First to “Read” the News:
News Analytics and High Frequency Trading

Bastian von Beschwitz* — Federal Reserve Board

Donald B. Keim** — Wharton School

Massimo Massa*** — INSEAD

January 11, 2017

Abstract

We investigate whether providers of news analytics affect the stock market. We exploit a unique identification strategy based on inaccurate news analytics that were released to the market. We document a causal effect of news analytics on the market, irrespective of the informational content of the news. Coverage in news analytics speeds up the market reaction in terms of stock price response and trading volume, but temporarily increases illiquidity and can result in temporary price distortions that might increase volatility and reduce market stability. Furthermore, we document that traders learn dynamically about the precision of news analytics.

JEL classification: G10, G12, G14

Keywords: Liquidity, Stock Price Reaction, News Analytics, Information, High Frequency Trading.

---

* Bastian von Beschwitz, Federal Reserve Board, International Finance Division, 20th Street and Constitution Avenue N.W., Washington, D.C. 20551, tel. +1 202 475 6330, e-mail: bastian.vonbeschwitz@insead.edu (corresponding author).

** Donald B. Keim, Wharton School, University of Pennsylvania, Philadelphia, PA 19104; keim@wharton.upenn.edu

*** Massimo Massa, INSEAD, Finance Department, Bd de Constance, 77305 Fontainebleau Cedex, France, tel. + 33-(0)160-724-481, email: massimo.massa@insead.edu

An earlier version of this paper was titled "Media-Driven High Frequency Trading : Evidence from News Analytics". We are grateful to RavenPack for providing their data, and Malcolm Bain in particular for his expertise on different RavenPack releases. Thanks also to the technical personnel at WRDS, especially Mark Keintz, for making the construction of the intraday-market indexes possible. We thank Joseph Engelberg, Nicholas Hirschey, Todd Gormley, Markus Leippold, Joel Peress, Ryan Riordan, Paul Tetlock, Sarah Zhang and conference participants at the NBER Microstructure Meeting, European Winter Finance Summit, FIRS, and DGF for valuable comments. We acknowledge the financial support of the Wharton-INSEAD Center for Global Research and Education. All remaining errors are our responsibility.

Introduction

The recent decade has witnessed three major phenomena. The first has been the rise of algorithmic and high frequency trading (HFT).[1] HFT now accounts for nearly 50% of trading volume (Gerig, 2015) and the race for higher execution speeds has driven latency of the fastest traders down to the nanosecond level (Gai, Yao and Ye, 2013). The second is the rise of algorithmic processing of news releases (“news analytics”). The third is an increase in the number of “flash crashes” – i.e., sudden strong deviations of prices from fundamentals that are quickly reversed (e.g. Brogaard et al. (2015), Golub, Keane and Poon (2012)). This raises the question of whether there is a link between these phenomena. In particular, given that one of the main benefits of financial markets is the aggregation of information and assimilation into prices, which role does the information generated by algorithmic news processing play in a world dominated by HFT?

The question is tricky as HFTs trade mainly in reaction to quotes and prices – i.e., they react to information that is already inside the market system. In contrast, news analytics allow its users to react faster to events that are not yet reflected in asset prices. For example, RavenPack, a major provider of news analytics whose data we use in this study, uses computer algorithms to determine for each article in the Dow Jones Newswire the article’s relevance to each company mentioned in it, and whether it is positive or negative. This processing is completed and then electronically delivered to RavenPack’s subscribers within a third of a second. While this is slow compared to the speed with which HFTs can react to price movements, news analytics companies such as RavenPack provide the fastest way to react to information that is not yet reflected in asset prices.

In this paper, we study how news analytics has affected the way financial markets incorporate public information. Two features make news analytics particularly interesting. On the upside, news analytics likely increase the speed with which markets incorporate information and thus increase their efficiency. On the downside, an ~~when~~ algorithm ~~s~~ “reading” news inaccurately~~, this~~ can lead to unintended consequences as trading programs automatically initiate trades on an incorrect assessment of the news content. For example, in April 2013, an incorrect twitter feed about a White House explosion caused a mini flash crash. Some quickly blamed algorithmic trading for the reaction, while others argued that human traders were mainly responsible.[2] In either ~~any~~ case, news~~-~~reading algorithms might be more

[1] Throughout the paper, we will use the term HFT to refer to any kind of algorithmic trading. For example, our definition includes hedge funds which trade algorithmically, but are not co-located.

[2] See for example “The Trading Robots Really Are Reading Twitter”- http://finance.yahoo.com/news/trading-robots-really-reading-twitter-124443495.html and “#hashcrash: The anatomy of an investment panic” http://goinfront.com/blog/article/497

likely to misinterpret news than human traders and contribute ~~. This raises the question whether news analytics have contributed~~ to some of the mini flash crashes that we observe ~~or whether these worries are unfounded~~.

Investigating the issue ~~While the question~~ of how news analytics affects the stock market, while ~~is~~ important, especially for policy considerations, is tricky as ~~its effect is not easy to isolate because~~ the *response to news analytics normally cannot be distinguished from the reaction to the news itself*. In this paper, we ~~We are able to~~ address this identification issue by exploiting a unique identification strategy based on inaccuracies in news analytics. We identify these inaccuracies by comparing older and newer versions of RavenPack. We use the back-filled analytics of increasingly more sophisticated versions of Ravenpack to identify inaccuracies in the old version that was released to the market. Evidence of market reactions to such inaccuracies would suggest a causal impact of news analytics on stock the stock market.

We test the following hypotheses: First, we ask whether inaccuracies in news analytics lead to price distortions analogous to "mini" flash crashes – i.e., whether they trigger price reactions that are subsequently reversed (*Hypothesis 1*). Second, we ask whether news analytics increase the speed with which traders react to public signals and thus the speed at which the market incorporates information, leading to higher market efficiency (*Hypothesis 2*). Third, we investigate whether there is an impact on market liquidity. We consider two competing effects of news analytics on liquidity. On the one hand, news analytics improve information efficiency because trading on it is partially revealing (e.g., Kyle 1985). On the other hand, high frequency traders acting as market makers (e.g. Menkveld (2013), Hagströmer and Nordén (2013)) could use news analytics to reduce liquidity provision after a news release to avoid being picked off by informed order flow from traders that have better, proprietary news analytics software. These "market maker HFTs" may not want to use RavenPack for directional trading, but may rather use RavenPack to inform them when to reduce liquidity provision. If the first information improvement effect prevails, news analytics increase liquidity (*Hypothesis 3a*), while if the liquidity reduction effects prevails, news analytics will decrease liquidity (*Hypothesis 3b*). Finally, we ask whether high frequency traders dynamically learn about the signal precision of news analytics. If this is the case, we expect a stronger price reaction to news analytics in stocks in which news analytics have been more informative in the past (*Hypothesis 4*).

To identify inaccuracies in news analytics, we focus on differences in the "relevance score", which measures the importance of an article for a certain company. The relevance score is very important: highly relevant articles that are positive (negative) are followed by positive (negative) stock returns, while there is almost no reaction to articles with a low relevance score. Differences in relevance scores between the old and new versions are due to an improved performance of the algorithm in identifying companies in the article and determining the article's relevance to the company.

We use these differences in relevance scores to define three categories of articles: High-relevance articles Released as High-relevance articles (HRH) are articles that were correctly released to the market; Low-relevance articles Released as High-relevance articles (LRH) are false positives, i.e. articles that are wrongly attributed to a company; and High-relevance articles Released as Low-relevance articles (HRL) are false negatives, i.e. articles that the old version of RavenPack failed to attribute to the correct company.

To study Hypothesis 1, we focus on LRH articles. We find that the market indeed reacts to such false positives, but the effect is not persistent. The market initially overreacts to the incorrect information, realizes the inaccuracy, and quickly corrects after 30 seconds. This price distortion is analogous to a "mini" flash crash, thus confirming Hypothesis 1 and the causal effect of Ravenpack on stock prices.

To test the remaining hypotheses, we focus on the comparison between HRH and HRL articles. These two article groups are of similar relevance according to the most recent version of RavenPack, but only HRH articles were correctly classified, and released to the market, as highly relevant. On the other hand, HRL articles were incorrectly released as not relevant in the old version and thus for these articles there should be no causal effect of RavenPack on stock prices. Comparing the market response to HRH and HRL articles provides another way to assess the causal effect of RavenPack.

We find that the market reacts differently to HRH and HRL articles. The share of stock price reaction concentrated in the first 5 seconds after an article compared to the total reaction over 120 seconds is significantly greater for articles that were released as highly relevant (HRH) than for those highly-relevant articles that the old technology mislabelled as having low relevance (HRL). This difference in speed of the stock price response is 1.3 percentage points or 10% relative to the mean.

Not only does the market react faster, but it also reacts in the sentiment direction indicated by Ravenpack. Indeed, the sentiment direction of an article as determined by RavenPack predicts the stock price reaction to the article better when RavenPack consistently identifies the article as having high relevance (HRH) then when the old technology mislabelled it as having low relevance (HRL). This implies that traders use RavenPack to trade in the direction of the sentiment indicator provided by the news analytics.

In addition to the faster stock price response, we also document an increase in the share of trade volume concentrated in the first 5 seconds compared to the two minutes after an article. This increase is consistent with the theoretical prediction that investors with a speed advantage trade aggressively on signals that they can exploit before other traders (e.g., Foucault, Hombert, and Rosu (2015)). Taken together, these findings confirm *Hypothesis 2*.

Next, we find that a stock becomes more illiquid immediately after the release of an HRH article (i.e., consistently identified as relevant). Both the illiquidity measure of Amihud (2002) and the effective spread increase more in the five seconds after an HRH article relative to the five seconds after an HRL articles. This finding confirms *Hypothesis 3b* and rejects *Hypothesis 3a*.

Finally, we document that high frequency traders dynamically learn about the signal precision of RavenPack. More specifically, the causal effect of RavenPack on 5-second announcement returns is stronger if RavenPack has been more informative in the past – i.e., if RavenPack's sentiment scores accurately predicted 2-minute announcement returns in the past for that industry. A one standard deviation increase in informativeness almost doubles the causal effect of RavenPack's sentiment score on 5-second stock price returns. These findings suggest that algorithmic traders learn dynamically about the precision of RavenPack, and that they rely more heavily on RavenPack's sentiment scores if these scores have been informative in the past. Such learning could be programmed into their algorithms (machine learning) or can come from manually updating their algorithms over time. This finding confirms *Hypothesis 4*.

A series of robustness checks confirm our results. First, one potential concern could be that our results are driven by the fact that HRH articles are systematically different from HRL articles. We address this issue in two ways. First, we show that the long-run stock price reaction to HRH and HRL articles is very similar and that they are not significantly different in a number of characteristics. Second, we use the fact that RavenPack has back-filled the data of all versions to February 2004 to conduct placebo tests during the time before RavenPack went live. If our results were driven by general differences between the two article types, rather than a causal impact of RavenPack, then our tests should find significant price reactions before RavenPack went live. However, for all the tests we report insignificant differences in price reactions (between HRH and HRL articles) before RavenPack went live, suggesting that general differences between the HRH and HRL articles are not driving our results. Moreover, the stock price reactions to HRH and HRL articles start to diverge exactly at the moment when RavenPack went live and the increase in the difference between HRH and HRL articles is significant. All of this suggests a direct causal impact of RavenPack on the stock market.

Overall, our tests show that news analytics have a significant impact on the market in terms of returns, trading volume and liquidity in a manner predicted by several models. This effect goes beyond the underlying influence of the news itself. While our study can only detect the effect of RavenPack, there are other providers of news analytics, and high frequency traders may conduct algorithmic news processing in house. Thus, the total effect of algorithmic news processing is likely much larger than the effect of RavenPack that we measure in this paper.

Importantly, our results have normative implications relating to recent discussions about the regulation of high-speed sources of information and the effects of algorithmic trading.[3] We show that news analytics allow the market to incorporate information more quickly and be more efficient, but that they induce distortionary liquidity effects.[4] Furthermore, inaccuracies in news analytics can lead to stock price reactions, which are unrelated to fundamental news and are quickly reversed – i.e., they lead to price distortions analogous to “mini” flash crashes. Such distortions can increase volatility and reduce market stability.

Our results contribute to three major strands of literature. First, we contribute to the growing empirical literature on high frequency trading.[5] Several papers show that high frequency traders in general improve price efficiency (e.g. Brogaard, Hendershott and Riordan (2014), Chaboud et al. (2013), Boehmer, Fong and Wu (2015)). In contrast to these studies, we are able to examine one specific channel of their informational advantage and provide evidence of an increased speed of price adjustment to that information.

Second, our paper is the first to show the *causal* impact of news analytics on stock markets. Thus, our paper differs from the existing literature that investigates the correlation between the market and news analytics (e.g. Riordan, Storkenmaier, Wagener, and Zhang (2013), Gross-Klugmann and Hautsch (2011), Sinha (2012), Zhang (2013)) without passing judgment on whether there is a causal impact of news analytics on the market.

Third, our results are consistent with recent models of high frequency trading in which some traders have an informational advantage. For example, Foucault, Hombert, and Rosu (2015) model a situation in which a speculator receives information one period ahead of the market maker in a set-up similar to Kyle (1985); in Martinez and Rosu (2013) some agents have a short lived informational advantage; and in Dugast and Foucault (2014), speculators face a trade-off between processing a signal faster or more

[3] “FBI joins SEC in computer trading probe”, Financial Times March 5, 2013.
[4] It is questionable, whether the increased efficiency yields sufficient welfare gains to justify the investments in fast trading technology. For a theoretical paper on the welfare effects of high frequency trading see Biais, Foucault and Moinas (2015). Also, improved price efficiency can lead to lower incentives to gather private information (Weller, 2015).
[5] Examples of this literature include Hendershott and Riordan (2013), Hendershott, Jones, and Menkveld (2011), Baron, Brogaard and Kirilenko (2014), Menkveld (2013), Jovanovic and Menkveld (2010), Riordan and Storkenmaier (2012), Boehmer, Fong, and Wu (2015), Hasbrouck and Saar (2013), Benos and Sagade (2012), Clark-Joseph (2013), Hirschey (2013), Brogaard et al. (2014). A survey of this literature is provided by Jones (2013).

accurately. Faster traders in these models make markets more informationally efficient, but also more unstable. We find support for both effects in our analysis.

2. Test design, identification strategy, and data sources

In this section we first describe the RavenPack news analytics data and how it is used in our identification strategy and tests. After a brief description of our stock market data, we then present summary statistics for the variables used in our tests. Detailed definitions of all variables are in Appendix 1.

2.1 RavenPack

RavenPack provides real-time news analytics based on the Dow Jones Newswire. This service analyzes all the articles on the Dow Jones Newswire with a computer algorithm and delivers article-level relevance and sentiment metrics to its users. It determines which companies are mentioned in the article, how relevant the article is to the company and reports different sentiment indicators about whether the article is good or bad news for the company. The latency – i.e. the time from the release of the Dow Jones Newswire to the release of the RavenPack metrics – is approximately 300 milliseconds. RavenPack claims it has the "timeliest company sentiment indicators in the marketplace."[6] As such, RavenPack is ideally suited for the use of algorithmic and high frequency traders engaging in algorithmic news trading. In this paper, we use a broad definition of HFT, which includes both, specialized high frequency trading firms that are co-located and other professional traders that engage in algorithmic trading. For example, numerous hedge funds have been subscribers to RavenPack since its inception.[7]

2.1.1 Ravenpack – definition of variables

We extract from RavenPack the following variables. *Article Category* is a variable determining the topic of the article and the role played by the company in the article. For example, *Article Category* might be "acquisition – completed – acquirer" for a company announcing the completion of an acquisition of another company or "rating – change – negative – rater" for a rating company that just downgraded another company. The identification of the news topic is based on a purely algorithmic approach, and a large percentage of articles cannot be classified in this way. *Article Category Identified* is a dummy variable equal to 1 if *Article Category* is identified by RavenPack, and zero otherwise.

[6] "RavenPack Enables Trading Programs with Sentiment on 10,000 Global Equities," RavenPack press release from May 28, 2009.

[7] Confidential discussions with RavenPack managers provided us with a very consistent overview of market penetration, suggesting that major institutional investors are in fact users of this service.

There are two major sentiment scores in RavenPack. The *Composite Sentiment Score* (CSS) is based on several individual RavenPack sentiment measures. It takes a value ranging from 100 (positive) to 0 (negative), where 50 is a neutral article. It is available for each article. The *Event Sentiment Score* (ESS) is coded in the same way as CSS, but only available if the category of the article can be identified. We aggregate these two scores into a single sentiment variable called *Sentiment Direction*, which is first based on ESS and uses CSS only if ESS is either missing or equal to 50 (neutral).

Relevance is an index provided by RavenPack that indicates the relevance of an article to the company. This takes values ranging from 0 (least relevant) to 100 (most relevant). If the type of the article can be identified and the company plays an important role in the main context of the story – e.g. is an acquirer or announces a buyback – then the *Relevance* score is 100. If the company is mentioned in the title, but the type of article cannot be identified, then *Relevance* ranges between 90 and 100. If the company is mentioned, but plays an unimportant role, then it gets a low *Relevance* score. For example, a bank advising an acquisition typically gets a score around 20. We would not expect such articles to affect the bank's or news agency's stock prices very much.

In line with this, RavenPack recommends "filtering for *Relevance* greater than or equal to 90 as this helps reduce noise in the signal". To examine this claim, Figure 1 plots the market reaction to news as a function of the Relevance Score. We report the cumulative returns from t-30 to t+120 seconds around the news events from April 1, 2009 to September 10, 2012. We multiply the returns by the sentiment direction of the article. The articles with *Relevance* greater than 90 do indeed have an important effect on stock prices, but we find there is no reaction to articles with *Relevance* below 90. Thus, we will refer to articles with *Relevance* below 90 as having low relevance. This analysis suggests that RavenPack is good at filtering out the relevant news for a company and identifying the sentiment of an article.

2.1.2 Ravenpack – test design using different product versions

RavenPack released its first version (v. 1.0) to the market on April 1, 2009,[8] [9] and a revised version of the service (v. 2.0) with additional features on June 6, 2011. The most recent version we use (v. 3.0) was released on September 10, 2012. RavenPack has provided us with data from each of the release-specific algorithms, each having been back-filled to February 2004. Importantly, the stock-specific metrics from

[8] Even though the official release date of the RavenPack service was May 2009, some customers had access to the service as early as from April 1, 2009. Thus, we refer to April 1, 2009 as the introduction of RavenPack. Before April 2009 RavenPack had a pre-existing service that also released sentiment information on the Dow Jones News Wire. However, this service was meant more for longer term news analysis, such as charting sentiment over several days. The prior service was not provided timely enough to be used at high frequency.

[9] RavenPack 1.0 was actually released on Sept 6, 2010. A predecessor to v.1.0, that was similar to v.1.0, is the version that was released on April 1, 2009. This predecessor version was not made available to us, but RavenPack confirmed that it was very similar to RavenPack 1.0.

these three releases can sometimes differ. RavenPack doesn't change the overall definition of its algorithm over time, so as not to distort its customers' trading strategies which might be based on the specific way a variable is defined. However, corrections have been made to the way companies are identified in an article and how the relevance of an article to a company is determined.[10] This means that there are articles which might have been associated with a company in one RavenPack release, but not in another. These differences in the relevance of articles to companies in the different versions will provide the basis for our tests. Assuming that the most recent version of RavenPack (v. 3.0, which we hereafter refer to as New RavenPack) is the most accurate, we can identify inaccuracies in RavenPack 1.0 and RavenPack 2.0 (we will refer to those versions as Old RavenPack) that were released to the market. If the market reacts to these inaccuracies, it is a sign of a causal effect of RavenPack on the stock market.

