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Public information arrival and stock return volatility: Evidence from news sentiment and Markov Regime-Switching Approach

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ABSTRACT

Using computational linguistic analysis of intraday firm-level news releases, this study models the relation between public information flows and stock volatility under different regimes. We analyze how the hourly return volatility of S&P100 stocks from 2000 to 2010 are linked to the various linguistics-based sentiment scores of the news releases, which are obtained from the RavenPack News Analytics Database. Results from the Markov Regime-Switching GARCH (MRS-GARCH) model indicate that firm-specific news sentiment is more significant in quantifying intraday volatility persistence in the calm (low-volatility) state than the turbulent (high-volatility) state. Furthermore, the impact of news sentiment differs across industries and firm size.

1. Introduction

Over the past few decades, a significant strand of the finance literature has studied the role of news on the dynamics of security price formation, the price discovery process and the behavior of market participants. Specifically, significant work has been conducted on examining how the arrival of public information contributes to stock return volatility (Jones, Lamont, & Lumsdaine, 1998; Kalev, Liu, Pham, & Jarnecic, 2004; Cousin & de Launois, 2008; Laakkonen & Lanne, 2009; Berger, Chaboud, & Hjalmarsson, 2009; Park, 2010; Ang & Timmermann, 2011; Fostel & Geanakoplos, 2012; Cheng, Leung, & Yu, 2014). While these studies conclude that the arrival of public information induces stock return volatility persistence and has a positive effect on stock return volatility, how and when different types of public information influence stock return volatility remains debatable.

Meanwhile, a growing body of compelling anecdotal evidence suggests that news arrivals do not resolve uncertainty; rather, they induce volatility. This is in stark contrast to the rationale of market efficiency. On 3 May 1998, a Sunday *New York Times* article reported a potential development of new cancer-curing drugs and highlighted EntreMed as the company with the licensing rights to the development (Kolata, 1998). This was followed by a meteoric rise in EntreMed's stock price from $12.063 at the Friday close to open at $85 and close near $52 on Monday. The enthusiasm spilled over to other biotechnology stocks. However, the *New York Times*, CNN and CNBC had already reported the same news on the therapy of tumors in an article approximately six months earlier. On the morning of 25 August 2000, a fake negative report claiming the resignation of the CEO of Emulex—a

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Californian maker of network products—and impending profit revision was released and circulated online. The stock price of Emulex fell by more than 50% from $113.06 to $50 in less than 30 min (Benning, 2000). The stock trading of Emulex was forced to halt for three hours to prevent the price from going into free fall. These examples highlight two interesting phenomena. First, the media sentiment of news plays an important role in explaining price rises and falls. Second, to the extent that the market overreacts to the news content, volatility rises.

The literature on the relation between public information arrival and volatility is divided into two streams. The first stream provides a theoretical explanation of the volatility persistence existing in the stock return. An appealing answer comes from the literature on the Mixture of Distribution Hypothesis (MDH), which argues that the variance of returns at a given interval is proportional to the rate of information arrival in the market (Clark, 1973; Tauchen & Pitts, 1983; Harris, 1986, 1987; Andersen, 1996). The second stream examines the asymmetric effect of different news on stock return volatility. This stream is linked to the theory proposed by Veronesi (1999), who suggests that because of the asymmetric information about the state of the economy, investors overreact to bad news in good times and underreact to good news in bad times. veronesi1999's theory shows that the sentiment of news plays an important role in explaining stock return volatility, and its effect depends on the level of volatility.

Other studies, such as Laakkonen and Lanne (2009) and Chen and Ghysels (2011), have a different conclusion. Laakkonen and Lanne (2009) find that bad news increases volatility more in good times than in bad times, while good news has no effects on volatility in good and bad times. Chen and Ghysels (2011) find that moderately good news reduces volatility, while both very good news and bad news increase volatility, with the latter having a greater effect. They find that the asymmetries disappear over longer horizons.

While their findings are interesting, both studies have the same problem of endogeneity. In Chen and Ghysels (2011), news flow is proxied by the five-minute return, and news is considered good (bad) if the return is positive (negative). In Laakkonen and Lanne (2009), news flow is proxied by macroeconomic news announcements, and news is considered good (bad) if the five-minute return following the announcement is positive (negative). Therefore, both classifications are endogenous to the stock volatility.

In this paper, we take both the MDH and quality of news into consideration and empirically examine the role of public news arrivals on stock return volatility. Our study can contribute to the existing literature in the following directions. First, we use a novel news database that utilities a text analytic algorithm to classify the news type based on its textual content known as the news sentiment. Rather than classifying news type (good versus bad) based on stock returns, this classification is not subject to endogeneity problem. Second, our evidence suggests that the effect of news sentiment on stock return volatility is significant, and its magnitude depends on volatility states of the stock. Third, sector and firm size variations are observed for the news effects. As volatility is an essential input in dynamic hedging strategies, derivatives pricing models and risk management issues, our results imply that the impact of news sentiment could be incorporated to improve the hedging outcomes.

The news database employed in this study is provided by RavenPack News Analytics Dow Jones Edition. RavenPack tracks and continuously monitors relevant news on tens of thousands of companies, government organizations, influential people, key geographical locations, and all major currencies and traded commodities. The source includes Dow Jones Newswires, regional editions of the *Wall Street Journal* and Barron's and Internet sources including financial sites, blogs, and local and regional newspapers. It provides analytics on the news content of more than 170,000 entities in over 100 countries and covers over 98% of the investable global market. RavenPack uses a proprietary computational linguistic analysis algorithm to quantify positive and negative perceptions on facts and opinions reported in the news textual content. The core of the algorithm is divided into two steps. First, RavenPack uses historical data to build a database of words that have affected the stock price. It then compares words in the news story to the words in the database and generates the sentiment score, which is used to determine the news type. Since the news type is classified based on its textual content rather than post-announcement returns, it does not suffer from the problem of endogeneity as the news sentiment itself is not affected by return volatility per se.

In addition to the sentiment score, for each news story, RavenPack provides information on the relevance of the news to the firm, the topic of the news and the novelty of the news (i.e. whether the news story is recycled news). In our empirical analysis, we construct a composite measure that takes into account the number, the relevance and the sentiment of the news.

As our news database only contains firm-specific news stories, to control for macroeconomic news, we construct a dummy variable to capture the extreme market (index level) movement that is caused by market-wide factors. We model the conditional volatility of the hourly stock returns of S&P 100 stocks from 1 January 2000 to 31 December 2010 using GARCH modeling techniques.[1] Specifically, conditional stock return volatilities are estimated using GARCH and Markov Regime-Switching GARCH (MRS-GARCH) models. GARCH models are widely employed in the study related to the MDH (e.g. Kalev, Liu, Pham, & Jarnecic, 2004; Kalev & Duong, 2011) due to their advantages of capturing the typical stylized facts of financial return series such as volatility clustering (Marcucci, 2005). However, due to the presence of structural breaks, policy changes and other shocks in the real economy, the stock price may shift from one regime to another over time (Marcucci, 2005; Ang & Timmermann, 2011). Therefore, it is important to employ the MRS-type models when the structural breaks are likely to exist (Guo, Chen, & Huang, 2011).

To test the MDH argument, we follow Kalev, Liu, Pham, and Jarnecic (2004) by including the weighted number of positive and negative news variables in the conditional variance equation and adding the weighted event score[2] in the mean equation to

[1] We also use the daily data in the same period to calculate idiosyncratic volatility as the robustness check in our research.

[2] Event score is defined as *ESS* in the Section 2.2, which is a granular score that ranges from 0 to 100. It specifies whether the news story conveys positive or negative sentiment about the stock.

control for the effects of news sentiment on the stock return. In our MRS-GARCH models, we consider two regimes of volatility—the calm state and the turbulent state—where the unconditional variance of the latter is higher than the former. We summarize the empirical findings as follows.

First, firm-specific news effects induce the stock return volatility persistence in the calm state rather than in the turbulent state. Second, while news has a positive effect on conditional volatility in both states, the level of the effect depends on the quality of news and the states of the return volatility. Specifically, both good news and bad news have greater effects in the calm state than in the turbulent state. The effect of bad news is greater than that of good news in the calm state, while both effects are similar in the turbulent state.

Additionally, it is argued that firms are heterogeneous and their stock return volatilities depend on which industry/sector they belong to as well as on their sizes (Hammoudeh, Yuan, Chiang, & Nandha, 2010; Smith & Yamagata, 2011; Chang, Hsu, & McAleer, 2013; Sharma, Narayan, & Zheng, 2014). For instance, Smith and Yamagata (2011) study the volatility feedback effects for firms of S&P 500 from 1974 to 2007 and find that Information Technology (IT) sector behaves rather differently compared with the rest. Since our sample stocks belong to various sectors and their sizes vary considerably, the news effect on return volatility may differ across sectors and firm size.[3]

We find empirical evidence to support this conjecture. The news effect for stocks that belong to the IT sector is considerably higher. News effects are greater in heavy industry sectors in the calm state, while they are similar across all sectors in the turbulent state. The news effect contributes more to the volatility persistence of large stocks than small stocks. News effects are greater for small stocks in the calm state, and they are greater for large stocks in the turbulent state.

Section 2 provides a brief description of our financial data and news variables. Section 3 presents the theory of MDH, and the GARCH and MRS-GARCH models. Section 4 presents the empirical results and discusses their implications. Section 5 outlines various robustness checks, and Section 6 concludes.

2. Data and sample

2.1. Return series

Our stock price samples comprise hourly and daily data of S&P 100 stocks from 1 January 2000 to 31 December 2010. The hourly data are sourced from the Thomson Reuters Tick History (TRTH) database, which contains microsecond-time-stamped tick data dating back to January 1996. The database covers 35 million over-the-counter (OTC) and exchange-traded instruments worldwide, which are provided by the Securities Industry Research Center of Australasia (SIRCA). Our daily data are obtained from the Center for Research in Security Prices (CRSP) database.[4] Define $\{S_{i,0}, S_{i,1},\ldots, S_{i,T-1}, S_{i,T}\}$ as the sequence of hourly closing prices for firm i at times $\{0, 1,\ldots, T\text{-}1, T\}$. The hourly return for firm i at time t is:

$$r_{i,t} = 100 \times \log\left(S_{i,t}/S_{i,t-1}\right) \tag{1}$$

2.2. Public information arrival

We use the news database RavenPack News Analytics[5] to proxy for public information arrivals. RavenPack offers an analytical output for each news article that is related to the individual firm on a global basis. The sources of the news articles include the Dow Jones Newswires, the *Wall Street Journal* and Barron's. Among dozens of analytical outputs in the database, we use the news relevance score (*REL*), event sentiment score (*ESS*), event novelty score (*ENS*) and composite sentiment score (*CSS*) in this study.[6]

REL indicates how strongly the news story is related to a particular company. A high REL_i suggests that the news story is highly relevant to stock i.

ESS is a granular score that ranges from 0 to 100. It specifies whether the news story conveys positive or negative sentiment about the stock. The score is constructed as follows. First, a set of news (training set) is categorized by a group of financial experts according to the degree to which they have short-term positive or negative share price effects. Second, their classification is encapsulated in an algorithm that generates a score range from 0 to 100. A high score (above 50) indicates positive sentiment, while a low score (below 50) indicates negative sentiment.

ENS is a score that ranges from 0 to 100. It measures how 'new' or 'novel' a news story is in the previous 24 hours. The first story reporting a categorized event about one or more companies is considered the most novel and receives a score of 100. Note that both the *ESS* and *ENS* will be provided by RavenPack only if the *REL* score is 100.

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3 Although S&P 100 firms are all large, there is a significant size variation across firms. For instance, the market capitalization (as at the end of 2010) of Exxon Mobil is almost 40 times of that for Weyerhauser.

4 For reason of data completeness and data availability, 85 S&P 100 firms are included in the hourly sample. For the daily sample, we employ the criteria of Fu (2009) to calculate the idiosyncratic volatility in Section 5. Based on this criteria, 79 S&P 100 firms are contained in our daily sample. The complete company list can be found in Appendix A.

5 Details of the RavenPack News Analytics can be found in Mitra and Mitra (2011).

6 See Appendix B for details of how these scores are constructed by RavenPack.

CSS is a sentiment score that ranges from 0 to 100. It represents the news sentiment of a given story by combining various sentiment analysis techniques. The direction of the score is determined by emotionally charged words and phrases embedded in the news story, which is typically rated by experts as having a short-term positive or negative share price effect. A high score (above 50) indicates positive sentiment, while a low score (below 50) indicates negative sentiment.

We construct three hourly weighted scores using the *REL*, *ESS*, *ENS* and *CSS*. For firm i at time t, the weighted event score[7] is:

$$WESS_{i,t} = \frac{1}{T}\sum_{all\ \tau} \frac{\left(ESS_{i,\tau} - 50\right)ENS_{i,\tau}}{100} \tag{2}$$

where τ is the actual time when the individual news story is received ($\tau \in [t\text{-}1, t]$) and T is the total number of news stories received in the hourly interval $[t\text{-}1, t]$. The weighted number of negative news for firm i at time t is:

$$WNN_{i,t} = \sum_{all\ \tau} \frac{I\left(CSS_{i,\tau} < 50\right)\left|CSS_{i,\tau} - 50\right|REL_{i,\tau}}{100} \tag{3}$$

where $I(\cdot)$ is the indicator function that gives 1 when the condition inside the parentheses is true and 0 otherwise. The weighted number of positive news for firm i at time t is:

$$WNP_{i,t} = \sum_{all\ \tau} \frac{I\left(CSS_{i,\tau} > 50\right)\left|CSS_{i,\tau} - 50\right|REL_{i,\tau}}{100} \tag{4}$$

The rationale behind the above weighting system is simple. In the case of *WESS*, the *ESS* is weighted by the novelty score. News that has already been reported by other news sources and belonged to a chain of related news stories is expected to have a lower effect on the stock return volatility. Thus, they are assigned with a lower weight because they are not 'new' to the market.

In the case of *WNN* and *WNP*, news is weighted by the relevance score since we expect investors to react less on news that is remotely relevant to the stock. Hence, a low weight is given to news with a low *REL* score.

