. They find that momentum strategies work better among stocks with low analyst coverage. Their results support the hypothesis that analysts do not distribute new information, but present old information to new investors. This gradual diffusion of company information across investors is especially pronounced for negative news.

2.2.2 Corporate News in the Media

Direct evidence of whether corporate news diffuses slowly through investors' population can be drawn from studies about the media coverage of such news. For example, the

[8] See Michaely, Thaler, and Womack (1995).

[9] See Ikenberry, Lakonishok, and Vermaelen (1995).

aforementioned study of Davies and Canes (1978) discovers price reactions on days of analysts' recommendations to their clients, as well as on days when the same recommendations are made public in the Wall Street Journal a few days later. Similar results are obtained by Barber and Loeffler (1993). They show that recommendations from analysts in the Dartboard column of the Wall Street Journal induce positive abnormal returns for two days, that are partly reversed over the subsequent 25 trading days, and that volume nearly doubles on the two days following the publication. For stocks randomly picked by throwing a dart, such effects are not observable. In a case study about the information release of the invention of a new cancer-curing drug, Huberman and Regev (2001) show that information published 5 months ago in a journal read predominantly by specialists, and then republished in various popular newspapers still has a strong impact on market prices on the second release date, because the information is allocated to a broader group of investors.

Other studies related to ours investigate whether post-event price drifts are stronger if they are accompanied by higher media coverage. They do not focus on a special corporate event. They define events endogenously by abnormal returns. A positive (negative) event occurs if there is an unusually high (low) abnormal return on that trading day. Pritamani and Singal (2001) find that initial price reactions, as well as post-event price drifts, are stronger for events accompanied by news, especially earnings news and analyst recommendations in the Wall Street Journal or the Dow Jones News Wire on the event date, and are associated with unusually high trading volume as proxy for the precision of the information signal. Chan (2003) divides stocks with and without news stories in a month, and then uses returns to further divide these groups into deciles. Based on these portfolios, he finds that there is a drift for stocks with news, especially for stocks with bad news (i.e. with the lowest abnormal returns). This effect is stronger for smaller stocks. The initial price moves are partly reversed if this movement was not accompanied by public news. Fang and Peress (2007) show that stocks without media coverage outperform those named in four nationwide newspapers. This is especially true for small stocks with low analyst coverage, which are primarily owned by individuals. Mitchell and Mulherin (1994) point out that a direct relation exists between the stock market activity and the number of news from the *Dow Jones Broadtape*, as well as from the *Wall Street Journal*, but that this relation is not particularly strong.

To infer more information from news stories, some researchers use computational linguistic methods. Tetlock (2007) constructs a sentiment measure based on the wording in the "Abreast of the Market" column in the *Wall Street Journal*, and shows that media pessimism is able to predict movements of market prices and trading volumes, but that there also exits influence of market returns on media pessimism. Tetlock, Saar-Tsechansky, and Macskassy (2007) extend this analysis and in addition, show that negative words in news stories can forecast low earnings, especially if the news stories focus on firms' fundamentals. Das and Chen (2007) and Antweiler and Frank (2004) focus on the wording of messages posted on internet message boards. While Das and Chen (2007) show that an aggregated tech stock sentiment measure, derived from the posted messages, is related to stock returns, Antweiler and Frank (2004) find that their *Bullishness* indicator helps to predict stock market volatility, but that the effect is economically small. Antweiler and Frank (2005) also use computational linguistic methods, but they do not look at whether news is good or bad news, but instead focus on the topic being covered. Besides showing that stock prices reverse subsequentially to an initial jump after the arrival of a news shock, they reveal stronger price and volume effects for smaller firms and if the economy is in a recession.

Other evidence of influence from media coverage on firm performance comes from Bhattacharya, Galpin, Ray, and Yu (2007). They classify all reports from the *Dow Jones Interactive Publications Libary* concerning 458 internet IPOs and 458 matched firms from 1996 to 2000 to be either good, neutral or bad news, and find that media coverage explains only a small part of the differences between returns of newly issued stocks and stocks of the matched firms. Contrary evidence of the role of media coverage about a firm's CEO and the influence on firm's performance is provided by Nguyen-Dang (2005) and Malmendier and Tate (2007). While Nguyen-Dang (2005) reports higher returns and Tobin's Qs for firms with CEOs who attract higher levels of media coverage, Malmendier and Tate (2007) find that if a firm's CEO is awarded with a prestigious nationwide media award, the subsequent corporate stock return underperform the market as well as matched firms.

3 Description of the Data

We base our analysis a unique data set that is provided by Media Tenor, a media research institute that screens the leading daily newspapers and TV news shows in Germany with the help of 240 media analysts. According to strict rules from the Media Tenor codebook, that "was developed in cooperation with the scientific community"[10], the analysts classify the news as positive, neutral or negative. They evaluate the explicit wording and the implicit context. Both have to be either positive or negative if a news story is regarded as positive or negative, respectively. All other news falls into the category neutral. Media Tenor analysts do not only evaluate headlines but encode every single unit of information from all articles or news stories of more than 5 lines in newspapers (section news, business, and politics) or 5 seconds in the TV news. Media Tenor provided this data for companies that were included in the German stock market indexes for large (DAX) and medium-sized (MDAX) companies. This includes news coverage of 125 companies from July 1998 to October 2006. On average, 112 companies are included in the data every day. Table 1 reveals that the range of the market capitalization is fairly large. While a few large companies exist, there is also a number of small companies that are included in our data set. More than 25% of all companies have an average market capitalization below 400 million euros, which could be regarded as small, especially in an international comparison.

Table 2 shows the number of all, good, and bad news within the different newspapers and TV news. 5 daily newspapers and 7 daily TV news shows are covered every single day by the Media Tenor analysts. For the newspapers, the number of daily printed copies printed is available. Unfortunately, such numbers do not exist for the TV news shows. From the website of the broadcast station of the main German news show, the *ARD Tagesschau*, one can see that it is viewed by roughly 10 million people (to compare, the German population is about 82 million people).[11] All other TV news have lower audience ratings. Altogether, more than 300,000 articles and TV contributions were analyzed. More than one third could be clearly classified as either positive or negative, whereas the positive articles outbalance the negative ones. From Figure 1, one can see that the total number

[10] See http://www.mediatenor.com/smi_MT_research.php (July 10th, 2007) for further details.

[11] See http://intern.tagesschau.de/flash/index.php (July 9th, 2007).

of monthly news slightly grew over our observation period and that the ratio from good to bad news has fallen slightly.

To support our understanding of which information events influence the price and volume of stocks, we relate the news coverage from Media Tenor to ad hoc announcements, that include all legally compulsory news releases from the 125 companies. These announcements come from the factiva information database, owned by Dow Jones, and include 3,816 ad hoc news. In addition, we received price, volume, and market capitalization data from Datastream.

4 Stock Market Reactions to Corporate News with Media Coverage

According to finance theory, market prices are driven by expectations about future fundamentals of stocks. New information leads to a revision of those expectations. How fast this happens is the central question investigated in this paper. To address this issue, one must define what an information event is. A large body of literature investigates specific corporate events that are either self-selected by the company's management or non-self-selected events.[12] Ikenberry and Ramnath (2002) point out that researchers might become "errantly excited over spurious results"[13], meaning that special events that are likely to produce post-event drifts are investigated more often and predominantly analyses that find such a drift are published. In our analysis we do not rely on a special event. We define an event day according to unusually high media coverage concerning a company. Thus, our analysis can include rumors and other stories that are not reflected in other corporate news, but may be important in the investors' expectation formation process. Since we look at all kinds of relevant news events, the critique of Fama (1998) that different events might (randomly) generate over- and underreaction but cancel out in aggregate, thus being consistent with market efficiency, is addressed. In addition, we have an independent measure, the Media Tenor analysts' ratings of whether news is good or bad news for the specific company. Because previous research has found that drifts after special corporate

[12]See Ikenberry and Ramnath (2002), p. 493.

[13]Ikenberry and Ramnath (2002), p. 490.

events are rather short-lived and to attenuate the joint hypothesis problem, that arises if the underlying pricing model is not valid, we only look at short-term reactions to news.[14]

4.1 General Results

The number of news about each company is too high to regard every single news report as an event, as Table 2 reveals. In fact, on average there is more than one news story for each of the 125 companies on every of the 2,117 trading days in our sample period. Therefore, we define an event if there is unusually high media coverage on a specific day. Our first measure is the news score. This is simply the number of news reports of the specific company, no matter whether it is good, bad or neutral news. The news score should measure the attention the stock receives on that day. An event is triggered if the number of news reports is three standard deviations[15] higher than on an average day for that specific company within our whole observation period.[16] Since we are looking at news from newspapers and TV, we has to make sure that we assign the news to the appropriate event date. At the earliest, newspapers can report the news from the previous day, whereas the TV news shows are broadcasted in the evenings after the close of the German market at 05.30 pm.[17] We therefore assign TV news to the next trading day's newspaper news. If an event (defined as above) occurs on a day, we regard the reason for this high media coverage as information from the day before. Thus, we define the day before the unusually high media coverage as the event day 0, where the new information most likely became public. The event window is 10 trading days before and 10 trading days after the event day 0. We do not regard a day as an event day, although their is

[14] See Fama (1998) and Ikenberry and Ramnath (2002) for a discussion of the "bad model problem".

[15] To analyze how sensitive our results are to the definition of an event, we also defined events if they are two or four standard deviations away from their means. In the first case we got much more events and thus more problems with overlapping event windows. In the latter case the number of events is only slightly reduced and the results remain qualitatively unchanged.

[16] We also compared the number of news reports on a day with the average number of reports the year before. The results remain qualitatively unchanged, but since we lose one year of observations by this methodology, we report results for the deviations from the average over the whole observation period.

[17] The main German marketplace closes at 05.30 pm. Some regional marketplaces trade to 08.00 pm. 3 of the 7 TV news shows are broadcasted before 08.00 pm. If we exclude the 11,842 news from those TV news shows, our results remain unchanged.

abnormally high media coverage, if it occurs within 20 days after another event[18], such that we prevent overlapping event windows.

The main focus of this paper is not on the news score measure, but on separate measures for good and bad news. A good (bad) news event occurs if the number of good (bad) news reports is three standard deviations higher than on an average day. In addition, the difference between good and bad news must be positive (negative). The event date 0 is the day before such an event is triggered. That leads to 2,123 news score events as well as 2,068 positive and 1,284 negative events (see Table 3).