Our analysis can be thought of as assuming two types of traders: HFTs that subscribe to RavenPack and human traders that rely on reading the article to determine its content. Further, we assume that human traders have an advantage in the precision with which they can derive a signal from the news, while HFTs have an advantage in terms of speed. This means that RavenPack allows traders to trade faster on a less precise signal. In the short run when only HFTs can react to news, RavenPack will have the largest impact, while in the long run, human traders determine the price reaction, because their signal is more precise.

In the empirical implementation we have to choose specific time intervals to constitute the short and the long run. We choose the short run to be 5 seconds, because this is long enough to capture the full reaction of HFTs (including slower HFTs that are not co-located and might not trade in the millisecond environment), while this time is too short for a human trader to read an article, process it and make a trading decision based on it. We choose two minutes as the long run, because this should be enough time to read an article and trade on it, while longer time windows will be more affected by noise. We provide robustness checks in which we use 10 seconds for the short run window and 5 minutes for the long-run window.

We define the following article types that we also list in Panel A of Table 1. *High relevance article Released as High relevance article* (HRH) is defined as an article that was classified as relevant in both Old and New RavenPack. We predict that such a correctly released article creates a fast and persistent market reaction. *High relevance article Released as Low relevance article* (HRL) is defined as an article with high relevance in New RavenPack, that was wrongly assigned low relevance in Old RavenPack.

[10] In addition, the number of companies covered by RavenPack has also increased between releases. There are 156 companies (3%), which are only covered in New RavenPack. We ensure by using company fixed effects that this difference in coverage is not driving our results.

Low relevance means either that the article was not at all assigned to the company or that the relevance score was below 90. We expect such an article to have a similar long run market reaction as an HRH article, because it is of similar relevance according to New RavenPack. However, we would expect a slower market reaction as it was not released to the market as a relevant article originally. *Low relevance article Released as High relevance article* (LRH) is defined as an article that was wrongly released to investors as having high relevance (as it has low relevance according to New RavenPack). For these article, we would expect an initial overreaction of high frequency traders which might later be reversed by human traders. Examples of all three article groups are provided in Appendix 4. A fourth article category is Low relevance articles Released as Low relevance articles (LRL), these are articles that have a relevance score below 90 in both versions.[11] We do not expect much market reaction to these articles.

These predictions allow for two potential empirical set-ups: First, we could study overreaction to false positives by comparing how the market reacts differently depending on whether a low relevance article was released as having high or low relevance, i.e. we can compare LRH and LRL. Second, we could study underreaction to false negatives by comparing how the market reacts differently depending on whether a high relevance article was released as having high or low relevance, i.e. we can compare HRH and HRL.

In both cases, we would assume that Old RavenPack contains no information on the relevance of the article over and above that contained in New RavenPack. This is a fairly strong assumption. Fortunately, this assumption is testable. Because we have data from 2004 and RavenPack went "live" in 2009, we can examine the market impact to the different types of articles during the time period when RavenPack could not have had any causal market impact, because it was not yet "live". To do this, we regress absolute return and turnover in the two minutes after the article on dummy variables equal to 1 for HRH, HRL and LRH (with LRL being the omitted category). To control for firm- and time-specific effects, we include firm, date and hour of the day fixed effects.

The results are presented in Panel B of Table 1. In addition to the three coefficients, we also test for the statistical significance of the difference between HRH and HRL articles. The coefficient of LRH is fairly large and significantly positive for both absolute returns and turnover, suggesting that LRH articles are significantly more important than LRL articles. This implies that a test of overreaction comparing LRH and LRL articles is not possible, because the two article types are fundamentally different. Thus,

11 LRL articles also include articles that have a relevance score below 90 in either Old RavenPack or New RavenPack and are not assigned to the company in the other version.

instead of comparing LRH and LRL articles, we will rely on graphical evidence to compare the reaction to LRH articles before and after RavenPack went "live".

However, the difference between the coefficients for HRH and HRL articles is small and insignificant for both turnover and absolute returns. Therefore, we conduct most of our tests based on the comparison between these two groups. To ensure further that differences in importance between HRH and HRL are not driving our results, we control for any potential differences between these groups by examining the speed of market reaction, i.e. the size of the short run reaction relative to the long-run reaction. Furthermore, we conduct placebo checks for all our tests showing that our results are not driven by differences in HRH and HRL articles, but by the causal effect of RavenPack.

2.2 Stock market data

We use intraday quotes and trade data from TAQ.[12] We use the TAQ National Best Bid and Offer (NBBO) file provided by WRDS for quotes. As a first step, we aggregate the trading volume at the frequency of one second, and compute second-by-second returns from the end-of-second bid-ask midpoint. We use bid-ask midpoints rather than trading prices to avoid the effects of bid-ask bounce. Even after this aggregation, the data for all the stocks in our 8-year sample is by far too large to be used in a standard panel set-up. Most microstructure studies thus have to limit their attention to a small number of stocks over a short time period. Because we are only interested in the market reaction around a company's news, we can limit our attention to a few minutes around the news. This simplification allows us to study all US common stocks over the full 8-year sample period.

To control for the overall market movements taking place during this period, we compute a second-by-second intraday market index from the total TAQ universe. We compute second-by-second returns, turnover and value-weighted volatility for the market index. We also compute returns for industry-specific indices for the 12 Fama French industries. The details of the index construction are explained in Appendix 2. To control for stock-specific information, we use the CRSP daily stock file and compute the prior month's return, volatility, turnover, Amihud (2002) illiquidity measure, and market capitalization.

We employ the following filters: To be included in our sample, a stock must be covered in CRSP and TAQ, must have SHRCD 10 or 11, must have a beginning of the day stock price of at least $1 and must have a beginning of the day percentage bid-ask spread of less than 10%. We exclude articles that occur outside trading hours or in the first or last 20 minutes of trading in the day. To avoid distortions from overlapping windows around articles, we exclude stale news defined as articles for which the company

[12] We use the usual filters of excluding all trades with zero size, negative prices, correction code different from 0 and bid ask quotes where the bid is above the asked.

had an article in the prior 15 minutes. We also exclude four companies that appear in articles mainly as information providers: McGraw-Hill, NASDAQ, CME and Moody's. Because we need an initial bid-ask midpoint to compute a first return and because we want to avoid a stock's turnover influencing the stock price we measure, we use seconds $t-480$ to $t-1$ as a burn-in period. Only articles for which the stock has a quote in those 8 minutes before the article are included in our analysis.

2.3 Summary statistics and comparison between HRH and HRL

In Table 2, Panel A, we report the number of article-firm combinations classified as HRH and HRL, both before and after RavenPack went live. In parentheses, we report the percentage of the total observations in that line. In Panel B, we report the number of companies included in articles in each classification. Since many companies have articles in both classifications, the number of observations in the two classifications does not add up to the total. The number of articles is not dramatically different before and after the introduction of RavenPack; indeed, there are fewer HRL articles after the introduction of RavenPack. This suggests that our results are not driven by a spurious connection between the number of articles and the existence of RavenPack.

The final sample consists of 321,912 article-firm combinations, starting with the release of RavenPack 1.0, over the period April 1, 2009 to September 10, 2012. In Panel A of Table 3, we report descriptive statistics for all our variables for the combined sample of articles classified as HRH and articles classified as HRL.

One concern with our analysis is that the information content of HRH and HRL articles might be different. Therefore, we compare their difference in terms of observable variables in Panel B. For this purpose, we regress each article characteristic on a dummy variable equal to 1 if the article is HRH (we refer to this variable as D(HRH)) as well as the fixed effects used in our regression, namely: Relevance, Category, Hour and Date Fixed Effects. We report the coefficient of D(HRH) as well as a t-statistic clustered on the firm level. There is no statistical significant difference between the two groups in terms of firm size, sentiment scores, time since the last article, turnover and illiquidity. Most importantly, we find no evidence that HRH are more important than HRL articles. The absolute returns both over the 2 minutes following an article and on the full trading day of the article are actually (insignificantly) lower for HRH articles. This suggests that HRH articles are not generally more important. The only significant differences between HRH and HRL articles are that stocks that are the subjects of HRH articles have a slightly lower return (0.03%) and volatility (1.5%) in the prior month than those associated with HRL articles, and that HRH articles cover fewer firms per article. However, these differences are small in economic terms (0.05, 0.09 and 0.22 standard deviations). In addition, we account for these differences with control variables in all our regressions. The fact that HRH and HRL articles are similar alleviates worries that our results are driven by differences in the article types. In addition, we run placebo tests to confirm that unobservable differences are not driving our results.

3. Results

Here we present the empirical results of our paper. Each subsection is dedicated to one of the hypotheses outlined in the introduction.

3.1 News analytics and temporary price distortions

In this section we examine *Hypothesis 1*, whether inaccuracies in news analytics lead to price distortions analogous to "mini" flash crashes, i.e. to an overreaction in stock price that is afterwards reversed. As explained in Section 1.1.2, we expect the market to overreact to LRH articles, i.e. articles that New RavenPack identifies as having low relevance, but that were incorrectly released as having high relevance in Old RavenPack.

We first consider graphical evidence. In Figure 2, we compare the market reaction of articles consistently released as relevant (HRH) with those released as relevant, but having low relevance in New RavenPack (LRH). We focus on the cumulative return from t−30 to t+120 seconds around the news events. We multiply returns with the sentiment direction of the article to be able to combine positive and negative news in one analysis. We exclude articles with neutral sentiment. Figure 2 shows that the market overreacts to LRH articles. In the short-run these articles have a price reaction that is very similar to HRH articles. However, after approximately 30 seconds – a reasonable time for a fast human trader to process the article – the stock price reaction to LRH articles starts to revert. After approximately 2 minutes, most of the short-run reaction to these articles has reversed. In contrast, articles classified as HRH have a longer-term effect on price, lasting more than two minutes. This finding is consistent with a causal effect of RavenPack that leads high frequency traders to trigger an initial overreaction to the article that is then corrected by human traders, a price distortion analogous to a flash crash (even though much smaller in magnitude).

Next, we provide a multivariate analysis. The problem in studying LRH articles in a regression set-up is that we do not have an appropriate control group for these articles as they are more relevant than LRL articles, but less relevant than HRH articles (see Panel B of Table 1). Therefore, we use LRH articles from the period before RavenPack went "live" as the control group. While these articles should be of similar relevance as LRH articles after RavenPack went "live", they could not have had any causal effect on stock prices as RavenPack at that time was not yet released to investors. In particular, we study whether LRH articles have a stronger short run stock price impact and a larger reversal after RavenPack goes "live", as compared to before.

The results are presented in Table 4. We regress the stock price reaction to the article on an interaction between the *Sentiment Direction* and a dummy equal to 1 after RavenPack went "live" in April 2009. In addition, we include various combinations of control variables and fixed effects. To control for stock-specific information, we use its market capitalization, return, volatility and turnover measured over the prior month, and our illiquidity measure based on Amihud (2002). For brevity, the coefficients on these control variables are only reported in the Internet Appendix. To control for characteristics of the news announcement, we include the sentiment and article-specific variables defined in section 1.1.1. Appendix 1 contains a description of all the variables.

In regressions 1 to 3, we use the short-run stock return from 1 second before to 5 second after the article as the dependent variable. We find that the short run stock return is significantly more positively correlated with the sentiment of the article after RavenPack went "live" in 2009. Given that LRH articles should not have changed in relevance after the introduction of RavenPack, this finding implies that there is an overreaction to these articles. Indeed, it seems plausible that HFTs trade in the direction of the sentiment of the article, because RavenPack (incorrectly) labelled the article as highly relevant.

Next, we study whether this overreaction is subsequently reversed. For this purpose, we use the stock price reaction from 6 to 120 seconds after the article as the dependent variable. We find that it is more *negatively* correlated with the article sentiment after RavenPack went "live", consistent with a reversal. While this result is not statistically significant, the negative magnitude of this coefficient is about the same as the positive magnitude of the coefficient in the regression above, implying that almost all of the short run overreaction is reversed in the two minutes after the article. The fact that this result is not significant can be explained by the small sample size due to the fact that we exclusively focus on LRH articles.[13]

Taken together, our graphical and regression analyses of LRH articles results confirm *Hypothesis 1* that inaccuracies in news analytics can cause short term overreaction that is afterwards reversed, a return pattern similar to a flash crash.

3.2 News analytics and speed of stock price response

[13] We observe significant effects of the constituents of the interaction in this regression. The positive and significant effect of *Sentiment Direction* is expected and shows that (even before the release of RavenPack) the market reacted to the sentiment of the article. The negative coefficient on *RavenPack Release* is surprising but not very meaningful as it shows that the average market reaction to articles was more negative after April 2009 (maybe due to the aftermath of the financial crisis).

In this section, we study *Hypothesis 2*, whether news analytics improve market efficiency by increasing the speed with which stock prices and traders react to news. We first provide some graphical evidence and then we provide a multivariate analysis.

3.2.1 Preliminary graphical evidence

As a first step, we conduct a purely time-series analysis and examine whether the market reaction to news is faster after RavenPack was introduced in April 2009. For this purpose, we focus only on the articles that are reported as highly relevant in both versions (HRH) and compare the market reaction for these articles in the time before and after RavenPack went live. We study the reaction in terms of cumulative returns within the first 120 seconds after an article. We multiply returns by the sentiment direction to be able to combine positive and negative news in one analysis.

We report the results in Figure 3. Because the news before and after the release of RavenPack differ in average importance, we standardize the average cumulative returns in each group by the total average cumulative return for that group after 120 seconds. Thus, the graph shows how much of the total reaction happens within a certain time period. In Panel A, we compare this share of stock price reaction before and after RavenPack went live. We see that there is a faster reaction after the introduction of RavenPack. After 10 seconds, 35.7% of the total reaction is incorporated into prices when RavenPack is live, while it is only 28.4% before April 2009.

For a better illustration, we display the difference between the two series in Panel B. It is striking to see that the faster reaction in the post-RavenPack time period occurs mainly in the first 5 seconds after an article is released, a time period in which only a computer could react to an article. From seconds 5 to 20, the difference stays more or less constant. After 20 to 30 seconds, it starts to decline and it is reduced to zero after 60 seconds, a time in which a fast human trader could react to an article. This finding suggests that the speed of reaction to news increases after April 2009. While these observations are consistent with news analytics improving market efficiency by increasing the speed of the market response after an article, the increase in market efficiency after April 2009 is not necessarily due only to newswire services such as RavenPack. Rather, it might also be caused by the rise of high frequency trading or any other phenomenon happening at the same time. The ideal experiment would be to randomly select a set of articles each day and not report news analytics for them. In our regression analysis in the next section, we come close to this idea by studying relevant articles that were released as having low relevance in Old RavenPack (HRL articles). This allows us to control for general time effects.

3.2.2 Regression analysis – speed of stock price response

In the rest of the paper, we will focus on false negatives, i.e. the articles that are highly relevant according to New RavenPack, but have been released as having low relevance in Old RavenPack (HRL). For these articles we have a good control group in the form of articles that have been reported as having high relevance in both versions (HRH). Comparing the market reaction to those two article groups allows us to see whether the market underreacts to relevant news when RavenPack does not classify it as relevant. In this case, the market will react quicker to a relevant article that is also reported as highly relevant (HRH).

We consider two alternative analyses for market reaction. First, we examine whether stock prices respond faster to HRH articles irrespective of the direction of the reaction. Then we study whether the sentiment of HRH articles predicts the directional stock price response better than the sentiment of HRL articles. For the first analysis, we define *Speed of Stock Price Response* as: $\frac{\text{Abs(Return t}-1\text{,t+5)}}{\text{Abs(Return t}-1\text{,t+5)+Abs(Return t+6,t+120)}}$ over the 120 seconds around the news event.[14] This variable measures the amount of the two-minute price change that takes place in the first five seconds after the release of the news. It is in the spirit of DellaVigna and Pollet (2008). It captures the degree of under-reaction by decomposing the market reaction into its short- and long-term components. The higher the value of *Speed of Stock Price Response*, the more the reaction to the news event concentrates in the first few seconds after the event – i.e., the less under-reaction.

In Table 5, we present the result of regressions of *Speed of Stock Price Response* on *D(HRH)*, which is a dummy variable that takes the value of one if the article was released as highly relevant to the market and zero if it was (incorrectly) released as having low relevance (HRL). In regressions 1 to 3, we estimate our main specification during the time in which RavenPack was live (Apr 1, 2009 – Sept 10, 2012). In regressions 4 to 6, we estimate a placebo test during the period before RavenPack was live. The models are estimated at the article level, thus allowing for both HRH and HRL articles that were released for the same firm or on the same day. This allows us to control in all regressions for unobserved heterogeneity with firm fixed effects and daily fixed effects. In addition, we also add fixed effects for the article category (e.g. mergers and acquisitions), the relevance score (from 90 to 100) and the hour during the day in which the article was released in regressions 2, 3, 5, and 6. In regressions 3 and 6, we add as additional controls the absolute return, turnover and volatility each for industry and market and for the two horizons from t−1 to t+5 and t−1 to t+120 seconds around the article. All standard errors are clustered at the firm level.

[14] We use $\text{Abs(Return t} - 1, \text{t} + 5) + \text{Abs(Return t} + 6, \text{t} + 120)$ rather than $\text{Abs(Return t} - 1, \text{t} + 120)$ in the denominator to constrain the variable between 0 and 1 rather than to allow it to approach infinity in cases where $\text{Abs(Return t} - 1, \text{t} + 120)$ is close to zero.

The results for regressions 1 to 3 show a positive and significant relation between *Speed of Stock Price Response* and *D(HRH)*, indicating that the stock price response is much quicker for an HRH article than for an HRL article. This result holds across all the different specifications and samples. It is not only statistically significant, but also economically relevant. If we focus on the main specification (specification 3), we find that HRH articles increase the *Speed of Stock Price Response* by 1.3 percentage points or 10% relative to the mean. We find similar results if we compute *Speed of Stock Price Response* using market-adjusted and industry-adjusted returns (reported in the Internet Appendix). This finding supports *Hypothesis 2* that news analytics increase market efficiency by increasing the speed of reaction to news.

One potential concern in this set-up is that our results are driven by the two article categories (i.e., HRH and HRL) having different informational content, i.e. the HRH articles being systematically more relevant. To address this issue, we use the fact that RavenPack has back-filled the data to February 2004. If our results are driven by general differences in the two categories, then there should be a difference in stock price reaction before RavenPack went live. In regressions 4 to 6, we report the results of this placebo test in the time period where RavenPack was not yet released to investors (February 1, 2004 – March 31, 2009). In contrast to the results in regressions 1 to 3 for the period when RavenPack was live, the placebo test does not show a statistically significant relation between *D(HRH)* and the *Speed of Stock Price Response*, thereby confirming that our main test is appropriate.

Another potential concern is that there might be a general trend in the difference of informational content between HRH and HRL articles, and that this trend is driving our results rather than the causal effect of RavenPack coverage on the market. To address this concern, we examine the relation between *Speed of Stock Price Response* and *D(HRH)* for different years before and after the introduction of RavenPack. To implement this analysis, we follow Gormley and Matsa (2011) and plot in Figure 4 the point estimates of a modified version of regression 3 in Table 5. In this modified regression set-up, we allow the effect of *D(HRH)* to vary by year. The control variables and the fixed effects are the same as in the main specification. Because RavenPack went "live" in the second quarter of 2009, we assign the first quarter of every year to the prior year. This way, years 2004 to 2008 were entirely before the release of RavenPack, while years 2009 to 2011 were completely after the release of RavenPack. We report the plot for this specification with one-year dummy variables in Panel A. In Panel B, we report the same regression but interacting *D(HRH)* with two-year dummy variables (with the first quarter shifted backwards as described above). We report 95% confidence intervals for the coefficients in both panels. In Panel C, we report the simple difference between *Speed of Stock Price Response* for HRH and HRL articles without any controls over different years (with the first quarter shifted backwards).

It is evident in the plots that the release of RavenPack magnifies the reaction to differences in versions. Before the introduction of RavenPack, the difference between HRH and HRL hovers around zero and there is no obvious time trend. After the introduction of RavenPack, the difference is much larger. This suggests the delivery of news analytics by RavenPack has an impact on the market that is separate and distinct from the underlying informational content of the news. It also suggests that our results are not driven by a spurious trend.