3. Methodology and model specification

3.1. Theory of MDH and effects of news sentiment on stock return volatility

The MDH was originally proposed by Clark (1973) and extended by Tauchen and Pitts (1983) and Harris (1986, 1987)). Building on the MDH, Lamoureux and Lastrapes (1990) argue that persistence in the conditional volatility of return reflects the time-series properties in the information arrival process. Andersen (1996) consider a modified version of MDH to examine the joint distribution for return volatility and trading volume at the daily level. His model allows for the arrival of public information and shows that the variance of returns at a given interval is proportional to the arrival rate. Kalev, Liu, Pham, and Jarnecic (2004) use the number of firm-specific announcements as a proxy for the rate of information arrival. Based on the argument of the MDH, they propose that the conditional volatility of the stock return at a given interval could be proportional to the number of news articles received. Following the theory of the MDH and the argument of Veronesi (1999), we propose the following:

$$h_t \propto f(n_t, Q_\tau) \tag{5}$$

where h_t is the conditional volatility of stock return at time t, n_t is number of relevant news arrivals at the interval $[t\text{-}1, t]$ and Q_τ is the sentiment of the news story received at time τ ($\tau \in [t\text{-}1, t]$), which is a non-negative value. Further, in our research, $f(n_t, Q_\tau)$ will be proxied by the variables $WNN_{i,t}$ and $WNP_{i,t}$.

3.2. GARCH model

The GARCH model is proposed by Bollerslev (1986), which is generalized from the seminal idea on ARCH model by Engle (1982). Over the past decade, GARCH-type models have become a standard approach in the research of financial volatility

[7] Note that since *ESS* is only available when *REL* is 100, *REL* is not used to construct the weighted event score. The results reported in this paper consider all the categories of news to construct the *WESS*. We also re-calculate *WESS* excluding the categories 'Insider-Trading' and 'Order-Imbalances'. The corresponding results and conclusions are robust.

(Chen, Su, & Huang, 2008; Garcia-Vega, Guariglia, & Spaliara, 2012; Ho, Shi, & Zhang, 2013). In this paper, we modify the GARCH(1,1) model by including the three weighted scores in the mean and variance equations:

$$\begin{aligned} r_{i,t} &= b_{i,0} + b_{i,1} WESS_{i,t} + \varepsilon_{i,t} \text{ where } \varepsilon_{i,t}|\Omega_{i,t-1} \sim t\left(0, h_{i,t}, v_i\right) \\ h_{i,t} &= c_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + \gamma_{i,1} WNN_{i,t} + \gamma_{i,2} WNP_{i,t} + d_i SPX_t \end{aligned} \tag{6}$$

where $\varepsilon_{i,t}$ is the error term for firm i at time t, $h_{i,t}$ is the conditional volatility for firm i at time t, $\Omega_{i,t-1}$ is the information set for firm i at time t-1, v_i is the degree of freedom of the Student's t-distribution[8] for firm i and SPX_t is the dummy variable that gives a value of 1 if the absolute value of the return of S&P 500 index is larger than 2% at time t and 0 otherwise.[9] The reason for including $WESS_{i,t}$ in the mean equation is that we want to control for the potential effect of news sentiment on the stock return (Veronesi, 1999; Hafez, 2009; Leinweber & Sisk, 2011; Moniz, Brar, Davies, & Strudwick, 2011).

The coefficients α_i and β_i reflect the dependence of the current return volatility of stock i upon its past levels. The summation of $\alpha_i + \beta_i$ captures the level of volatility persistence, which measures how fast the current shock dissipates. Large volatility persistence means the current shock will affect the volatility in the long run. Based on the results of Lamoureux and Lastrapes (1990) and Kalev, Liu, Pham, and Jarnecic (2004), the persistence of the conditional volatility of the stock return may be generated by serial correlation in the information arrival process. This implies that the volatility persistence will be significantly reduced after the inclusion of $WNN_{i,t}$ and $WNP_{i,t}$ in the conditional variance equation.

3.3. MRS-GARCH model

The main weakness of the GARCH model is that it assumes that the conditional volatility has only one regime over the entire period. However, this is not always true. Marcucci (2005) argues that, due to reasons such as structural breaks in the real economy and changes in market participants' expectations about the future, financial returns may exhibit sudden jumps and will not stay in the same regime over a long period.

In light of this, Hamilton (1988), Hamilton (1989) and Hamilton (1994) proposes the inclusion of regime-switching parameters to allow the jumps between state spaces. This idea has been widely applied to the dataset with potential structural breaks (Chen & Ghysels, 2011; Guo, Chen, & Huang, 2011; Ho, Shi, & Zhang, 2013). Extended from his work, MRS-GARCH models with different structures and algorithms are proposed (Cai, 1994; Hamilton & Susmel, 1994; Gray, 1996; Dueker, 1997; Lin, 1998; Klaassen, 2002).

In this paper, we employ Haas, Mittnik, and Paolella's (2004) two-state MRS-GARCH(1,1) model with the Student's t-innovations: [10, 11]

$$\begin{aligned} & r_{i,t} = b_{i,0} + b_{i,1} WESS_{i,t} + \varepsilon_{i,t} \\ & \varepsilon_{i,t} = \eta_{i,t} \sqrt{[(v_i - 2)/v_i] h_{s_{i,t},i,t}} \text{ where } \eta_{i,t} \overset{iid}{\sim} t(0, 1, v_i) \\ & GARCH_{i,1} = c_{i,1} + \alpha_{i,1} \varepsilon_{i,t-1}^2 + \beta_{i,1} h_{1,i,t-1} \\ & GARCH_{i,2} = c_{i,2} + \alpha_{i,2} \varepsilon_{i,t-1}^2 + \beta_{i,2} h_{2,i,t-1} \\ & h_{s_{i,t},i,t} = \begin{cases} GARCH_{i,1} + \gamma_{i,11} WNN_{i,t} + \gamma_{i,12} WNP_{i,t} + d_{i,1} SPX_t \text{ when } s_{i,t} = 1 \\ GARCH_{i,2} + \gamma_{i,21} WNN_{i,t} + \gamma_{i,22} WNP_{i,t} + d_{i,2} SPX_t \text{ when } s_{i,t} = 2 \end{cases} \end{aligned} \tag{7}$$

where $\varepsilon_{i,t}$ is the error term for firm i at time t, $s_{i,t}$ is the state that firm i lies in at time t,[12] $\eta_{i,t}$ is the independently and identically distributed Student's t-sequence, v_i is the degree of freedom of the Student's t-distribution for firm i and $h_{s_{i,t},i,t}$ is the conditional volatility for firm i in state $s_{i,t}$ at time t. The sequence $\{s_{i,t}\}$ is assumed to be a stationary, irreducible Markov process with discrete state space {1,2} and transition matrix $P_i = [p_{i,jk}]$, where $p_{i,jk} = P(s_{i,t+1} = k | s_{i,t} = j)$ is the transition probability of moving from

[8] The reason for using the Student's t-distribution assumption of the error terms rather than the normal distribution is that the former can accommodate the excess kurtosis of the innovations (Bollerslev, 1987). In addition, Susmel and Engle (1994) point out the importance of using the t-distribution instead of the normal for more efficient estimations than the Normal distribution.

[9] The dummy variable is the indicator of the extreme macroeconomic change in the market. As our news datasets only contain firm-specific news articles, including this variable helps to control for the macro-market effects on firm-specific conditional volatility.

[10] The reason for using this specification rather than those studied in Gray (1996), Klaassen (2002) and others is the path dependency problem of the MRS-GARCH-type models. In Haas, Mittnik, and Paolella (2004), this is solved by assuming two independent GARCH sequence, and they will only be recombined in the construction of likelihood. In contrast, Gray (1996), Klaassen (2002) and other similar studies solve this issue via certain recombining methods to generate GARCH sequence. It may cause difficulty in interpreting the meaning of system parameters, since current conditional variance will be affected by past values from both states. Details can be found in Haas, Mittnik, and Paolella (2004), and the authors refer to this as the analytical intractability problem. To avoid such issues, we adopt the MRS-GARCH proposed by Haas, Mittnik, and Paolella (2004) in this study.

[11] We do not include $WNN_{i,t}$ and $WNP_{i,t}$ in the conditional mean equation because, as suggested by existing literature (such as Kalev, Liu, Pham, and Jarnecic (2004)), news flow only affects volatility and it does not affect the return. We check this and find that the correlation between $WNN_{i,t}$ and $r_{i,t}$, and between $WNP_{i,t}$) and $r_{i,t}$ are very small and they are statistically insignificant. We do not include $WESS_{i,t}$ in the conditional variance equation because news type (i.e. captured by the news sentiment score) does not correlate with the level of volatility; while news type (good versus bad) is positively related to the stock return, both news types drive up the return volatility. Indeed, we find insignificant correlation between $WESS_{i,t}$ and the estimated $h_{s_{i,t},i,t}$ from the MRS-GARCH model without news variables.

[12] $s_{i,t} = 1$ is the calm state (low volatility) and $s_{i,t} = 2$ is the turbulent state (high volatility).

state j to state k $(j,k\in\{1,2\})$.[13] $\sqrt{(v_i-2)/v_i}$ is a scaling factor that ensures the conditional volatility of $\varepsilon_{i,t}$ is $h_{s_{i,t},i,t}$. Including this scaling factor will ensure that volatility persistence in state j is measured by $\alpha_{i,j}+\beta_{i,j}$, as in the GARCH models (Haas, Mittnik, & Paolella, 2004; Mullen, Ardia, Gil, Windover, & Cline, 2011).

As argued by Mullen, Ardia, Gil, Windover, and Cline (2011), Eq. (7) captures the volatility clustering as in the GARCH model, as well as allowing the structural breaks in unconditional variance. In the jth regime, the unconditional variance for firm i is:

$$\bar{\sigma}^2_{i,j} = \frac{c_{i,j}}{1-\alpha_{i,j}-\beta_{i,j}} \tag{8}$$

as long as $\alpha_{i,j}+\beta_{i,j}<1$; that is, the process is covariance stationary (Bollerslev, 1986; Haas, Mittnik, & Paolella, 2004). In this paper, we indicate state 1 as the calm state and state 2 as the turbulent state, so that $\sigma^2_{i,1}<\sigma^2_{i,2}$ is the restriction for firm i in our sample.

We estimate the parameters of the MRS-GARCH model using the MLE. The conditional density of $\varepsilon_{i,t}$ is given by Mullen, Ardia, Gil, Windover, and Cline (2011) as follows:

$$\begin{aligned}
&\Omega_{i,t-1} = \left\{\varepsilon_{i,t-1}, \varepsilon_{i,t-2}, \dots, \varepsilon_{i,1},\right\} \\
&\quad \theta_i = (b_{i,0}, b_{i,1}, c_{i,1}, c_{i,2}, \alpha_{i,1}, \alpha_{i,2}, \beta_{i,1}, \beta_{i,2}, \gamma_{i,11}, \\
&\qquad \gamma_{i,12}, \gamma_{i,21}, \gamma_{i,21}, d_{i,1}, d_{i,2}, p_{i,11}, p_{i,22}, v_i)' \\
&f\left(\varepsilon_{i,t}|s_{i,t}=j, \theta_i, \Omega_{i,t-1}\right) = \frac{\Gamma\left(\frac{v_i+1}{2}\right)}{\Gamma\left(\frac{v_i}{2}\right)\sqrt{\pi(v_i-2)h_{j,i,t}}}\left[1+\frac{\varepsilon^2_{i,t}}{(v_i-2)h_{j,i,t}}\right]^{-\frac{v_i+1}{2}}
\end{aligned} \tag{9}$$

where $\Omega_{i,t-1}$ is the information set for firm i at time t-1, θ_i is the vector of parameters, $\Gamma(\cdot)$ is the Gamma function and $f(\varepsilon_{i,t}|s_{i,t}=j,\theta_i,\Omega_{i,t-1})$ is the conditional density of $\varepsilon_{i,t}$. This stems from the fact that in state j, $\varepsilon_{i,t}$ follows a Student's t-distribution with mean 0, variance $h_{j,i,t}$ and degrees of freedom v_i given time t-1.

Plugging the filtered probability for firm i in state j at time t-1, $\rho_{j,i,t-1}=P(s_{i,t-1}=j|\theta_i,\Omega_{i,t-1})$ into Eq. (9) and integrating out the state variable $s_{i,t-1}$, the density function in Eq. (9) becomes:

$$f\left(\varepsilon_{i,t}|\theta_i, \Omega_{i,t-1}\right) = \sum_{j=1}^{2}\sum_{k=1}^{2} p_{i,jk}\rho_{j,i,t-1} f\left(\varepsilon_{i,t}|s_{i,t}=j, \theta_i, \Omega_{i,t-1}\right) \tag{10}$$

$\rho_{j,i,t-1}$ can be obtained by an integrative algorithm given in Hamilton (1989). The log-likelihood function corresponding to Eq. (7) is as follows:

$$L(\theta_i|\varepsilon_i) = \sum_{t=2}^{T} \ln f\left(\varepsilon_{i,t}|\theta_i, \Omega_{i,t-1}\right) \text{ where } \varepsilon_i = \left(\varepsilon_{i,1}, \varepsilon_{i,2}, \dots, \varepsilon_{i,T}\right)' \tag{11}$$

and the maximum likelihood estimator θ_i is obtained by maximizing Eq. (11).

4. Empirical results

4.1. Descriptive statistics of our dataset

The descriptive statistics of the four sentiment scores used to calculate $WESS_{i,t}$, $WNN_{i,t}$ and $WNP_{i,t}$ are summarized in Panel A of Table 1. In total, there are 6,372,379 news stories in our database, of which 406,782 have a *REL* of 100, which leads to the same number of available event sentiment and novelty scores. In Panel A of Table 1, the average *CSS* is around 50, indicating that on average, the news stories have neutral tone. For the *ESS*, the mean is 53.94, suggesting from experts' opinions that the news is overall slightly positive.

The descriptive statistics of our variables are summarized in Panel B of Table 1. There are 1,609,932 hourly sample points in our dataset. The mean stock return (measured in percentage), $r_{i,t}$, is close to 0. As the average event score is positive, the mean of $WESS_{i,t}$ is greater than 0. The mean of $WNN_{i,t}$ is slightly larger than the mean of $WNP_{i,t}$ (1.7950 and 1.5490), but with a larger variation (standard deviations of $WNN_{i,t}$ and $WNP_{i,t}$ are 10.9223 and 8.7758, respectively).

We report the preliminary analysis on the relation between information arrival and stock return volatility in Table 2. We use negative and positive news to measure the information arrival, while the latent stock return volatility is represented by the squared return. Overall, the mean correlation of $WNN_{i,t}$ and $WNP_{i,t}$ throughout the sample period (from 2000 to 2010) is 0.1691 and 0.1493, respectively. To test whether they are statistically significant, we employ the Wilcox sign test, which does not require a normal distribution of the estimates. At 5% level, both mean correlations of 85 sample stocks are significantly

[13] As discussed by Veronesi (1999) and Cousin & de Launois (2008), the assumption of two regimes is preferred to the simple market model.