4.1.1 Abnormal Returns

Market efficiency would lead to the testable hypothesis that abnormal returns (and volume) only exist on the day of the arrival of new information. No drift should exist due to overreaction or underreaction, should exist on the days after the event. We calculate abnormal returns of the stocks according to an OLS market model:[19]

$$\widehat{AR}_{i,t} = R_{i,t} - \widehat{\alpha}_i - \widehat{\beta}_i R_{m,t} \tag{1}$$

where $\widehat{\alpha}_i$ and $\widehat{\beta}_i$ are OLS values from the estimation window that include daily returns of the stock of company i and the market index m from event date t=-252 to t=-11. For the market index, we used either the DAX or the MDAX according to the index the company was included on the event day 0.[20] The reported cross-sectional averages of abnormal returns are calculated as:

$$AR_t = \frac{1}{N} \sum_{j=1}^{N} \widehat{AR}_{j,t} \tag{2}$$

where N is the number of events in the respective category. The cumulative abnormal returns are:

$$CAR_{-10,t} = \sum_{\tau=-10}^{t} AR_\tau \tag{3}$$

[18] We regard an event closely after another as associated with the previous event, and use it to infer a measure of delayed information diffusion. See Section 4.2.1.

[19] For further details, see Brown and Warner (1985) and MacKinlay (1997).

[20] We also applied the CDAX, that includes all traded stocks in Germany, as market index and in addition, calculated market adjusted returns as simply the difference between companies and market returns. The results are robust to those different procedures.

From the second and the third column in Table 3, and Figure 2, one can see the results for the news score events. Since we simultaneously consider positive, negative, and neutral news reports, we report the absolute values of the abnormal returns. As expected and in accordance with the efficient market hypothesis, there exists high abnormal absolute returns on the event day. On this day, the price of the respective companies changes 1.23% more than prices of other companies. This result is economically and statistically significant.[21] The results for the days after the event day are theoretically more difficult to explain. Although the main reaction to the news occurs on the event day itself, there is some reaction on the next day as well. For the next three days, abnormal high absolute returns are observed which indicate some post-event drift.

Surprisingly, the day before the event day also yields significantly positive absolute returns. There are two possible explanations for this phenomenon. First, there might be trading from insiders who trade using private information. Second, there might also be a delay in the news coverage of the newspapers and TV news for some corporate news, such that the majority of media picks up on a story two days after it actually happened. This pattern is more pronounced for good than for bad news. Closer insights into this question can be derived from the distribution of ad hoc announcements, which we will discuss in detail in Section 4.2.4.

To analyze the direction and strength of post-event drifts, we now turn to the analysis of good and bad news events separately (see sixth to eighth and eleventh to thirteenth column of Table 3 and Figure 3). For good news, we find an economically and statistically important reaction on the event day. The returns of the stocks are on average 1.12% higher than on other days. In addition, a significant post-event drift of 0.28% in the same direction as the initial reaction is present on the next day, indicating an initial underreaction to the information. But if one compares the cumulative abnormal returns on the event day and on the last day of our observation period (which are fairly close to each other; see $[1, 10]$ at the bottom of Table 3), then one can come to another conclusion. There is an appropriate price reaction on the event date and an overreaction on the next day that is reversed during the next few trading days. To further investigate this topic, we also provide abnormal returns from two days after the event until the end of our event

[21] We report the absolute values of the t-statistics throughout the remainder of this paper.

period (see $[2, 10]$). An abnormal return on event day one in the same direction as the initial price reaction could either be an underreaction or an overreaction to a news shock. In the first case, subsequent returns, i.e. $[2, 10]$, should move in the same direction or be insignificantly different from zero. If the price move on event day one is reversed within the next trading days, this abnormal return could be regarded as overreaction. Table 3 displays that there is no evidence for a post-event drift for positive news shocks if we look at the returns from event day one to event day ten. A more detailed analysis shows that an abnormal positive return does exist on the first day after the event, but that this abnormal return is completely reversed over the next nine trading days. This result is in line with the model of Hong and Stein (1999), that predicts an overreaction to news shocks caused by momentum traders who trade on feedback from the initial price reaction.

Abnormal stock returns are 1.24% lower on bad news event days than on normal trading days. On the next day the price decrease continues with a significantly abnormal return of -0.35%. What differs from the price reaction to good news is that the reaction on the day after the information release is not reversed over the following days. Instead, the negative price trend continues. The cumulative return is 0.51% lower on the last day of our observation period than after the initial price reaction, but the additional -0.17% in the nine following days are far from being significantly different from zero. Negative news seem to diffuse only slowly through all groups of investors. Hong, Lim, and Stein (2000) and Chan (2003) find no (or very small) drifts after good news, and stronger drifts after bad news. They conclude that bad firm-specific information diffuses only gradually across the investing public.

4.1.2 Abnormal Volume

To omit problems with non-stationary volumes, we relate the actual trading volumes within our event period to the average daily trading volume the four weeks before the event window. To make the abnormal trading volumes comparable through different companies, we standardized them. The abnormal trading volumes in euros are calculated as follows:

$$AVOL_t = \frac{1}{N} \sum_{j=1}^{N} AVOL_{j,t} \tag{4}$$

with

$$AVOL_{i,t} = \frac{volume_{i,t} - \overline{vol}_{i,t}}{\overline{vol}_{i,t}} \tag{5}$$

and

$$\overline{vol}_{i,t} = \frac{1}{20} \sum_{\tau=-30-t}^{-11-t} volume_{i,\tau} \tag{6}$$

By looking at Figures 2 and 3, one can observe a sharp increase in abnormal volumes on the event day. The trading volume roughly doubles for these days. The abnormal volume remains abnormally high for the next trading days. The volume before the event is also statistically abnormally high compared to the month before (see Table 3), but the t-statistics reveal which volumes are far from equalling zero. More important than the statistical significance is the economic one. To see whether the event influences the trading volume beyond the actual day of the information release, we compare the average trading volumes from day -10 to day -1 to the volumes from day 1 to day 10 in Table 4. We find that before and after the event, the average trading volume is significantly higher than in the 20 trading days before the event period. The differences in the trading volumes before and after the event reveal that investors trade significantly more on the days after the event. Whereas for positive news shocks the trading volume after the shock is 20% higher than before, the difference for negative shocks is 40%. This might be a sign that differences in the expectations are larger after bad news, and thus the information diffusion is slower.[22] This pattern is true for all cases we look at in the remaining sections.

4.2 Information Diffusion

The model of Hong and Stein (1999) predicts positive serial correlation for more periods if the information diffusion is slower, i.e. it takes longer before each group of investors receives the new information. In a test of the model, Hong, Lim, and Stein (2000) show that company size and analyst coverage as proxies for the speed of information diffusion do indeed affect the strength of the post-event serial correlation of stock prices. We now turn to additional tests of proxies for information diffusion, first a univariate and then in a multivariate setting in Section 4.3.

[22]See Pritamani and Singal (2001).

4.2.1 Multiple News Shocks

Our first measure of information diffusion is based on the empirical fact that we observe some serial correlation in the event days, meaning that it is more likely that there are abnormally many news reports about a company tomorrow if it is also in the news today. This is because some news needs to be discussed in the media. The more news coverage there is over some days, the slower we regard the information diffusion in the market. By definition, days with abnormal returns are only event days if there are no other event days the 20 days before (see Section 4.1). We think that abnormally high media coverage ten days after an event day is caused by the very same information event. We count the number of additional abnormal news days after the actual event day and call this measure the *multiple news score*. We then divide the news shocks in those that are not followed by another unusually high media coverage day and those where the media coverage was intense the next days.

Table 5 and Figure 4 show the results of this division. In accordance with the theoretical prediction, the positive serial correlations in the stock prices are strong for positive and negative multiple news shock events. In both cases, the initial price reaction is roughly doubled within the next ten trading days. If there was only one news shock, the stock prices show a reversal for positive news events and no significant drift for negative shocks. Also of interest is that the abnormal returns on the event days are much stronger for multiple news shocks. For negative shocks in stocks with a multiple news score, the abnormal volume has its peak not on the actual event day but one day later. This could be regarded as an additional sign for slower information diffusion.

4.2.2 Size

Another proxy for information diffusion is the size of the company. As shown by Hong, Lim, and Stein (2000) and Chan (2003), price drifts after large initial price reactions are much more pronounced for smaller (although not the very smallest) companies.[23] We made a median split of all companies according to their market capitalization separately

[23] Since the companies in our data are large and medium sized companies (see Table 1), we omit the problem with very small firms, pointed out in Hong, Lim, and Stein (2000).

for every day. If a news shock occurs, we assign this shock either to the large or medium-size group, based on the market capitalization of the company on the event day.

The initial price reactions at the day of the information release are large and similar in strength for positive and negative news shocks, as Table 6 and Figure 5 reveal. Most important, medium-sized companies react more strongly on the initial event date and show, in accordance with the hypothesis that the information diffusion is slower for smaller stocks, a significant drift in the same direction on the next trading day. A longer lasting post-event drift is only observed for negative news shocks in medium companies. This confirms the findings of Hong, Lim, and Stein (2000) and Chan (2003). The positive abnormal returns on the first day after a good information event are reversed within the next trading days.

4.2.3 Relative Attention

Similar to Hirshleifer, Lim, and Teoh (2006), we define a measure called *relative attention*. The underlying hypothesis is that investors are only able to process a limited number of news reports at the same time. Thus, if there are simultaneously several news shocks that affect different companies, the diffusion of this information will be slower. Therefore, we divide the news shocks into two groups. They are attributed to a high relative attention group if there is no more than one other news shock for another company on that day. If there are more than two simultaneous shocks, these were regarded as low relative attention events.

Table 7 and Figure 6 do not confirm our ex-ante hypothesis that information diffusion is generally slower for low attention stocks, as it was found by Hirshleifer, Lim, and Teoh (2006) for earnings surprises. Stronger post-event drifts and higher trading volumes[24] are found for low attention events, but only for negative shocks. In contrast to the findings of Hirshleifer, Lim, and Teoh (2006), the initial price reaction is slightly weaker for the high attention events. The generally observed pattern that abnormal returns tend to reverse after good news and continue after bad news could also be observed here.

[24]Seasholes and Zhu (2006) find that individual investors increase their purchases of stocks that hit an upper price limit if fewer other stocks simultaneously hit their limits in the Shanghai market.

4.2.4 Ad hoc announcements

Another proxy of information diffusion is whether the media coverage is accompanied by legally mandatory corporate announcements, so called ad hoc announcements. We argue that really important news such as earnings announcements, stock splits etc. (basically all events other event studies regarding corporate news look at), are accompanied by ad hoc announcements, but there are also additional news reports (such as rumors in the market or developing news stories) that are important for the investors in the process of expectation formation and that are not considered in previous studies. The latter ones might take more time to be reflected in stock prices, meaning that information diffusion is slower.