3.2.3 Regression analysis – directional stock price response

We now ask whether there is a relation between the stock price response and the sentiment direction of the news. That is, does the magnitude of the RavenPack-related stock price response (via correctly-labelled HRH articles) depend on whether the news is positive, negative, or neutral?

For this purpose, we ask whether the sentiment indicator in RavenPack better predicts the short run stock price reaction if an article is correctly classified as relevant (HRH) in RavenPack. We regress stock returns measured over the interval 1 second before to 5 seconds after the article on *D(HRH)*, *Sentiment Direction*, the interaction between *D(HRH)* and *Sentiment Direction*, and the fixed effects and control variables defined previously. We adopt the same econometric specification as before, but exclude any sentiment-related control variables as the effect of sentiment will be captured by *Sentiment Direction*. We report the results in Table 6. In Regressions 1 to 3, we estimate our main specification during the period when RavenPack was live (Apr 1, 2009 – Sept 10, 2012). The results show a positive and significant relation between returns and the interaction between *D(HRH)* and *Sentiment Direction*. That is, the RavenPack-induced stock price reaction is significantly different for positive versus negative news stories.

This result holds across all the different specifications. Similar results for market and industry adjusted returns are reported in the Internet Appendix. As before, the placebo test in Regressions 4 to 6 indicates there is not a statistically significant effect on returns during the period before RavenPack was live. These results confirm that news analytics have a directional impact on stock prices over and above the one of the underlying news.

3.3 News analytics and trade volume response

In the previous section, we saw that news analytics increase the speed at which prices adjust after news is publicly released via the Dow Jones Newswire. While the Dow Jones Newswire constitutes a public signal, RavenPack allows its subscribers to react to these public signals faster. Such a speed advantage in the reaction time to news is modelled in Foucault, Hombert, and Rosu (2015). Their model predicts that investors trade very aggressively when they receive a signal earlier than other market participants.

Therefore, we investigate whether the faster stock price response to an HRH article is accompanied by a faster trade volume response as well. We define *Speed of Trade Volume Response* as: $\frac{Turnover\ t-1,t+5}{Turnover\ t-1,t+120}$. The variable is defined using the same intervals as *Speed of Stock Price Response*. It captures the amount of trade volume that is concentrated in the first 5 seconds after the news event relative to the trading volume in the two minutes following the news event. We regress *Speed of Trade Volume Response* on *D(HRH)* using the same fixed effects and control variables defined above. The specification is identical to the specification for *Speed of Stock Price Response* employed in Table 5.

We report the results in Table 7. In regressions 1 to 3, we estimate our main specification during the period in which RavenPack was live (Apr 1, 2009 – Sept 10, 2012). As in the case of *Speed of Stock Price Response*, we find a strong positive and significant relation between *Speed of Trade Volume Response* and *D(HRH)*. This result holds across all specifications. *Speed of Trade Volume Response* is 0.5 percentage points larger for HRH articles than for HRL articles, or 9% relative to the mean. In regressions 4 to 6, we estimate a placebo test in the period in which RavenPack was not yet released to investors (Feb 1, 2004 – Mar 31, 2009). As was the case for *Speed of Stock Price Response*, the placebo test shows no significant difference in the speed of trade volume response between HRH and HRL articles during the period before RavenPack went live.

Overall, the results in these last two sections show that both stock prices react faster and traders trade more aggressively after articles that are covered in RavenPack, confirming that news analytics have a measurable impact on the stock market in addition to the information content of the news itself and improve price efficiency, as posited by *Hypothesis 2*.

3.4 News analytics and market liquidity

In this section, we examine Hypotheses 3a and 3b on the effect of news analytics on liquidity. The results in the previous two sections suggest that news analytics improve stock market efficiency by increasing the speed of reaction to news, which should lead to an increase in liquidity (Hypothesis 3a). This suggests that HFT use the informational content of news analytics services such as RavenPack to profit from the stock price reaction to news. However, several studies find that many HFTs act as market makers and supply liquidity to the market (e.g., Menkveld (2013), Hagströmer and Nordén (2013)). Such high frequency traders may use news analytics services differently. They may simply use the knowledge of a news release to anticipate an increase in informed order flow (coming for example from traders using proprietary news reading algorithms). Rather than trying to interpret the direction of the news themselves, they simply may withdraw from the market (or become less accommodating) after a news release to avoid being picked off. In this case, we expect a faster decline in liquidity for articles that are correctly covered in RavenPack (Hypothesis 3b). In this section, we examine which effect dominates.

We investigate this issue by regressing the change on market liquidity on our *D(HRH)* dummy and a set of control variables defined as in the previous specifications. We use two standard proxies for liquidity – the effective spread is the most widely-used and reliable measure of the bid-ask spread when using transaction-level data like the TAQ data used here, and the Amihud (2002) illiquidity measure is widely-considered the most reliable measure of price impact (see Goyenko, Holden and Trzcinka (2009)). The Amihud illiquidity measure is defined as:

$$\text{Amihud Illiquidity}_{ij} = \frac{1}{N_{ij}} \sum_{t}^{N_{ij}} \frac{|r_{it}|}{dolvol_{it}},$$

where r_{it} is the return for stock *i* during second *t*; $dolvol_{it}$ is the dollar volume for stock *i* during second *t*; and N_{ij} is the number of seconds in which stock *i* traded during interval *j*. Effective spread is defined as:

$$\text{Effective Spread}_{ij} = \frac{1}{N_{ij}} \sum_{t}^{N_{ij}} sign(buys_{it} - sells_{it}) * \frac{price_{it} - midquote_{it-1}}{midquote_{it-1}},$$

where $buys_{it}$ ($sells_{it}$) is the number of stocks bought (sold) for stock *i* during second *t*; $price_{it}$ is the last execution price for stock *i* during second *t*; $midquote_{it}$ is the last bid-ask midpoint for stock *i* during second *t* and N_{ij} is the number of seconds in which stock *i* traded during interval *j*.

Because these liquidity measures are positively autocorrelated, we standardize them with respect to their average computed before the article is released. Specifically, we compute:

$$Change\ in\ Amihud\ Illiquidity = \frac{\text{Amihud Illiquidity}_{t-1,t+5}}{\text{Amihud Illiquidity}_{t-1,t+5} + \text{Amihud Illiquidity}_{t-300,t-120}} \quad ; \text{ and}$$

$$Change\ in\ Effective\ Spread = \frac{Effective\ Spread_{t-1,t+5}}{Effective\ Spread_{t-1,t+5} + Effective\ Spread_{t-300,t-120}}.$$

The regression set-up is the same as in Tables 5 and 6.

We report tests of this hypothesis in Table 8. During the time period where RavenPack was live (Panel A), we observe an increase in both Amihud illiquidity and effective spread if an article is correctly released as relevant (HRH), while there is no significant effect in the placebo sample (Panel B). These results show that illiquidity increases (liquidity decreases) more after a news release delivered via RavenPack. This confirms *Hypothesis 3b* that liquidity providers withdraw from the market following an article covered in RavenPack, while it is inconsistent with *Hypothesis 3a*.

3.5 Learning about precision in news analytics

The underlying premise of our analysis is that the users of Ravenpack use news analytics in an “informed way”. In this section we directly test this premise. In particular, we are interested in whether they are dynamically learning about the signal precision of RavenPack. Such learning could be programmed into their algorithms (machine learning) or can come from manually updating their algorithms over time. If algorithmic traders learn about the precision of RavenPack, we would expect them to rely more on RavenPack’s sentiment indicators if these indicators were more informative in the past. If that is the case, there should be a stronger stock price reaction to news analytics in stocks in which news analytics have been informative in the past (*Hypothesis 4*).

We test *Hypothesis 4* by regressing the short run stock price response on a triple interaction between *Sentiment Direction*, *D(HRH)* and *Past Informativeness*. Thus, we test whether the causal effect of RavenPack on 5-second announcement returns documented in Table 6 is stronger if RavenPack has been more informative in the past. For an article related to industry *k*, we define *Past Informativeness* as the average *signed* two-minute post-article return for all articles related to industry *k* during the previous six months. This measure is higher if *Sentiment Direction* more accurately predicted two-minute post-article returns in the past for that industry.[15]

The results are reported in Table 9. In our main test in Panel A, we define *Past Informativeness* over six months and use the 12 Fama-French industry classifications. We find a significant increase of the causal effect of RavenPack sentiment information on 5 second stock returns if *Past Informativeness* is high. A one standard deviation increase in *Past Informativeness* increases this effect by 57% to 100% relative to the average result reported in Table 6.[16] In regressions 4 to 6 of Panel A, we show in a placebo test that this effect does not happen before Ravenpack went live. In Panel B, we report robustness checks using different definitions of Past Informativeness. In particular, we use 30 industries instead of the 12 Fama-French industries and 3 months instead of 6 months. In all cases, we find that the results are similar to those in Panel A.

---

[15] We confirm in Appendix 3 that the sentiment scores of articles with higher *Past Informativeness* do indeed better predict two-minute post-article returns. We show that *Sentiment Direction* of articles with a one standard deviation higher *Past Informativeness* predict a higher stock price response of 0.72 bp (1.15*0.627=0.72). This corresponds to an increase of 37% relative to the mean (0.72/1.92=37%).

[16] For Past Informativeness 6 month 12 FF: effect of 1 standard deviation: $0.225 * 1.15 = 0.25\ bp$, which is relative to the average effect from Table 7: $\frac{0.25}{0.452} = 57\%$

For Past Informativeness 6 month 30 FF: effect of 1 standard deviation: $0.319 * 1.46 = 0.46\ bp$, which is relative to average effect from Table 7: $\frac{0.46}{0.452} \approx 100\%$

In total, these results suggest that algorithmic traders learn dynamically about the precision of RavenPack and base their trades more on RavenPack's sentiment scores, if these scores have been informative in the past, thereby confirming *Hypothesis 4*.

4. Additional robustness checks

In this section, we consider some robustness checks for our main results in Tables 5, 6 and 7.

4.1 Difference in difference specification

We begin by considering a difference-in-difference analysis. Until now we have mainly focused on the significant effect of RavenPack on the stock market during the period when it was live. The placebo tests in Section 3 showed no effect for the pre-RavenPack period. However, it is possible that the placebo tests might not find significant results because of weak power. Even if this is unlikely as the pre-RavenPack sample is longer than the sample period for our main tests, we provide robustness checks for the placebo specification. We estimate a difference-in-difference specification for our entire sample period (February 1, 2004 – September 10, 2012) to study whether the difference between the pre- and post-RavenPack periods is statistically significant.

We report the results in Table 10. In Regressions 1-2 and 3-4, the dependent variables are *Speed of Stock Price Response* and *Speed of Trade Volume Response*, respectively. In Regressions 1 to 4, the explanatory variable of interest is the interaction between *D(HRH)* and *RavenPack Release*. *RavenPack Release* is a dummy variable taking the value of 1 after the release of RavenPack on April 1, 2009, and zero otherwise. In regression 5 and 6, the dependent variable is the return from 1 second before to 5 seconds after the article. The explanatory variable of interest is the triple interaction between *D(HRH)*, *RavenPack Release* and *Sentiment Direction*. In terms of fixed effects and control variables the regressions follow the original specifications in Tables 5, 6 and 7. We exclude the intermediate specification for brevity, but report it in the Internet Appendix.

The results in Table 10 are consistent with our previous findings. They confirm that the effect of the difference between HRH and HRL articles increases significantly after RavenPack went live. More specifically, the results in Regressions 1 to 4 show a strong positive and significant relation between both the *Speed of Stock Price Response* and the *Speed of Trade Volume Response* and the interaction between *RavenPack Release* and *D(HRH)*. The results in regressions 5 and 6 show an increase in the effect of *Sentiment Direction* on returns for articles classified as HRH after RavenPack went live. These results are in line with our previous findings that our results represent a causal effect of RavenPack on the market rather than a spurious correlation.

4.2 Alternative placebo tests

Our base sample for the placebo test is Feb 2004 − Apr 2009. This time period includes the financial crisis and the introduction of Regulation National Market System (Reg NMS), both of which had a significant impact on the market. Thus, it might be that our findings of no significant result in the placebo tests are related to these events. To address this issue, we conduct additional tests, which are reported in Table 11. In Panel A, we exclude the financial crisis and focus only on the period Feb 1, 2004 to Dec 31, 2007. In Panel B, we exclude the period before the introduction of Reg NMS. Reg NMS included several changes to market structure, one of the most important of which was the introduction of the trade-through rule (Rule 611), which essentially imposed a price priority rule across all markets (O'Hara and Ye (2011)). It has been argued that Reg NMS led to an increase in high frequency trading (Hasbrouck and Saar (2013)) and increased fragmentation of U.S. markets (O'Hara and Ye (2011)). Implementation of Rule 611 started on July 9, 2007 (Chung and Chuwonganant (2012)). Accordingly, we reduce our placebo sample and just focus on the period from July 9, 2007 to April 1, 2009.

In Regressions 1 to 4, the dependent variables are *Speed of Stock Price Response* and *Speed of Trade Volume Response* and the explanatory variable of interest is *D(HRH)*. In regression 5 and 6, the independent variable is the return from 1 second before to 5 seconds after the article and the explanatory variable of interest is the interaction between *D(HRH)* and *Sentiment Direction*. For both alternative placebo tests and for all the different dependent variables, there is no significant effect associated with RavenPack articles classified as HRH and the coefficients of interest are generally small. This suggests that the absence of significant results in our placebo sample in Section 2 is not driven by inclusion of the financial crisis or the pre-Regulation NMS time period, and suggests that our results are not due to confounding events, but are directly related to RavenPack having accurately delivered its news-related metrics to customers.

4.3 "Old RavenPack" definition: RavenPack 1.0 versus RavenPack 2.0

In our main specification, Old RavenPack included both RavenPack 1.0 and RavenPack 2.0. A concern is that the difference in reaction before and after the release of New RavenPack is driven by the transition from v.1.0 to v.2.0 in July 2011. Therefore, our next robustness check focuses only on RavenPack 1.0. We re-estimate the same specifications as before, but include only the period when RavenPack1.0 was live, i.e. April 1, 2009 to July 6, 2011. We report the results in Panel C of Table 11 using the same regression set-up as in Panels A and B. All specifications confirm the previous results and are similar in terms of economic magnitude.

4.4 Alternative length of event window

In our analyses we compare the stock price reaction in the short run, during which only high frequency traders can react to an article, to the stock price reaction in the long run during which human traders will have read, processed and traded on the article. In all of our prior analyses, we used 5 seconds as the short-run window and 120 seconds as the long-run window. In Table 12, we show robustness to choosing different windows lengths. In particular, we use 10 seconds as the alternative short window and 300 seconds as the alternative long window. In Panel A, we show that HRH articles have a faster *Speed of Stock Price Response* using all three possible additional combinations of event windows: 10 seconds / 120 seconds; 5 seconds / 300 seconds; and 10 seconds / 300 seconds. The results are statistically significant at the 1% threshold for all three specifications and even increase somewhat in economic magnitude. In Panel B, we repeat the same analysis for Speed of Stock Price Response. Once again the results are significant in all specifications. Finally, in Panel C we provide a robustness check on the analysis of how well the sentiment direction of an article predicts the short run stock return depending on whether the article is HRH (vs HRL). We show replacing the 5 second stock return with the 10 second stock return slightly increases the effect while staying significant at the 5% threshold.

Overall, our robustness tests confirm our findings that RavenPack has an impact on the market that is distinct from the underlying informational content of the news. The findings are not due to spurious correlation or other confounding effects.

Conclusion

We study how news analytics companies affect the stock market and, in particular, liquidity and market efficiency. We exploit an identification strategy based on inaccuracies in news analytics that were released to the market by RavenPack, a major provider of news analytics for algorithmic and high frequency traders. Comparing the market reaction to similar news items depending on whether the news has been correctly released to customers or not, we are able to determine the causal effect of news analytics on stock prices, irrespective of the informational content of the news.

We document that news analytics have a significant impact on the market that is separate from the information contained in the news. The speed of adjustment of both stock prices and trade volume in response to the information contained in a highly-relevant article is faster if the article was originally released by RavenPack as being relevant than if it was released as not relevant. However, in these cases we also find that liquidity is lower after the article. Thus, we observe two effects of news analytics on the stock market. On the positive side, news analytics improve market efficiency by speeding up market reaction to news. On the negative side, because only a subset of traders has access to this information, news analytics increase information asymmetry in the market and thus reduce liquidity.

We also consider the market response to low relevance articles that were released as having high relevance. We find that the market temporarily overreacts to these articles. Much of the initial price reaction to these articles corrects starting 30 seconds after the article. Thus, we show that inaccuracies in news analytics can lead to price distortions analogous to mini flash crashes. Furthermore, we provide evidence that algorithmic traders learn about the informativeness of news analytics dynamically. A series of econometric robustness checks (e.g., difference-in-difference specifications, different samples, placebo tests) confirm the results.

Our findings have normative implications in terms of the recent regulatory debate on high-speed information and the effects of algorithmic and high-frequency trading. We show that news analytics improve price efficiency, but at the cost of reducing liquidity and potentially distortionary price effects.

References

Amihud, Y., 2002. Illiquidity and Stock Returns: Cross-Section and Time-Series Effects. Journal of Financial Markets 5, 31–56.

Baron, Matthew, Jonathan Brogaard and Andrei Kirilenko, 2014, The Risk and Return in High Frequency Trading, Working Paper.

Benos, Evangelos and Satchit Sagade, 2012, High-frequency trading behaviour and its impact on market quality: evidence from the UK equity market, Working Paper.

Biais, Bruno, Thierry Foucault and Sophie Moinas, 2015, Equilibrium Fast Trading, Journal of Financial Economics.

Boehmer, Ekkehart, Kingsley Fong, and Julie Wu, 2015, International evidence on algorithmic trading, Working Paper.

Brogaard, Jonathan, Terrence Hendershott, and Ryan Riordan, 2014, High frequency trading and price Discovery,The Review of Financial Studies, 27, n. 8. .

Brogaard, Jonathan, Björn Hagströmer, Lars Norden, and Ryan Riordan, 2014, Trading fast and slow: colocation and market quality, Working Paper.

Brogaard, Jonathan, Al Carrion, Thibaut Moyaert, Ryan Riordan, Andriy Shkilko, Konstantin Sokolov, 2015, High-Frequency Trading and Extreme Price Movements, Working Paper.

Chaboud, Alain, Ben Chiquoine, Erik Hjalmarsson, and Clara Vega, 2013, Rise of the Machines: Algorithmic Trading in the Foreign Exchange Market, Journal of Finance, forthcoming.

Chan, W. S., 2003, Stock price reaction to news and no-news Drift and reversal after headlines, Journal of Financial Economics, 702, 223-260.

Chung, Kee H., and Chairat Chuwonganant, 2012, Regulation NMS and Market Quality, Financial Management, 41, 285-317.

Clark-Joseph, Adam D., 2013, Exploratory Trading, Working Paper.

Das, Sanjiv R., and Mike Y. Chen, Yahoo! for Amazon: Sentiment Extraction from Small Talk on the Web, Management Science 53, 1375-1388.

DellaVigna, S., and Pollet, J., 2009, Investor Inattention, Firm Reaction, and Friday Earnings Announcements, Journal of Finance, 64, 709-749.

Dugast, Jerome and Thierry Foucault, 2014, False News, Informational Efficiency, and Price Reversals, Working Paper.

Foucault, Thierry, Johan Hombert and Ioanid Rosu, 2015, News Trading and Speed, Journal of Finance, forthcoming.

Gai, Jiading, Chen Yao and Mao Ye, 2013, The Externalities of High Frenquency Trading, Working Paper.

Garcia, Diego, Sentiment during Recessions, Journal of Finance 68, 1267–1300.

Gerig, Ausin, 2015, High-Frequency Trading Synchronizes Prices in Financial Markets, Working Paper.