Table 1
Dataset descriptive statistics. This table presents the summary descriptive statistics of all the variables employed in this study. The summary statistics include mean value (*Mean*), standard deviation (*Std Dev.*), median value (*Median*), 25 percentile (Q_1), 75 percentile (Q_3), skewness (*Skew*) and number of observations (*N*) for each variable. $CSS_{i,\tau}$ and $REL_{i,\tau}$ are the composite sentiment score and relevance score of each news story. Only when $REL_{i,\tau}$ is 100, $ESS_{i,\tau}$ and $ENS_{i,\tau}$ will be provided, which are the event sentiment score and event novelty score, respectively. $r_{i,t}$ is the return in percentage, $WESS_{i,t}$ is the weighted event sentiment score, $WNN_{i,t}$ is the weighted number of negative news stories and $WNP_{i,t}$ is the weighted number of positive news stories. The sample period is from January 1, 2000 to December 31, 2010.

	Mean	*Std Dev.*	*Median*	Q_1	Q_3	*Skew*	*N*
Panel A: *Descriptive statistics of news database*							
$CSS_{i,\tau}$	49.85	5.15	50	50	52	−1.2639	6372379
$ESS_{i,\tau}$	53.97	14.57	54	44	67	−0.2703	406782
$REL_{i,\tau}$	37.63	32.48	33	7	48	0.7884	6372379
$ENS_{i,\tau}$	83.13	24.08	100	75	100	−1.4502	406782
Panel B: *Descriptive statistics of variables*							
$r_{i,t}$	0.0017	1.5731	0.0000	−0.3300	0.3351	9.9174	1609932
$WESS_{i,t}$	0.3152	3.8262	0.0000	0.0000	0.0000	1.5378	1609932
$WNN_{i,t}$	1.7950	10.9223	0.0000	0.0000	0.5100	26.4468	1609932
$WNP_{i,t}$	1.5490	8.7758	0.0000	0.0000	0.1000	24.4936	1609932

positive, which suggest that both negative and positive news may positively affect the stock return volatility. We compute the correlations for both $WNN_{i,t}$ and $WNP_{i,t}$ in each year. They range roughly from 0.15 to 0.40 and they are statistically significant at the 5% level. The correlation statistics gradually increase from 2000 to 2007, then suddenly decrease in 2008 before they go up again in 2009. The pattern seems to be in line with the burst of the Dot-Com bubble at the beginning of the 21 century and the Global Financial Crisis in 2008.

Our empirical results reveal that both $WNN_{i,t}$ and $WNP_{i,t}$ exhibit positive effects in the conditional variance equations. The estimates of $\gamma_{i,1}$ and $\gamma_{i,2}$ are significant at the 1% level in all 85 sample stocks. It is worth noting that the mean, median and both quartiles of $WNP_{i,t}$ estimates are larger than the corresponding statistics of $WNN_{i,t}$, implying that positive news may have a higher influence on stock return volatility.

The estimates of d_i in the model without news variables are positive and significant, indicating that extreme market changes have considerable effects on the conditional return volatility of individual stock. After including the news variables in the models, the estimates of d_i are smaller, which implies that after controlling for firm-specific news arrivals, the effect of extreme macro-related price change is smaller on individual stock return volatilities.

Table 2
Summary of correlation between information arrival and stock return volatility. This table presents the summary descriptive statistics of correlation between news variables and stock volatility. The correlations are summarized over the entire period (*All*) and in each year for all the stocks. For explanations of other variables, please see Table 1.

	Mean	*Std. Dev.*	*Median*	Q_1	Q_3	*Skew*	Period
Panel A: *Overall correlation*							
$WNN_{i,t}$	0.1691*	0.1072	0.1599	0.0998	0.2359	0.8819	All
$WNP_{i,t}$	0.1493*	0.0832	0.1426	0.0902	0.1952	0.5504	All
Panel B: *Yearly correlation*							
$WNN_{i,t}$	0:1318*	0.1374	0.0858	0.0510	0.1862	2.6231	2000
$WNN_{i,t}$	0:1952*	0.1615	0.1545	0.0865	0.2675	1.4365	2001
$WNN_{i,t}$	0.2135*	0.1762	0.1592	0.0889	0.3011	1.3086	2002
$WNN_{i,t}$	0.2191*	0.1652	0.1808	0.1014	0.3031	1.3005	2003
$WNN_{i,t}$	0.2179 *	0.1621	0.1715	0.1042	0.3021	1.1579	2004
$WNN_{i,t}$	0.2396 *	0.1716	0.2030	0.1131	0.2995	1.1002	2005
$WNN_{i,t}$	0.2570*	0.1873	0.1872	0.1371	0.3529	1.1689	2006
$WNN_{i,t}$	0.2497*	0.1693	0.2182	0.1408	0.2852	1.2884	2007
$WNN_{i,t}$	0.1896*	0.1381	0.1597	0.0904	0.2490	1.5015	2008
$WNN_{i,t}$	0.2850*	0.1621	0.2502	0.1630	0.3789	0.9126	2009
$WNN_{i,t}$	0.2076*	0.1425	0.1790	0.1099	0.2835	1.0718	2010
$WNP_{i,t}$	0.1360*	0.1028	0.1095	0.0752	0.1826	1.4708	2000
$WNP_{i,t}$	0.2074*	0.1534	0.1758	0.0888	0.3005	1.0983	2001
$WNP_{i,t}$	0.2074 *	0.1452	0.1820	0.0977	0.2587	1.4170	2002
$WNP_{i,t}$	0.2469*	0.1492	0.2056	0.1427	0.3084	1.2563	2003
$WNP_{i,t}$	0.2987*	0.1853	0.2530	0.1590	0.4116	0.6214	2004
$WNP_{i,t}$	0.3353*	0.1890	0.2970	0.2029	0.4679	0.4653	2005
$WNP_{i,t}$	0.3346*	0.1641	0.3218	0.2052	0.4324	0.4341	2006
$WNP_{i,t}$	0.3053*	0.1602	0.2766	0.1771	0.4226	0.6218	2007
$WNP_{i,t}$	0.1927*	0.1334	0.1597	0.0867	0.2767	0.9369	2008
$WNP_{i,t}$	0.2862*	0.1485	0.2747	0.1694	0.3791	0.8192	2009
$WNP_{i,t}$	0.2451 *	0.1445	0.2010	0.1302	0.3538	0.5724	2010

* The mean is significant at 5% level from the Wilcox sign test.

Table 3
Summary output of hourly data with GARCH(1,1) models. This table presents the summary descriptive statistics of the hourly regression results from the GARCH(1,1) models in this study. The data are firstly fitted into the models without news variables (reduced models) and then the models with news variables (full models). $R.V.$ stands for the reduction in volatility persistence, which is equal to $\alpha_i+\beta_i$ minus $\alpha_i+\beta_i$*. The sample period is from January 1, 2000 to December 31, 2010. The number of observations here is 85. For explanations of other variables, please see Table 1.

	Mean	Std Dev.	Median	Q_1	Q_3	Skew
$\alpha_i+\beta_i$	0.9952	0.0041	0.9964	0.9941	0.9977	−1.8774
$\alpha_i+\beta_i$*	0.9912	0.0066	0.9934	0.9891	0.9951	−1.6653
$R.V.$	0.0040	0.0038	0.0031	0.0016	0.0057	0.5727
$\gamma_{i,1}$*	0.0479	0.0369	0.0402	0.0196	0.0664	1.4199
$\gamma_{i,2}$*	0.0636	0.0580	0.0412	0.0213	0.0837	1.6187
d_i *	17.3100	10.0309	15.9600	9.5350	21.4700	1.3125
d_i*	15.2600	9.0741	13.4900	8.3850	17.9700	1.4396

* Estimates of full models.

4.2. GARCH framework

We fit our data into the GARCH specifications, as described in Eq. (6). The summary of models with and without news variables in the conditional variance equations are reported in Table 3.

The estimated coefficients of the GARCH(1,1) models without news variables reported in Table 3 indicate that the level of volatility persistence ($\alpha_i+\beta_i$) is remarkably large. As discussed earlier, if information flow induces stock return volatility, the volatility persistence should be reduced after the inclusion of the news variables. Out of 85 stocks, volatility persistence is reduced in 81 of them, though the overall degree of reduction is marginal; the average reduction is 0.004. As discussed in Section 3.3, this may be due to methodological biases in long time series.

4.3. MRS-GARCH framework

For reasons discussed in Section 3.3, the MRS-GARCH framework is considered to be a more appropriate specification. The summary of modeling results (with and without news variables in the conditional variance equations) is reported in Table 4.

Comparing the Akaike Information Criterion (AIC) of models with news variables, MRS-GARCH is the preferred specification in 76 out of 85 cases.[14] Additionally, as indicated by various diagnostic statistics reported in Table 5, on average, MRS-GARCH outperforms the GARCH specification. The results of the MRS-GARCH models without the news variables suggest that the estimated volatility persistence varies in different states. The descriptive statistics show that the estimates of $\alpha_{i,1}+\beta_{i,1}$ are smaller than $\alpha_{i,2}+\beta_{i,2}$, implying that volatility persistence is higher in the turbulent state than in the calm state, with a median of 0.9998 against 0.5881.[15] The estimates of dummy variable $d_{i,1}$ are generally much larger than the estimates of $d_{i,2}$. In the turbulent state, the estimates of $d_{i,2}$ are significant at the 1% level in only 41 out of 85 stocks compared to 83 out of 85 in the calm state.

In order to control for the multiple testing problems, we compute the false discovery rates. For $d_{i,1}$ and $d_{i,2}$, the generated π_0 are 0.0238 and 0.5229, respectively. According to the q-value, the cumulative number of significant calls is 85 (40) for $d_{i,1}$ ($d_{i,2}$) at 1% level. This result indicates that the influence of extreme macro-market changes on stock return volatility in the turbulent state is less than that in the calm state. The estimates of transition probabilities $p_{i,11}$ and $p_{i,22}$ are also considerably different, with medians of 0.2937 and 0.6892 respectively. Transitional probabilities measure how long the conditional volatility will stay in one regime, given that it currently lies in that regime. A large estimate suggests that conditional volatility will stay in the same regime for a long period. Based on our empirical results, when the stock lies in the turbulent state, the conditional return volatility of that stock will remain in the turbulent state for a longer period of time than in the case of the calm state.

Consider the model with news variables. The stories are quite different. In the calm state, the volatility persistence $\alpha_{i,1}+\beta_{i,1}$ is significantly reduced. The median reduction is 0.1131 (i.e. around 20%). However, the volatility persistence in the turbulent state ($\alpha_{i,2}+\beta_{i,2}$) varies across our stock sample. The mean and median reductions are 0.1828 and 0.0001, respectively, indicating that in several stocks, the reductions are quite remarkable. However, for most stocks, the level of volatility persistence remains largely unchanged. It suggests that the news effects tend to induce stock return volatility persistence in the calm state rather than in the turbulent state. In the calm state, 84 out of 85 estimates of $\gamma_{i,11}$ are significant at the 1% level, whereas 82 out of 85 estimates of $\gamma_{i,12}$ are significant (84 if the 5% level cut-off is used). However, in the turbulent state, only 29 and 28 estimates for $\gamma_{i,21}$ and $\gamma_{i,22}$ respectively are significant at the 1% level. In terms of the false discovery rates, the generated π_0 of $\gamma_{i,11}$, $\gamma_{i,12}$, $\gamma_{i,21}$ and $\gamma_{i,22}$ are 0.0119, 0.0357, 0.6655 and 0.6774, respectively. According to the q-value, the corresponding cumulative numbers of significant calls at the 1% level are 85, 84, 28 and 28, respectively. Besides, all the individual estimates that are statistically significant are positive in both states, which indicates that both good and bad news generally has positive effects on return volatility in both states. Finally, the medians of estimated coefficients suggest that bad news in the calm state has a greater effect on return volatility compared to good news, but the effects of both good and bad news are similar and are much smaller in the turbulent state.

[14] We also generate the Bayesian Information Criterion (BIC), which suggests that MRS-GARCH is preferred in 74 out of 85 cases.

[15] The reason for reporting the median as the central tendency here is to avoid the potential effects caused by extremely high or low estimates.

Table 4
Summary output of hourly data with MRS-GARCH(1,1) models. This table presents the summary descriptive statistics of the hourly regression results from the MRS-GARCH(1,1) models in this study. The data are firstly fitted into the models without news variables (reduced models) and then the models with news variables (full models). *R.V. in S* $_1$ stands for the reduction in volatility persistence in state 1 (calm state), which is equal to $\alpha_{i,1}+\beta_{i,1}$ minus $\alpha_{i,1}+\beta_{i,1}{}^*$. *R.V. in S* $_2$ stands for the reduction in volatility persistence in state 2 (turbulent state), which is equal to $\alpha_{i,2}+\beta_{i,2}$ minus $\alpha_{i,2}+\beta_{i,2}{}^*$. The sample period is from January 1, 2000 to December 31, 2010. The number of observations here is 85. For explanations of other variables, please see Tables 1 and 3.

	Mean	*Std Dev.*	*Median*	Q_1	Q_3	*Skew*
$\alpha_{i,1}+\beta_{i,1}$	0.5645	0.1698	0.5881	0.4872	0.6794	−0.3787
$\alpha_{i,1}+\beta_{i,1}{}^*$	0.4373	0.1538	0.4442	0.3125	0.5096	1.2639
R.V. in S $_1$	0.1272	0.1585	0.1131	0.0304	0.2082	0.1815
$\gamma_{i,11}{}^*$	0.1766	0.2052	0.0821	0.0353	0.2430	1.7755
$\gamma_{i,12}{}^*$	0.1036	0.1120	0.0663	0.0307	0.1370	2.0200
$d_{i,1}$	21.1700	12.6116	18.9900	12.1500	26.3900	1.6694
$d_{i,1}{}^*$	13.5600	10.5270	10.9400	5.9750	17.1500	2.0002
$p_{i,11}$	0.3800	0.2903	0.2937	0.1855	0.4366	1.1713
$p_{i,11}{}^*$	0.6007	0.3139	0.4341	0.3520	0.9981	0.3380
$\alpha_{i,2}+\beta_{i,2}$	0.9710	0.1308	0.9998	0.9995	0.9999	−4.3299
$\alpha_{i,2}+\beta_{i,2}{}^*$	0.7882	0.3072	0.9996	0.3939	0.9998	−0.7852
R.V. in S $_2$	0.1828	0.2937	0.0001	−0.0001	0.5077	1.0241
$\gamma_{i,21}{}^*$	0.0356	0.0765	−0.0002	−0.0007	0.0295	3.0921
$\gamma_{i,22}{}^*$	0.0416	0.1086	−0.0002	−0.0005	0.0301	4.9880
$d_{i,2}$	0.5555	1.9610	0.0780	0.0333	0.2086	4.4249
$d_{i,2}{}^*$	4.1100	6.7319	0.0772	0.0281	7.1950	1.5784
$p_{i,22}$	0.7162	0.1446	0.6892	0.6406	0.7382	0.5121
$p_{i,22}{}^*$	0.7420	0.2121	0.6525	0.5590	0.9974	0.1932

* Estimates of full models.