By combining the ad hoc data with the media coverage data, three interesting cases emerge: How large are the returns if there is (i) an event accompanied by an ad hoc announcement, (ii) an event without an ad hoc announcement, or (iii) no event but an ad hoc announcement. The first case is the most interesting in our analysis. Figure 7 shows that 387, respectively 198 of the 3,816 total ad hoc announcements occur on the same day as a positive or negative news shock is measured. That means there are statistically highly significant more ad hoc announcements than on normal trading days. Most other days in our event window do not show an abnormal number of announcements, except for the day before positive news shocks. As we started to discuss in Section 4.1.1, abnormal returns the day before the actual event day could be either due to insider trading, or because the reaction of the news coverage in the media is delayed in a few cases. The results from Figure 7 supports the later view. In Table 8 we report the returns for the aforementioned cases. The return on days with a positive (negative) event and ad hoc news is 0.90% higher (2.85% lower) than on event days without an ad hoc announcement. To see whether we picked up the important news and thus validate our measure, we also look at absolute returns on ad hoc announcement days for which our measure does not report an information shock. We choose absolute returns on days where our news score measure indicates an abnormal number of news reports, because we have no exogenous measure whether an ad hoc announcement is good or bad news for the respective company. The returns on the ad hoc but not event days are significantly smaller (see Panel B of Table 8). Since the difference to ad hoc days where a news shock is indicated is roughly

1.52%, we are confident that our measure filters out the more important news from the less important news.

The results in Table 9 and Figure 8 show that the reaction of the stock prices are much stronger if a news shock is accompanied by an ad hoc announcement, especially for bad news, but that the drift for the next day is stronger if there was no announcement the day before. These results support the hypothesis that less salient information is incorporated more slowly into stock prices. The differences in trading volumes for events with and without ad hoc news are remarkable. For bad news with ad hoc announcements, the trading volume is more than 300% higher on such an event day than on a normal trading day, whereas it does not even double if there are no additional ad hoc announcements.

4.3 Multivariate Results

In this section we provide a multivariate model with the different proxies for the information diffusion, as well as some other independent variables to explain the short-term and the mid-term drifts, as well as the variance of stock prices after the arrival of new information. In addition, we test whether the difference of the trading volume before and after the news shock could be explained by our set of variables.

The used proxies for the information diffusion are the multiple news score, ranging from 1 (for only the initial event day being abnormal) to 8 where 8 of the eleven days from t=0 to t=10 show abnormal news coverage, the size (measured as market capitalization), the relative attention measure (ranging from 1 to 14), and a dummy for ad hoc announcements. For additional explanatory variables, we include the absolute return and volume of the event day.[25] The dependent variables are the whole post-event drift from event day one to event day ten, as well as the subdivision into the drift for event day one and the drift from event day two until the end of the event window. Besides those drift variables, other dependent variables are the standard deviation of the returns for the ten days after the event, as proxy for the difference of the opinions of the market participants,

[25] Pritamani and Singal (2001) find that large price changes capture the magnitude and volume changes capture the precision of information signals.

and the difference between the average abnormal volume in the ten days after the event and the average abnormal volume in the ten days before the event.

In Panel A of Table 10, we report descriptive statistics of the dependent variables that confirm aforementioned findings. The average return over the whole post-event period is close to zero for positive news and -0.43% for negative news (see Columns P1 and N1 in Table 10). Columns P2 and P3 show a pattern within those ten trading days for positive information shocks. The drift in the direction of the initial price reaction is nearly reversed over the following days. For negative news, the highest contribution to the post-event drift comes from the day after the event (0.34%), while the subsequent returns are only -0.09% (see Columns N2 and N3). The standard deviation and the difference in the volumes before and after the news shock are higher for negative news.

In the multivariate models, reported in Panel B of Table 10, we are not mainly interested in the direction of the drifts but in the question of what causes a post-event drift. Thus, we take the absolute values of our drift variables and relate them to the above explained independent variables. The results reveal that basically three variables influence the drifts, the variance and the trading volume after positive and negative news shocks. The first is the absolute return on the event day itself. The higher this return is, the stronger the short-term and the mid-term drifts, as well as the standard deviation after an event are. For example, the absolute drift one day after the event is 0.28% higher if the initial return increases by 1%. This number is remarkably similar for drifts after good and bad news shocks. The difference in the volumes before and after the shocks are only related with the initial return for negative shocks. Among the proxies for the information diffusion, two can explain dependent variables. The strongest influence is the size of the company, as also reported by other authors. The smaller the company, the stronger are the short- and mid-term drifts, the higher is the standard deviation and the stronger is the increase in trading volume, at least for negative news. That means the information diffusion for smaller companies is slower as predicted by the model of Hong and Stein (1999). This size effect is stronger for bad news. The multiple news scores have a positive influence on the dependent variables, except for the short-term drift after good news. This indicates that the more days there are with unusually high media coverage within the ten days after the event, as sign for the necessity to further discuss a topic and thus the difference of opinions, the stronger is the drift, the standard deviation of the returns, and the increase in trading volume after the event. The relative attention measure only slightly influences the short-term drift and the standard deviation for positive events. The short-term drift and the post-event standard deviation are high if the relative attention measure is low, which indicates high relative attention. These results run against our hypothesis and existing empirical evidence that information diffusion is slower for stocks that receive lower relative attention by the investors. Whether an information event is accompanied by an ad hoc announcement is important for the initial return (see Section 4.2.4), but does not play an important role for the information diffusion on the days after the event in a multivariate setting. The higher the volume on the event day is, the higher is the difference between the trading volume before and after positive shocks. Altogether, the independent variables explain the price and volume patterns better after bad news; as obvious from the higher R^2s.

5 Conclusion

From a unique data set we are able to derive a measure for the arrival of new information to the market. This measure does not only include news reported by the companies themselves, but also incorporates other news such as rumors. It is derived from the news coverage of companies in the largest German daily newspapers and TV news and was evaluated by analysts from the media research institute Media Tenor. We thus have an exogenous measure for the rating of the news. In addition, we derive several measures for the speed of the information diffusion through different groups of investors; thus we can test the predictions of the model of Hong and Stein (1999).

We find that stock prices do strongly react on days that our measure defines as news shock days in a way one would expect. Prices rise if a day is identified as good news day and fall if there are abnormally many bad news on that day. The price reactions are particulary large if the news shock is accompanied by an ad hoc announcement. In addition, in accordance with other empirical analyses, we find only a short-term positive post-event price drift for good news shocks with a subsequent reversal, but a larger drift after bad news that does continue (or at least does not reverse) over the following nine trading days. Trading volume is abnormally high for several days after positive and negative events. Furthermore, we confirm the theoretical prediction that the price drift is stronger for companies where the information diffusion is slower, i.e. for smaller companies and for companies with more abnormal news coverage.

References

Abarbanell, J. S., and V. L. Bernard, 1992, "Tests of Analysts' Overreaction/Underreaction to Earnings Information as Explanation for Anomalous Stock Price Behavior," *Journal of Finance*, 47, 1181–1207.

Antweiler, W., and M. Z. Frank, 2004, "Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards," *Journal of Finance*, 59, 1259–1294.

Antweiler, W., and M. Z. Frank, 2005, "Do US Stock Markets Typically Overreact to Corporate News Stories?," *Working Paper*.

Bagnoli, M., M. Clement, and S. G. Watts, 2006, "Around-the-Clock Media Coverage and the Timing of Earnings Announcements," *Working Paper*.

Balsara, N. J., L. Zheng, A. Vidozzi, and L. Vidozzi, 2006, "Explaining Momentum Profits with an Epidemic Diffusion Model," *Journal of Economics and Finance*, 30, 407–422.

Barber, B. M., and D. Loeffler, 1993, "The "Dartboard" Column: Second-Hand Information and Price Pressure," *Journal of Financial and Quantitative Analysis*, 28, 273–284.

Barber, B. M., and T. Odean, 2007, "All that Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors," *Review of Financial Studies*, forthcoming.

Barberis, N., A. Shleifer, and R. Vishny, 1998, "A Model of Investor Sentiment," *Journal of Financial Economics*, 49, 307–343.

Bernard, V. L., and J. K. Thomas, 1989, "Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium," *Journal of Accounting Research*, 27, 1–36.

Bernard, V. L., and J. K. Thomas, 1990, "Evidence That Stock Prices Do Not Fully Reflect the Implications of Current Earnings for Future Earnings," *Journal of Accounting and Economics*, 13, 305–340.

Bhattacharya, U., N. Galpin, R. Ray, and X. Yu, 2007, "The Role of the Media in the Internet IPO Bubble," *Working Paper*.

Brav, A., and J. B. Heaton, 2002, "Competing Theories of Financial Anomalies," *Review of Financial Studies*, 15, 575–606.

Brown, S. J., and J. B. Warner, 1985, "Using Daily Stock Returns: The Case of Event Studies," *Journal of Financial Economics*, 14, 3–31.

Chan, W. S., 2003, "Stock Price Reaction to News and No-News: Drift and Reversal After Headlines," *Journal of Financial Economics*, 70, 223–260.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 1998, "Investor Psychology and Security Market Under- and Overreactions," *Journal of Finance*, 53, 1839–1885.

Das, S. R., and M. Y. Chen, 2007, "Yahoo! for Amazon: Sentiment Extraction from Small Talk on the Web," *Management Science*, forthcoming.

Davies, P. L., and M. Canes, 1978, "Stock Prices and the Publication of Second-Hand Information," *Journal of Business*, 51, 43–56.

Davis, A. K., J. M. Piger, and L. M. Sedor, 2006, "Beyond the Numbers: An Analysis of Optimistic and Pessimistic Language in Earnings Press Releases," *Federal Reserve Bank of St. Louis Working Paper 2006-005A*.

DellaVigna, S., and J. Pollet, 2004, "Strategic Release of Information on Friday: Evidence from Earnings Announcements," *Working Paper*.

DeLong, J. B., A. Shleifer, L. H. Summers, and R. J. Waldmann, 1990, "Positive Feedback Investment Strategies and Destabilizing Rational Expectations," *Journal of Finance*, 45, 379–395.

Fama, E. F., 1970, "Efficient Capital Markets: A Review of Theory and Empirical Work," *Journal of Finance*, 25, 383–417.

Fama, E. F., 1998, "Market Efficiency, Long-Term Returns, and Behavioral Finance," *Journal of Financial Economics*, 49, 283–306.

Fama, E. F., L. Fisher, M. C. Jensen, and R. Roll, 1969, "The Adjustment of Stock Prices to New Information," *International Economic Review*, 10, 1–21.

Fang, L., and J. Peress, 2007, "Media Coverage and the Cross-Section of Stock Returns," *Working Paper*.