Golub, Anton, John Keane and Ser-Huang Poon, 2012, High Frequency Trading and Mini Flash Crashes, Working Paper.

Gormley, Todd A., and David A. Matsa, 2011, Growing Out of Trouble? Corporate Responses to Liability Risk, Review of Financial Studies 24, 2781-2821.

Goyenko, Ruslan, Craig W. Holden, and Charles Trscinka, 2009, Do liquidity measures measure liquidity?, Journal of Finance Economics, 92, 153-181.

Groß-Klußmann, Axel and Nikolaus Hautsch, 2011, When machines read the news: Using automated text analytics to quantify high frequency news-implied market reactions, Journal of Empirical Finance, 18, 321-340.

Hagströmer, Björn , Nordén, Lars, 2013. The diversity of high frequency traders, Journal of Financial Markets, 16, 741-770.

Hasbrouck, Joel and Gideon Saar, 2013, Low-Latency Trading, Journal of Financial Markets 16, 646–679.

Hendershott, Terrence and Ryan Riordan, 2013, Algorithmic Trading and the Market for Liquidity, Journal of Financial and Quantitative Analysis 48, 1001-1024.

Hendershott, Terrence, Charles M. Jones and Albert J. Menkveld, 2011, Does Algorithmic Trading Improve Liquidity?, Journal of Finance, 66, 1-33.

Hirschey, Nicholas, 2013, Do High-Frequency Traders Anticipate Buying and Selling Pressure?, Working Paper.

Hu, Grace X., Jun Pan and Jiang Wang, 2013, Early Peek Advantage?, Working Paper.

Jegadeesh, Narasimhan, and Di Wu, 2013, Word power: A new approach for content analysis, Journal of Financial Economics 110, 712-729.

Jones, Charles, 2013, What do we know about high-frequency trading?, Working Paper.

Jovanovic, Boyan and Albert J. Menkveld, 2011, Middlemen in Limit-Order Markets, Working Paper.

Kim, Oliver and Robert E. Verrecchia, 1994, Market liquidity and volume around earnings announcements, Journal of Acccounting and Economics.

Kyle, Albert, 1985. Continuous auctions and insider trading, Econometrica 53, 1315-1336.

Martinez, Victor H., and Ioanid Rosu 2013, High Frequency Traders, News and Volatility, Working Paper.

Menkveld, Albert, 2013, High frequency trading and the *new market* makers, Journal of Financial Markets, 16, 712-740.

O'Hara, Maureen and Mao Ye, 2011, Is market fragmentation harming market quality?, Journal of Financial Economics, 100, 459–474.

Riordan, Ryan, Andreas Storkenmaier, Martin Wagener and S. Sarah Zhang, 2013, Public information arrival: Price discovery and liquidity in electronic limit order markets, Journal of Banking and Finance, 37, 1148-1159.

Riordan, Ryan and Andreas Storkenmaier, 2012, Latency, liquidity and price discovery, Journal of Financial Markets, 15, 416-437.

Sinha, Nitish Rajan, 2012, Underreaction to News in the US Stock Market, Working Paper.

Weller, Brian, 2015, Efficient Prices at Any Cost: Does Algorithmic Trading Deter Information Acquisition?, Working Paper.

Zhang, Sarah S., 2013, Need for Speed: An Empirical Analysis of Hard and Soft Information in a High Frequency World, Working Paper.

Figure 1: Market reaction by Relevance Score

This figure displays the cumulative signed return from t-30 to t+120 seconds around the news events from 1 April 2009 to 10 September 2012. Signed returns are returns are multiplied with the sentiment direction of the article. We exclude articles with neutral sentiment. *Low Relevance* refers to articles with a Relevance Score below 90 in both RavenPack versions, while *High Relevance* refers to articles that have a Relevance Score greater or equal than 90 in both RavenPack versions.

Cumulative signed return

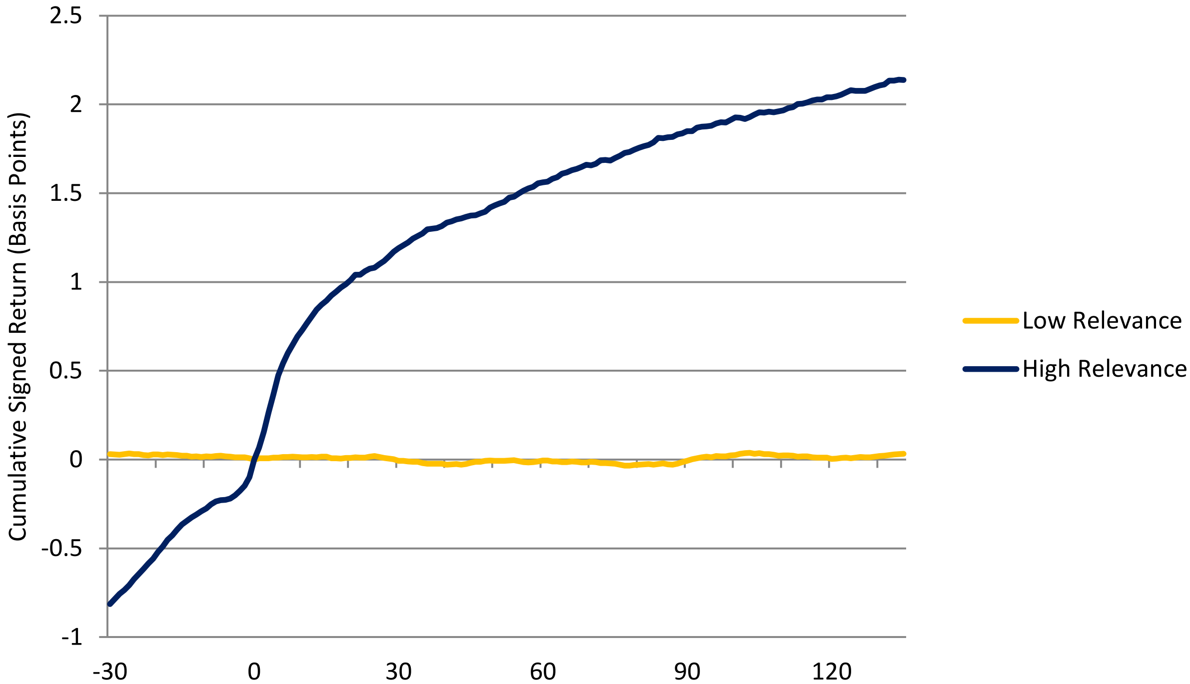


Figure 2: Difference in Stock Price Response between HRH and LRH Articles

This figure displays the cumulative return from t-30 to t+120 seconds around the news events during the period when RavenPack was live, April 1, 2009 to September 10, 2012. Returns are multiplied with the sentiment direction of the article. We exclude articles with neutral sentiment. HRH refers to articles that have a relevance scores greater or equal 90 in both RavenPack versions, while LRH refers to articles that had a relevance score greater or equal 90 in the old RavenPack version while having Relevance below 90 in the new RavenPack version.

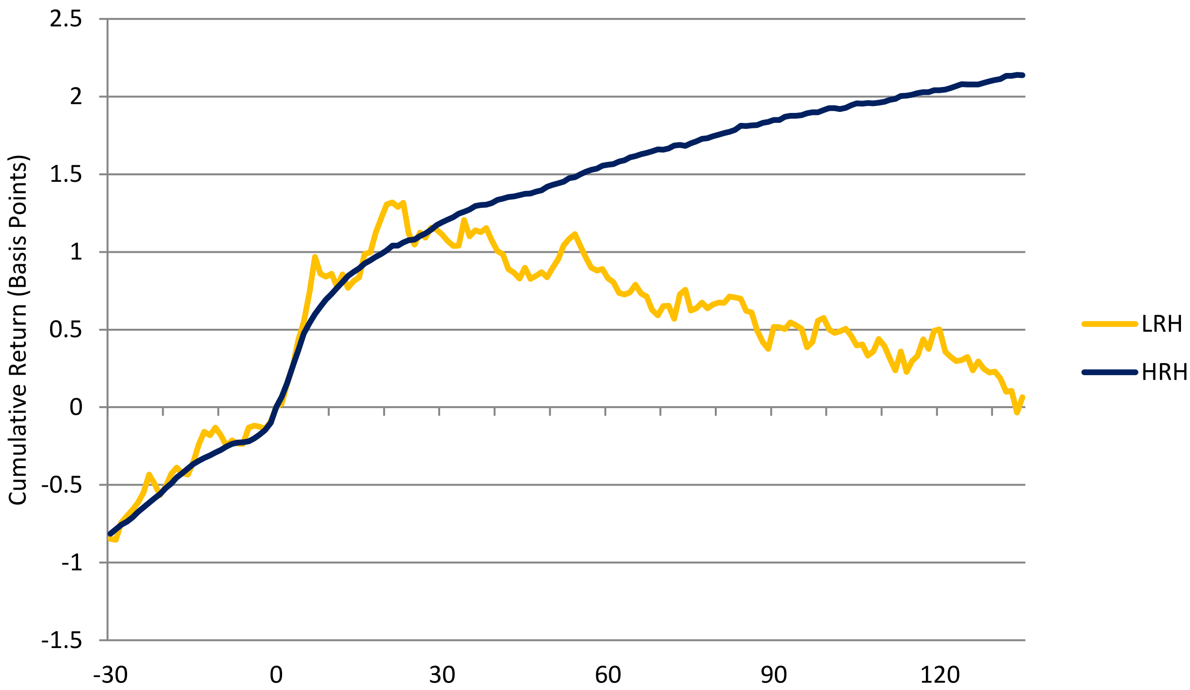
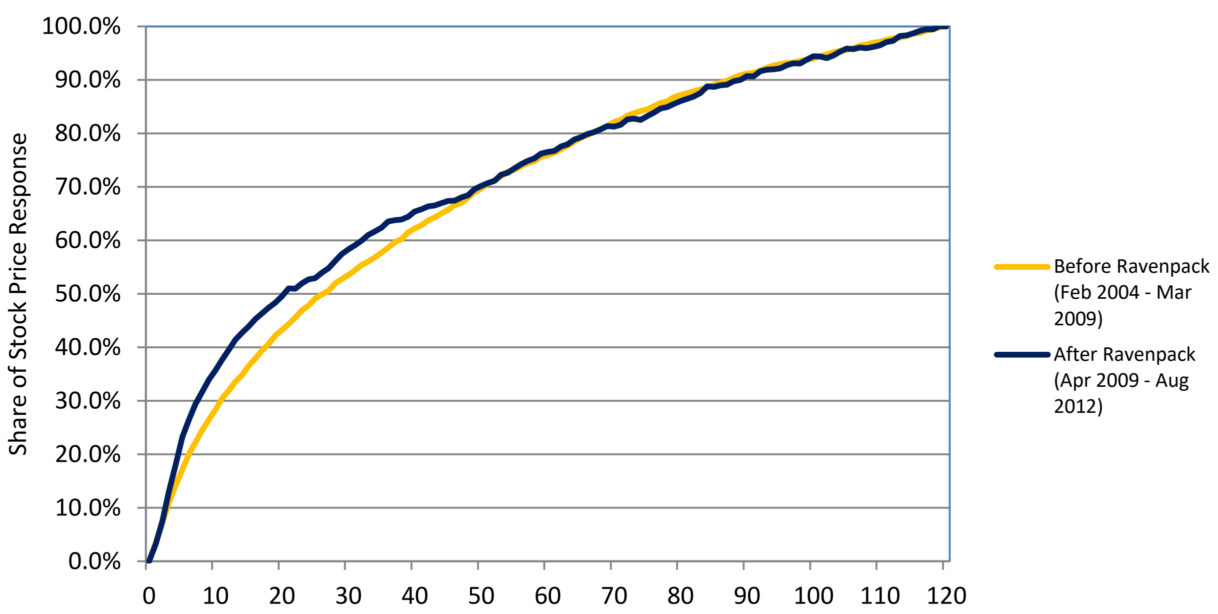


Figure 3: Difference in market reaction after RavenPack is live

The figure in Panel A displays the share of the total stock price response to news within the first 120 seconds after an article. We compare the reaction to articles before (Feb 2004 – Mar 2009) and after RavenPack went live (April 2009 to 10 September 2012). Returns are multiplied with the sentiment direction of the article. We exclude articles with neutral sentiment. We standardize the average cumulative return within each group by dividing it by the total average cumulative return for that group after 120 seconds. We only include articles that are consistently reported as relevant (HRH) in both versions. In Panel B, we display the difference between the two series from Panel A.

Panel A: Share of Stock Price Reaction before vs. after RavenPack is live



Panel B: Difference in Share of Stock Price Reaction before vs. after RavenPack is live

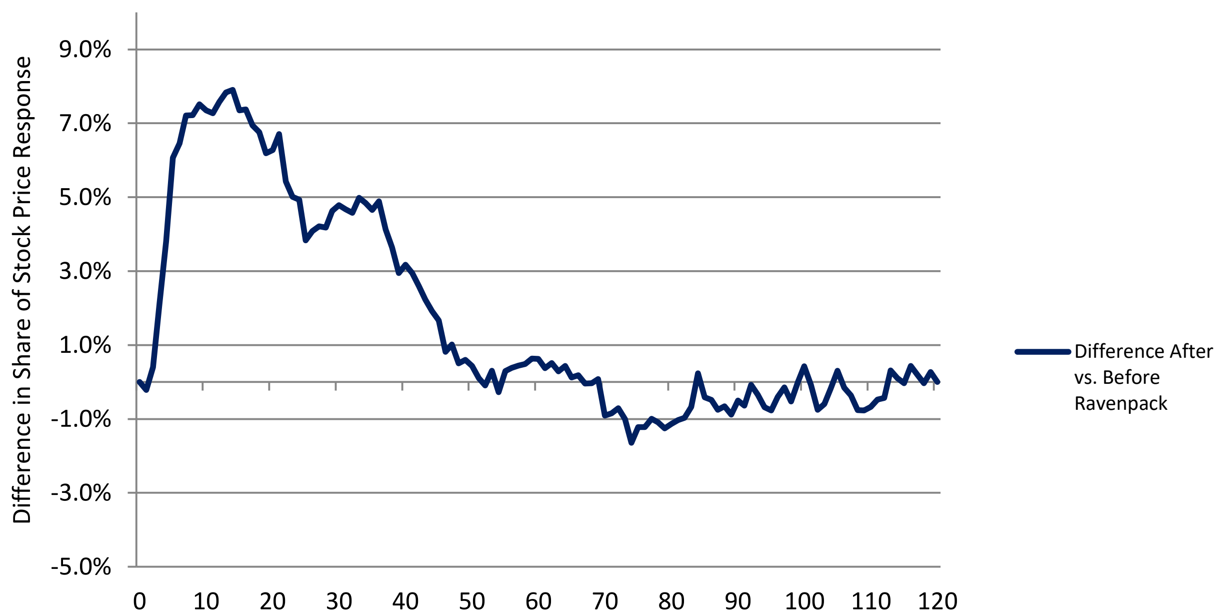
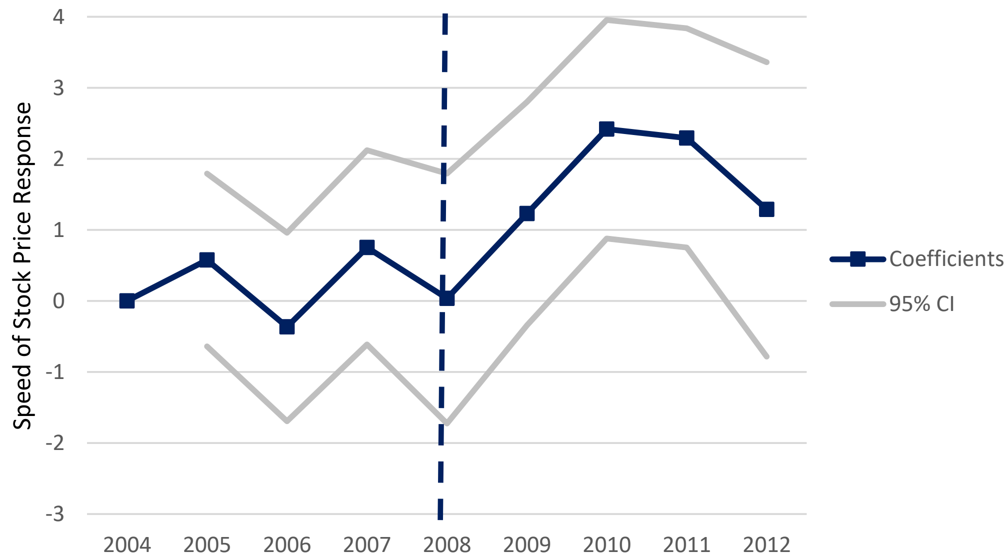


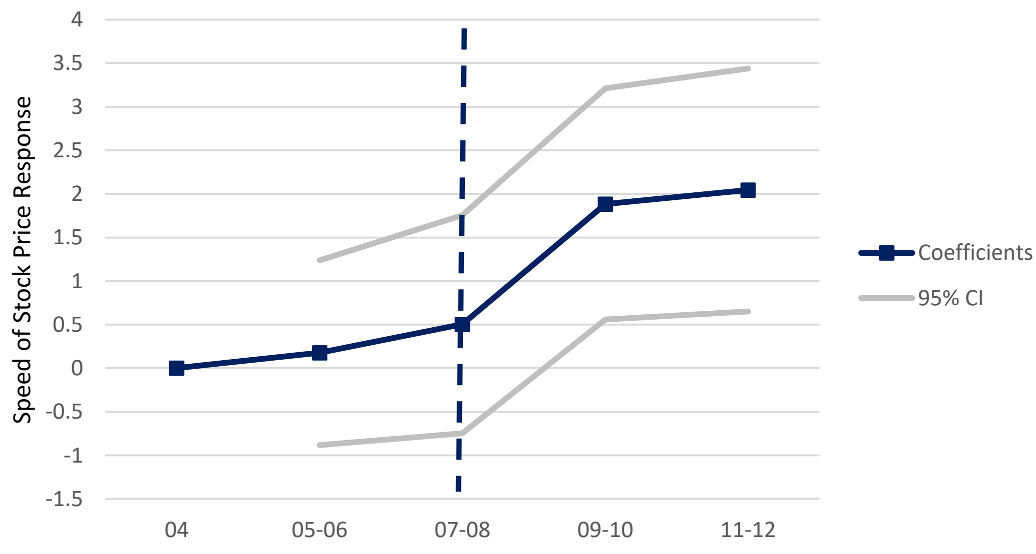
Figure 4: Difference in Speed of Stock Price Response (HRH vs. HRL) Over Time

The figure in Panel A reports the point estimates from an OLS regression of Speed of Stock Price Response ($\frac{\text{Abs(Return t}-1\text{,t+5)}}{\text{Abs(Return t}-1\text{,t+5)+Abs(Return t+6,t+120)}}$) on D(HRH) interacted with yearly dummy variables from 2004 to 10 September 2012. We assign the first quarter of a year to the prior year, i.e. the 2009 dummy covers a time period from 1 April 2009 to 1 April 2010. Controls and fixed effects are the same as in table 4 regression 3. The vertical line indicates the introduction of RavenPack on 1 April 2009. In Panel B, we report the same regression but interacting the HRH dummy variable with two-year dummy variables (with the first quarter shifted backwards). In Panel C, we report the difference between Speed of Stock Price Response for HRH and HRL articles over different years (with the first quarter shifted backwards).