Overall, our results are partly consistent with Laakkonen and Lanne (2009), who argue that bad news in general increases volatility more than good news. In particular, they claim that bad news increases volatility more in good times than in bad times, while there is no difference between the volatility effects of good news in good and bad times. In their paper, good (bad) times are defined similarly to our notion of calm (turbulent) state. Contrary to their claim, our empirical results show that the effect of good news on return volatility is greater in the calm state than that in the turbulent state. This apparent contradiction can be explained by the differences in the sources and classifications of news. Firstly, Laakkonen and Lanne (2009) only collect the macroeconomic news announcements, while our news database comprises firm-specific news. Secondly, they classify news types based on their immediate effects on stock returns. News is considered 'good' if the five-minute return following the news announcement is positive and 'bad' if the return is negative. As discussed earlier, such classification suffers from the problem of endogeneity. In contrast, our sentiment scores are calculated based on the content analysis technique, which is not affected by the level of stock return volatility.

Similar to our GARCH estimation, the estimates of both $d_{i,1}$ and $d_{i,2}$ are smaller (based on the median) in models with news variables than in models without news variables. The difference in medians between estimates of $d_{i,1}$ (10.9400 and 18.9900) is much greater than the difference between the estimated $d_{i,2}$ (0.0772 and 0.0780), which is consistent with our interpretation of news effects; that is, the influence of news on return volatility is higher in the calm state than in the turbulent state.

For transition probabilities, the estimates of $p_{i,11}$ generally increase after including the news variables, while the estimates of $p_{i,22}$ remain unchanged. On average, the estimates of $p_{i,22}$ are larger than the estimates of $p_{i,11}$, suggesting that due to the news effects, the conditional volatility stays in the calm state for a longer period, but it is comparatively shorter than its turbulent state counterpart.

Table 5
Model diagnostics. This table presents the summary descriptive statistics of the model diagnostics of the GARCH and MRS-GARCH specifications. Q_{10} is the Ljung–Box test statistics for the standardized residuals at lag 10. Q^2_{10} is the Ljung–Box test statistics for the squared standardized residuals at lag 10. $ARCH_{10}$ is the ARCH Lagrange multiplier test statistics at lag 10. BDS_{10} is the Brock–Dechert–Scheinkman test statistics at order 10. For explanations of other variables, please see Tables 1 and 3.

	Mean	*Std Dev.*	*Median*	Q_1	Q_3	*Skew*
Panel A: GARCH model						
Q_{10}	17.3369	13.0172	14.2142	9.1656	21.4232	2.1365
Q^2_{10}	61.3950	89.8664	21.4667	5.1911	70.6721	1.9498
$ARCH_{10}$	55.6767	79.8321	20.7286	5.0603	66.1853	1.9913
BDS_{10}	4.0660	3.0412	4.1818	2.7903	5.4162	0.0068
Panel B: MRS-GARCH model						
Q_{10}	16.9948	11.5335	14.6341	9.4737	20.1174	1.8062
Q^2_{10}	51.9693	75.5913	16.9596	4.0379	66.8680	1.9381
$ARCH_{10}$	50.5372	72.1684	16.8569	4.0246	67.4174	1.8769
BDS_{10}	−0.3043	1.6352	−0.0258	−1.5878	0.6549	0.0306

Table 6
Summary output of hourly data across sectors. This table presents the sector by sector summary descriptive statistics of the hourly regression results from the MRS-GARCH(1,1) models in this study. For explanations of the variables, please see Tables 1, 3 and 4.

Panel A: Consumer discretionary									
	$\alpha_{i,1}+\beta_{i,1}$	$\alpha_{i,1}+\beta_{i,1^*}$	*R.V. in S* $_1$	$\gamma_{i,11^*}$	$\gamma_{i,12}{}^*$	$d_{i,1}$	$d_{i,1}{}^*$	$p_{i,11}$	$p_{i,11}{}^*$
Mean	0.5572	0.4334	0.1238	0.1106	0.0717	21.5400	13.2200	0.4514	0.7277
Std Dev.	0.1790	0.2047	0.1789	0.1123	0.0617	10.9415	6.2039	0.2852	0.2772
Median	0.5608	0.3822	0.1892	0.0815	0.0530	21.0700	15.0200	0.3707	0.7508
	$\alpha_{i,2}+\beta_{i,2}$	$\alpha_{i,2}+\beta_{i,2^*}$	*R.V. in S* $_2$	$\gamma_{i,21^*}$	$\gamma_{i,22}{}^*$	$d_{i,2}$	$d_{i,2}{}^*$	$p_{i,22}$	$p_{i,22}{}^*$
Mean	0.9997	0.7751	0.2246	0.0392	0.0330	0.1826	3.4730	0.7428	0.8034
Std Dev.	0.0004	0.3355	0.3355	0.0709	0.0639	0.1724	5.5000	0.1388	0.2079
Median	0.9998	0.9960	0.0030	−0.0004	−0.0002	0.1248	0.2540	0.6892	0.8605
Panel B: Consumer staples									
	$\alpha_{i,1}+\beta_{i,1}$	$\alpha_{i,1}+\beta_{i,1}{}^*$	*R.V. in S* $_1$	$\gamma_{i,11^*}$	$\gamma_{i,12}{}^*$	$d_{i,1}$	$d_{i,1}{}^*$	$p_{i,11}$	$p_{i,11}{}^*$
Mean	0.5099	0.4375	0.0724	0.1000	0.0684	9.9920	7.3390	0.4649	0.5254
Std Dev.	0.1586	0.0880	0.1439	0.0937	0.0455	3.9563	3.2696	0.3513	0.3086
Median	0.5739	0.4695	0.0768	0.0539	0.0567	8.7520	7.3080	0.3500	0.3532
	$\alpha_{i,2}+\beta_{i,2}$	$\alpha_{i,2}+\beta_{i,2^*}$	*R.V. in S* $_2$	$\gamma_{i,21^*}$	$\gamma_{i,22}{}^*$	$d_{i,2}$	$d_{i,2}{}^*$	$p_{i,22}$	$p_{i,22}{}^*$
Mean	0.9029	0.8389	0.0640	0.0666	0.0461	1.6040	2.0710	0.7097	0.6567
Std Dev.	0.2139	0.2757	0.1785	0.1552	0.0885	3.6099	3.6555	0.1977	0.2198
Median	0.9999	0.9998	0.0002	−0.0001	−0.0002	0.0470	0.0111	0.6394	0.5432
Panel C: Energy									
	$\alpha_{i,1}+\beta_{i,1}$	$\alpha_{i,1}+\beta_{i,1^*}$	*R.V. in S* $_1$	$\gamma_{i,11^*}$	$\gamma_{i,12^*}$	$d_{i,1}$	$d_{i,1^*}$	$p_{i,11}$	$p_{i,11^*}$
Mean	0.4713	0.4144	0.0568	0.4319	0.2321	26.8600	21.2900	0.3498	0.4404
Std Dev.	0.1167	0.0769	0.0645	0.2881	0.1491	9.3563	8.2185	0.2578	0.1910
Median	0.4891	0.3933	0.0613	0.3977	0.2702	26.1200	20.1900	0.2647	0.3823
	$\alpha_{i,2}+\beta_{i,2}$	$\alpha_{i,2}+\beta_{i,2}$	*R.V. in S* $_2$	$\gamma_{i,21}$	$\gamma_{i,22}$	$d_{i,2}$	$d_{i,2}$	$p_{i,22}$	$p_{i,22}$
Mean	0.9995	0.9997	−0.0002	−0.0007	−0.0006	0.0760	0.0528	0.7216	0.6316
Std Dev.	0.0003	0.0001	0.0002	0.0005	0.0004	0.0736	0.0736	0.1344	
Median	0.9996	0.9997	−0.0001	−0.0005	−0.0007	0.0663	0.0228	0.7266	0.6333
Panel D: Financials									
	$\alpha_{i,1}+\beta_{i,1}$	$\alpha_{i,1}+\beta_{i,1^*}$	*R.V. in S* $_1$	$\gamma_{i,11^*}$	$\gamma_{i,12^*}$	$d_{i,1}$	$d_{i,1^*}$	$p_{i,11}$	$p_{i,11^*}$
Mean	0.6904	0.5985	0.0919	0.1273	0.0527	28.1000	18.1600	0.2579	0.5162
Std Dev.	0.1745	0.2120	0.1963	0.1483	0.0596	20.6907	20.3891	0.2773	0.3839
Median	0.7156	0.5558	0.1611	0.0814	0.0340	27.1600	9.9700	0.1907	0.3212
	$\alpha_{i,2}+\beta_{i,2}$	$\alpha_{i,2}+\beta_{i,2^*}$	*R.V. in S* $_2$	$\gamma_{i,21^*}$	$\gamma_{i,22}{}^*$	$d_{i,2}$	$d_{i,2^*}$	$p_{i,22}$	$p_{i,22^*}$
Mean	0.9997	0.8756	0.1241	0.0033	0.0054	0.1958	5.1630	0.7302	0.8115
Std Dev.	0.0002	0.2271	0.2270	0.0058	0.0096	0.1847	8.8597	0.1075	0.1936
Median	0.9997	0.9991	0.0004	−0.0001	−0.0001	0.1207	0.4404	0.7013	0.8561
Panel E: Health care									
	$\alpha_{i,1}+\beta_{i,1}$	$\alpha_{i,1}+\beta_{i,1^*}$	*R.V. in S* $_1$	$\gamma_{i,11^*}$	$\gamma_{i,12^*}$	$d_{i,1}$	$d_{i,1^*}$	$p_{i,11}$	$p_{i,11^*}$
Mean	0.4698	0.3811	0.0886	0.1575	.0824	12.7100	7.9700	0.5927	0.7677
Std Dev.	0.1981	0.1386	0.1439	0.2659	0.1097	4.6116	4.8599	0.3540	0.2994
Median	0.5231	0.3080	0.0654	0.0423	0.0463	11.5000	6.3930	0.5043	0.9982
	$\alpha_{i,2}+\beta_{i,2}$	$\alpha_{i,2}+\beta_{i,2^*}$	*R.V. in S* $_2$	$\gamma_{i,21^*}$	$\gamma_{i,22^*}$	$d_{i,2}$	$d_{i,2^*}$	$p_{i,22}$	$p_{i,22^*}$
Mean	0.8622	0.5995	0.2628	0.0498	0.0492	1.9970	3.9440	0.7836	0.8157
Std Dev.	0.2901	0.3455	0.3371	0.0644	0.0531	4.0380	3.5003	0.1960	0.2404
Median	0.9997	0.3719	0.0122	0.0366	0.0352	0.1411	5.2780	0.7386	0.9970
Panel F: Industrials									
	$\alpha_{i,1}+\beta_{i,1}$	$\alpha_{i,1}+\beta_{i,1^*}$	*R.V. in S* $_1$	$\gamma_{i,11^*}$	$\gamma_{i,12^*}$	$d_{i,1}$	$d_{i,1^*}$	$p_{i,11}$	$p_{i,11^*}$
Mean	0.5288	0.3946	0.1342	0.1603	0.1030	18.8500	11.7200	0.3658	0.5880
Std Dev.	0.0827	0.1009	0.1042	0.1471	0.0880	5.6190	4.5788	0.2033	0.2883
Median	0.5193	0.4370	0.1103	0.1075	0.0663	18.9900	10.4900	0.3094	0.4341
	$\alpha_{i,2}+\beta_{i,2}$	$\alpha_{i,2}+\beta_{i,2^*}$	*R.V. in S* $_2$	$\gamma_{i,21^*}$	$\gamma_{i,22^*}$	$d_{i,2}$	$d_{i,2^*}$	$p_{i,22}$	$p_{i,22^*}$
Mean	0.9998	0.8061	0.1936	0.0284	0.0269	0.1322	4.0670	0.6551	0.7130
Std Dev.	0.0002	0.3026	0.3027	0.0491	0.0490	0.1273	6.8222	0.1328	0.2033
Median	0.9999	0.9997	0.0000	−0.0003	−0.0002	0.0780	0.0500	0.6598	0.6351

Table 6 (*continued*)

Panel G: Information technology									
	$\alpha_{i,1}+\beta_{i,1}$	$\alpha_{i,1}+\beta_{i,1}$*	*R.V. in S* 1	$\gamma_{i,11}$*	$\gamma_{i,12}$*	$d_{i,1}$	$d_{i,1}$*	$p_{i,11}$	$p_{i,11}$*
Mean	0.6233	0.3694	0.2539	0.1671	0.0932	27.8600	14.5900	0.2791	0.7074
Std Dev.	0.1695	0.1294	0.1807	0.1822	0.0802	7.0595	7.4498	0.2587	0.3375
Median	0.6606	0.2920	0.2695	0.0555	0.0862	26.3900	10.9400	0.1766	0.9959
	$\alpha_{i,2}+\beta_{i,2}$	$\alpha_{i,2}+\beta_{i,2}$*	*R.V. in S* 2	$\gamma_{i,21}$*	$\gamma_{i,22}$*	$d_{i,2}$	$d_{i,2}$*	$p_{i,22}$	$p_{i,22}$*
Mean	0.9999	0.5986	0.4013	0.0566	0.1118	0.0637	7.1860	0.7108	0.7887
Std Dev.	0.0001	0.3844	0.3844	0.0715	0.2455	0.1022	7.3206	0.1046	0.2414
Median	0.9999	0.2994	0.7005	0.0250	0.0226	0.0345	8.8030	0.7095	0.9945
Panel H: Materials									
	$\alpha_{i,1}+\beta_{i,1}$	$\alpha_{i,1}+\beta_{i,1}$*	*R.V. in S* 1	$\gamma_{i,11}$*	$\gamma_{i,12}$*	$d_{i,1}$	$d_{i,1}$*	$p_{i,11}$	$p_{i,11}$*
Mean	0.6926	0.4482	0.2444	0.2991	0.2491	28.1300	21.8600	0.1739	0.4670
Std Dev.	0.1866	0.1494	0.1697	0.2970	0.2173	15.0020	12.7244	0.1103	0.2980
Median	0.6596	0.4970	0.1336	0.2457	0.1729	21.4000	18.5000	0.1855	0.3583
	$\alpha_{i,2}+\beta_{i,2}$	$\alpha_{i,2}+\beta_{i,2}$*	*R.V. in S* 2	$\gamma_{i,21}$*	$\gamma_{i,22}$*	$d_{i,2}$	$d_{i,2}$*	$p_{i,22}$	$p_{i,22}$*
Mean	0.9995	0.8726	0.1269	0.0282	0.0575	0.1444	5.2370	0.6523	0.6579
Std Dev.	0.0006	0.2833	0.2835	0.0659	0.1300	0.0754	11.5911	0.1442	0.1930
Median	0.9997	0.9994	0.0001	−0.0007	−0.0004	0.1540	0.0612	0.6549	0.5978
Panel I: Utilities									
	$\alpha_{i,1}+\beta_{i,1}$	$\alpha_{i,1}+\beta_{i,1}$*	*R.V. in S* 1	$\gamma_{i,11}$*	$\gamma_{i,12}$*	$d_{i,1}$	$d_{i,1}$*	$p_{i,11}$	$p_{i,11}$*
Mean	0.6177	0.5449	0.0728	0.1437	0.0641	10.6100	7.6680	0.2793	0.3795
Std Dev.	0.0831	0.0312	0.0527	0.0892	0.0156	3.8943	2.4862	0.1954	0.0889
Median	0.6505	0.5628	0.0875	0.1180	0.0696	11.8700	6.8670	0.2194	0.3637
	$\alpha_{i,2}+\beta_{i,2}$	$\alpha_{i,2}+\beta_{i,2}$*	*R.V. in S* 2	$\gamma_{i,21}$*	$\gamma_{i,22}$*	$d_{i,2}$	$d_{i,2}$*	$p_{i,22}$	$p_{i,22}$*
Mean	0.9991	0.9995	−0.0004	−0.0002	−0.0002	0.0686	0.0547	0.6577	0.6018
Std Dev.	0.0008	0.0005	0.0007	0.0004	0.0001	0.0200	0.0248	0.0200	0.0488
Median	0.9989	0.9997	−0.0001	−0.0003	−0.0003	0.0600	0.0586	0.6487	0.5914

* Estimates of full models.