Gervais, S., and T. Odean, 2001, "Learning to Be Overconfident," *Review of Financial Studies*, 14, 1–27.

Grinblatt, M., and B. Han, 2002, "The Disposition Effect and Momentum," *Working Paper*.

Grossman, S. J., and J. Stiglitz, 1980, "On the Impossibility of Informationally Efficient Markets," *American Economic Review*, 70, 393–408.

Hirshleifer, D., S. S. Lim, and S. H. Teoh, 2006, "Driven to Distraction: Extraneous Events and Underreaction to Earnings News," *Working Paper*.

Hirshleifer, D., and S. H. Teoh, 2006, "Limited Investor Attention and Stock Market Misreactions to Accounting Information," *Working Paper*.

Hong, H., T. Lim, and J. C. Stein, 2000, "Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies," *Journal of Finance*, 55, 265–295.

Hong, H., and J. C. Stein, 1999, "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets," *Journal of Finance*, 54, 2143–2184.

Hong, H., and J. C. Stein, 2007, "Disagreement and the Stock Market," *Journal of Economic Perspectives*, 21, 109–128.

Huberman, G., and T. Regev, 2001, "Contagious Speculation and a Cure for Cancer: A Nonevent that Made Stock Prices Soar," *Journal of Finance*, 56, 387–396.

Ikenberry, D., J. Lakonishok, and T. Vermaelen, 1995, "Market Underreaction to Open Market Share Repurchases," *Journal of Financial Economics*, 39, 181–208.

Ikenberry, D. L., and S. Ramnath, 2002, "Underreaction to Self-Selected News Events: The Case of Stock Splits," *Review of Financial Studies*, 15, 489–526.

Jegadeesh, N., and W. Kim, 2005, "Value of Analyst Recommendations: International Evidence," *Working Paper*.

Kyle, A. S., 1985, "Continous Auctions and Insider Trading," *Econometrica*, 53, 1315–1325.

MacKinlay, A. C., 1997, "Event Studies in Economics and Finance," *Journal of Economic Literature*, 35, 13–39.

Malmendier, U., and G. Tate, 2007, "Superstar CEOs," *Working Paper*.

Mankiw, N. G., and R. Reis, 2002, "Sticky Information versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve," *Quarterly Journal of Economics*, 117, 1295–1328.

Michaely, R., R. H. Thaler, and K. L. Womack, 1995, "Price Reactions to Dividend Initiations and Omissions: Overreaction or Drift?," *Journal of Finance*, 50, 573–608.

Mitchell, M. L., and J. H. Mulherin, 1994, "The Impact of Public Information on the Stock Market," *Journal of Finance*, 49, 923–950.

Nguyen-Dang, B., 2005, “Is More News Good News? Media Coverage of CEOs, Firm Value, and Rent Extraction,” *Working Paper*.

Nofsinger, J. R., and R. W. Sias, 1999, “Herding and Feedback Trading by Institutional and Individual Investors,” *Journal of Finance*, 54, 2263–2295.

Odean, T., 1998, “Volume, Volatility, Price, and Profit When All Traders Are Above Average,” *Journal of Finance*, 53, 1187–1934.

Peng, L., 2005, “Learning with Information Capacity Constraints,” *Journal of Financial and Quantitative Analysis*, 40, 307–329.

Peng, L., and W. Xiong, 2006, “Investor Attention, Overconfidence and Category Learning,” *Journal of Financial Economics*, 80, 563–602.

Pritamani, M., and V. Singal, 2001, “Return Predictability Following Large Price Changes and Information Releases,” *Journal of Banking and Finance*, 25, 631–656.

Seasholes, M. S., and N. Zhu, 2006, “Individual Investors and Information Diffusion,” *Working Paper*.

Sims, C. A., 2003, “Implications of Rational Inattention,” *Journal of Monetary Economics*, 50, 665–690.

Stickel, S. E., 1995, “The Anatomy of the Performance of Buy and Sell Recommendations,” *Financial Analysts Journal*, 51, 25–39.

Tetlock, P. C., 2007, “Giving Content to Investor Sentiment: The Role of Media in the Stock Market,” *Journal of Finance*, 62, 1139–1168.

Tetlock, P. C., M. Saar-Tsechansky, and S. Macskassy, 2007, “More Than Words: Quantifying Language to Measure Firms’ Fundamentals,” *Journal of Finance*, forthcoming.

Womack, K. L., 1996, “Do Brokerage Analysts’ Recommendations Have Investment Value?,” *Journal of Finance*, 51, 137–167.

Table 1: Number and Size of the Companies

This table reports the number and size of the companies in our data set. Size is the average market value over the whole observation period and is reported in millions of euros.

		Size Percentiles	
No. of Companies		Max	84,137
Total Companies	125	95%	35,629
Mean No. of Comp.		90%	23,826
per Trading Day	112	75%	4,909
Size		Median	1,207
Mean	6,839	25%	397
Std. Dev.	13,47	90%	200
Skewness	3.09	95%	154
Kurtosis	13.81	Min	23

Table 2: Number of News in Different Newspapers and TV News

This table reports the number of total news, as well as positive and negative news for 125 companies in different large German daily newspapers and daily TV news. For the newspapers, the daily number of copies at the end of 2006 is reported. *For TV news no such numbers are available. The most seen TV news format is the *Tagesschau*. The broadcast station reports on its own website that on average 10 million people watch the news every day (see http://intern.tagesschau.de/flash/index.php (July 9th, 2007).

	circulation	All News	Positive News	Negative News
Frankfurter Allgemeine Zeitung	462,366	80,935	15,349	11,408
Die Welt	356,615	69,989	13,987	11,303
Sueddeutsche Zeitung	554,881	67,561	12,245	11,986
Frankfurter Rundschau	179,936	39,904	7,245	7,874
Bild	4,481,326	7,881	1,735	1,596
ARD Tagesthemen	*	10,451	3,529	3,775
ZDF Heute Journal	*	7,406	2,277	2,161
RTL aktuell	*	4,974	1,303	1,203
ZDF Heute	*	3,501	783	1,009
SAT1 18:30	*	3,367	934	775
ARD Tagesschau	*	3,273	598	1,030
Pro7 Nachrichten	*	2,976	885	679
total		302,218	60,870	54,799

Table 3: Abnormal Returns and Volume for News Shocks

This table reports average abnormal returns (AR), cumulative abnormal returns (CAR) and abnormal relative trading volumes (AVOL) for news shocks regarding the news score, positive news, and negative news in event time. The abnormal returns for shocks to the news score are the differences between absolute abnormal returns and their mean. The returns are reported in percentages. The reported t-values are robust absolute t-statistics. *** (**, *) indicates significance at the 1% (5%, 10%) level.

	News Score Events				Positive Events					Negative Events				
Obs.	2.123				2.068					1.284				
Day	AR	t-value	AVOL	t-value	AR	t-value	CAR	AVOL	t-value	AR	t-value	CAR	AVOL	t-value
-10	-0.0093	(0.23)	0.1207**	(2.25)	-0.0351	(0.75)	-0.0351	0.0694**	(2.07)	-0.0112	(0.16)	-0.0112	0.1229*	(1.75)
-9	-0.0661*	(1.87)	0.1142***	(3.14)	-0.0918*	(1.92)	-0.1269	0.0790**	(2.15)	0.0038	(0.06)	-0.0074	0.1122***	(2.84)
-8	-0.0509	(1.48)	0.1321***	(2.96)	-0.0258	(0.55)	-0.1528	0.0972**	(2.21)	0.1663**	(2.49)	0.1589	0.1229**	(2.47)
-7	-0.0375	(1.05)	0.0635**	(2.11)	0.0418	(0.83)	-0.1110	0.0550**	(2.08)	-0.0121	(0.19)	0.1468	0.0605*	(1.92)
-6	0.0272	(0.61)	0.1123**	(2.52)	0.0422	(0.79)	-0.0688	0.1394***	(2.68)	0.0522	(0.74)	0.1990	0.0484	(1.58)
-5	-0.0374	(1.06)	0.1014**	(2.53)	-0.0155	(0.30)	-0.0843	0.1012**	(2.46)	-0.0724	(1.03)	0.1266	0.0776**	(2.36)
-4	-0.0930***	(2.77)	0.0944***	(2.96)	-0.0521	(0.99)	-0.1364	0.1159***	(3.10)	0.0327	(0.50)	0.1594	0.0407	(1.05)
-3	0.0116	(0.26)	0.1345***	(4.07)	0.0282	(0.49)	-0.1082	0.1219***	(3.60)	0.0932	(1.27)	0.2526	0.1253***	(2.94)
-2	-0.0054	(0.15)	0.1929***	(4.59)	0.0800	(1.64)	-0.0282	0.1497***	(4.35)	0.0024	(0.03)	0.2550	0.1809***	(3.09)
-1	0.2403***	(3.25)	0.3247***	(6.92)	0.2550***	(4.63)	0.2268	0.2704***	(5.22)	-0.0795	(0.60)	0.1755	0.4439***	(5.14)
0	1.2303***	(14.66)	1.1139***	(17.02)	1.1223***	(12.45)	1.3491	0.8654***	(16.80)	-1.2412***	(8.13)	-1.0657	1.1495***	(11.27)
1	0.5750***	(9.52)	0.9955***	(12.71)	0.2825***	(4.11)	1.6316	0.7308***	(12.07)	-0.3477***	(2.97)	-1.4134	1.0752***	(8.87)
2	0.1131**	(2.57)	0.5954***	(10.35)	-0.0226	(0.42)	1.6090	0.4915***	(9.18)	0.0691	(0.86)	-1.3443	0.6318***	(6.78)
3	0.1584***	(3.56)	0.4750***	(8.86)	-0.0411	(0.79)	1.5679	0.3667***	(9.28)	-0.0065	(0.08)	-1.3508	0.4599***	(5.71)
4	0.0283	(0.73)	0.4177***	(6.85)	-0.0824*	(1.65)	1.4854	0.3180***	(7.80)	-0.0215	(0.29)	-1.3723	0.4322***	(4.55)
5	-0.0210	(0.52)	0.4235***	(6.49)	0.0029	(0.06)	1.4884	0.2345***	(5.85)	-0.0075	(0.10)	-1.3799	0.5090***	(5.28)
6	0.0583	(1.09)	0.4087***	(6.83)	0.0005	(0.01)	1.4888	0.2507***	(7.27)	-0.0327	(0.32)	-1.4126	0.4801***	(5.20)
7	0.0242	(0.54)	0.3292***	(6.68)	0.0300	(0.48)	1.5188	0.1966***	(5.95)	0.0377	(0.44)	-1.3749	0.3588***	(4.90)
8	0.0575	(1.12)	0.3862***	(6.50)	-0.0401	(0.76)	1.4787	0.2269***	(4.15)	0.0511	(0.54)	-1.3237	0.4096***	(6.01)
9	-0.0246	(0.66)	0.3215***	(5.77)	-0.0938*	(1.83)	1.3849	0.1995***	(4.74)	-0.1202	(1.64)	-1.4439	0.2700***	(5.44)
10	-0.0481	(1.28)	0.3316***	(5.51)	-0.0429	(0.88)	1.3420	0.2159***	(5.30)	-0.1354*	(1.69)	-1.5794	0.3963***	(4.29)
[1, 10]							-0.0071 (0.04)					-0.5136* (1.81)		
[2, 10]							-0.2896* (1.95)					-0.1660 (0.68)		