Panel A: Estimate of coefficient on D(HRH) interacted with yearly dummies



Panel B: Estimate of coefficient on D(HRH) interacted with two-year dummies



Panel C: Comparing the difference in mean

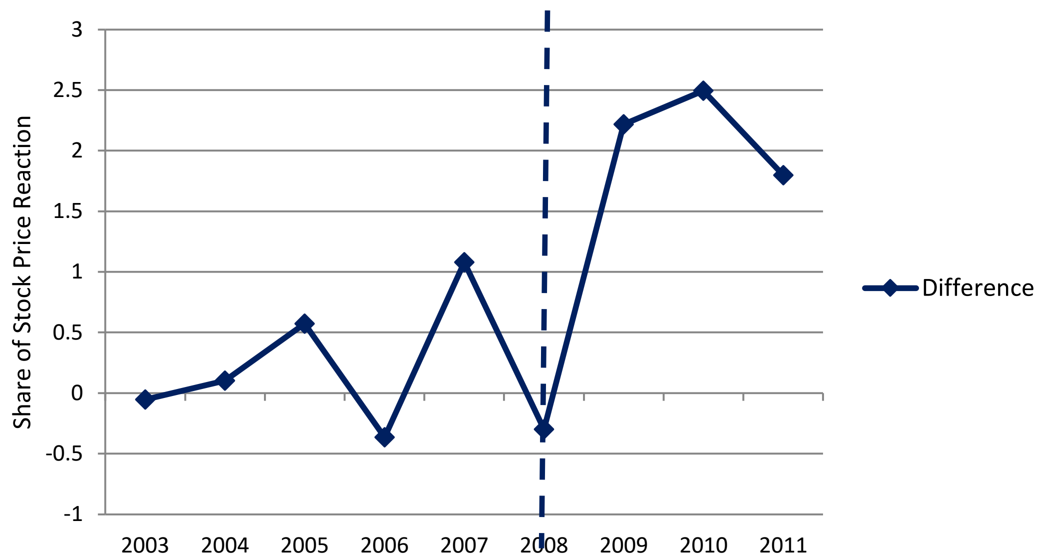


Table 1: Overview of Four Article Types

In Panel A, we present our predictions for the market reaction to different articles. In Panel B, we present the results of article-level regressions that examine the market reaction to different types of articles in the time period where RavenPack was not yet sold to investors (February1, 2004 – March 31, 2009). The dependent variables are the absolute returns and turnover in the two minutes after the article. Returns are based on mid-quotes. The explanatory variable of interest are D(HRH), D(HRL) and D(RLH), which are dummy variables for these article categories (LRL is the omitted category. At the bottom of the table we display the t-statistic for the difference between HRH and HRL articles. All standard errors are clustered at the firm level. T-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Predictions for the market reaction of the different article types

		New RavenPack	
		High Relevance Article	**Low Relevance Article**
Old RavenPack	**High Relevance Article**	HRH: Fast and persistent market reaction	LRH: Fast market reaction that mean-reverts (overreaction).
	Low Relevance Article	HRL: Slow market reaction (underreaction)	LRL: No stock price reaction

Panel B: Stock price reaction to the different article types BEFORE RavenPack went "live"

Dependent Variable:	Absolute Return t−1,t+120	Turnover t−1,t+120
D (HRH)	3.235***	0.335***
	(36.37)	(33.75)
D (HRL)	3.118***	0.325***
	(11.74)	(9.08)
D (LRH)	2.494***	0.311***
	(9.24)	(9.34)
Number of Observations	2214726	2214726
R^2	0.151	0.184
Hour Fixed Effects	Yes	Yes
Date and Firm Fixed Effects	Yes	Yes
Difference coefficients of D(HRH) and D(HRL)	0.117	0.010
(t-stat)	(0.43)	(0.29)

Table 2: Number of observations

This table displays the number of articles and companies in subsamples of our data. The before-RavenPack sample consists of articles from February 1, 2004 to March 31, 2009. The after-RavenPack sample consists of articles from April 1, 2009 to September 10, 2012. . HRH refers to articles that have a relevance scores greater or equal 90 in both RavenPack versions, while HRL refers to articles that had a Relevance smaller than 90 in the old RavenPack version while having Relevance greater or equal than 90 in the new RavenPack version. In Panel A, we report the number of article-firm combinations in each category. In parenthesis we report the percentage of the total in the respective line. In Panel B, we report the number of companies that articles in the group span. Since many companies have articles in both groups, the two groups do not add up to the total.

Panel A: Number of articles

	HRL	HRH	Total
Before RavenPack release	17,621	464,543	482,164
	(3.7%)	(96.3%)	(100%)
After RavenPack release	7,342	314,570	321,912
	(2.3%)	(97.7%)	(100%)
Total	24,963	779,113	804,076
	(3.1%)	(96.9%)	(100%)

Panel B: Number of companies

	HRL	HRH	Total
Before RavenPack release	1,774	5,016	5,188
	(34.2%)	(96.7%)	(100.0%)
After RavenPack release	1,294	3,978	4,011
	(32.3%)	(99.2%)	(100.0%)
Total	2,370	5,200	5,385
	(44.0%)	(96.6%)	(100.0%)

Table 3: Summary Statistics – Relevant articles, Apr 2009 to Sept 2012

This table displays summary statistics for the 321,912 article-company combinations after RavenPack went "live" (April 1, 2009 to September 10, 2012). These article-company observations are classified as relevant in the new RavenPack (i.e. they are HRH or HRL). *Market capitalization* is the number of shares outstanding multiplied by the prior day closing price. *Average volatility prior month* is the average squared return in the 20 trading days before the article. *Average turnover prior month* is the mean of trading volume divided by shares outstanding in the 20 trading days before the article. *Absolute return $t-1$, $t+5$* is the absolute stock return from 1 second before to 5 seconds after the article. *Speed of Stock Price Response* is defined as $\frac{\text{Abs(Return t}-1\text{,t+5)}}{\text{Abs(Return t}-1\text{,t+5)+Abs(Return t+6,t+120)}}$. *Turnover $t-1$, $t+5$* is trading volume divided by shares outstanding from 1 second before to 5 seconds after the article. *Speed of Trade Volume Response* is defined as $\frac{\text{Turnover t}-1\text{,t+5}}{\text{Turnover t}-1\text{,t+120}}$. *Return on trading day* is the stock return over the entire trading day that the article was released. *Absolute return on trading day* is its absolute value. *Time since last company article* is the time since the company was last mentioned in an article. *Number of firms in article* defines the number of companies mentioned in the article. *Composite Sentiment Score* is a sentiment score that is provided by RavenPack and takes a value from 100 (positive) to 0 (negative). *Absolute Composite Sentiment Score* is defined as Abs (Composite Sentiment Score – 50). *Neutral Composite Sentiment Score* is a dummy variable equal to 1 if the *Composite Sentiment Score* equals 50. *Article Category Identified* is a dummy variable equal to 1 if the article category (e.g. merger and acquisitions) is identified by RavenPack. *Event Sentiment Score* is a sentiment score that is provided by RavenPack and takes a value from 100 (positive) to 0 (negative); this is available only for articles for which the category is identified. *Absolute Event Sentiment Score* is defined as Abs (Event Sentiment Score – 50). *Neutral Event Sentiment Score* is a dummy variable equal to 1 if the *Event Sentiment Score* equals 50. In Panel A, we report descriptive statistics. In Panel B we report the difference between articles that were consistently released as relevant in both RavenPack versions (HRH) and those that were released as having low relevance (HRL). The difference is defined as the regression coefficient of D(HRH) in a regression of the respective variable on D(HRH) and Relevance, Category, Hour and Date Fixed Effects. D(HRH) is a dummy equal to 1 if the article is HRH. We also report t-statistics for the coefficient clustered at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Descriptive Statistics

	Mean	25th Percentile	Median	75th Percentile	Standard Deviation
Market capitalization ($ million)	13185.0	157.4	1782.9	30027.4	37016.1
Average return prior month (%)	0.12	-0.57	0.10	0.79	0.65
Average volatility prior month (%)	9.69	1.19	4.79	20.4	17.7
Average turnover prior month (%)	1.17	0.27	0.83	2.29	1.23
Absolute Return t−1,t+5 (basis points)	1.95	0	0	4.43	9.46
Absolute Return t−1,t+120 (basis points)	11.4	0	5.00	27.4	21.7
Speed of Stock Price Response (%)	13.2	0	0	50	24.7
Signed Return t−1,t+5 (basis points)	0.60	-1.38	0	1.97	10.2
Signed Return t−1,t+120 (basis points)	1.89	-15.1	0	18.5	25.6
Turnover t−1,t+5 (basis points)	0.041	0	0	0.084	0.14
Turnover t−1,t+120 (basis points)	0.86	0	0.24	1.81	2.22
Speed of Trade Volume Response (%)	5.80	0	0	16.8	13.9
Return on trading day (%)	0.23	-3.29	0.056	3.92	4.02
Absolute return on trading day (%)	2.48	0.22	1.45	5.65	3.18
Time since last company article (hours)	32.2	0.49	6.42	103.1	57.6
Number of companies in article	2.14	1	1	3	4.30
Composite Sentiment Score	50.0	47	50	52	4.19
Absolute Composite Sentiment Score	2.07	0	2	5	3.65
Neutral Composite Sentiment Score	0.47	0	0	1	0.50
Article category identified	0.35	0	0	1	0.48
Event Sentiment Score	51.8	37	50	67	12.9
Absolute Event Sentiment Score	3.83	0	0	13	6.71
Neutral Event Sentiment Score	0.69	0	1	1	0.46
Past Informativeness 6 month 12FF	1.67	0.58	1.39	3.46	1.15
Past Informativeness 3 month 12FF	1.58	0.41	1.22	3.29	1.23
Past Informativeness 6 month 30FF	1.69	0.39	1.34	3.66	1.46
Number of Observations	321,912				

Panel B: Comparison between Accurately Classified as Relevant (HRH) vs. Misclassified (HRL)

	Standard Deviation	Difference between HRH and LRH after fixed effects	T- Statistic	Difference in terms of Standard Deviations
Market capitalization ($ million)	37016.1	-921.79	-0.25	-0.0249
Average return prior month (%)	0.65	-0.0319***	-3.05	-0.04908
Average volatility prior month (%)	17.7	-1.526*	-1.70	-0.08621
Average turnover prior month (%)	1.23	-0.0773	-0.94	-0.06285
Average illiquidity prior month (percentile)	26.4	-2.0874	-0.84	-0.07907
Absolute Return t−1,t+120 (basis points)	21.7	-0.3433	-0.77	-0.01582
Turnover t−1,t+120 (basis points)	2.22	0.0731	1.19	0.032928
Return on trading day (%)	4.02	-0.0953	-1.58	-0.02371
Absolute return on trading day (%)	3.18	-0.1242	-0.93	-0.03906
Time since last company article (hours)	57.6	3.32	1.24	0.057639
Number of companies in article	4.30	-0.95***	-3.23	-0.22093
Composite Sentiment Score	4.19	-0.0679	-0.63	-0.01621
Absolute Composite Sentiment Score	3.65	0.0105	0.06	0.002877
Neutral Composite Sentiment Score	0.50	-0.0353	-0.67	-0.0706
Event Sentiment Score	12.9	-0.7440	-1.09	-0.05767
Absolute Event Sentiment Score	6.71	-0.0986*	-1.77	-0.01469
Neutral Event Sentiment Score	0.46	-0.0020	-0.97	-0.00435

Table 4: Overreaction to News Analytics (LRH articles)

This table contains the results of article-level regressions that examine how well the sentiment direction of LRH articles predicts stock returns before and after the release of RavenPack. In regressions 1 to 3, the dependent variable is the return from 1 second before to 5 seconds after the article (measured in basis points). In regressions 4 to 6, we study the return from 6 to 120 seconds after the article to determine a potential reversal of the short run reaction. Returns are based on mid-quotes. The explanatory variable of interest is an interaction between *RavenPack Release* and *Sentiment Direction*. RavenPack Release is a dummy variable equal to 1 during the time in which RavenPack was "live" (April 1, 2009 – September 10, 2012) and equal to 0 before RavenPack was "live" (February1, 2004 – March 31, 2009). *Sentiment Direction* is a variable indicating the sentiment of the article derived from RavenPack sentiment indices; it takes the value +1 for positive sentiment, 0 for neutral sentiment and −1 for negative sentiment. In all regressions we include the following firm specific control variables: Company size, Return prior month, Volatility prior month, Turnover prior month, Illiquidity prior month. In regressions 2, 3, 5 and 6 we add fixed effects for the article category (e.g. mergers and acquisitions), the relevance score (from 90 to 100) and the hour during the day in which the article was released. In regressions 3 and 6, we include absolute return, turnover, and volatility each for industry and market from t−1 to t+5 seconds around the article. All variables are defined in Appendix 1. All standard errors are clustered at the firm level. T-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable:		Return t−1, t+5			Return t+6, t+120	
	(1)	(2)	(3)	(4)	(5)	(6)
RavenPack Release * Sentiment Direction	0.465**	0.533**	0.563***	-0.602	-0.666	-0.660
	(2.31)	(2.48)	(2.60)	(-1.24)	(-1.32)	(-1.31)
RavenPack Release	-0.252	-0.258	-0.309	-1.739***	-1.659***	-1.643***
	(-1.50)	(-1.44)	(-1.62)	(-3.92)	(-3.71)	(-3.42)
Sentiment Direction	0.258**	0.098	0.099	1.532***	1.517***	1.538***
	(2.28)	(0.80)	(0.81)	(5.10)	(4.58)	(4.64)
Article category identified		-1.177***	-1.217***		0.043	-0.316
		(-3.14)	(-3.04)		(0.04)	(-0.27)
Time since last article		0.112**	0.107**		0.373***	0.357***
		(2.40)	(2.30)		(2.91)	(2.78)
Number of firms in article		-0.179**	-0.171**		-0.397*	-0.415*
		(-2.19)	(-2.12)		(-1.70)	(-1.79)
Number of Observations	20588	20588	20588	20588	20588	20588
R^2	0.003	0.009	0.014	0.007	0.013	0.018
Relevance, Category and Hour Fixed Effects	No	Yes	Yes	No	Yes	Yes
Market control variables	No	No	Yes	No	No	Yes
Firm specific control variables	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Speed of Stock Price Response to News Articles

This table contains the results of article-level regressions that examine the effect of an article covered in RavenPack on stock price, measured by absolute returns. The dependent variable is *Speed of Stock Price Response* (in percent) defined as $\frac{\text{Abs(Return t}-1,\text{t}+5)}{\text{Abs(Return t}-1,\text{t}+5)+\text{Abs(Return t}+6,\text{t}+120)}$ and measured in seconds around an article. Returns are based on mid-quotes. The explanatory variable of interest is D(HRH), a dummy variable equal to 1 if an article was consistently released as highly relevant in both RavenPack versions and 0 if it was originally released as having low relevance (HRL). In regressions 1 to 3, we estimate the various specification during the time in which RavenPack was "live" (April 1, 2009 – September 10, 2012). In regressions 4 to 6, we run a placebo test for the time period where RavenPack was not yet sold to investors (February1, 2004 – March 31, 2009). In all regressions we include firm and date fixed effects and the following firm specific control variables: Company size, Return prior month, Volatility prior month, Turnover prior month, Illiquidity prior month. In regressions 2, 3, 5 and 6 we add fixed effects for the article category (e.g. mergers and acquisitions), the relevance score (from 90 to 100) and the hour during the day in which the article was released. In regressions 3 and 6, we include additional controls: the absolute return, turnover, and volatility each for industry and market and for the two horizons from t−1 to t+5 and t−1 to t+120 seconds around the article. All variables are defined in Appendix 1. All standard errors are clustered at the firm level. T-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable:	Speed of Stock Price Response					
	Main Test - RavenPack is "live"			Placebo Test - Before RavenPack is "live"		
	(1)	(2)	(3)	(4)	(5)	(6)
D(HRH)	1.469***	1.333***	1.321***	-0.048	-0.058	-0.012
	(3.50)	(3.15)	(3.19)	(-0.16)	(-0.20)	(-0.04)
Absolute Composite Sentiment Score		-0.004	-0.002		-0.032**	-0.032**
		(-0.22)	(-0.11)		(-2.29)	(-2.31)
Neutral Composite Sentiment Score		-0.107	-0.115		-0.338***	-0.357***
		(-0.87)	(-0.96)		(-3.30)	(-3.52)
Article category identified		0.522	1.395		-3.574	-4.141
		(0.10)	(0.28)		(-0.54)	(-0.68)
Absolute Event Sentiment Score		0.098***	0.089***		0.021*	0.022*
		(5.13)	(4.78)		(1.70)	(1.85)
Neutral Event Sentiment Score		-0.818	-0.958		-1.202***	-1.150***
		(-1.29)	(-1.56)		(-2.92)	(-2.82)
Time since last article		0.099***	0.086**		0.069***	0.062**
		(2.85)	(2.54)		(2.72)	(2.44)
Number of firms in article		-0.060	-0.058		-0.149***	-0.170***
		(-0.70)	(-0.69)		(-2.65)	(-3.06)
Number of Observations	249065	249065	249065	400303	400303	400303
R^2	0.035	0.039	0.084	0.032	0.033	0.049
Relevance, Category and Hour Fixed Effects	No	Yes	Yes	No	Yes	Yes
Date and Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Market control variables	No	No	Yes	No	No	Yes
Firm specific control variables	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Directional Stock Price Response to Article Sentiment

This table contains the results of article-level regressions that examine how well the sentiment direction of an article predicts the 5-second return reaction to an article depending on whether the article is covered in RavenPack. The dependent variable is the return from 1 second before to 5 seconds after the article (measured in basis points). Returns are based on mid-quotes. The explanatory variable of interest is an interaction between D(HRH) and *Sentiment Direction*. D(HRH) is a dummy variable equal to 1 if an article was consistently released as highly relevant in both RavenPack versions and 0 if it was originally released as having low relevance (HRL). *Sentiment Direction* is a variable indicating the sentiment of the article derived from RavenPack sentiment indices; it takes the value +1 for positive sentiment, 0 for neutral sentiment and −1 for negative sentiment. In regressions 1 to 3, we estimate the various specification during the time in which RavenPack was "live" (April 1, 2009 – September 10, 2012). In regressions 4 to 6, we run a placebo test for the time period where RavenPack was not yet sold to investors (February1, 2004 – March 31, 2009). In all regressions we include firm and date fixed effects and the following firm specific control variables: Company size, Return prior month, Volatility prior month, Turnover prior month, Illiquidity prior month. In regressions 2, 3, 5 and 6 we add fixed effects for the article category (e.g. mergers and acquisitions), the relevance score (from 90 to 100) and the hour during the day in which the article was released. In regressions 3 and 6, we include absolute return, turnover, and volatility each for industry and market from t−1 to t+5 seconds around the article. All variables are defined in Appendix 1. All standard errors are clustered at the firm level. T-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable:	Return t-1, t+5					
	Main Test - RavenPack is "live"			Placebo Test - Before RavenPack is "live"		
	(1)	(2)	(3)	(4)	(5)	(6)
D(HRH) * Sentiment Direction	0.407***	0.452***	0.452***	0.081	0.116	0.114
	(3.09)	(3.39)	(3.40)	(0.79)	(1.10)	(1.09)
D(HRH)	0.187*	0.125	0.125	0.137	0.103	0.102
	(1.86)	(1.19)	(1.18)	(1.28)	(0.94)	(0.93)
Sentiment Direction	0.118	-0.010	-0.009	0.421***	0.184*	0.187*
	(0.92)	(-0.08)	(-0.07)	(4.23)	(1.81)	(1.84)
Article category identified		1.151**	0.932*		0.304	0.370
		(1.97)	(1.86)		(0.70)	(0.84)
Time since last article		0.043***	0.043***		0.237***	0.239***
		(3.38)	(3.40)		(13.20)	(13.28)
Number of firms in article		-0.150***	-0.145***		-0.221***	-0.220***
		(-5.05)	(-4.90)		(-9.37)	(-9.31)
Number of Observations	321860	321860	321860	481939	481939	481939
R^2	0.063	0.066	0.069	0.057	0.062	0.063
Relevance, Category and Hour Fixed Effects	No	Yes	Yes	No	Yes	Yes
Date and Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Market control variables	No	No	Yes	No	No	Yes
Firm specific control variables	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Speed of Trade Volume Response to News Articles