4.4. Sectoral variations

Our 85 stock samples belong to ten different sectors.[16] We report the sectoral results in Table 6. It is worth noting that the estimates of volatility persistence and news effects are different across sectors.

Consider the models without news variables. In the calm state, stocks belonging to the Energy sector have the lowest median volatility persistence (0.4891), while stocks belonging to the Financials sector have the highest median value (0.7156). For sectors such as Consumer Discretionary, Consumer Staples, Health Care and Industrials, the medians are similar (around 0.55). For sectors such as IT, Materials and Utilities, the medians are slightly higher (around 0.65). However, in the turbulent state, there are no significant differences across sectors. The reported medians are around 0.9998, which is similar to the overall median of $\alpha_{i,2}+\beta_{i,2}$ reported in Table 4.

Consider the model with news variables. In the calm state, most sectors have median reductions that are ranged from 0.07 to 0.16. Stocks from the Energy sector have the lowest median reduction (0.0613), while stocks from the IT sector have the highest median reduction (0.2695). In the turbulent state, the reduction is around 0, indicating that the level of volatility persistence $\alpha_{i,2}+\beta_{i,2}$ in models with and without news variables are similar across all sectors. The only two exceptions are the Health Care and IT sectors. The medians of estimated $\alpha_{i,2}+\beta_{i,2}$ are significantly smaller in models with news variables, indicating that for these two sectors, there are significant news effects in both the calm and the turbulent state.

There are also sectoral variations in the estimated coefficients of the news variables. The medians of both estimated $\gamma_{i,11}$and $\gamma_{i,12}$ for stocks belonging to the Energy sector are the highest (0.3977 and 0.2702), followed by Materials (0.2457 and 0.1729), Utilities (0.1180 and 0.0696) and Industrials (0.1075 and 0.0663). This suggests that the news effects on the stock return volatility is generally higher in heavy industries than in other industries. Furthermore, in six out of nine sectors, the median estimate of $\gamma_{i,11}$ is higher than that of $\gamma_{i,12}$, implying that bad news has a greater effect than good news in the calm state. In Consumer Staples and Health Care sectors, the effects of good and bad news are essentially the same. The only sector in which the median estimates of $\gamma_{i,12}$ is significantly higher is IT. It appears that on average, bad news has a greater influence. In seven out of nine sectors in the turbulent state, the effects of both bad and good news are not significantly different from 0. The only two exceptions are Health Care and IT, where the medians of estimated $\gamma_{i,21}$ are slightly higher than $\gamma_{i,22}$, and the medians of estimated

[16] We use the Global Industry Classification Standard (GICS) to identify the ten sectors. The results of nine out of ten sectors are reported, except for Telecommunications Services, as there are only two companies in that sector, and both fail to meet our selection criterion for calculating the idiosyncratic volatility; thus, they are excluded from our daily dataset. The results are available upon request.

$\gamma_{i,21}$ and $\gamma_{i,22}$ are lower than the respective medians of estimated $\gamma_{i,11}$ and $\gamma_{i,12}$. Overall, these results are consistent with our earlier findings; both good and bad news have smaller effects in the turbulent state than in the calm state. The effects of good and bad news in the turbulent state are essentially the same.

Our sectoral results are largely consistent with the existing literature. Many studies demonstrate that stock volatility varies across sectors (Hammoudeh, Yuan, Chiang, & Nandha, 2010; Smith & Yamagata, 2011; Sharma, Narayan, & Zheng, 2014). Our evidence suggests that the level of volatility persistence in the calm state varies across sectors. Also, we find that information arrival varies across sectors. For instance, the number of news stories of Financials is much greater than that of Health Care. Heavy industries such as Energy, Materials and Utilities have fewer news articles than the Financials counterpart. When the news flow of a firm is small, the available information about the firm is limited. If news arrives, investors will pay more attention and react to the news. This implies that the marginal effect of each news release on return volatility is generally higher in firms belonging to industries that have lower news flow. Since our sample covers the period of the Dot-Com bubble burst, it is not surprising that news stories of IT firms play a more important role in investment and trading decisions, and therefore it further contributes to the large difference in the level of volatility persistence reduction led by news for IT stocks compared with other stocks.

4.5. Firm size variations

Eighty-five stocks are evenly divided into three categories based on their market capitalization as at 2010. There are 29, 28 and 28 stocks classified as small, medium and large stocks respectively. Table 7 shows that the estimates of volatility persistence and the news effects vary across firm size.

Consider models without news variables. In the calm state, medium stocks have the smallest median estimates of volatility persistence (0.5444). The medians of estimated $\alpha_{i,1}+\beta_{i,1}$ are around the same in small and large stocks (0.6259 and 0.6200). Again, in the turbulent state, there are no significant differences across firm size. The reported medians are about 0.9998—the same as the overall median of $\alpha_{i,2}+\beta_{i,2}$ reported in Table 4.

Consider the model with news variables. In the calm state, medium stocks have the lowest median reduction in volatility persistence (0.1099) and it is similar to the median reduction of small stocks (0.1131). The median of reduction for large stocks is the largest compared to their medium and small counterparts. (0.1448). In the turbulent state, the reductions in small and

Table 7
Summary output of hourly data across firm size. This table presents the market capital size by market capital size summary descriptive statistics of the hourly regression results from the MRS-GARCH(1,1) models in this study. For explanations of the variables, please see Tables 1, 3 and 4.*

Panel A: Small stocks									
	$\alpha_{i,1}+\beta_{i,1}$	$\alpha_{i,1}+\beta_{i,1^*}$	R.V. in S_1	$\gamma_{i,11^*}$	$\gamma_{i,12^*}$	$d_{i,1}$	$d_{i,1}$	$p_{i,11}$	$p_{i,11^*}$
Mean	0.6021	0.4690	0.1331	0.2627	0.1341	25.0600	16.8700	0.2992	0.4957
Std Dev.	0.1020	0.1084	0.1145	0.2071	0.1133	16.5923	11.2818	0.1651	0.2533
Median	0.6259	0.4851	0.1131	0.2111	0.0881	20.8300	14.5100	0.2816	0.3888
	$\alpha_{i,2}+\beta_{i,2}$	$\alpha_{i,2}+\beta_{i,2^*}$	R.V. in S_2	$\gamma_{i,21^*}$	$\gamma_{i,22^*}$	$d_{i,2}$	$d_{i,2^*}$	$p_{i,22}$	$p_{i,22^*}$
Mean	0.9993	0.8951	0.1042	0.0388	0.0366	0.1520	3.0480	0.6647	0.6665
Std Dev.	0.0014	0.2356	0.2350	0.1039	0.0865	0.2450	7.2492	0.0931	0.1699
Median	0.9997	0.9997	0.0000	−0.0004	−0.0004	0.0780	0.0631	0.6599	0.5978
Panel B: Medium stocks									
	$\alpha_{i,1}+\beta_{i,1}$	$\alpha_{i,1}+\beta_{i,1^*}$	R.V. in S_1	$\gamma_{i,11^*}$	$\gamma_{i,12^*}$	$d_{i,1}$	$d_{i,1^*}$	$p_{i,11}$	$p_{i,11^*}$
Mean	0.5369	0.4561	0.0808	0.1857	0.1149	18.2700	12.7900	0.4455	0.5570
Std Dev.	0.1792	0.1832	0.1600	0.2223	0.1229	9.7161	9.6602	0.3149	0.3226
Median	0.5444	0.4478	0.1099	0.1015	0.0666	18.5300	10.8300	0.3192	0.4198
	$\alpha_{i,2}+\beta_{i,2}$	$\alpha_{i,2}+\beta_{i,2^*}$	R.V. in S_2	$\gamma_{i,21^*}$	$\gamma_{i,22^*}$	$d_{i,2}$	$d_{i,2^*}$	$p_{i,22}$	$p_{i,22^*}$
Mean	0.9364	0.7939	0.1425	0.0372	0.0379	1.0560	2.9610	0.7371	0.7364
Std Dev.	0.1883	0.3053	0.2701	0.0670	0.0651	2.7498	4.6747	0.1597	0.2107
Median	0.9998	0.9995	0.0001	−0.0003	−0.0001	0.1141	0.0633	0.6926	0.6725
Panel C: Large stocks									
	$\alpha_{i,1}+\beta_{i,1}$	$\alpha_{i,1}+\beta_{i,1^*}$	R.V. in S_1	$\gamma_{i,11^*}$	$\gamma_{i,12^*}$	$d_{i,1}$	$d_{i,1^*}$	$p_{i,11}$	$p_{i,11^*}$
Mean	0.5532	0.3857	0.1675	0.0781	0.0607	20.0500	10.9000	0.3980	0.7531
Std Dev.	0.2105	0.1539	0.1872	0.1379	0.0869	9.4171	9.9877	0.3507	0.3131
Median	0.6200	0.3656	0.1448	0.0330	0.0264	18.5700	8.6380	0.2505	0.9967
	$\alpha_{i,2}+\beta_{i,2}$	$\alpha_{i,2}+\beta_{i,2^*}$	R.V. in S_2	$\gamma_{i,21^*}$	$\gamma_{i,22^*}$	$d_{i,2^*}$	$d_{i,2^*}$	$p_{i,22}$	$p_{i,22^*}$
Mean	0.9762	0.6716	0.3045	0.0308	0.0506	0.4733	6.3590	0.7486	0.8259
Std Dev.	0.1250	0.3412	0.3384	0.0498	0.1568	1.9746	7.5373	0.1618	0.2283
Median	0.9998	0.7977	0.0140	0.0037	0.0092	0.0411	3.0340	0.7347	0.9965

* Estimates of full models.

medium stocks are close to 0. For large stocks, the median of estimated $\alpha_{i,2}+\beta_{i,2}$ with news variables is considerably smaller than the median in models without news variables (0.7977 against 0.9998). In sum, news effects induce the conditional volatility of large stocks more in both the calm and turbulent states.

There are variations in the estimated coefficients of news variables across the firm size categories. In the calm state, the median estimates of both $\gamma_{i,11}$ and $\gamma_{i,12}$ are the highest in small stocks (0.2111 and 0.0881), followed by medium stocks (0.1015 and 0.0666) and large stocks (0.0330 and 0.0264). This suggests that smaller stocks are affected by the news more in the calm state, and the effects of bad news are higher than good news. In the turbulent state, there are remarkable differences. Firstly, most estimates of $\gamma_{i,11}$ and $\gamma_{i,12}$ are significant at the 1% level; however, most estimates of $\gamma_{i,21}$ and $\gamma_{i,22}$ are insignificant even at the 10% level. In small stocks, there are only five significant estimates at the 5% level for both $\gamma_{i,21}$ and $\gamma_{i,22}$. In medium stocks, there are 11 significant estimates, and in large stocks, there are 14 and 15 significant estimates of $\gamma_{i,21}$ and $\gamma_{i,22}$, respectively. In contrast, the medians of estimated $\gamma_{i,21}$ and $\gamma_{i,22}$ in both small and medium stocks are close to 0. For large stocks, the medians are both positive and significantly different from 0 (0.0037 and 0.0092). The mean and median of estimated $\gamma_{i,21}$ in large stocks are smaller than the mean and median of $\gamma_{i,22}$ respectively, suggesting that the overall effects of good news are higher than bad news. Consequently, we can conclude that the news effects is only significant in large stocks in the turbulent state, and good news have a greater impact than bad news.

Our evidence of varying volatility persistence across firm size categories is consistent with existing studies including (Smith & Yamagata, 2011; Chang, Hsu, & McAleer, 2013; Sharma, Narayan, & Zheng, 2014) and many others, who suggest that return volatility varies across firm sizes. The smaller the firm is, the fewer relevant news stories are released, and thus the higher the marginal effects on the return volatility because investors pay more attention to the limited available information. On the other hand, since there is more news being released for large firms, they are more transparent to investors. Therefore, there is less chance for factors other than public information arrival to induce the stock return volatility of large stocks. Consequently, after controlling for news effects, the reduction in volatility persistence is relatively greater for large firms.