Table 4: Differences in Abnormal Volumes before and after a News Shock

This table reports the average daily abnormal trading volume before (vol[-10,-1]) and after (vol[1,10]) positive and negative event days, as well as the difference of both. The t-statistics are for tests against the hypothesis that the abnormal volume is zero for rows 3 and 4, and that the differences in those abnormal volumes are equal in the row 5. *** (**, *) indicates significance at the 1% (5%, 10%) level.

	positive news shocks		negative news shocks	
	abn. volume	t-stat.	abn. volume	t-stat.
vol[-10,-1]	0,1461***	(4.46)	0,1340***	(4.44)
vol[1,10]	0,3503***	(9.89)	0,5204***	(7.30)
difference	0,2042***	(6.61)	0,3864***	(5.60)

Table 5: Abnormal Returns for Events with and without Multiple News Scores

This table reports average abnormal returns (AR) and cumulative abnormal returns (CAR) for positive and negative news shocks in event time. The shocks are divided according to the number of days with abnormally high media coverage from day t=0 to day t=10. The category *One News Shock* includes those events where abnormal media coverage is only existent on the event day itself. The *Multiple News Shocks* category contains all those events that are followed by additional abnormal media coverage within the next 10 trading days. The returns are reported in percentages. The reported t-values are robust absolute t-statistics. *** (**, *) indicates significance at the 1% (5%, 10%) level.

	Positive News Shocks						Negative News Shocks					
	One News Shock			Multiple News Shocks			One News Shock			Multiple News Shocks		
Obs.	1.761			307			988			296		
Day	AR	t-value	CAR	AR	t-value	CAR	AR	t-value	CAR	AR	t-value	CAR
-10	-0.0497	(0.99)	-0.0497	0.0486	(0.38)	0.0486	-0.0078	(0.10)	-0.0078	-0.0226	(0.15)	-0.0226
-9	-0.1119**	(2.24)	-0.1616	0.0231	(0.16)	0.0717	0.0736	(1.05)	0.0658	-0.2291	(1.50)	-0.2517
-8	-0.0399	(0.78)	-0.2015	0.0549	(0.44)	0.1266	0.1939***	(2.64)	0.2597	0.0739	(0.48)	-0.1778
-7	0.0626	(1.13)	-0.1390	-0.0771	(0.61)	0.0495	0.0125	(0.17)	0.2722	-0.0941	(0.67)	-0.2719
-6	0.0312	(0.54)	-0.1078	0.1056	(0.74)	0.1552	0.0284	(0.39)	0.3006	0.1320	(0.73)	-0.1400
-5	0.0236	(0.47)	-0.0842	-0.2400	(1.22)	-0.0848	-0.1107	(1.59)	0.1899	0.0555	(0.28)	-0.0845
-4	-0.0253	(0.44)	-0.1095	-0.2056*	(1.66)	-0.2904	0.0953	(1.29)	0.2852	-0.1760	(1.27)	-0.2605
-3	0.0603	(1.03)	-0.0493	-0.1559	(0.82)	-0.4463	0.1114	(1.28)	0.3966	0.0326	(0.25)	-0.2279
-2	0.1286**	(2.45)	0.0793	-0.1983	(1.50)	-0.6446	-0.0165	(0.18)	0.3801	0.0655	(0.37)	-0.1624
-1	0.2626***	(4.42)	0.3419	0.2109	(1.44)	-0.4337	-0.0982	(0.60)	0.2819	-0.0174	(0.09)	-0.1797
0	1.0021***	(10.33)	1.3440	1.8118***	(7.57)	1.3781	-1.0791***	(7.00)	-0.7971	-1.7825***	(4.28)	-1.9623
1	0.2404***	(3.36)	1.5844	0.5242**	(2.46)	1.9023	-0.1908	(1.55)	-0.9880	-0.8712***	(2.97)	-2.8335
2	-0.1092**	(1.96)	1.4752	0.4743***	(2.70)	2.3766	0.0928	(1.24)	-0.8952	-0.0098	(0.04)	-2.8433
3	-0.0369	(0.68)	1.4382	-0.0652	(0.40)	2.3114	0.0279	(0.35)	-0.8673	-0.1212	(0.51)	-2.9645
4	-0.0852	(1.59)	1.3530	-0.0664	(0.48)	2.2449	-0.0722	(0.94)	-0.9395	0.1475	(0.74)	-2.8169
5	-0.0301	(0.63)	1.3229	0.1926	(1.36)	2.4375	-0.0135	(0.15)	-0.9530	0.0123	(0.07)	-2.8046
6	-0.0262	(0.51)	1.2967	0.1534	(1.06)	2.5909	0.0782	(0.90)	-0.8748	-0.4030	(1.19)	-3.2075
7	-0.0537	(1.04)	1.2430	0.5100*	(1.69)	3.1009	-0.0545	(0.68)	-0.9293	0.3454	(1.32)	-2.8622
8	-0.0487	(0.84)	1.1943	0.0092	(0.07)	3.1101	0.1276	(1.39)	-0.8016	-0.2042	(0.74)	-3.0664
9	-0.0979*	(1.76)	1.0965	-0.0707	(0.53)	3.0394	-0.0043	(0.06)	-0.8059	-0.5072***	(2.73)	-3.5735
10	-0.0739	(1.41)	1.0225	0.1352	(1.00)	3.1745	-0.0651	(0.93)	-0.8710	-0.3703	(1.44)	-3.9438
[1, 10]	-0.3215* (1.84)			1.7964*** (3.82)			-0.0739 (0.27)			-1.9815** (2.40)		
[2, 10]	-0.5618*** (3.60)			1.2722*** (2.96)			0.1170 (0.50)			-1.1104 (1.56)		

Table 6: Abnormal Returns for Events for Large and Medium-Size Companies

This table reports average abnormal returns (AR) and cumulative abnormal returns (CAR) for positive and negative news shocks in event time. The shocks are divided according to the size of the company. A median split for market capitalization is made on every trading day. The news shocks are then assigned to either the *Large Companies* or the *Medium Companies* category based on the size categorization on the event day. The returns are reported in percentages. The reported t-values are robust absolute t-statistics. *** (**, *) indicates significance at the 1% (5%, 10%) level.

	Positive News Shocks						Negative News Shocks					
	Large Companies			Medium Companies			Large Companies			Medium Companies		
Obs.	1.091			977			692			592		
Day	AR	t-value	CAR	AR	t-value	CAR	AR	t-value	CAR	AR	t-value	CAR
-10	-0.1047**	(2.01)	-0.1047	0.0426	(0.53)	0.0426	0.1186	(1.39)	0.1186	-0.1629	(1.40)	-0.1629
-9	-0.0898	(1.59)	-0.1946	-0.0940	(1.19)	-0.0514	-0.0503	(0.75)	0.0683	0.0670	(0.58)	-0.0959
-8	-0.0721	(1.25)	-0.2666	0.0258	(0.34)	-0.0257	0.0528	(0.77)	0.1211	0.2989**	(2.48)	0.2030
-7	0.0002	(0.00)	-0.2664	0.0883	(0.99)	0.0626	0.0518	(0.72)	0.1729	-0.0868	(0.77)	0.1163
-6	0.0677	(1.18)	-0.1988	0.0138	(0.15)	0.0764	-0.0004	(0.01)	0.1725	0.1138	(0.89)	0.2301
-5	-0.0769	(1.28)	-0.2757	0.0531	(0.61)	0.1295	-0.0966	(1.38)	0.0759	-0.0441	(0.34)	0.1860
-4	-0.0977	(1.61)	-0.3734	-0.0011	(0.01)	0.1284	0.0687	(0.92)	0.1446	-0.0094	(0.08)	0.1767
-3	0.0419	(0.58)	-0.3315	0.0128	(0.14)	0.1411	0.0573	(0.63)	0.2019	0.1353	(1.15)	0.3119
-2	0.0944	(1.53)	-0.2371	0.0640	(0.83)	0.2052	0.0004	(0.00)	0.2023	0.0048	(0.03)	0.3168
-1	0.1703***	(2.78)	-0.0668	0.3495***	(3.71)	0.5546	-0.2439***	(2.74)	-0.0416	0.1126	(0.42)	0.4293
0	0.9387***	(8.92)	0.8719	1.3272***	(8.84)	1.8819	-1.0066***	(7.46)	-1.0483	-1.5155***	(5.21)	-1.0861
1	0.1954**	(2.33)	1.0673	0.3798***	(3.41)	2.2617	-0.0580	(0.57)	-1.1062	-0.6863***	(3.07)	-1.7725
2	-0.0149	(0.26)	1.0524	-0.0312	(0.33)	2.2305	0.0496	(0.64)	-1.0566	0.0919	(0.61)	-1.6806
3	0.0139	(0.23)	1.0663	-0.1026	(1.18)	2.1280	-0.0318	(0.41)	-1.0884	0.0231	(0.15)	-1.6574
4	-0.1168**	(2.05)	0.9495	-0.0441	(0.52)	2.0839	0.0247	(0.31)	-1.0637	-0.0756	(0.57)	-1.7330
5	-0.0053	(0.10)	0.9442	0.0122	(0.16)	2.0961	0.0063	(0.08)	-1.0575	-0.0237	(0.16)	-1.7567
6	0.0348	(0.57)	0.9790	-0.0378	(0.50)	2.0582	0.0028	(0.03)	-1.0547	-0.0742	(0.38)	-1.8309
7	0.0334	(0.56)	1.0123	0.0262	(0.23)	2.0844	0.0200	(0.23)	-1.0347	0.0584	(0.37)	-1.7725
8	0.0178	(0.31)	1.0301	-0.1047	(1.15)	1.9797	-0.0616	(0.57)	-1.0963	0.1830	(1.12)	-1.5895
9	-0.1305**	(2.27)	0.8996	-0.0529	(0.61)	1.9268	-0.0172	(0.23)	-1.1135	-0.2407*	(1.82)	-1.8302
10	0.0409	(0.76)	0.9406	-0.1365	(1.61)	1.7903	-0.1239	(1.55)	-1.2374	-0.1488	(1.02)	-1.9790
[1, 10]	0.0686 (0.37)			-0.0916 (0.33)			-0.1892 (0.70)			-0.8929* (1.69)		
[2, 10]	-0.1267 (0.76)			-0.4714* (1.86)			-0.1312 (0.53)			-0.2066 (0.47)		

Table 7: Abnormal Returns for Events with Different Relative Attention

This table reports average abnormal returns (AR) and cumulative abnormal returns (CAR) for positive and negative news shocks in event time. The shocks are divided according to the relative attention they receive on the event day. If there are two or less simultaneous events for different companies on the same trading day, these companies are assigned to the *High Relative Attention* group. If there are more than two simultaneous events it is a *Low Relative Attention* shock. The returns are reported in percentages. The reported t-values are robust absolute t-statistics. *** (**, *) indicates significance at the 1% (5%, 10%) level.