This table contains the results of article-level regressions that examine the effect of an article covered in RavenPack on the market for a stock, measured by turnover. The dependent variable is *Speed of Trade Volume Response* (in percent), which is defined as the turnover from 1 second before the article to 5 second after the article divided by the turnover from 1 second before the article to 120 seconds after the article. The explanatory variable of interest is D(HRH), a dummy variable equal to 1 if an article was consistently released as highly relevant in both RavenPack versions and 0 if it was originally released as having low relevance (HRL). In regressions 1 to 3, we estimate the various specification during the time in which RavenPack was "live" (April 1, 2009 – September 10, 2012). In regressions 4 to 6, we run a placebo test for the time period where RavenPack was not yet sold to investors (February1, 2004 – March 31, 2009). In all regressions we include firm and date fixed effects and the following firm specific control variables: Company size, Return prior month, Volatility prior month, Turnover prior month, Illiquidity prior month. In regressions 2, 3, 5 and 6 we add fixed effects for the article category (e.g. mergers and acquisitions), the relevance score (from 90 to 100) and the hour during the day in which the article was released. In regressions 3 and 6, we include additional controls: the absolute return, turnover, and volatility each for industry and market and for the two horizons from t−1 to t+5 and t−1 to t+120 seconds around the article. All variables are defined in Appendix 1. All standard errors are clustered at the firm level. T-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable:	Speed of Trade Volume Response					
	Main Test - RavenPack is "live"			Placebo Test - Before RavenPack is "live"		
	(1)	(2)	(3)	(4)	(5)	(6)
D(HRH)	0.656***	0.516**	0.533**	0.033	-0.002	0.022
	(3.12)	(2.40)	(2.52)	(0.24)	(-0.02)	(0.16)
Absolute Composite Sentiment Score		-0.008	-0.006		-0.018***	-0.017**
		(-0.94)	(-0.74)		(-2.65)	(-2.52)
Neutral Composite Sentiment Score		-0.171**	-0.164**		-0.085	-0.089*
		(-2.55)	(-2.48)		(-1.64)	(-1.70)
Article category identified		-4.034***	-3.973***		-0.716	-0.690
		(-2.93)	(-3.37)		(-0.47)	(-0.45)
Absolute Event Sentiment Score		0.060***	0.056***		0.023***	0.024***
		(5.70)	(5.37)		(3.57)	(3.70)
Neutral Event Sentiment Score		-0.973***	-1.018***		-0.394*	-0.368*
		(-2.84)	(-3.01)		(-1.82)	(-1.71)
Time since last article		0.109***	0.101***		0.091***	0.087***
		(5.74)	(5.38)		(6.01)	(5.83)
Number of firms in article		-0.107***	-0.112***		-0.168***	-0.173***
		(-2.61)	(-2.75)		(-6.35)	(-6.55)
Number of Observations	272215	272215	272215	418252	418252	418252
R^2	0.029	0.032	0.059	0.026	0.027	0.038
Relevance, Category and Hour Fixed Effects	No	Yes	Yes	No	Yes	Yes
Date and Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Market control variables	No	No	Yes	No	No	Yes
Firm specific control variables	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: The Effect of News Articles on Liquidity

This table contains the results of article-level regressions that examine the effect of an article being covered in RavenPack on illiquidity. In regressions 1 to 3, the dependent variable is *Change in Amihud Illiquidity* defined as $\frac{\text{Amihud Illiquidity}_{t-1,t+5}}{\text{Amihud Illiquidity}_{t-1,t+5}+\text{Amihud Illiquidity}_{t-300,t-120}}$ in seconds around the article. In regressions 4 to 6, the dependent variable is *Change in Effective Spread* defined as $\frac{Effective\ Spread_{t-1,t+5}}{Effective\ Spread_{t-1,t+5}+Effective\ Spread_{t-300,t-120}}$ in seconds around the article. The explanatory variable of interest is D(HRH), a dummy variable equal to 1 if an article was consistently released as highly relevant in both RavenPack versions and 0 if it was originally released as having low relevance (HRL). In Panel A, we estimate our main specification during the time in which RavenPack was live (April 1, 2009 – September 10, 2012). In Panel B, we run a placebo test in the time period where RavenPack was not yet being sold to investors (February 1, 2004 – March 31, 2009). In all regressions we include firm and date fixed effects and the following firm specific control variables: Company size, Return prior month, Volatility prior month, Turnover prior month, Illiquidity prior month. In regressions 2, 3, 5 and 6, we add fixed effects for the article category (e.g. mergers and acquisitions), the relevance score (from 90 to 100) and the hour during the day in which the article was released. In regressions 3 and 6, we include additional controls: the absolute return, turnover, and volatility each for industry and market from t−1 to t+5 seconds around the article. All variables are defined in Appendix 1. All standard errors are clustered at the firm level. T-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Main Specification – RavenPack is "live"

Dependent Variable:	Change in Effective Spread			Change in Amihud Illiqudity		
	(1)	(2)	(3)	(4)	(5)	(6)
D(HRH)	0.009*	0.013***	0.013***	0.016**	0.014**	0.014**
	(1.91)	(2.76)	(2.77)	(2.35)	(2.03)	(1.98)
Absolute Composite Sentiment Score		0.000**	0.000**		-0.000	-0.000
		(2.15)	(2.33)		(-0.86)	(-0.37)
Neutral Composite Sentiment Score		-0.004***	-0.004***		0.001	0.001
		(-2.80)	(-2.84)		(0.23)	(0.36)
Article category identified		-0.120	-0.127		-0.042	-0.039
		(-1.47)	(-1.50)		(-0.49)	(-0.45)
Absolute Event Sentiment Score		0.001***	0.001***		0.001**	0.001**
		(3.51)	(3.46)		(2.29)	(2.25)
Neutral Event Sentiment Score		-0.017**	-0.018**		-0.022**	-0.023**
		(-2.22)	(-2.36)		(-2.07)	(-2.24)
Time since last article		-0.004***	-0.005***		0.003***	0.003***
		(-11.16)	(-11.80)		(5.09)	(3.72)
Number of firms in article		0.014***	0.014***		-0.006***	-0.005***
		(15.02)	(15.18)		(-4.65)	(-4.02)
Number of Observations	252306	252306	252306	115953	115953	115953
R^2	0.162	0.165	0.171	0.095	0.097	0.126
Relevance, Category and Hour Fixed Effects	No	Yes	Yes	No	Yes	Yes
Date and Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Market control variables	No	No	Yes	No	No	Yes
Firm specific control variables	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Placebo Test - Before RavenPack is "live"

Dependent Variable:	Change in Effective Spread			Change in Amihud Illiqudity		
	(1)	(2)	(3)	(4)	(5)	(6)
D(HRH)	-0.000	0.005	0.004	0.009	0.007	0.006
	(-0.11)	(1.62)	(1.51)	(1.42)	(1.13)	(1.05)
Absolute Composite Sentiment Score		0.000***	0.000***		-0.000	-0.000
		(2.90)	(2.90)		(-1.04)	(-0.99)
Neutral Composite Sentiment Score		-0.002**	-0.002*		-0.005**	-0.005**
		(-1.99)	(-1.94)		(-2.24)	(-2.21)
Article category identified		-0.008	-0.007		0.031	0.020
		(-0.14)	(-0.12)		(0.34)	(0.23)
Absolute Event Sentiment Score		0.001***	0.001***		0.001***	0.001***
		(7.59)	(7.83)		(2.82)	(3.11)
Neutral Event Sentiment Score		-0.013***	-0.011***		-0.005	-0.004
		(-3.14)	(-2.63)		(-0.54)	(-0.45)
Time since last article		-0.002***	-0.003***		0.005***	0.005***
		(-9.80)	(-10.94)		(8.63)	(7.82)
Number of firms in article		0.008***	0.008***		-0.008***	-0.008***
		(15.63)	(14.85)		(-7.84)	(-8.07)
Number of Observations	411981	411981	411981	178496	178496	178496
R^2	0.156	0.161	0.167	0.070	0.072	0.081
Relevance, Category and Hour Fixed Effects	No	Yes	Yes	No	Yes	Yes
Date and Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Market control variables	No	No	Yes	No	No	Yes
Firm specific control variables	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Directional Stock Price Response conditional on Past Informativeness of RavenPack

This table contains the results of article-level regressions that examine how well the past performance of RavenPack affects the stock price impact of RavenPack. The dependent variable is the return from 1 second before to 5 seconds after the article (measured in basis points). Returns are based on mid-quotes. The explanatory variable of interest is a triple interaction between *D(HRH)* and *Sentiment Direction* and *Past Informativeness*. *Past Informativeness* is the average signed return (in basis points) from t-1 to t+120 seconds around articles over the previous 6 month for stocks within the same industry. D(HRH) is a dummy variable equal to 1 if an article was consistently released as highly relevant in both RavenPack versions and 0 if it was originally released as having low relevance (HRL). *Sentiment Direction* is a variable indicating the sentiment of the article derived from RavenPack sentiment indices; it takes the value +1 for positive sentiment, 0 for neutral sentiment and −1 for negative sentiment. In Panel A, we estimate our main specification using *Past Informativeness* measured over the previous six months and using the 12 industry categories of Fama French. In regressions 1 to 3, we estimate the various specification during the time in which RavenPack was "live" (April 1, 2009 – September 10, 2012). In regressions 4 to 6, we run a placebo test for the time period where RavenPack was not yet sold to investors (February1, 2004 – March 31, 2009). In Panel B, we report a robustness check using 30 FF industry categories (instead of 12) and *Past Informativeness* measured over the previous three months (instead of a six). In all regressions we include firm and date fixed effects and the following firm specific control variables: Company size, Return prior month, Volatility prior month, Turnover prior month, Illiquidity prior month. In regressions 2, 3, 5 and 6, we add fixed effects for the article category (e.g. mergers and acquisitions), the relevance score (from 90 to 100) and the hour during the day in which the article was released. In regressions 3 and 6, we add additional controls: the absolute return, turnover, and volatility each for industry and market and for the two horizons from t−1 to t+5 seconds around the article. Control variables are defined in Appendix 1. All standard errors are clustered at the firm level. T-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Main Test

Dependent Variable:	Return t−1, t+5					
	Main Test - RavenPack is "live"			Placebo Test - Before RavenPack is "live"		
	(1)	(2)	(3)	(4)	(5)	(6)
Past Informativeness 6 month 12FF * D(HRH) * Sentiment Direction	0.221***	0.213***	0.225***	-0.178*	-0.165	-0.168
	(2.92)	(2.77)	(2.85)	(-1.71)	(-1.60)	(-1.63)
Past Informativeness 6 month 12FF * Sentiment Direction	-0.025	-0.034	-0.049	0.354***	0.311***	0.310***
	(-0.35)	(-0.46)	(-0.65)	(3.51)	(3.10)	(3.10)
Past Informativeness 6 month 12FF * D(HRH)	0.044	0.026	0.037	0.050	0.049	0.051
	(0.77)	(0.45)	(0.63)	(0.57)	(0.56)	(0.58)
D(HRH) * Sentiment Direction	0.020	0.075	0.056	0.497**	0.507**	0.512**
	(0.11)	(0.42)	(0.31)	(2.50)	(2.51)	(2.55)
Past Informativeness 3 month 12FF	-0.078	-0.055	-0.145**	-0.043	-0.031	-0.098
	(-1.29)	(-0.90)	(-2.29)	(-0.48)	(-0.35)	(-1.11)
D(HRH)	0.112	0.083	0.064	0.002	-0.030	-0.037
	(0.83)	(0.61)	(0.46)	(0.01)	(-0.17)	(-0.21)
Sentiment Direction	0.155	0.048	0.075	-0.393**	-0.531***	-0.525***
	(0.90)	(0.27)	(0.42)	(-2.04)	(-2.71)	(-2.69)
Article category identified		1.262**	1.044**		0.336	0.422
		(2.14)	(2.07)		(0.76)	(0.94)
Time since last article		0.043***	0.044***		0.239***	0.240***
		(3.40)	(3.44)		(13.12)	(13.19)
Number of firms in article		-0.152***	-0.146***		-0.222***	-0.220***
		(-5.09)	(-4.93)		(-9.32)	(-9.26)
Number of Observations	321860	321860	321860	472827	472827	472827
R^2	0.064	0.066	0.070	0.058	0.063	0.064
Relevance, Category and Hour Fixed Effects	No	Yes	Yes	No	Yes	Yes
Date and Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Market control variables	No	No	Yes	No	No	Yes
Firm specific control variables	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Robustness check: Different measures of Past Informativeness

Dependent Variable:	Return t−1, t+5					
	(1)	(2)	(3)	(4)	(5)	(6)
Past Informativeness 6 month 30FF * D(HRH) * Sentiment Direction	0.305***	0.313***	0.319***			
	(3.13)	(3.21)	(3.25)			
Past Informativeness 6 month 30FF * Sentiment Direction	-0.152	-0.169*	-0.178*			
	(-1.61)	(-1.79)	(-1.88)			
Past Informativeness 6 month 30FF * D(HRH)	-0.024	-0.028	-0.028			
	(-0.68)	(-0.80)	(-0.79)			
Past Informativeness 6 month 30FF	0.019	0.026	-0.001			
	(0.57)	(0.78)	(-0.03)			
Past Informativeness 3 month 12FF * D(HRH) * Sentiment Direction				0.196***	0.188**	0.192**
				(2.66)	(2.52)	(2.51)
Past Informativeness 3 month 12FF * Sentiment Direction				-0.031	-0.040	-0.044
				(-0.44)	(-0.56)	(-0.60)
Past Informativeness 3 month 12FF * D(HRH)				-0.001	-0.017	-0.006
				(-0.02)	(-0.32)	(-0.12)
Past Informativeness 3 month 12FF				-0.063	-0.046	-0.112**
				(-1.23)	(-0.87)	(-2.07)
D(HRH) * Sentiment Direction	-0.133	-0.103	-0.115	0.082	0.137	0.132
	(-0.79)	(-0.62)	(-0.67)	(0.47)	(0.78)	(0.74)
D(HRH)	0.242**	0.188*	0.188*	0.194	0.158	0.141
	(2.23)	(1.68)	(1.66)	(1.50)	(1.20)	(1.06)
Sentiment Direction	0.384**	0.288*	0.305*	0.167	0.058	0.065
	(2.36)	(1.77)	(1.84)	(0.98)	(0.33)	(0.37)
Article category identified		1.253**	1.036**		1.240**	1.029**
		(2.13)	(2.05)		(2.13)	(2.07)
Time since last article		0.043***	0.043***		0.043***	0.044***
		(3.40)	(3.43)		(3.40)	(3.44)
Number of firms in article		-0.152***	-0.146***		-0.151***	-0.146***
		(-5.09)	(-4.93)		(-5.06)	(-4.91)
Number of Observations	321860	321860	321860	321860	321860	321860
R^2	0.064	0.066	0.070	0.063	0.066	0.070
Relevance, Category and Hour Fixed Effects	No	Yes	Yes	No	Yes	Yes
Date and Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Market control variables	No	No	Yes	No	No	Yes
Firm specific control variables	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Difference in Difference Analysis

This table contains the results of article-level regressions implementing a difference in difference set-up for our whole sample from February 1, 2004 to September 10, 2012 as a robustness check to tables 3 to 5. In regressions 1 and 2, the dependent variable is *Speed of Stock Price Response* (in percent), defined as $\frac{\text{Abs(Return t}-1\text{,t}+5)}{\text{Abs(Return t}-1\text{,t}+5)+\text{Abs(Return t}+6\text{,t}+120)}$ and measured in seconds around an article. In regressions 3 and 4, the dependent variable is *Speed of Trade Volume Response* (in percent), defined as the turnover from 1 second before the article to 5 second after the article divided by the turnover from 1 second before the article to 120 seconds after the article. In regressions 1 to 4, the explanatory variable of interest is the interaction between *D(HRH)* and *RavenPack Release*. D(HRH) is a dummy variable equal to 1 if an article was consistently released as highly relevant in both RavenPack versions and 0 if it was originally released as having low relevance (HRL). *RavenPack Release* is a dummy variable taking the value of 1 for articles after RavenPack went "live" on April 1, 2009, and zero otherwise. In regressions 5 and 6, the dependent variable is the return (in percent) measured from 1 second before to 5 seconds after the article. The explanatory variable of interest is a triple interaction between *HRH*, *RavenPack Release* and *Sentiment Direction*, where *Sentiment Direction* is a variable indicating the sentiment of the article derived from RavenPack sentiment indices. It takes the value +1 for positive sentiment, 0 for neutral sentiment and −1 for negative sentiment. In all regressions we include firm and date fixed effects and the following firm specific control variables: Company size, Return prior month, Volatility prior month, Turnover prior month, Illiquidity prior month. In regressions 2, 4, and 6, we add fixed effects for the article category (e.g. mergers and acquisitions), the relevance score (from 90 to 100) and the hour during the day in which the article was released as well as additional controls: the absolute return, turnover, and volatility each for industry and market from t−1 to t+5 seconds around the article. In regression 2 and 4, we also include those values for t−1 to t+120 seconds around the article. All variables are defined in the Appendix. All standard errors are clustered at the firm level. T-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable:	Speed of Stock Price Response		Speed of Trade Volume Response		Return t-1, t+5	
	(1)	(2)	(3)	(4)	(5)	(6)
RavenPack Release * D(HRH) * Sentiment Direction					0.336**	0.330**
					(2.11)	(2.06)
RavenPack Release * D(HRH)	1.702***	1.713***	0.501*	0.476*	0.101	0.109
	(3.71)	(3.81)	(1.71)	(1.66)	(0.73)	(0.77)
RavenPack Release * Sentiment Direction					-0.314**	-0.294*
					(-2.03)	(-1.89)
D(HRH) * Sentiment					0.072	0.114
					(0.70)	(1.09)
D(HRH)	-0.053	-0.070	0.082	0.044	0.095	0.025
	(-0.19)	(-0.25)	(0.57)	(0.31)	(0.95)	(0.24)
Sentiment Direction					0.430***	0.222**
					(4.33)	(2.20)
Absolute Composite Sentiment Score		-0.025**		-0.013**		
		(-2.38)		(-2.52)		
Neutral Composite Sentiment Score		-0.269***		-0.111***		
		(-3.43)		(-2.70)		
Absolute Event Sentiment Score		0.044***		0.035***		
		(4.45)		(6.24)		
Neutral Event Sentiment Score		-1.019***		-0.536***		
		(-3.04)		(-2.99)		
Article category identified		-1.660		-2.200**		0.580**
		(-0.36)		(-2.04)		(2.13)
Time since last article		0.049**		0.082***		0.165***
		(2.43)		(7.04)		(13.33)
Number of firms in article		-0.117**		-0.136***		-0.201***
		(-2.49)		(-6.15)		(-10.98)
Number of Observations	649368	649368	690467	690467	803799	803799
R^2	0.026	0.051	0.019	0.037	0.046	0.052
Relevance, Category and Hour Fixed Effects	No	Yes	No	Yes	No	Yes
Date and Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Market control variables	No	Yes	No	Yes	No	Yes
Firm specific control variables	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Additional Robustness Checks