5. Robustness check

5.1. Asymmetric MRS GARCH-in-Mean model

The MRS-GARCH model described by Eq. (7) only allows the regime-switching for the conditional volatility. To check the robustness of our results, we also consider the Markov regime switching in the mean equation as well as the asymmetric GARCH effects. Below is the asymmetric MRS GARCH-in-Mean (GARCH-M) model[17]:

$$
\begin{aligned}
r_{i,t} &= b_{s_{i,t},i,0} + b_{s_{i,t},i,1} WESS_{i,t} + \lambda_{s_{i,t}} h_{s_{i,t},i,t} + \varepsilon_{s_{i,t},i,t} \\
\varepsilon_{s_{i,t},i,t} &= \eta_{i,t}\sqrt{[(v_i-2)/v_i] h_{s_t,i,t}} \text{ where } \eta_{i,t} \overset{iid}{\sim} t(0,1,v_i) \\
GARCH_{i,1} &= c_{i,1} + \alpha_{i,1}^{+}\left(\varepsilon_{1,i,t-1}^{+}\right)^2 + \alpha_{i,1}^{-}\left(\varepsilon_{1,i,t-1}^{-}\right)^2 + \beta_{i,1} h_{1,i,t-1} \\
GARCH_{i,2} &= c_{i,2} + \alpha_{i,2}^{+}\left(\varepsilon_{2,i,t-1}^{+}\right)^2 + \alpha_{i,2}^{-}\left(\varepsilon_{2,i,t-1}^{-}\right)^2 + \beta_{i,2} h_{2,i,t-1} \\
h_{s_{i,t},i,t} &= \begin{cases} GARCH_{i,1} + \gamma_{i,11} WNN_{i,t} + \gamma_{i,12} WNP_{i,t} + d_{i,1} SPX_t \text{ when } s_{i,t}=1 \\ GARCH_{i,2} + \gamma_{i,21} WNN_{i,t} + \gamma_{i,22} WNP_{i,t} + d_{i,2} SPX_t \text{ when } s_{i,t}=2 \end{cases}
\end{aligned}
\tag{12}
$$

where $\varepsilon_{s_{i,t},i,t}^{+}=\varepsilon_{s_{i,t},i,t}$ when $\varepsilon_{s_{i,t},i,t} \geq 0$ and is otherwise 0. $\varepsilon_{s_{i,t},i,t}^{-}=\varepsilon_{s_{i,t},i,t}$ when $\varepsilon_{s_{i,t},i,t} < 0$ and is otherwise 0. The overall estimated results are reported in Table 8.

Comparing the results of Table 4 with Table 8, all of our previous conclusions still hold. Without news variables, the volatility persistence in turbulent state is higher than that in the calm state (medians are 0.9999 and 0.5355, respectively). After the inclusion of news variables, the reduction in volatility persistence in the calm state is considerably higher than that in the turbulent state (medians are 0.0805 and 0.0001, respectively). Both negative and positive news positively affects conditional volatility. In the calm state, the median of the marginal effect of negative news is comparatively higher (0.0789) than that of positive news (0.0609). In the turbulent state, the marginal effects are similar and they are very close to 0. Table 4 also indicates that macro shocks, captured by *SPX*, increase the conditional volatility more in the calm state than in the turbulent state. The estimated transition probabilities suggest that the expected duration of the turbulent state is longer than that of the calm state. To sum up, our conclusions are robust to alternative regime switching and GARCH specifications.

5.2. MRS-GARCH model controlling for seasonality

As argued by Andersen and Bollerslev (1997, 1998), standard time series models of volatility fail to capture strong intraday seasonality when applied to high frequency return data. Using flexible fourier form, Andersen, Bollerslev, Diebold, and Vega

[17] We have adopted the idea of a recent study by Reher and Wilfling (2015) to derive this asymmetric specification. Besides, to keep a consistent model structure with the MRS-GARCH employed in this study, the asymmetric MRS-GARCH model investigated in Mullen, Ardia, Gil, Windover, and Cline (2011) is also considered. Hence,the volatility persistence of firm i in state $s_{i,t}$ estimated by this specification is $(\alpha_{s_{i,t},i,t}{}^{+}+\alpha_{s_{i,t},i,t}{}^{-})/2+\beta_{s_{i,t},i,t}$.

Table 8
Asymmetric MRS-GARCH-M(1,1) models. This table presents the summary descriptive statistics of hourly regression results from the asymmetric MRS-GARCH-M(1,1) models in this study. For explanations of the variables, please see Tables 1, 3 and 4.*

	Mean	*Std Dev.*	*Median*	Q_1	Q_3	*Skew*
$(\alpha^+_{i,1}+\alpha^-_{i,1})/2+\beta_{i,1}$	0.5059	0.1654	.5355	0.4190	0.6050	0.0023
$(\alpha^+_{i,1}+\alpha^-_{i,1})/2+\beta_{i,1*}$	0.4144	0.1379	0.4292	0.3091	0.4812	1.5255
R.V. in S $_1$	0.0915	0.1591	0.0805	−0.0024	0.1642	0.2709
$\gamma_{i,11*}$	0.1564	0.1876	0.0789	0.0341	0.2080	2.0434
$\gamma_{i,12*}$	0.0911	0.0974	0.0609	0.0293	0.1144	2.0744
$d_{i,1}$	20.1186	13.2423	17.6995	10.4010	26.3887	1.0093
$d_{i,1*}$	11.6957	8.4658	10.3737	5.4432	16.0278	1.4520
$p_{i,11}$	0.3481	0.2798	0.2778	0.1559	0.3923	1.3790
$p_{i,11*}$	0.6163	0.3073	0.4325	0.3659	0.9981	0.3168
$(\alpha^+_{i,2}+\alpha^-_{i,2})/2+\beta_{i,2}$	0.9704	0.1332	0.9999	0.9996	1.0000	−4.2748
$(\alpha^+_{i,2}+\alpha^-_{i,2})/2+\beta_{i,2*}$	0.7870	0.3056	0.9995	0.3963	0.9999	−0.7832
R.V. in S $_2$	0.1834	0.2923	0.0001	0.0000	0.5034	1.0216
$\gamma_{i,21*}$	0.0393	0.0796	−0.0001	−0.0006	0.0423	2.8223
$\gamma_{i,22*}$	0.0513	0.1143	−0.0001	−0.0005	0.0678	4.4758
$d_{i,2}$	0.5445	1.8534	0.1069	0.0441	0.2084	4.5248
$d_{i,2*}$	4.0530	6.6028	0.0781	0.0236	7.2165	1.5398
$p_{i,22}$	0.6942	0.1431	0.6676	0.6091	0.7368	0.8652
$p_{i,22*}$	0.7379	0.2147	0.6498	0.5663	0.9975	0.1917

* Estimates of full models.

(2003) and Harju and Hussain (2011)) explicitly account for intraday seasonal patterns in modeling the volatility of high frequency returns. We employ a similar approach and include a seasonality term to control for their effects on the intraday data.

$$r_{i,t} = b_{s_{i,t},i,0} + b_{s_{i,t},i,1} WESS_{i,t} + \sum_{q=1}^{Q} \left(\delta_{q,i} \sin\left(\frac{2\pi qt}{T}\right) + \theta_{q,i} \cos\left(\frac{2\pi qt}{T}\right)\right) + D_{s,i} + D_{e,i} + \varepsilon_{i,t} \quad (13)$$

where $D_{s,i}$ and $D_{e,i}$ are the dummy variables indicating the start and end of the trading hours, respectively. Since there are seven trading hours per day, we set $Q=7$. The results are reported in Table 9.

Comparing the results of Table 4 with Table 9, all of our earlier conclusions regarding the news effects still hold. Despite the slight change in magnitudes, negative news continues to have larger positive effects than positive news in the calm state (medians are 0.0457 and 0.0321, respectively). In the turbulent state, the news effects are similar and close to 0. After the inclusion of news variables, the reduction of volatility persistence in the calm state is larger than that in the turbulent state (median

Table 9
MRS-GARCH(1,1) models controlling for seasonality. This table presents the summary descriptive statistics of hourly regression results from the MRS-GARCH(1,1) models controlling for seasonality in this study. For explanations of the variables, please see Tables 1, 3 and 4.

	Mean	*Std Dev.*	*Median*	Q_1	Q_1	*Skew*
$\alpha_{i,1}+\beta_{i,1}$	0.4933	0.1530	0.4875	0.4092	0.5735	0.6160
$\alpha_{i,1}+\beta_{i,1*}$	0.4532	0.1304	0.4470	0.3803	0.5132	1.5337
R.V. in S $_1$	0.0401	0.1405	0.0471	−0.0232	0.1073	−0.0648
$\gamma_{i,11*}$	0.1125	0.1763	0.0457	0.0108	0.1571	2.7888
$\gamma_{i,12*}$	0.0606	0.0839	0.0321	0.0084	0.0723	2.3529
$d_{i,1}$	18.7626	12.6824	15.5812	11.2294	22.6145	2.0167
$d_{i,1*}$	13.1915	10.5904	10.4849	5.6983	17.1536	1.9432
$p_{i,11}$	0.5872	0.2689	0.6143	0.4069	0.7222	−0.1997
$p_{i,11*}$	0.6817	0.2679	0.6099	0.4627	0.9976	−0.0463
$\alpha_{i,2}+\beta_{i,2}$	0.9709	0.1238	0.9997	0.9966	0.9999	−4.5848
$\alpha_{i,2}+\beta_{i,2*}$	0.7799	0.3165	0.9986	0.3870	0.9999	−0.7879
R.V. in S $_2$	0.1910	0.3047	0.0002	−0.0004	0.5771	1.0074
$\gamma_{i,21*}$	0.0223	0.0579	−0.0002	−0.0008	0.0167	3.2424
$\gamma_{i,22*}$	0.0265	0.0861	−0.0001	−0.0004	0.0200	6.2451
$d_{i,2}$	0.5977	1.9451	0.1352	0.0600	0.2529	4.3878
$d_{i,2*}$	3.9178	6.3389	0.1334	0.0538	7.1952	1.5421
$p_{i,22}$	0.5485	0.2744	0.5338	0.3586	0.6947	0.0300
$p_{i,22*}$	0.6817	.2693	0.5798	0.4351	0.9956	0.0287

* Estimates of full models.

reductions are 0.0471 and 0.0002, respectively). Without news variables, the median of volatility persistence in the calm state is 0.4875, which is still smaller than that in the turbulent state (0.9997). The median effect of macro shock continues to be larger in the calm state. The only difference is that after controlling for the intraday seasonality, the expected duration of the calm state is slightly longer than that of the turbulent state. To sum up, our conclusions are robust to accounting for the intraday seasonality in the MRS-GARCH model.

5.3. A two-state GARCH model with the NBER business cycle

As described in Section 3.3, the calm and the turbulent states are identified by the fitted MRS-GARCH model. As a robustness check, we consider an alternative way of identifying the calm and the turbulent states. We use the NBER business cycle[18] to divide our sample period into the calm period and the turbulent period based on the peak and the trough turning point dates. Specifically, we define the period between Mar 1, 2001 and Oct 30, 2001 (inclusive) as well as the period between Dec 1, 2007 and May 30, 2009 (inclusive) as the turbulent period. Other periods are defined as the calm period. Using this definition, we employ the following two-state GARCH model.

$$\begin{aligned}
r_{i,t} &= b_{s_{i,t},i,0} + b_{s_{i,t},i,1} WESS_{i,t} + \varepsilon_{s_{i,t},i,t} \\
\varepsilon_{s_{i,t},i,t} &= \eta_{i,t}\sqrt{[(v_i-2)/v_i]h_{s_t,i,t}} \text{ where } \eta_{i,t} \overset{iid}{\sim} t(0,1,v_i) \\
GARCH_{i,1} &= c_{i,1} + \alpha_{i,1}\varepsilon^2_{1,i,t-1} + \beta_{i,1}h_{1,i,t-1} \\
GARCH_{i,2} &= c_{i,2} + \alpha_{i,2}\varepsilon^2_{2,i,t-1} + \beta_{i,2}h_{2,i,t-1} \\
h_{s_{i,t},i,t} &= \begin{cases} GARCH_{i,1} + \gamma_{i,11} WNN_{i,t} + \gamma_{i,12} WNP_{i,t} + d_{i,1} SPX_t \text{ when } s_{i,t} = 1 \\ GARCH_{i,2} + \gamma_{i,21} WNN_{i,t} + \gamma_{i,22} WNP_{i,t} + d_{i,2} SPX_t \text{ when } s_{i,t} = 2 \end{cases}
\end{aligned} \tag{14}$$

where $s_{i,t}=1$ and 2 indicate the periods of calm and turbulent states, respectively. Different from the MRS-GARCH model, $s_{i,t}$ in Eq. (14) is not latent and is fully defined by the NBER business cycle as described above. Results are reported in Table 10.

Results from Table 10 are largely consistent with that from Table 4. Both negative and positive news increase the conditional volatility, and the marginal effect of the former is larger than the latter (medians are 0.0140 and 0.0119). After the inclusion of news, the level of volatility persistence reduction in the calm state continues to be larger than that in the turbulent state (medians of reduction are 0.0203 and 0.0022). Since the latent state structure of each stock may not be perfectly consistent with the NBER business cycle, our GARCH model may overestimate the volatility persistence if regime-switching is still present within the identified states, which is evidenced by the large estimated volatility persistence in the calm state (the median is 0.9658). Nevertheless, the fact that volatility persistence in the turbulent state continues to be larger (the median is 0.9933) is consistent with our previous finding. Finally, although the magnitudes change considerably, macro shock continues to have a positive and larger impact on the conditional volatility in the calm state than that in the turbulent state. To sum up, our results based on the MRS-GARCH specification is robust to alternative definition of calm and turbulent period.

5.4. Idiosyncratic volatility

As mentioned earlier, our news database only contains firm-specific news stories. While the use of the dummy variable SPX_t may capture the effect of macroeconomic (market) news, stock returns may also be affected by other firm-specific characteristics such as firm size. As a robustness check, we estimate the idiosyncratic volatility (IV) using the Fama–French three-factor model (Fama & French, 1993), where IV should be orthogonal to firm-specific characteristics and other unobserved macro shocks:

$$R_{i,t} - r_t = \alpha_{i,\tau} + b_{i,\tau}\left(R_{m,t} - r_t\right) + s_{i,\tau} SMB_t + h_{i,\tau} HML_t + \zeta_{i,t} \tag{15}$$

where τ is the τth month between 2000 and 2010, t is the tth day in month τ, $R_{i,t}$ is the daily return of stock i without multiplying by 100, r_t is the one-month Treasury bill rate, $R_{m,t}$-r_t is the daily excess return on a broad market portfolio and SMB_t is the daily difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks. HML_t is the daily difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks. $R_{m,t}$-r_t, SMB_t and HML_t are commonly known as the Fama–French three factors (Fama & French, 1993; Fama & French, 1996).[19]

[18] The data are available from http://www.nber.org/cycles.html.

[19] The data are available from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data _library.html. As the only available frequency is the daily data, our news variables will be aggregated on a daily basis. The algorithm is the same as described in Eqs. (2), (3), (4), except that the t stands for the tth day rather than the tth hour.

Table 10
Two-State GARCH(1,1) models with the NBER business cycle. This table presents the summary descriptive statistics of hourly regression results from the two-state MRS-GARCH(1,1) models with the NBER business cycle in this study. For explanations of the variables, please see Tables 1, 3 and 4.