	Positive News Shocks						Negative News Shocks					
	High Relative Attention			Low Relative Attention			High Relative Attention			Low Relative Attention		
Obs.	885			1.183			622			662		
Day	AR	t-value	CAR	AR	t-value	CAR	AR	t-value	CAR	AR	t-value	CAR
-10	-0.0182	(0.24)	-0.0182	-0.0478	(0.80)	-0.0478	-0.0424	(0.46)	-0.0424	0.0182	(0.17)	0.0182
-9	-0.0596	(0.82)	-0.0778	-0.1159*	(1.83)	-0.1637	0.0574	(0.61)	0.0150	-0.0466	(0.53)	-0.0284
-8	-0.0641	(0.89)	-0.1419	0.0028	(0.04)	-0.1609	0.1436	(1.52)	0.1586	0.1875**	(1.99)	0.1591
-7	0.0034	(0.05)	-0.1386	0.0706	(1.02)	-0.0903	-0.0649	(0.74)	0.0937	0.0376	(0.40)	0.1967
-6	0.0454	(0.58)	-0.0932	0.0398	(0.54)	-0.0505	0.0767	(0.84)	0.1704	0.0292	(0.28)	0.2259
-5	-0.1134	(1.26)	-0.2066	0.0577	(0.96)	0.0072	-0.0748	(0.66)	0.0956	-0.0701	(0.82)	0.1558
-4	-0.0956	(1.20)	-0.3022	-0.0195	(0.28)	-0.0123	0.0157	(0.18)	0.1112	0.0488	(0.51)	0.2046
-3	0.1228	(1.37)	-0.1795	-0.0426	(0.58)	-0.0549	0.0493	(0.49)	0.1605	0.1345	(1.27)	0.3391
-2	0.0207	(0.29)	-0.1588	0.1244*	(1.88)	0.0695	0.1758	(1.48)	0.3363	-0.1604	(1.48)	0.1787
-1	0.2242**	(2.49)	0.0654	0.2780***	(4.04)	0.3475	-0.1513	(0.64)	0.1850	-0.0121	(0.09)	0.1666
0	1.0325***	(8.32)	1.0979	1.1895***	(9.34)	1.5370	-1.2051***	(5.74)	-1.0201	-1.2752***	(5.77)	-1.1086
1	0.4065***	(3.67)	1.5043	0.1898**	(2.18)	1.7267	-0.3067**	(2.01)	-1.3268	-0.3862**	(2.20)	-1.4948
2	0.0151	(0.18)	1.5194	-0.0508	(0.73)	1.6760	0.0774	(0.67)	-1.2494	0.0614	(0.54)	-1.4334
3	-0.0631	(0.81)	1.4563	-0.0247	(0.35)	1.6513	0.0546	(0.55)	-1.1949	-0.0639	(0.49)	-1.4973
4	0.0090	(0.13)	1.4653	-0.1509**	(2.17)	1.5004	0.0172	(0.16)	-1.1777	-0.0579	(0.56)	-1.5552
5	-0.0348	(0.53)	1.4306	0.0311	(0.49)	1.5316	0.0019	(0.02)	-1.1758	-0.0164	(0.14)	-1.5716
6	-0.0459	(0.69)	1.3847	0.0352	(0.51)	1.5668	-0.1949	(1.08)	-1.3707	0.1196	(1.14)	-1.4520
7	0.1100	(0.94)	1.4947	-0.0299	(0.45)	1.5369	0.1192	(0.84)	-1.2515	-0.0389	(0.38)	-1.4908
8	0.0494	(0.70)	1.5441	-0.1071	(1.41)	1.4298	0.0841	(0.59)	-1.1673	0.0202	(0.16)	-1.4706
9	-0.1003	(1.37)	1.4438	-0.0890	(1.26)	1.3408	-0.1114	(1.01)	-1.2787	-0.1286	(1.31)	-1.5992
10	-0.0505	(0.71)	1.3933	-0.0372	(0.55)	1.3036	-0.2325**	(1.97)	-1.5112	-0.0442	(0.41)	-1.6434
[1, 10]	0.2955 (1.28)			-0.2334 (1.01)			-0.4911 (1.30)			-0.5349 (1.27)		
[2, 10]	-0.1110 (0.54)			-0.4232** (2.03)			-0.1844 (0.54)			-0.1487 (0.43)		

Table 8: Returns for Days with and without Events and Ad hoc Announcements

This table reports raw returns for days with an ad hoc announcement and an event simultaneously and for days with no ad hoc announcements but an event along with the difference between these two (Panel A). Additionally, the absolute returns on high news score days with ad hoc announcement compared to days with ad hoc news but no event can be seen in Panel B. The returns are reported in percentages. The reported t-values are absolute t-statistics. *** (**, *) indicates significance at the 1% (5%, 10%) level.

Panel A	positive news shocks		negative news shocks	
	obs.	return	obs.	return
ad hoc, event	387	2.0449	198	-3.5233
no ad hoc, event	1,463	1.1451	948	-0.9385
combined	1,850	1.3333	1,146	-1.3851
difference		0.8998***		-2.5848***
t-statistic		(3.83)		(5.89)

Panel B	news score shocks	
	obs.	abs. return
ad hoc, event	440	4.3632
ad hoc, no event	3,376	2.8436
combined	3,816	3.0189
difference		1.5196***
t-statistic		(7.14)

Table 9: Abnormal Returns for Events with and without Ad hoc Announcements

This table reports average abnormal returns (AR) and cumulative abnormal returns (CAR) for positive and negative news shocks in event time. The shocks are divided according to whether they are accompanied by an ad hoc announcement on the event day or not. The returns are reported in percentages. The reported t-values are robust absolute t-statistics. *** (**, *) indicates significance at the 1% (5%, 10%) level.

	Positive News Shocks						Negative News Shocks					
	with Ad hoc Announcement			without Ad hoc Announcement			with Ad hoc Announcement			without Ad hoc Announcement		
Obs.	387			1.463			198			948		
Day	AR	t-value	CAR	AR	t-value	CAR	AR	t-value	CAR	AR	t-value	CAR
-10	-0.0009	(0.01)	-0.0009	-0.0383	(0.67)	-0.0383	-0.4120**	(2.18)	-0.4120	0.0197	(0.24)	0.0197
-9	-0.1275	(1.12)	-0.1283	-0.0907	(1.58)	-0.1290	0.1040	(0.56)	-0.3081	0.0009	(0.01)	0.0206
-8	0.0683	(0.68)	-0.0601	-0.0667	(1.14)	-0.1957	0.1633	(0.83)	-0.1447	0.1579**	(2.02)	0.1785
-7	0.1348	(1.26)	0.0748	0.0210	(0.33)	-0.1747	-0.0046	(0.03)	-0.1494	-0.0313	(0.41)	0.1472
-6	-0.0648	(0.55)	0.0099	0.0626	(0.93)	-0.1121	0.0148	(0.06)	-0.1346	0.0638	(0.81)	0.2110
-5	0.0991	(0.91)	0.1090	-0.0764	(1.17)	-0.1885	-0.0192	(0.11)	-0.1538	-0.1342	(1.60)	0.0768
-4	-0.0250	(0.23)	0.0840	-0.0459	(0.69)	-0.2344	-0.0626	(0.33)	-0.2164	0.0142	(0.19)	0.0910
-3	0.0205	(0.19)	0.1045	0.0322	(0.43)	-0.2022	0.1911	(1.10)	-0.0253	0.0897	(1.00)	0.1807
-2	0.1405	(1.19)	0.2450	0.0578	(0.97)	-0.1444	-0.1948	(1.04)	-0.2201	0.0504	(0.51)	0.2311
-1	0.3459***	(2.74)	0.5909	0.2001***	(2.94)	0.0557	-0.4275*	(1.84)	-0.6476	-0.0386	(0.24)	0.1925
0	1.9618***	(7.62)	2.5527	0.9716***	(10.12)	1.0273	-3.3176***	(5.08)	-3.9652	-0.8262***	(5.76)	-0.6337
1	0.3227*	(1.93)	2.8570	0.3273***	(3.93)	1.3563	-0.3834	(1.01)	-4.3486	-0.3529***	(2.67)	-0.9866
2	0.2148*	(1.67)	3.0719	-0.0743	(1.13)	1.2820	0.2664	(1.09)	-4.0822	0.0739	(0.79)	-0.9127
3	0.0864	(0.72)	3.1442	-0.0593	(0.93)	1.2234	0.3953	(1.47)	-3.6869	-0.1226	(1.31)	-1.0353
4	-0.0356	(0.29)	3.1086	-0.1321**	(2.17)	1.0887	0.0563	(0.31)	-3.6306	-0.0346	(0.39)	-1.0903
5	0.0206	(0.19)	3.1292	-0.0296	(0.54)	1.0481	-0.3477**	(2.25)	-3.9783	0.0236	(0.27)	-1.0667
6	-0.0057	(0.06)	3.1236	0.0085	(0.14)	1.0649	-0.6482	(1.44)	-4.6265	0.0915	(0.91)	-0.9797
7	0.1172	(0.99)	3.2408	0.0128	(0.16)	1.0777	0.3559	(1.10)	-4.2705	-0.0453	(0.48)	-1.0302
8	-0.0524	(0.42)	3.1884	-0.0324	(0.49)	1.0378	0.5753**	(2.16)	-3.6952	0.0226	(0.20)	-1.0062
9	0.0300	(0.23)	3.2184	-0.1356**	(2.18)	0.9022	-0.0055	(0.02)	-3.7084	-0.1432*	(1.72)	-1.1494
10	-0.0133	(0.12)	3.2052	-0.0486	(0.81)	0.8400	-0.2164	(1.09)	-3.9248	-0.1218	(1.23)	-1.2784
[1, 10]	0.6525* (1.86)			-0.1873 (0.82)			0.0404 (0.08)			-0.6447* (1.90)		
[2, 10]	-0.3482 (1.10)			-0.5163*** (2.66)			0.4238 (0.64)			-0.2918 (0.94)		

Table 10: Multivariate Explanations for the Post-Event Drift and Volume

This table reports descriptive statistics for five variables measuring the post event information diffusion (Panel A) along with OLS models to explain these variables (Panel B). The descriptive statistics for the drift variables are on returns, while they are absolute returns in the models. The independent variables are the *multiple news score*, ranging from 1 for only the initial event day being abnormal to 8 where 8 of the eleven day from t=0 to t=10 show abnormal news coverage, the *size*, measured as market capitalization, the *relative attention* measure, ranging from 1 to 14, and a dummy for *ad hoc announcements*. As additional explanatory variables, we include the absolute return (*ret[0]*) and volume (*vol[0]*) of the event day. The returns are reported in percentages. The robust absolute t-statistics are from OLS models with 125 company clusters. *** (**, *) indicates significance at the 1% (5%, 10%) level.