This table contains the results of different robustness checks. All regressions are at the article-level. In Panel A, we implement an alternative Placebo test which excludes the financial crisis and only includes the time period from February 1, 2004 to December 31, 2007 before RavenPack was "live". In Panel B, we implement an alternative Placebo test which excludes the time period before the introduction of Regulation NMS. It includes the time period from July 10, 2008 to April 1, 2009 before RavenPack was "live". In Panel C, we implement a robustness test, in which we include only the time when RavenPack 1 was active, i.e. from April 1, 2009 to July 6, 2011. In all cases, the dependent variable in Regressions 1 and 2 is *Speed of Stock Price Response* (in percent) defined as $\frac{\text{Abs(Return t}-1\text{,t+5)}}{\text{Abs(Return t}-1\text{,t+5)+Abs(Return t+6,t+120)}}$. In Regressions 3 and 4, the dependent variable is *Speed of Trade Volume Response* (in percent), defined as the turnover from 1 second before the article to 5 seconds after the article divided by the turnover from 1 second before the article to 120 seconds after the article. In Regressions 1 to 4, the explanatory variable of interest is D(HRH), a dummy variable equal to 1 if an article was consistently released as highly relevant in both RavenPack versions and 0 if it was originally released as having low relevance (HRL). In Regressions 5 and 6, the dependent variable is the return (measured in basis points) from 1 second before to 5 seconds after the article. In Regressions 5 and 6, the explanatory variable of interest is an interaction between *D(HRH)* and *Sentiment Direction*, where *Sentiment Direction* is a variable indicating the sentiment of the article derived from RavenPack sentiment indices. It takes the value +1 for positive sentiment, 0 for neutral sentiment and −1 for negative sentiment. In all regressions we include firm and date fixed effects and the following firm specific control variables: Company size, Return prior month, Volatility prior month, Turnover prior month, Illiquidity prior month. In regressions 2, 4, and 6, we add fixed effects for the article category (e.g. mergers and acquisitions), the relevance score (from 90 to 100) and the hour during the day in which the article was released as well as additional controls: the absolute return, turnover, and volatility each for industry and market from t−1 to t+5 seconds around the article. In regression 2 and 4, we also include those values for t−1 to t+120 seconds around the article. All variables are defined in Appendix 1. All standard errors are clustered at the firm level. T-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Alternative Placebo Test – Pre-RavenPack "live", excluding the Financial Crisis

Dependent Variable:	Speed of Stock Price Response		Speed of Trade Volume Response		Return t-1, t+5	
	(1)	(2)	(3)	(4)	(5)	(6)
RavenPack Release * D(HRH)					0.065	0.100
					(0.62)	(0.93)
D(HRH)	-0.039	0.004	0.013	0.028	0.235**	0.212*
	(-0.12)	(0.01)	(0.08)	(0.18)	(2.16)	(1.91)
Sentiment Direction					0.383***	0.108
					(3.82)	(1.04)
Absolute Composite Sentiment Score		-0.032**		-0.013*		
		(-2.05)		(-1.67)		
Neutral Composite Sentiment Score		-0.384***		-0.050		
		(-3.35)		(-0.84)		
Absolute Event Sentiment Score		0.010		0.011		
		(0.75)		(1.43)		
Neutral Event Sentiment Score		-1.087**		-0.558**		
		(-2.39)		(-2.25)		
Article category identified		-12.770***		-1.544		0.514
		(-9.24)		(-0.96)		(1.39)
Time since last article		0.066**		0.091***		0.275***
		(2.29)		(5.31)		(13.35)
Number of firms in article		-0.065		-0.120***		-0.198***
		(-1.03)		(-4.03)		(-7.53)
Number of Observations	318018	318018	332238	332238	386563	386563
R^2	0.031	0.043	0.030	0.039	0.070	0.077
Relevance, Category and Hour Fixed Effects	No	Yes	No	Yes	No	Yes
Date and Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Market control variables	No	Yes	No	Yes	No	Yes
Firm specific control variables	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Alternative Placebo Test – Pre-RavenPack "live", excluding pre Regulation NMS period

Dependent Variable:	Speed of Stock Price Response		Speed of Trade Volume Response		Return t-1, t+5	
	(1)	(2)	(3)	(4)	(5)	(6)
RavenPack Release * D(HRH)					0.144	0.164
					(0.48)	(0.55)
D(HRH)	0.349	0.047	0.337	0.144	-0.086	-0.096
	(0.53)	(0.07)	(1.35)	(0.57)	(-0.32)	(-0.35)
Sentiment Direction					0.502*	0.338
					(1.69)	(1.15)
Absolute Composite Sentiment Score		-0.048*		-0.030***		
		(-1.89)		(-2.78)		
Neutral Composite Sentiment Score		-0.408**		-0.162*		
		(-2.18)		(-1.85)		
Absolute Event Sentiment Score		0.060***		0.055***		
		(2.68)		(4.87)		
Neutral Event Sentiment Score		-1.976***		-0.234		
		(-2.58)		(-0.63)		
Article category identified		4.962		-0.697		-0.629
		(0.40)		(-0.26)		(-0.49)
Time since last article		0.091*		0.082***		0.111***
		(1.90)		(3.13)		(4.40)
Number of firms in article		-0.739***		-0.449***		-0.201***
		(-6.77)		(-9.30)		(-4.48)
Number of Observations	123039	123039	128309	128309	142920	142920
R^2	0.061	0.095	0.065	0.090	0.083	0.087
Relevance, Category and Hour Fixed Effects	No	Yes	No	Yes	No	Yes
Date and Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Market control variables	No	Yes	No	Yes	No	Yes
Firm specific control variables	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Old RavenPack Definition: RavenPack 1.0 versus RavenPack 2.0

Dependent Variable:	Speed of Stock Price Response		Speed of Trade Volume Response		Return t-1, t+5	
	(1)	(2)	(3)	(4)	(5)	(6)
RavenPack Release * D(HRH)					0.720***	0.744***
					(3.80)	(3.94)
D(HRH)	1.176**	1.194**	0.728***	0.622**	0.114	0.114
	(2.25)	(2.30)	(2.71)	(2.31)	(0.72)	(0.70)
Sentiment Direction					0.031	-0.123
					(0.16)	(-0.66)
Absolute Composite Sentiment Score		0.046*		0.018		
		(1.83)		(1.45)		
Neutral Composite Sentiment Score		-0.110		-0.062		
		(-0.63)		(-0.67)		
Absolute Event Sentiment Score		0.094***		0.049***		
		(4.31)		(4.08)		
Neutral Event Sentiment Score		-0.956		-1.389***		
		(-1.29)		(-3.31)		
Article category identified		-3.757		-4.385***		0.814
		(-1.34)		(-3.29)		(1.40)
Time since last article		0.151***		0.149***		0.092***
		(3.09)		(5.75)		(4.47)
Number of firms in article		-0.147		-0.231***		-0.175***
		(-1.29)		(-4.41)		(-4.09)
Number of Observations	123617	123617	137602	137602	160336	160336
R^2	0.050	0.096	0.054	0.084	0.090	0.097
Relevance, Category and Hour Fixed Effects	No	Yes	No	Yes	No	Yes
Date and Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Market control variables	No	Yes	No	Yes	No	Yes
Firm specific control variables	Yes	Yes	Yes	Yes	Yes	Yes

Table 12: Alternative Length of Event Window

This table contains the results of robustness check to Tables 4, 5 and 7 using a different lengths for short and long term reactions. We estimate the various specification during the time in which RavenPack was "live" (April 1, 2009 – September 10, 2012). Panel A provides a robustness check to Table 4 and thus the dependent variable is *Speed of Stock Price Response* (in percent). In the main specification, this variable is defined as $\frac{\text{Abs(Return t−1,t+5)}}{\text{Abs(Return t−1,t+5)+Abs(Return t+6,t+120)}}$. In Regressions 1 and 2 we instead define it as $\frac{\text{Abs(Return t−1,t+10)}}{\text{Abs(Return t−1,t+10)+Abs(Return t+11,t+120)}}$. In Regressions 3 and 4 as $\frac{\text{Abs(Return t−1,t+5)}}{\text{Abs(Return t−1,t+5)+Abs(Return t+6,t+300)}}$ and in Regressions 5 and 6 as $\frac{\text{Abs(Return t−1,t+10)}}{\text{Abs(Return t−1,t+10)+Abs(Return t+11,t+300)}}$. Panel B provides a robustness check to Table 5 and thus the dependent variable is *Speed of Trade Volume Response* (in percent). In the main specification, this variable is defined as $\frac{Turnover\ t-1,t+5}{Turnover\ t-1,t+120}$. In Regressions 1 and 2 we instead define it as $\frac{Turnover\ t-1,t+10}{Turnover\ t-1,t+120}$. In Regressions 3 and 4 as $\frac{Turnover\ t-1,t+5}{Turnover\ t-1,t+300}$ and in Regressions 5 and 6 as $\frac{Turnover\ t-1,t+10}{Turnover\ t-1,t+300}$. Panel C provides a robustness check to Table 7. In Table 7, we examine how well the sentiment direction of an article predicts the 5-second return reaction to an article depending on whether the article is covered in RavenPack. In Panel C, we use the 10-second return reaction instead. Whenever market control variables is indicated as "Yes", we include as additional controls: the absolute return, turnover, and volatility each for industry and market for the respective horizons used as dependent variables. All variables are defined in Appendix 1. All standard errors are clustered at the firm level. T-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Panel A: Speed of Stock Price Response

Window Length:	10 sec/120 sec		5 sec/300 sec		10 sec/300 sec	
	(1)	(2)	(3)	(4)	(5)	(6)
D(HRH)	1.906***	1.797***	1.281***	1.184***	1.733***	1.671***
	(3.79)	(3.58)	(4.17)	(3.92)	(4.44)	(4.33)
Absolute Composite Sentiment Score		-0.018		-0.008		-0.022
		(-0.94)		(-0.69)		(-1.50)
Neutral Composite Sentiment Score		-0.201		-0.112		-0.207*
		(-1.41)		(-1.28)		(-1.93)
Article category identified		-5.309		-1.584		-7.592
		(-0.88)		(-0.32)		(-1.58)
Absolute Event Sentiment Score		0.106***		0.083***		0.100***
		(5.16)		(5.63)		(6.10)
Neutral Event Sentiment Score		-0.449		-1.052**		-0.833
		(-0.63)		(-2.17)		(-1.49)
Time since last article		0.123***		0.091***		0.106***
		(3.15)		(3.63)		(3.62)
Number of firms in article		0.138		0.031		0.097
		(1.38)		(0.48)		(1.30)
Number of Observations	249064	249064	279646	279646	279645	279645
R^2	0.034	0.084	0.037	0.083	0.039	0.087
Relevance, Category and Hour Fixed Effects	No	Yes	No	Yes	No	Yes
Date and Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Market control variables	No	Yes	No	Yes	No	Yes
Firm specific control variables	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Speed of Trade Volume Response

Window Length:	10 sec/120 sec		5 sec/300 sec		10 sec/300 sec	
	(1)	(2)	(3)	(4)	(5)	(6)
D(HRH)	0.754***	0.603**	0.336***	0.256**	0.511***	0.418***
	(2.61)	(2.09)	(3.20)	(2.40)	(3.43)	(2.82)
Absolute Composite Sentiment Score		-0.023**		-0.004		-0.014**
		(-2.18)		(-0.95)		(-2.35)
Neutral Composite Sentiment Score		-0.337***		-0.114***		-0.232***
		(-3.92)		(-3.24)		(-4.87)
Article category identified		-1.556		-2.015***		-0.283
		(-0.40)		(-3.63)		(-0.11)
Absolute Event Sentiment Score		0.073***		0.044***		0.062***
		(5.86)		(6.77)		(7.88)
Neutral Event Sentiment Score		-1.047**		-0.606***		-0.569**
		(-2.46)		(-2.90)		(-2.18)
Time since last article		0.133***		0.062***		0.084***
		(5.45)		(6.01)		(6.34)
Number of firms in article		-0.153***		-0.075***		-0.119***
		(-2.89)		(-3.53)		(-4.19)
Number of Observations	272215	272215	293804	293804	293804	293804
R^2	0.031	0.064	0.033	0.055	0.037	0.061
Relevance, Category and Hour Fixed Effects	No	Yes	No	Yes	No	Yes
Date and Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Market control variables	No	Yes	No	Yes	No	Yes
Firm specific control variables	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Directional Stock Price Response to Article Sentiment

Dependent Variable:		Return t-1, t+10	
	(1)	(2)	(3)
D(HRH) * Sentiment Direction	0.418**	0.480***	0.487***
	(2.33)	(2.66)	(2.69)
D(HRH)	0.333**	0.221	0.229
	(2.05)	(1.32)	(1.36)
Sentiment Direction	0.297*	0.154	0.149
	(1.68)	(0.87)	(0.84)
Article category identified		0.951	0.774
		(1.61)	(1.47)
Time since last article		0.077***	0.077***
		(4.91)	(4.92)
Number of firms in article		-0.208***	-0.204***
		(-5.60)	(-5.51)
Number of Observations	321860	321860	321860
R^2	0.067	0.070	0.072
Relevance, Category and Hour Fixed Effects	No	Yes	Yes
Date and Firm Fixed Effects	Yes	Yes	Yes
Market control variables	No	No	Yes
Firm specific control variables	Yes	Yes	Yes

Appendix 1: Variable Definitions

This table displays the variable definitions for all variables used in the regressions. Article variables (sentiment scores, relevant scores, etc.) are based on RavenPack 3. When we winsorize, we set outliers to the allowed extreme value; e.g., "smaller 10" means that any value below 10 is set to 10. For all variables, winsorizing affects less than 1% of observations on either side.

Variable Name	**Definition**	**Winsorizing**
HRH	High relevance article Released as High relevance article. Dummy variable equal to 1 if an article has a relevance of 90 or higher in both RavenPack versions. When used in regressions, it is equal to 0 if an article has a relevance score of 90 or higher in the new RavenPack version (RavenPack 3), but was not covered or had a relevance score below 90 in the old RavenPack version. (the old RavenPack version is RavenPack 1 until July 6, 2011 and RavenPack 2 afterwards).	*None*
HRL	High relevance article Released as Low relevance article. Dummy variable equal to 1 if an article has a relevance score of 90 or higher in the new RavenPack version (RavenPack 3), but was not covered or had a relevance score below 90 in the old RavenPack version. (the old RavenPack version is RavenPack 1 until July 6, 2011 and RavenPack 2 afterwards).	*None*
LRH	Low relevance article Released as High relevance article. Dummy variable equal to 1 if an article has a relevance score below 90 or is not covered in the new RavenPack version (RavenPack 3), but had a Relevance Score greater or equal than 90 in the old RavenPack version. (the old RavenPack version is RavenPack 1 until July 6, 2011 and RavenPack 2 afterwards).	*None*
Company size	Log(prior day closing price * shares outstanding)	*Smaller 10*
Volatility prior month	Average squared return of the stock in the prior 20 trading days	*Larger 200%*
Turnover prior month	Average volume divided by shares outstanding in the prior 20 trading days	*Larger 100%*
Return prior month	Average return in the prior 20 trading days	*Larger 3% & Smaller -3%*
Illiquidity prior month	Percentile rank of all article-firm combinations of a day according to Amihud Illiqudity = $\text{mean}_{\text{over past 20 trading days}}\left(\frac{\lvert \text{ret}_{\text{daily}} \rvert}{\text{dollar volume}_{\text{daily}}}\right)$. *The most illiquid firms are assigned 100 the most liquid 1.*	*None*
Relevance	Score provided by RavenPack that indicates the relevance of an article to a company and takes values from 0 (least relevant) to 100 (most relevant).	
Event Sentiment Score	Sentiment score that is provided by RavenPack; takes a value from 100 (positive) to 0 (negative). It is available only for articles for which the category is identified.	*None*
Absolute Event Sentiment Score	Abs (*Event Sentiment Score* – 50)	*None*
Neutral Event Sentiment Score	Dummy variable equal to 1 if *Event Sentiment Score* equals 50 or if it is missing.	*None*
Composite Sentiment Score	Sentiment score that is provided by RavenPack; takes a value from 100 (positive) to 0 (negative). It is available for each article.	*None*
Absolute Composite Sentiment Score	Abs (*Composite Sentiment Score* – 50)	*None*
Neutral Composite Sentiment Score	Dummy variable equal to 1 if *Composite Sentiment Score* equals 50.	*None*
Article category identified	Dummy variable equal to 1 if the category (e.g. "merger") of the article is identified	*None*
Number of firms in article	Log (Number of firms in article)	*None*
Time since last article	Log (Time since last article in seconds)	*None*
Sentiment Direction	Variable indicating the sentiment of the article based on RavenPack sentiment indices. It can take the values 1 (positive sentiment), 0 (neutral sentiment) and −1 (negative sentiment). It is first based on *Event Sentiment Score* (*ESS*). If *ESS* is larger 50, this variable is 1, if *ESS* is smaller than 50, it is −1. If *ESS* is missing or 50, we consult *Composite Sentiment Score* (*CSS*). If *CSS* is greater than 50 we set this variable to 1, if *CSS* is smaller than 50 we set it to −1, if *CSS* equals 50 we set it to zero.	*None*
Return t-1, t+5	Stock return from 1 second before to 5 seconds after the article. Returns are computed from mid-quotes.	*Larger 2%, smaller -2%*
Return t+6, t+120	Stock return from 6 seconds after to 120 seconds after the article. Returns are computed from mid-quotes.	*Larger 2%, smaller -2%*

Speed of Stock Price Response	$\frac{Abs(Return\ t-1,t+5)}{Abs(Return\ t-1,t+5)+Abs(Return\ t+6,t+120)}$	*None*
Speed of Stock Price Response – Market Adjusted	$\frac{Abs(Market\ Adjusted\ Return\ t-1,t+5)}{Abs(Market\ Adjusted\ Return\ t-1,t+5)+Abs(Market\ Adjusted\ Return\ t+6,t+120)}$ Set to missing if: $Abs(Return\ t-1,t+5)+Abs(Return\ t+6,t+120)$ = *0.*	*None*
Speed of Stock Price Response – Industry Adjusted	$\frac{Abs(Industry\ Adjusted\ Return\ t-1,t+5)}{Abs(Industry\ Adjusted\ Return\ t-1,t+5)+Abs(Industry\ Adjusted\ Return\ t+6,t+120)}$ Set to missing if: $Abs(Return\ t-1,t+5)+Abs(Return\ t+6,t+120)$ = *0.*	*None*
Speed of Trade Volume Response	$\frac{Turnover\ t-1,t+5}{Turnover\ t-1,t+120}$	*None*
$Amihud\ Illiquidity_{ij}$	$\frac{1}{\mathrm{N_{ij}}}\sum_{\mathrm{t}}^{\mathrm{N_{ij}}}\frac{\lvert \mathrm{r_{it}} \rvert}{\mathrm{dolvol_{it}}}$, where r_{it} is the return for stock i during second t; $dolvol_{it}$ is the dollar volume for stock i during second t; and N_{ij} is the number of seconds in which stock i traded during interval j.	*Larger 2*
$Effective\ Spread_{ij}$	$\frac{1}{\mathrm{N_{ij}}}\sum_{\mathrm{t}}^{\mathrm{N_{ij}}} sign(buys_{it}-sells_{it})*\frac{price_{it}-midquote_{it-1}}{midquote_{it-1}}$, where $buys_{it}$ ($sells_{it}$) is the number of stocks bought (sold) for stock i during second t; $price_{it}$ is the last execution price for stock i during second t; $midquote_{it}$ is the last bid-ask midpoint for stock i during second t and Nij is the number of seconds in which stock i traded during interval j.	*Larger 3*
Change in Amihud Illiquidity	$\frac{\mathrm{Amihud\ Illiquidity}_{t-1,t+5}}{\mathrm{Amihud\ Illiquidity}_{t-1,t+5}+\mathrm{Amihud\ Illiquidity}_{t-300,t-120}}$	*None*
Change in Effective Spread	$\frac{Effective\ Spread_{t-1,t+5}}{Effective\ Spread_{t-1,t+5}+Effective\ Spread_{t-300,t-120}}$ in seconds around the article.	*None*
Signed Return t-1, t+120	$Return_{t-1,t+120}*Sentiment\ Direction$ This variable is set to missing if Sentiment Direction is equal to zero.	*Larger 2%*
Past Informativeness 6 month 12FF	$Mean(Signed\ Return_{t-1,t+120})$, the mean is taken over the prior six calendar months within the same industry following 12 Fama French industry classification	*None*
Past Informativeness 3 month 12FF	Same definition as *Past Informativeness 6 month 12FF*, but using 3 month instead of 6 month.	*None*
Past Informativeness 6 month 30FF	Same definition as *Past Informativeness 6 month 12FF*, but using 30 Fama French industry classification instead of 12 Fama French industry classification.	*None*
Market return t-1, t+5	Value-weighted return of all common stocks in TAQ (which are also in CRSP) from 1 second before to 5 seconds after the article. Returns are computed from mid-quotes.	*None*
Industry return t-1, t+5	Value-weighted return of all common stocks in the same 12 Fama French Industry from 1 second before to 5 seconds after the article. Returns are computed from mid-quotes.	*None*
Market turnover t-1, t+5	Total dollar trading volume of all common stocks in TAQ (which are also in CRSP) from 1 second before to 5 seconds after the article divided by total market capitalization at t-2.	*None*
Market volatility t-1, t+5	Value weighted average squared second return of all common stocks in TAQ (which are also in CRSP) averaged from 1 second before to 5 seconds after the article.	*Larger 20 bp*
Market adjusted return t-1, t+5	*Return* (*t-1, t+5*) − *Market Return* (*t-1, t+5*)	*Larger 2%, smaller -2%*
Industry adjusted return t-1, t+5	*Return* (*t-1, t+5*) − *Industry Return* (*t-1, t+5*)	*Larger 2%, smaller -2%*

Appendix 2: Intraday Market and Industry Returns

We compute second-by-second value-weighted average returns, trading volume, and value weighted average volatility for the market and for 12 industry indices (as defined by Fama and French).[17] In constructing these indices, we use information from the CRSP daily file, the TAQ National Best Bid and Offer (NBBO) file provided by WRDS for second-by-second quotes and the TAQ trades file. We link TAQ to CRSP using ticker symbols. We include in our sample all stocks that are covered in CRSP and TAQ and have share codes of 10 or 11 in CRSP. We assign stocks to industry indexes using CRSP SIC codes (data item SICCD) with lists obtained from Ken French's website. At the quote and trade level we apply the following filters: We exclude all trades with zero size, negative prices, TAQ Correction Code not equal to 0, and bid-ask quotes where the bid is above the ask. In addition, we exclude all quotes where the bid-ask spread is larger than 30%.