	Mean	*Std Dev.*	*Median*	Q_1	Q_1	*Skew*
$\alpha_{i,1}+\beta_{i,1}$	0.9130	0.1618	0.9658	0.9234	0.9830	−2.7508
$\alpha_{i,1}+\beta_{i,1^*}$	0.7652	0.2503	0.9393	0.4945	0.9714	−0.5444
R.V. in S_1	0.1478	0.2007	0.0203	0.0080	0.3623	1.0121
$\gamma_{i,11^*}$	0.0525	0.0943	0.0140	0.0043	0.0655	4.1548
$\gamma_{i,12^*}$	0.0337	0.0513	0.0119	0.0037	0.0539	2.7961
$d_{i,1}$	4.7370	4.6172	3.0966	1.3815	7.2766	1.8250
$d_{i,1^*}$	2.3004	3.1052	1.2772	0.8421	2.2738	2.8632
$\alpha_{i,2}+\beta_{i,2}$	0.9933	0.0107	0.9949	0.9897	0.9973	2.9042
$\alpha_{i,2}+\beta_{i,2^*}$	0.9738	0.0826	0.9933	0.9807	0.9964	−4.7624
R.V. in S_2	0.0195	0.0790	0.0022	0.0006	0.0067	5.0342
$\gamma_{i,21^*}$	0.0033	0.0069	0.0014	0.0002	0.0032	4.4080
$\gamma_{i,22^*}$	0.0023	0.0069	0.0006	0.0000	0.0014	4.6014
$d_{i,2}$	1.1306	2.6101	0.5161	0.2596	0.9546	5.3821
$d_{i,2^*}$	0.5542	0.6152	0.3871	0.2078	0.6895	3.7578

* Estimates of full models.

Table 11
Summary output of idiosyncratic volatility. This table presents the summary descriptive statistics of the daily idiosyncratic volatility regression results from the MRS-GARCH(1,1) models in this study. The number of observations here is 79. For explanations of the variables, please see Tables 1, 3 and 4.

	Mean	*Std Dev.*	*Median*	Q_1	Q_3	*Skew*
$\alpha_{i,1}+\beta_{i,1}$	0.8969	0.1135	0.9317	0.8703	0.9751	−2.0652
$\alpha_{i,1}+\beta_{i,1^*}$	0.3860	0.3183	0.2989	0.1018	0.6562	0.5780
R.V. in S_1	0.5110	0.3295	0.5920	0.2255	0.7941	−0.5031
$\gamma_{i,11^*}$	0.0848	0.1542	0.0349	0.0173	0.0802	4.5468
$\gamma_{i,12^*}$	0.0478	0.0691	0.0270	0.0136	0.0612	3.4633
$d_{i,1}$	0.5421	0.6085	0.4319	0.1749	0.8170	1.6579
$d_{i,1^*}$	0.3079	0.5424	0.1748	−0.0339	0.5432	1.1550
$p_{i,11}$	0.8260	0.2549	0.9419	0.7921	0.9891	−1.9280
$p_{i,11^*}$	0.6190	0.4025	0.8095	0.2164	0.9955	−0.3673
$\alpha_{i,2}+\beta_{i,2}$	0.9932	0.0243	0.9996	0.9990	0.9998	−4.5256
$\alpha_{i,2}+\beta_{i,2^*}$	0.9355	0.1770	0.9990	0.9861	0.9995	−3.4626
R.V. in S_2	0.0576	0.1667	0.0006	0.0001	0.0084	3.4119
$\gamma_{i,21^*}$	0.0075	0.0256	−0.0007	−0.0014	0.0008	3.4938
$\gamma_{i,22^*}$	0.0115	0.0553	−0.0003	−0.0013	0.0014	7.3642
$d_{i,2}$	0.1562	0.5688	−0.0091	−0.0403	0.0819	4.5514
$d_{i,2^*}$	0.1965	0.3578	0.0804	0.0283	0.3066	3.7328
$p_{i,22}$	0.8310	0.2596	0.9504	0.7881	0.9923	−1.8610
$p_{i,22^*}$	0.7718	0.2707	0.9483	0.5427	0.9955	−0.8088

* Estimates of full models.

We follow Fu (2009) to fit Eq. (15) using monthly return and extract the daily error series $\zeta_{i,t}$ for each firm i. We rescale $\zeta_{i,t}$ by a factor of 100 and we use it to replace the dependent variable in the mean equation in Eq. (7). Therefore, $h_{s_{i,t},i,t}$ is the corresponding IV for each firm i in the state $s_{i,t}$ at time t.[20] Results are reported in Table 11.

Consider the models without news variables in Table 11. Both medians of the estimates: $d_{i,1}$ and $d_{i,2}$ using daily returns are much smaller than corresponding medians using hourly returns, which may be due to the fact that IV is, to some extents, orthogonal to the macroeconomic shock. The difference between the medians of estimated $\alpha_{i,1}+\beta_{i,1}$ and $\alpha_{i,2}+\beta_{i,2}$ (0.9317 and 0.9996) is much smaller, which suggests that after controlling for the Fama–French three factors, the volatility persistence is similar in the calm state and in the turbulent state. The difference between the median estimates of $p_{i,11}$ and $p_{i,22}$ (0.9419 and 0.9504) is very small, suggesting that in general, the expected time of staying in the calm state is about the same as that in the turbulent state.

Consider the models with news variables in Table 11. The median estimates of volatility persistence reduction is also larger in the calm state than in the turbulent state (0.5920 and 0.0006), with the latter being close to 0. The median of $\gamma_{i,11}$ is higher than the median of $\gamma_{i,12}$ (0.0349 and 0.0270), and both are positive and larger than the medians of $\gamma_{i,21}$ and $\gamma_{i,22}$, respectively. The estimates of $\gamma_{i,21}$ and $\gamma_{i,22}$ are generally close to 0. This result is consistent with prior results using raw hourly returns: (1) news effects induce the return volatility persistence in the calm state rather than in the turbulent state; (2) the effects of

[20] Due to data availability, we can only estimate IV at the daily level.

good and bad news on volatility are both positive; (3) bad news has a greater effect on return volatility than good news in the calm state, and (4) the influence of both bad and good news are much smaller and are about the same in the turbulent state.

6. Conclusion

This study empirically examines the role of public news arrivals on stock return volatility using a novel news database that utilities a text analytic algorithm to quantify the relevance and sentiment of each news story based on its textual content. The news database is provided by RavenPack News Analytics Dow Jones Edition. It tracks and continuously monitors relevant news on tens of thousands of companies, government organizations, influential people, key geographical locations, and all major currencies and traded commodities. To form the basis of the theory behind our empirics, we merge two streams of the literature. The MDH literature proposed by Clark (1973), Tauchen and Pitts (1983), Harris (1986, 1987) and Andersen (1996) argues that the variance of returns at a given interval is proportional to the rate of information arrival in the market. Led by Veronesi (1999), the literature on the asymmetric effect of different news on stock return volatility argues that in the presence of asymmetric information, investors overreact to bad news in good times and underreact to good news in bad times. This stream of literature suggests that news sentiment plays an important role in explaining stock return volatility, and its effect depends on the level of volatility.

To test veronesi1999's argument, we classify news types using the sentiment score based on RavenPack's proprietary algorithm. Unlike extant studies that use the stock returns to classify the news type, our classification overcomes the problem of endogeneity, where the observed variations in returns could be driven by volatility. Using the MRS-GARCH models with two states on the hourly returns of S&P 100 stocks from 1 January 2000 to 31 December 2010, we find empirical support for the MDH. We also find evidence suggesting that under different regimes, there is an asymmetric effect of good news and bad news on stock return volatility. We find that firm-specific news is more likely to cause the persistence of stock return volatility in the calm state than in the turbulent state. While news has a positive effect on conditional volatility in both states, the level of the effect depends on the quality of news and the state of the return volatility. Specifically, both good and bad news have greater effects in the calm state than in the turbulent state. In the calm state, the effect of bad news is greater than that of good news, while both effects are similar in the turbulent state. We find that the news effect differs across sectors and firm sizes. On average, the news effects for stocks that belong to the IT sector are greater. In the calm state, news effects are greater in heavy industry sectors. In the turbulent state, news effects are similar across all sectors. The news effect contributes more to the volatility persistence of large stocks than small stocks. In the calm state, news effects are greater for small stocks, while they are greater for large stocks in the turbulent state. Finally, we conduct a number of robustness checks and our conclusion is robust to different GARCH specifications, the control of intraday seasonality in return volatility, and the use of idiosyncratic volatility.

Our results can provide useful information for professional investors who read newswire messages like Dow Jones. They spend a considerable amount of money on finding the available information and emphasize the importance of speed and accuracy of news. Newswire messages represent much of the overall information that traders receive on a real-time basis. As news can significantly affect volatility in the calm state, these newswire messages may help traders to anticipate the potential movement of volatility for assets that they are monitoring. Therefore, traders can adjust their strategies proactively in response to the changes in news flows and sentiment. In today's electronic trading environment, passive algorithmic trading strategies primarily based on automating the trading process may require closer monitoring of news sentiment to manage unexpected market risk. Our findings suggest that news sentiment can be used to enhance the accuracy of dynamic hedging strategies, derivatives pricing models and risk management issues.

Our results also provide several new directions for future research. Since a substantial proportion of volatility persistence in the MRS-GARCH model can be attributed to firm-specific news sentiment, one implication of this finding is that news sentiment can improve pricing models and hedging strategies. Another potential research avenue would be to explore the impact of different news categories. News such as earnings reports may have different impact on the volatility dynamics than other news such as mergers and acquisitions.

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Appendix A. Selected S&P 100 companies list

This Appendix A presents the list of 85 companies in our sample. The company's name (*Name*), its ticker symbol (*Ticker*), its industrial classification (*Sector*), and its market capitalization as of December 2010 (*Market Cap*) are reported.

Name	Ticker	Sector	Market Cap
3M	MMM	Industrials	$61,443,668
ABBOTT LABORATORIES	ABT	Health Care	$74,116,001
ALCOA	AA	Materials	$15,728,980
ALLSTATE	ALL	Financials	$16,992,040
ALTRIA GROUP	MO	Consumer Staples	$51,424,771
AMAZON.COM	AMZN	Consumer Discretionary	$81,180,000
AMER.ELEC.PWR.	AEP	Utilities	$17,299,441
AMERICAN EXPRESS	AXP	Financials	$51,375,240
AMGEN	AMGN	Health Care	$51,166,800
APACHE	APA	Energy	$45,592,567
APPLE	AAPL	Information Technology	$295,455,299
AT&T	T*	Telecommunications Services	$173,667,732
AVON PRODUCTS	AVP	Consumer Staples	$12,481,270
BAKER HUGHES	BHI	Energy	$24,697,440
BANK OF AMERICA	BAC	Financials	$134,535,965
BANK OF NEW YORK MELLON	BK	Financials	$37,494,212
BAXTER INTL.	BAX	Health Care	$29,396,722
BERKSHIRE HATHAWAY ‘B’	BRKB	Financials	$198,516,054
BOEING	BA	Industrials	$47,983,009
BRISTOL MYERS SQUIBB	BMY	Health Care	$44,989,520
CAPITAL ONE FINL.	COF	Financials	$19,450,489
CATERPILLAR	CAT	Industrials	$59,832,135
CISCO SYSTEMS	CSCO	Information Technology	$114,400,650
CITIGROUP	C	Financials	$76,927,236
COCA COLA	KO	Consumer Staples	$150,744,840
COLGATE-PALM.	CL	Consumer Staples	$39,771,132
COMCAST ‘A’	CMCSA*	Consumer Discretionary	$60,999,687
CONOCOPHILLIPS	COP	Energy	$99,947,356
COSTCO WHOLESALE	COST	Consumer Staples	$31,303,757
CVS CAREMARK	CVS	Consumer Staples	$47,391,510
DELL	DELL	Information Technology	$25,988,900
DEVON ENERGY	DVN	Energy	$33,877,065
DOW CHEMICAL	DOW	Materials	$39,848,789
E I DU PONT DE NEMOURS	DD	Materials	$45,755,423
EMC	EMC	Information Technology	$47,385,733
EMERSON ELECTRIC	EMR	Industrials	$43,031,333
ENTERGY	ETR	Utilities	$12,660,570
EXXON MOBIL	XOM	Energy	$364,064,480
FEDEX	FDX	Industrials	$29,205,140
FORD MOTOR	F	Consumer Discretionary	$63,511,717
FREEPORT-MCMOR.CPR.& GD.	FCX*	Materials	$56,742,525
GENERAL DYNAMICS	GD	Industrials	$26,400,832
GENERAL ELECTRIC	GE	Industrials	$194,155,227
GILEAD SCIENCES	GILD*	Health Care	$29,064,408
GOLDMAN SACHS GP.	GS	Financials	$85,346,375
HALLIBURTON	HAL	Energy	$37,155,300
HJ HEINZ	HNZ	Consumer Staples	$15,713,046
HOME DEPOT	HD	Consumer Discretionary	$56,902,380
HONEYWELL INTL.	HON	Industrials	$41,624,280
INTEL	INTC	Information Technology	$115,896,330
INTERNATIONAL BUS.MCHS.	IBM	Information Technology	$180,220,333
JOHNSON & JOHNSON	JNJ	Health Care	$169,351,299
JP MORGAN CHASE & CO.	JPM	Financials	$165,874,676
LOCKHEED MARTIN	LMT	Industrials	$24,188,860
LOWE'S COMPANIES	LOW	Consumer Discretionary	$33,958,320
MCDONALDS	MCD	Consumer Discretionary	$80,874,336
MEDTRONIC	MDT	Health Care	$40,700,437
MERCK & CO.	MRK	Health Care	$111,079,130
MICROSOFT	MSFT	Information Technology	$241,923,880
MORGAN STANLEY	MS	Financials	$41,142,121
NIKE ‘B’	NKE	Consumer Discretionary	$41,343,280
NORFOLK SOUTHERN	NSC	Industrials	$22,449,519
OCCIDENTAL PTL.	OXY	Energy	$79,735,166
ORACLE	ORCL	Information Technology	$157,313,800
PEPSICO	PEP	Consumer Staples	$103,286,730
PFIZER	PFE	Health Care	$140,290,120

Appendix A. (*continued*)

Name	Ticker	Sector	Market Cap
PROCTER & GAMBLE	PG	Consumer Staples	$182,922,355
QUALCOMM	QCOM	Information Technology	$79,777,880
SCHLUMBERGER	SLB	Energy	$113,657,814
SOUTHERN	SO	Utilities	$32,247,005
SPRINT NEXTEL	S*	Telecommunications Services	$12,639,240
TEXAS INSTS.	TXN	Information Technology	$37,941,920
TIME WARNER	TWX*	Consumer Discretionary	$35,200,360
UNION PACIFIC	UNP	Industrials	$45,548,494
UNITED PARCEL SER.	UPS	Industrials	$71,926,780
UNITED TECHNOLOGIES	UTX	Industrials	$72,522,296
UNITEDHEALTH GP.	UNH	Health Care	$39,215,460
US BANCORP	USB	Financials	$51,806,765
WAL MART STORES	WMT	Consumer Staples	$189,617,880
WALGREEN	WAG	Consumer Staples	$36,568,053
WELLS FARGO & CO	WFC	Financials	$163,078,157
WEYERHAEUSER	WY	Materials	$10,146,017
WILLIAMS COS.	WMB	Energy	$14,461,200
XEROX	XRX	Information Technology	$16,100,099

* The company is excluded from the calculation of idiosyncratic volatility.