	Positive News Shocks					Negative News Shocks				
	(P1)	(P2)	(P3)	(P4)	(P5)	(N1)	(N2)	(N3)	(N4)	(N5)
	drift[1,10]	drift[1,2]	drift[2,10]	sd[1,10]	Δvol[1,10]	drift[1,10]	drift[1,2]	drift[2,10]	sd[1,10]	Δvol[1,10]
Panel A: Descriptive Statistics										
median	-0.0747	0.1396	-0.3309	1.5459	0.0827	-0.5566	-0.1136	-0.3407	1.7272	0.0740
mean	0.0503	0.3371	-0.2953	1.8541	0.2042	-0.4349	-0.3400	-0.0949	2.2053	0.3864
std.dev.	7.7400	3.2205	6.9303	1.5085	1.2853	10.6241	4.3563	9.0547	2.1374	2.3007
Panel B: Multivariate OLS										
ret[0]	0.3212**	0.2804***	0.1390*	0.1484***	0.0222	0.5544***	0.2800***	0.3467**	0.1413***	0.0694*
	(2.49)	(4.50)	(1.69)	(3.82)	(1.43)	(3.02)	(4.45)	(2.47)	(7.25)	(1.78)
vol[0]	0.0519	-0.0453	0.0435	-0.0300	0.1235**	-0.1823	-0.0340	-0.1576*	-0.0311*	0.0974
	(0.35)	(0.86)	(0.33)	(0.86)	(2.39)	(1.58)	(0.93)	(1.69)	(1.89)	(1.62)
mult. news	0.8890*	0.3324	0.7076*	0.3302***	0.3227***	1.6444**	0.3250**	1.4369**	0.5783*	0.5629**
	(1.70)	(1.65)	(1.83)	(2.80)	(4.28)	(2.21)	(2.19)	(2.01)	(1.93)	(2.36)
size	-0.9326**	-0.3809**	-0.9160***	-0.4071***	-0.0177	-2.5887***	-1.0554***	-2.0625***	-0.8716***	-0.2999**
	(2.55)	(2.39)	(2.98)	(3.60)	(0.31)	(4.07)	(4.02)	(3.55)	(4.04)	(2.16)
rel. attention	-0.0259	-0.0297*	-0.0361	-0.0190*	0.0006	0.0028	0.0605	0.0380	-0.0134	-0.0206
	(0.57)	(1.74)	(0.85)	(1.68)	(0.06)	(0.02)	(1.32)	(0.38)	(0.64)	(0.93)
ad hoc news	-0.2221	-0.0968	0.0395	-0.0411	0.0959	-0.1918	-0.1208	-0.2135	-0.0903	-0.0295
	(0.53)	(0.57)	(0.12)	(0.39)	(1.23)	(0.29)	(0.36)	(0.39)	(0.45)	(0.12)
cons.	4.5466***	1.5586***	4.6963***	1.8128***	-0.3362**	6.4515***	2.5577***	5.6372***	2.4306***	-0.1730
	(4.94)	(3.63)	(6.47)	(7.71)	(2.59)	(5.70)	(5.36)	(6.30)	(8.50)	(0.62)
R^2	0.05	0.13	0.02	0.13	0.09	0.15	0.17	0.10	0.21	0.13
obs.	1,737	1,737	1,737	1,737	1,737	1,113	1,113	1,113	1,113	1,113