Most stocks do not have quotes available for every second. Some stocks are relatively illiquid and only have valid quotes every few minutes. To be able to compute the first return of the day, we need past quotes. The closing quotes of the prior day are problematic in that (1) they often are not prices at which market makers would actually be willing to trade, and (2) they are informationally "stale" as they do not incorporate information released overnight. Therefore, we use the time from 9:00 to 9:35 as a burn-in period and use the last valid bid-ask midquote of this time period as the initial price to compute the first return. We exclude from the sample for that specific day all stocks that do not have a quote in this time period. We also exclude stocks for which the midpoint of the initial quote is below $1 and for which this initial quote has a bid ask spread of more than 10%.[18] This way we insure that our index is not driven by outliers due to large bid-ask spreads.

We compute value-weighted average returns for the market and the 12 Fama French industry indices by computing the second-to-second change in aggregate market capitalization for the respective samples. We compute a company's market capitalization by multiplying the bid-ask midpoint by the shares outstanding from CRSP.[19] We use bid-ask midpoints rather than transaction prices to avoid bid-ask bounce. We compute aggregate trading volume per second by summing the individual stock dollar trading volume per second for all stocks in the respective samples. A stock's trading volume is equal to number of shares traded during the second multiplied by the transaction prices of the trades. We compute value-

[17] Thanks to the technical personnel at WRDS, especially Mark Keintz, for making the construction of these indexes possible. The composition of the industry indexes are from Ken French's Website.
[18] The difference between the cut-off for the initial spread (10%) and the general spread cut-off (30%) is intended. We only want to include stocks for which a typical spread is below 10% and for these stocks we treat any quote with a spread above 30% as an outlier that needs to be removed.
[19] Since the index composition changes day to day, we are not able to compute an overnight return. This is no problem as we are only interested in intra-day returns.

weighted average volatility for the market and for the 12 Fama French industries based on squared second-by-second returns. The value weights are based on the firm's market capitalization at the end of the prior day using the closing price and shares outstanding in CRSP. Individual stock returns used to compute value-weighted average volatility are based on the second-by-second change in bid-ask midpoints. If there is no quote for a second, the return is set to 0. If the return is larger than 10%, it is set to 10%. We verify that all our filters affect only a small number of firms or quotes.

Appendix 3: Verify that Past Informativeness predicts Informativeness

This table contains the results of article-level regressions that examine how well the sentiment direction of an article predicts the 120-second return reaction to an article depending on Past Informativeness. The dependent variable is the return from 1 second before to 120 seconds after the article (measured in basis points). Returns are based on mid-quotes. The explanatory variable of interest is an interaction between *Sentiment Direction* and *Past Informativeness*. *Sentiment Direction* is a variable indicating the sentiment of the article derived from RavenPack sentiment indices; it takes the value +1 for positive sentiment, 0 for neutral sentiment and −1 for negative sentiment. *Past Informativeness* is the average signed return (in basis points) from t-1 to t+120 seconds around articles over the previous 6 months (or 3 months) for stocks within the same industry. We use either the 12 industry categories of Fama French or the 30 industry categories of Fama French. In all regressions we include firm and date fixed effects and the following firm specific control variables: Company size, Return prior month, Volatility prior month, Turnover prior month, Illiquidity prior month. We also include fixed effects for the article category (e.g. mergers and acquisitions), the relevance score (from 90 to 100) and the hour during the day in which the article was released and absolute return, turnover, and volatility each for industry and market from t−1 to t+120 seconds around the article. All variables are defined in Appendix 1. All standard errors are clustered at the firm level. T-statistics are below the parameter estimates in parenthesis; ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively.

Dependent Variable:	Return t-1, t+120			
	(1)	(2)	(3)	(4)
Past Informativeness 6 month 12FF * Sentiment Direction		0.627***		
		(13.61)		
Past Informativeness 6 month 30FF * Sentiment Direction			0.476***	
			(11.65)	
Past Informativeness 3 month 12FF * Sentiment Direction				0.525***
				(12.81)
Sentiment Direction	1.923***	0.638***	0.941***	0.858***
	(32.04)	(7.00)	(10.71)	(10.16)
Past Informativeness 6 month 12FF		-0.005		
		(-0.09)		
Past Informativeness 6 month 30FF			-0.027	
			(-0.79)	
Past Informativeness 3 month 12FF				-0.062
				(-1.44)
Article category identified	0.593	0.821	0.894	0.762
	(0.26)	(0.37)	(0.40)	(0.35)
Time since last article	0.503***	0.503***	0.502***	0.502***
	(17.69)	(17.64)	(17.62)	(17.62)
Number of firms in article	-0.544***	-0.562***	-0.558***	-0.559***
	(-10.62)	(-10.85)	(-10.81)	(-10.80)
Number of Observations	803799	794687	794687	794687
R^2	0.043	0.044	0.044	0.044
Relevance, Category and Hour Fixed Effects	Yes	Yes	Yes	Yes
Date and Firm Fixed Effects	Yes	Yes	Yes	Yes
Market control variables	Yes	Yes	Yes	Yes
Firm specific control variables	Yes	Yes	Yes	Yes

Appendix 4: Examples of HRL and LRH articles

Below, we give examples of articles where different RavenPack versions disagree. We report the name of the company that the article is associated with, date and time of the article and the *Relevance, Sentiment Direction* and *Category* information both in the Old RavenPack and in New RavenPack. We also report the stock price response in seconds around the article as well as the article's headline and body.

We provide two examples of HRL articles. Example A constitutes an article that was assigned to Associated Bank in both versions, but while New RavenPack assigned the maximum relevance of 100, Old RavenPack only assigned a lower Relevance of 61. This difference comes from the fact that New RavenPack correctly identifies this article as a positive earnings release while Old RavenPack cannot determine its category. However, both versions agree on the article being positive. The stock price reaction to this article is slow. There is no price update in the first 8 seconds after the article and most of the stock price response happens after about 60 seconds.

Example B constitutes a different type of HRL article, where the versions disagree about identifying the company. New RavenPack assigns this article to Internet Capital Group, while Old RavenPack did not realize that this article is about this company. The article is a buyback announcement, which is both relevant and positive news to the company. Accordingly, New RavenPack gives it a high *Relevance* and a positive *Sentiment Direction*. In the stock price reaction we can see that the information is only slowly incorporated into prices and that there is not stock price response until about 30 seconds after the article.

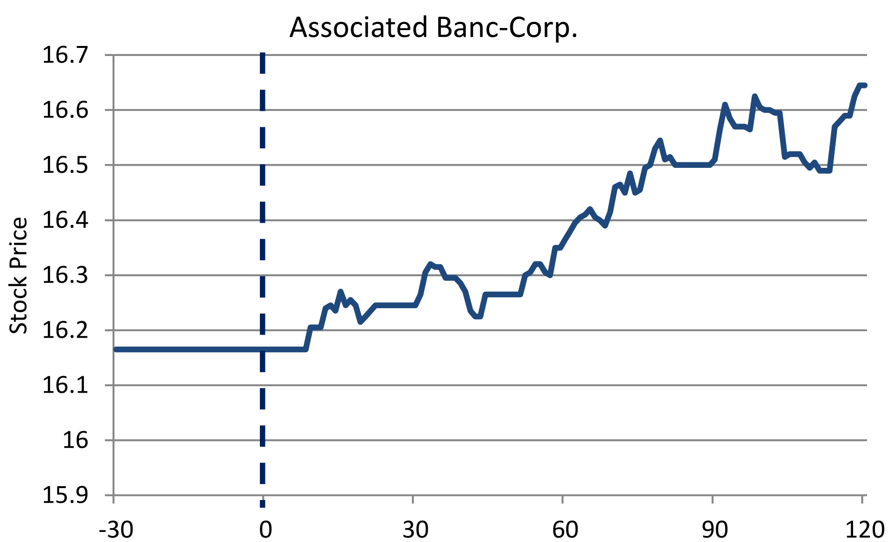
As comparison, we present an HRH article in Example C. This article is a buyback announcement for Genzyme Corporation. In both RavenPack versions it is identified as a relevant and positive article for this company. A large part of the stock price reaction takes place in the first 5 seconds after the article.

Example D constitutes an LRH article. Both RavenPack versions assign this article to Netsuite. However, they disagree about the relevance. While Old RavenPack assigns it a high *Relevance* of 96, New RavenPack assigns only a 20. Reading the article, we realize that this story is mainly about another company (Suite Cloud) and that this story seems not very relevant to Netsuite. Still, we see an immediate stock price reaction of Netsuite, which is partially corrected after 30 seconds.

A. High-relevance article Released as Low-relevance article (HRL) – Example One

<u>Company:</u> ASSOCIATED BANC-CORP.
<u>Date and Time:</u> 13:18:03 on April 16, 2009

	Relevance Score	Sentiment Direction	Category
Old RavenPack	61	Positive	N/A
New RavenPack	100	Positive	earnings-per-share-positive



<u>Headline:</u> PRESS RELEASE: Associated Reports First Quarter Earnings of $0.28 Per Common Share, Up from $0.11 for the Fourth Quarter of 2008

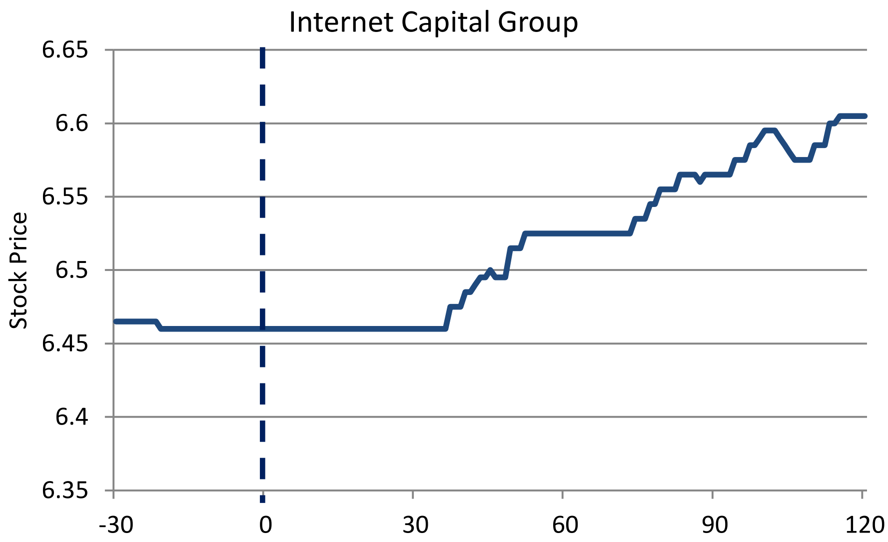
<u>Article body:</u>
GREEN BAY, Wis.--(BUSINESS WIRE)--April 16, 2009--
Associated Banc-Corp (NASDAQ: ASBC):
-- Net income available to common shareholders was $35.4 million for the first quarter compared to $13.6 million for the fourth quarter of 2008
-- Net interest income for the quarter was $189.3 million compared to $191.8 million for the fourth quarter of 2008
-- Total deposits grew by 4.7% to $15.9 billion at March 31, 2009 compared to $15.2 billion at December 31, 2008 and were up 14.3% from $13.9 billion at March 31, 2008
-- Mortgage loans originated for sale exceeded $1 billion during the quarter
-- Provision for loan losses of $105.4 million exceeded net charge offs of $57.6 million by $47.8 million, increasing allowance for loan losses to 1.97% of loans at March 31, 2009, up from 1.63% at December 31, 2008
-- Tangible common equity ratio remained stable at 6.10%
-- Quarterly dividend reduced to $0.05 per common share to preserve capital

(article continues for several pages and is cut here)

B. High-relevance article Released as Low-relevance article (HRL) – Example Two

<u>Company:</u> INTERNET CAPITAL GROUP INC.
<u>Date and Time:</u> 14:22:29 on January 7, 2010

	Relevance Score	Sentiment Direction	Category
Old RavenPack	N/A	N/A	N/A
New RavenPack	100	Positive	buybacks



<u>Headline:</u> `*DJ Internet Cap Grp Repurchased 400,000 Shrs In Qtr Ended Dec 31`

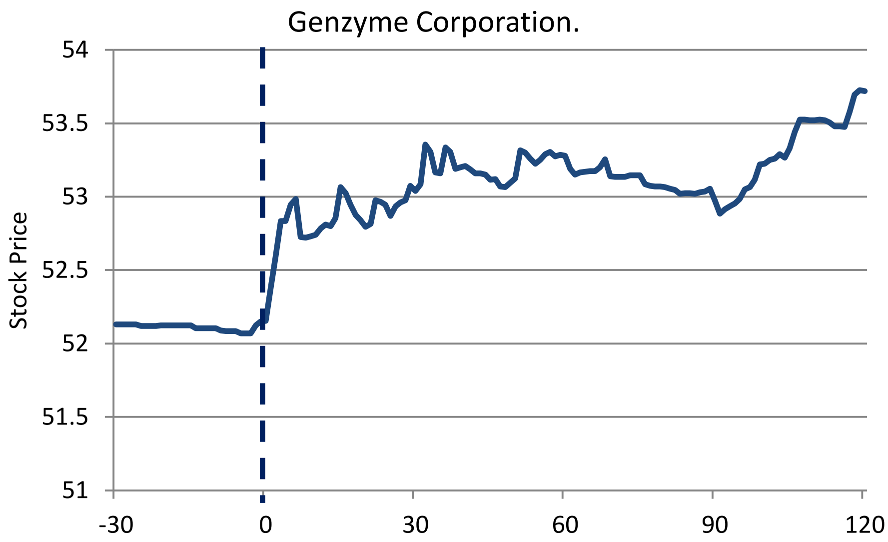
<u>Article body:</u>

`(MORE TO FOLLOW) Dow Jones Newswires (212-416-2400)`

C. High-relevance article Released as High-relevance article (HRH)

Company: GENZYME CORPORATION
Date and Time: 13:15:02 on May 6, 2010

	Relevance Score	Sentiment Direction	Category
Old RavenPack	100	Positive	buybacks
New RavenPack	100	Positive	buybacks



Headline: `* PRESS RELEASE: Genzyme Announces $2 Billion Stock Repurchase`

Article body:

Company Will Explore Strategic Alternatives for Three Businesses

New Initiatives Part of Plan for Growth Through 2015

CAMBRIDGE, Mass.--(BUSINESS WIRE)--May 06, 2010--

Genzyme Corp. (NASDAQ: GENZ) today announced that its Board of Directors has voted to pursue several actions to increase shareholder value. The company will initiate a $2 billion stock buyback, under which $1 billion of stock will be repurchased in the near term and financed with debt. The additional $1 billion of stock will be repurchased during the next 12 months.

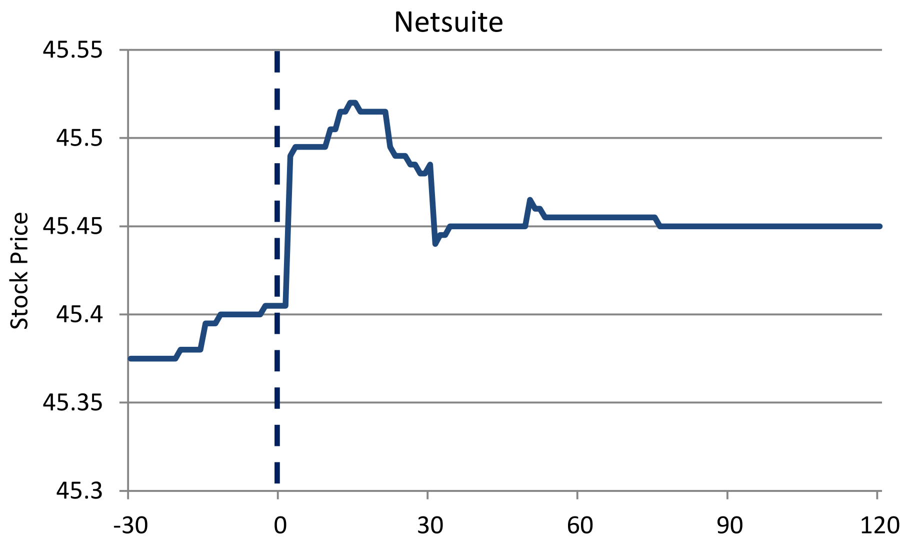
The company also plans to pursue strategic alternatives for its Genetic testing, Diagnostic products and Pharmaceutical intermediates businesses. Options could include divestiture, spin-out, or management buy-out.

(article continues for several pages and is cut here)

D. Low-relevance article Released as High-relevance article (LRH)

<u>Company:</u> NETSUITE INC.
<u>Date and Time:</u> 10:28:15 on May 23, 2012

	Relevance Score	Sentiment Direction	Category
Old RavenPack	96	Positive	N/A
New RavenPack	20	Positive	N/A



<u>Headline:</u> PRESS RELEASE: SPS Commerce Named SuiteCloud Developer Network Partner of the Year by NetSuite

<u>Article body:</u>
MINNEAPOLIS, May 23, 2012 (GLOBE NEWSWIRE) -- SPS Commerce (Nasdaq:SPSC), a leading provider of on-demand supply chain management solutions, today announced that it has been named NetSuite's SuiteCloud Developer Network Partner for 2012. This award was given to SPS Commerce at SuiteWorld 2012 in San Francisco.

"We are honored to be recognized with this distinguished honor by NetSuite," said Archie Black, CEO of SPS Commerce. "Our companies have worked together since 2007 to bring cloud-based solutions to companies across the globe. Our joint customers are leveraging integrated solutions to advance their e-commerce, retail and logistics operations. We would like to congratulate our partners, Celigo, Retail Anywhere and Forward Hindsight, which also received awards from NetSuite at SuiteWorld."

Pre-wired to integrate directly with NetSuite, SPS Commerce's cloud-based supply chain services improve the way suppliers, retailers, distributors and 3PLs build their trading partner relationships and manage and fulfill orders with pre-built integrations using 3,000 order management models across 1,500 retailers, grocers and distributors. SPS' Retail Universe, a social network for the supply chain, is designed to help the community's 40,000 members form new business partnerships based on product or integration requirements.