Figure 1: Number of Positive and Negative News Articles

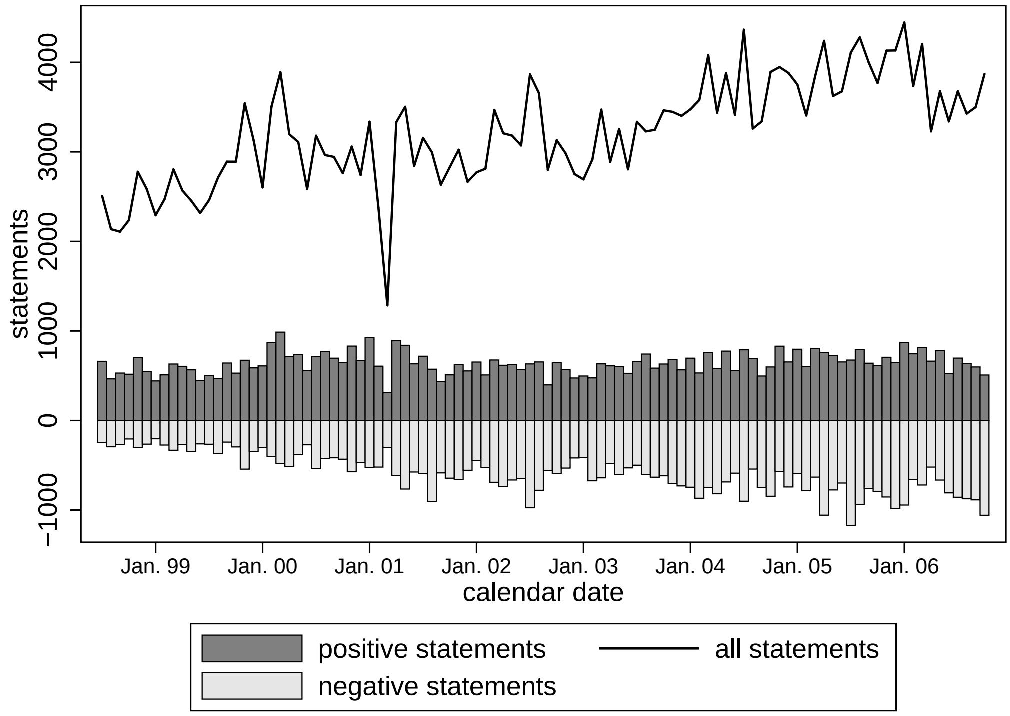

Figure 2: Events with High Absolute News Scores

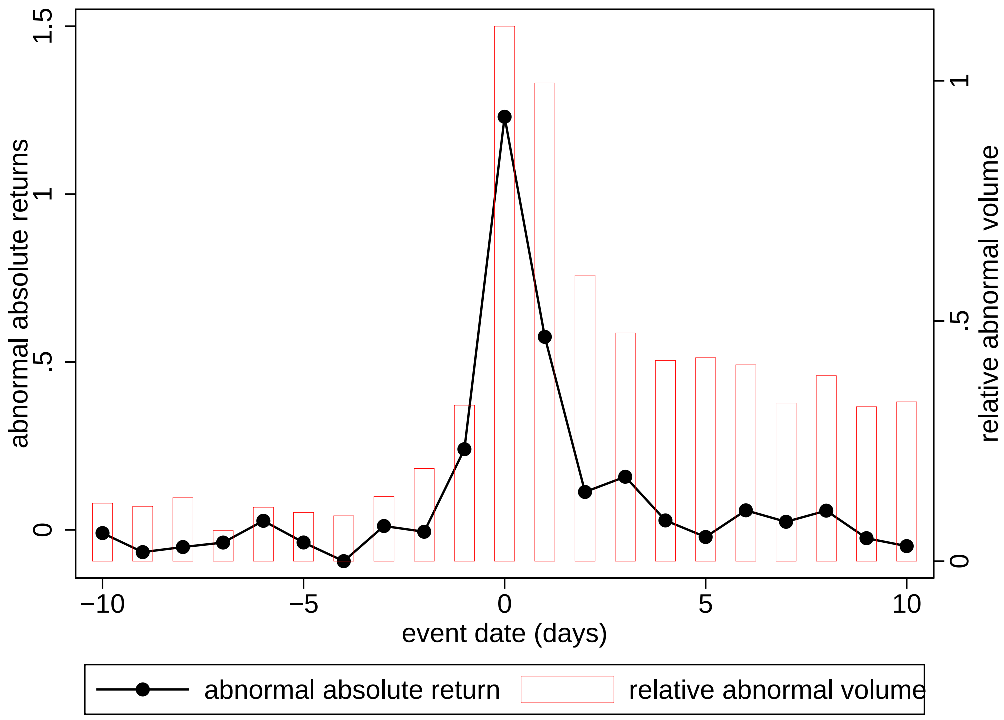

Figure 3: Positive and Negative News Shocks

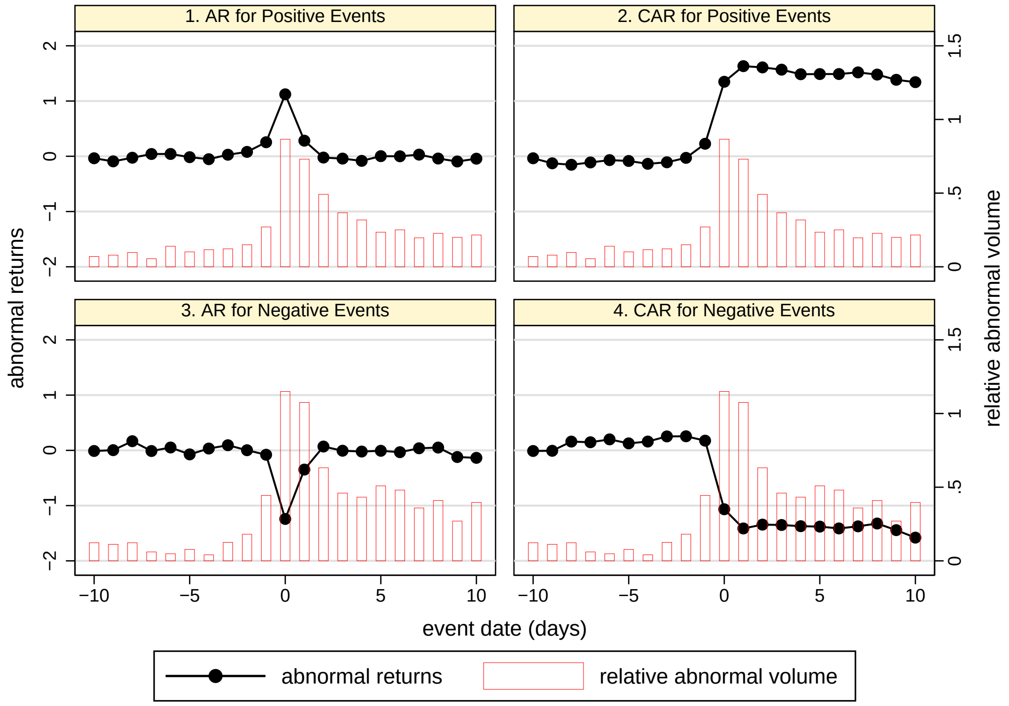

Figure 4: Events with and without Multiple News Shocks

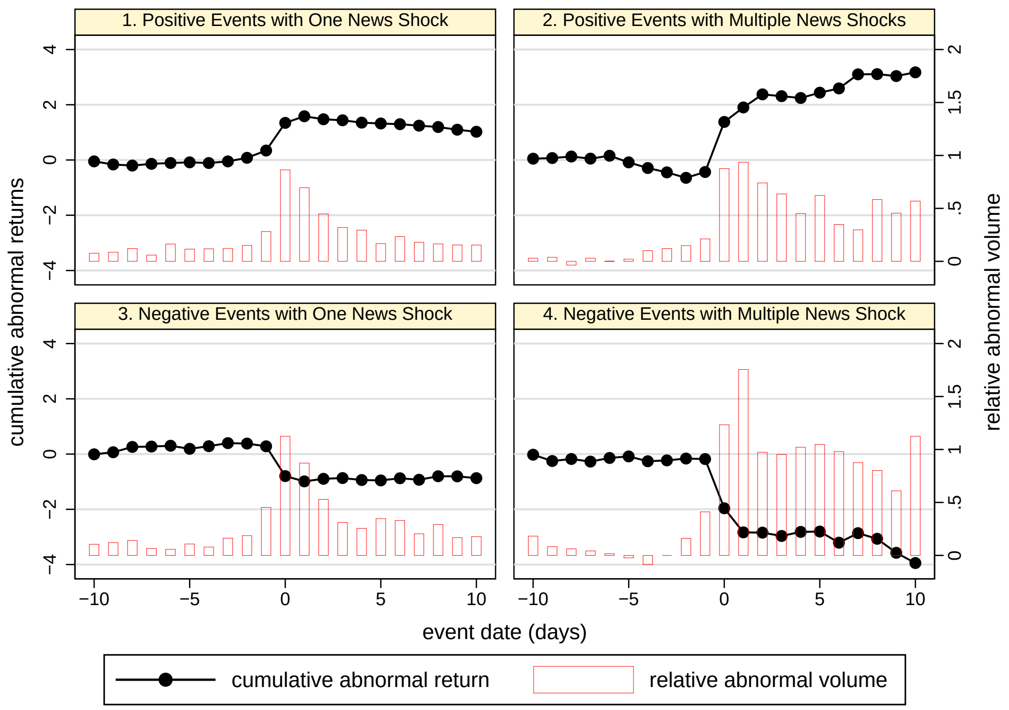

Figure 5: Events for Large and Medium Size Companies

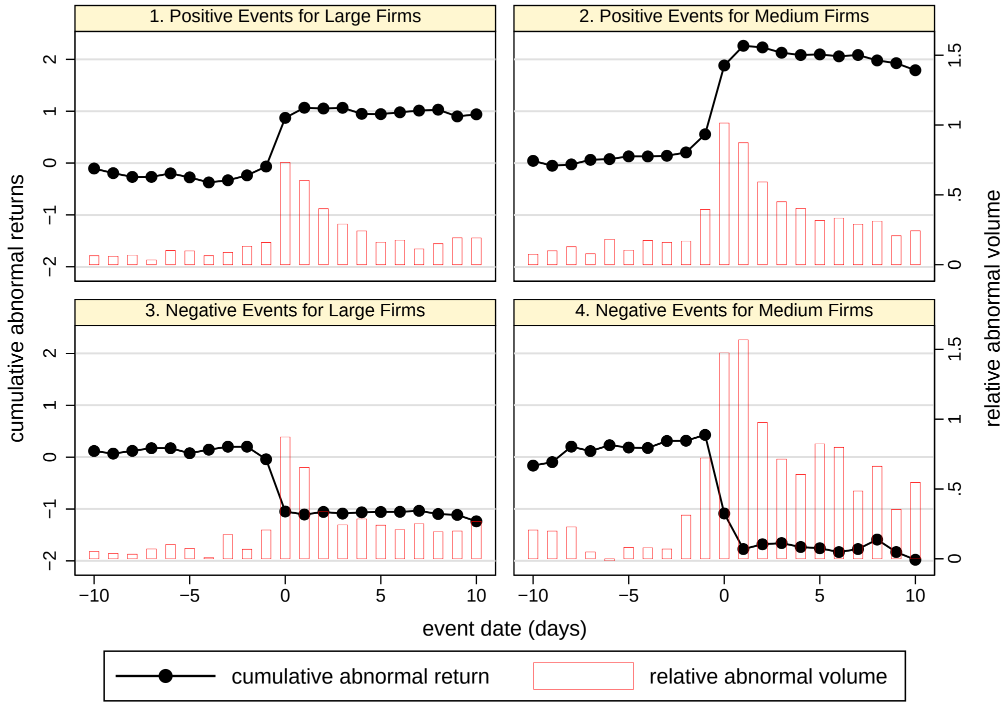

Figure 6: Events with Different Relative Attention

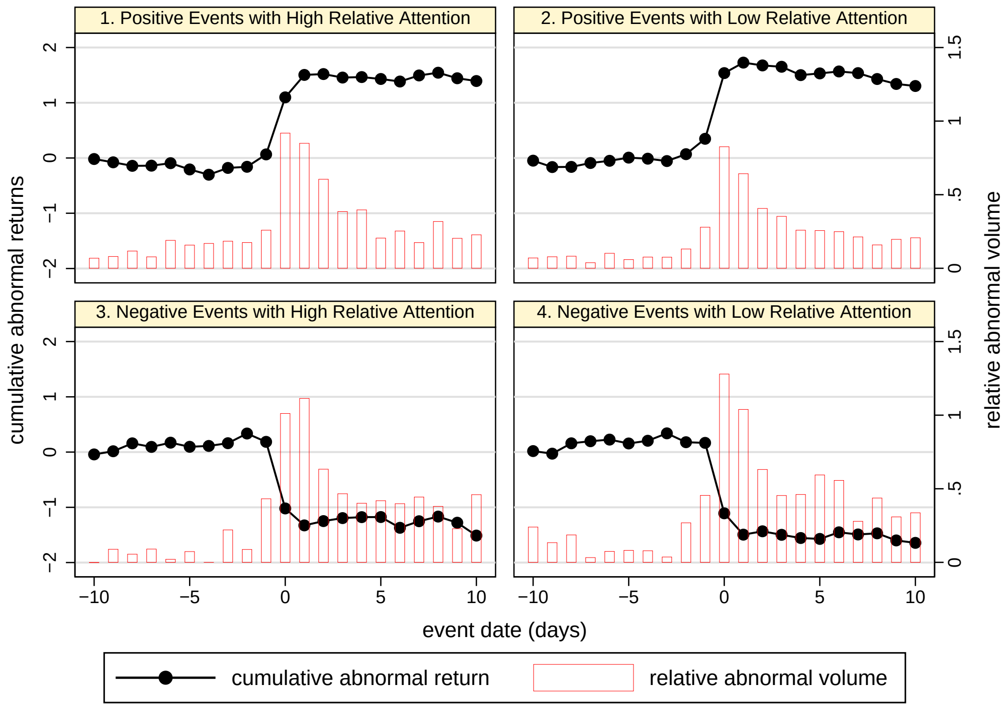

Figure 7: Number of Ad hoc Announcements on Event Days

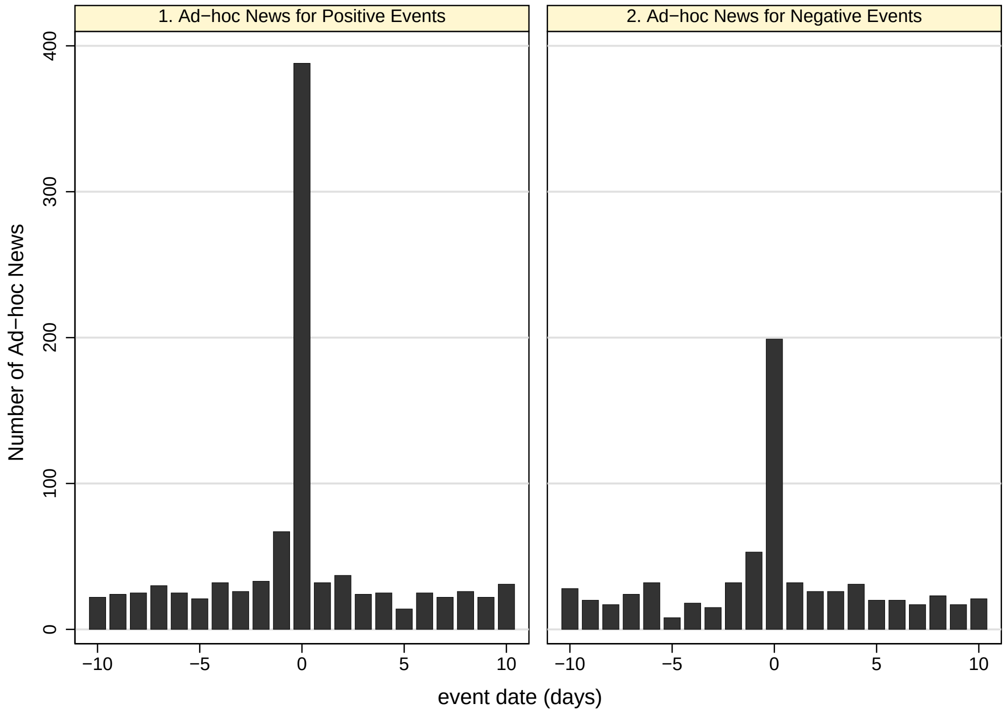

Figure 8: Events with and without Ad hoc Announcements