Appendix B. RavenPack algorithm

B.1. Expert consensus tagging methodology

RavenPack's Expert Consensus Methodology underpins the *ESS* score and entails a group of financial experts manually tagging a set of stories that is later used as a basis for automated computer classification using a Bayes Classifier.

B.1.1. Step one: a Classification Base is defined

When developing a new sentiment series that uses the Expert Consensus Methodology, the first step is to develop a Classification Base, or define the types of stories that contain the content relevant for tagging. The ideal Classification Base contains only stories that contain news that affect the target market or asset class.

B.1.2. Step two: experts build an internal Tagging Guide

When developing a new sentiment series that requires manual tagging, a team of in-house experts with extensive backgrounds in linguistics, finance, and economics first develop and agree upon a set of parameters and basic assumptions that will guide sentiment tagging. This Tagging Guide ensures that the assumptions used in identifying story sentiment are consistent and agreed upon. It provides rules for when to identify stories as positive, negative or neutral.

B.1.3. Step three: a large sample is tagged

A sample of up to 28,000 stories in the Classification Base developed in step one is drawn from RavenPack's news database for a fixed date range. Stories are randomly selected for tagging. Up to ten experts read and classify all story headlines in the sample using the Tagging Guide developed in step two.

The Tagging Guide is built to avoid disagreements in story sentiment among experts. Even so, stories that were not classified by 80% of expert taggers as having the same sentiment are automatically given the NA code. Stories that contain both positive and negative sentiment are judged based on the story's overall effect on the market. Stories with equal amounts of positive and negative sentiment are tagged as neutral.

B.1.4. Step four: software is trained from sample to automate tagging

Once an appropriate sample of stories has been tagged, a Bayes Classifier uses supervised learning to discern patterns in expert tagging and establish rules for future automation. This automated tagging process must meet exceptional levels of accuracy in order to be made available to clients. In cases when accuracy is not sufficiently high, step three is repeated with a larger sample set. Accuracy levels vary by classifier but range from 80% to 96%.

B.1.5. Step five: generate historical analysis and enable real-time tagging

After the classifier has been trained to reach acceptable levels of accuracy, historical analysis is generated and real-time tagging is enabled. This process involves several consistency checks of historical data and generation of volume statistics. When this process is complete, the series is published.

B.1.6. Step six: quarterly re-evaluation

Because training is based on a limited data range, there always exists the possibility that new economic terminology, trends, types of reporting, market forces, etc. may emerge after the sample period used in step three. In order to account for these trends, classifiers are re-evaluated on a quarterly basis. This process involves completing step three for stories sampled outside of the date range of the original sample or most recent quarterly re-evaluation. The results of this expert classification are compared to the results of automated classification. If the accuracy level is 10% lower than the level when the series was originally released, a new series is developed.

B.2. Market response methodology

RavenPack's Market Response methodology underpins the *CSS* score and is based on a Rule Base that identifies and maps individual words or word combinations in the story headline to the price impact on stocks of companies mentioned in the headline. The price impact is measured in the hours ahead of the arrival of the news item and is transformed into an impact score using advanced machine learning techniques.

B.2.1. Step one: a Classification Base is defined

When developing a new impact series that uses the Market Response methodology, the first step is to develop a Classification Base, or define the types of stories that contain the content relevant for measuring the market impact. The ideal Classification Base contains only stories that contain news that affect the target market or asset class.

B.2.2. Step two: a large sample is analyzed to create a Rule Base

A sample of up to 30,000 headline stories in the Classification Base developed in step one is drawn from RavenPack's news database for a fixed date range. The headlines of these stories are extracted and parsed into words to form a list of candidates of individual words and word combinations that are typical for such headline stories. Based on statistical measures, about 4,000 of these words and word combinations have been identified as promising in relations to predicting market impact.

B.2.3. Step three: create an impact score using the Rule Base

Once a Rule Base has been established, different advanced machine learning techniques are applied with the objective of creating an Impact Score that identifies the probability of the volatility of a particular stock to be either higher or lower than the volatility of the market.

B.2.4. Step four: generate historical analysis and enable real-time tagging

Applying step two and three on the target story type, historical analysis is generated and the real-time creation of Impact Scores is enabled. This process involves several consistency checks of historical data. When this process is complete, the series is published.

B.2.5. Step five: quarterly re-evaluation

Because story sampling is based on a limited data range, there always exists the possibility that new economic terminology, trends, types of reporting, market forces, etc. may emerge after the sample period used in step two and three. In order to account for these trends, scores are re-evaluated on a quarterly basis.

This process involves completing step two for stories sampled outside of the date range of the original sample or most recent quarterly re-evaluation. Statistical measures are used with the purpose of identifying additional words or word combinations that, from a statistical perspective, seem promising in terms of market impact. Such words and word combinations are added to the Rule Base and are then used under step three to continuously maintain and improve the impact series to reflect current market conditions.

B.3. Factors in the event sentiment score

In addition to the expert consensus survey data, the Event Sentiment Score (*ESS*) has a strength component that is influenced by a variety of factors, depending on the type of event. RavenPack systematically extracts information from every news story to model these factors and determine how positive or negative each event should be. Here is a list of some of these factors:

B.3.1. Emotional factor:

There are 5 scales containing groups of words and phrases in the RavenPack emotional magnitude component of *ESS*. Each component contains words that signify the magnitude of an event as described by the author of the story.

1. *Low magnitude*: Contains adjective words such as ‘low, minor, small, or inconsequential’ and phrases such as ‘below the mark or not meaningful’
2. *Moderate magnitude*: Contains words such as ‘moderate, mellow, or dainty’ and phrases such as ‘nothing much or fairly flat’
3. *Substantial magnitude*: Contains words such as ‘substantial, durable, considerable or extensive’ and phrases such as ‘fairly considerable or significantly large’

4. *Severe magnitude*: Contains words such as 'severe, commanding, destructive, or excruciating' and phrases such as 'extremely high or highly elevated'
5. *Critical magnitude*: Contains words such as 'critical, devastation, massacre, or catastrophic' and phrases such as 'super colossal or most damaging'

B.3.2. Analyst rating factor

Covers over 150 different broker and analyst rating scales for stocks (e.g. strong buy, buy, hold, sell, strong sell).

B.3.3. Credit rating factor

Consolidates the three main credit ratings scales by Moody's, Fitch, and S&P (e.g. AAA, AA, BB, C, etc.) into one normalized scale.

B.3.4. Fundamental comparison factor

Extracts and calculates numerical differences between actual or estimated values in earnings, revenues, dividends, and any other financial or economic announcement. Performs arithmetic, and translates fundamental percentage changes into a normalized score within the *ESS* ranges.

References

Andersen, T. G. (1996). Return volatility and trading volume: An information flow interpretation of stochastic volatility. *Journal of Finance*, *51*, 169–204.
Andersen, T. G., & Bollerslev, T. (1997). Intraday periodicity and volatility persistence in financial markets. *Journal of Empirical Finance*, *4*, 115–158.
Andersen, T. G., & Bollerslev, T. (1998). Deutsche mark–dollar volatility: Intraday activity patterns, macroeconomic announcements, and longer run dependencies. *The Journal of Finance*, *53*, 219–265.
Andersen, T. G., Bollerslev, T., Diebold, F. X., & Vega, C. (2003). Micro effects of macro announcements: Real-time price discovery in foreign exchange. *American Economic Review*, *93*, 38–62.
Ang, A., Timmermann, A., 2011. Regime changes and financial markets. Technical report. National Bureau of Economic Research.
Benning, J. (2000). The lesson of emulex. *Online journalism review*, *8*.
Berger, D., Chaboud, A., & Hjalmarsson, E. (2009). What drives volatility persistence in the foreign exchange market? *Journal of Financial Economics*, *94*, 192–213.
Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*, 307–327.
Bollerslev, T. (1987). A conditional heteroskedastic time series model for speculative prices and rates of return. *The Review of Economics and Statistics*, *69*, 542–547.
Cai, J. (1994). A Markov model of switching-regime arch. *Journal of Business & Economic Statistics*, *12*, 309–316.
Chang, C. L., Hsu, H. K., & McAleer, M. (2013). Is small beautiful? size effects of volatility spillovers for firm performance and exchange rates in tourism. *The North American Journal of Economics and Finance*, *26*, 519–534.
Chen, X., & Ghysels, E. (2011). News–good or bad–and its impact on volatility predictions over multiple horizons. *Review of Financial Studies*, *24*, 46–81.
Chen, C. R., Su, Y., & Huang, Y. (2008). Hourly index return autocorrelation and conditional volatility in an EAR–GJR–Garch model with generalized error distribution. *Journal of Empirical Finance*, *15*, 789–798.
Cheng, L. T., Leung, T., & Yu, W. (2014). Information arrival, changes in r-square and pricing asymmetry of corporate news. *International Review of Economics and Finance*, *33*, 67–81.
Clark, P. K. (1973). A subordinated stochastic process model with finite variance for speculative prices. *Econometrica*, *41*, 135–155.
Cousin, J. G., & de Launois, T. (2008). News intensity and conditional volatility on the US stock market. *AFFI* (pp. 2007).
Dueker, M. J. (1997). Markov switching in garch processes and mean-reverting stock-market volatility. *Journal of Business & Economic Statistics*, *15*, 26–34.
Engle, R. F. (1982). Autoregressive conditional heteroskedasticity with estimates of variance of united kingdom inflation. *Econometrica*, *50*, 987–1007.
Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*, 3–56.
Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *Journal of Finance*, *51*, 55–84.
Fostel, A., & Geanakoplos, J. (2012). Why does bad news increase volatility and decrease leverage? *Journal of Economic Theory*, *147*, 501–525.
Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics*, *91*, 24–37.
Garcia-Vega, M., Guariglia, A., & Spaliara, M. E. (2012). Volatility, financial constraints, and trade. *International Review of Economics and Finance*, *21*, 57–76.
Gray, S. F. (1996). Modeling the conditional distribution of interest rates as a regime-switching process. *Journal of Financial Economics*, *42*, 27–62.
Guo, F., Chen, C. R., & Huang, Y. S. (2011). Markets contagion during financial crisis: A regime-switching approach. *International Review of Economics and Finance*, *20*, 95–109.
Haas, M., Mittnik, S., & Paolella, M. S. (2004). A new approach to Markov-switching garch models. *Journal of Financial Econometrics*, *2*, 493–530.
Hafez, P. A. (2009). *Impact of news sentiment on abnormal stock returns.* RavenPack White Paper.
Hamilton, J. D. (1988). Rational-expectations econometric analysis of changes in regime: An investigation of the term structure of interest rates. *Journal of Economic Dynamics and Control*, *12*, 385–423.
Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica*, *57*, 357–384.
Hamilton, J. D. (1994). *Time series analysis.* Princeton: Princeton University Press.
Hamilton, J. D., & Susmel, R. (1994). Autoregressive conditional heteroskedasticity and changes in regime. *Journal of Econometrics*, *64*, 307–333.
Hammoudeh, S., Yuan, Y., Chiang, T., & Nandha, M. (2010). Symmetric and asymmetric us sector return volatilities in presence of oil, financial and economic risks. *Energy Policy*, *38*, 3922–3932.
Harju, K., & Hussain, S. M. (2011). Intraday seasonalities and macroeconomic news announcements. *European Financial Management*, *17*, 367–390.
Harris, L. (1986). A transaction data study of weekly and intradaily patterns in stock returns. *Journal of Financial Economics*, *16*, 99–117.
Harris, L. (1987). Transaction data tests of the mixture of distributions hypothesis. *Journal of Financial and Quantitative Analysis*, *22*, 127–141.
Ho, K. Y., Shi, Y., & Zhang, Z. (2013). How does news sentiment impact asset volatility? evidence from long memory and regime-switching approaches. *North American Journal of Economics and Finance*, *26*, 436–456.
Jones, C. M., Lamont, O., & Lumsdaine, R. L. (1998). Macroeconomic news and bond market volatility. *Journal of Financial Economics*, *47*, 315–337.
Kalev, P. S., & Duong, H. N. (2011). Firm-specific news arrival and the volatility of intraday stock index and future returns. In G. Mitra, & L. Mitra (Eds.), *The Handbook of News Analytics in Finance* (pp. 271–286). United Kingdom: Wiley.
Kalev, P. S., Liu, W. M., Pham, P. K., & Jarnecic, E. (2004). Public information arrival and volatility of intraday stock returns. *Journal of Banking & Finance*, *28*, 1441–1467.
Klaassen, F. (2002). Improving garch volatility forecasts with regime-switching garch. *Empirical Economics*, *27*, 363–394.
Kolata, G. (1998). Hope in lab: A special report: A cautious awe greets drugs that eradicate tumors in mice. *New York Times*, *1998*.
Laakkonen, H., & Lanne, M. (2009). Asymmetric news effects on volatility: Good vs. bad news in good vs. bad times. *Studies in Nonlinear Dynamics & Econometrics*, *14*, 1–38.
Lamoureux, C. G., & Lastrapes, W. D. (1990). Heteroskedasticity in stock return data: Volume versus garch effects. *Journal of Finance*, *45*, 221–229.

Leinweber, D., & Sisk, J. (2011). Relating news analytics to stock returns. In G. Mitra, & L. Mitra (Eds.), *The Handbook of News Analytics in Finance* (pp. 149–171). United Kingdom: Wiley.

Lin, G. (1998). *Nesting regime-switching garch models and stock market volatility, returns and the business cycle.* (PhD dissertation) University of California.

Marcucci, J. (2005). Forecasting stock market volatility with regime-switching garch models. *Studies in Nonlinear Dynamics & Econometrics*, *9*.

Mitra, G., & Mitra, L. (2011). *The handbook of news analytics in finance. Vol. 596*, United Kingdom: Wiley.

Moniz, A., Brar, G., Davies, C., & Strudwick, A. (2011). The impact of news flow on asset returns: An empirical study. In G. Mitra, & L. Mitra (Eds.), *The Handbook of News Analytics in Finance* (pp. 211–228). United Kingdom: Wiley.

Mullen, K., Ardia, D., Gil, D., Windover, D., & Cline, J. (2011). Deoptim: An r package for global optimization by differential evolution. *Journal of Statistical Software*, *40*, 1–26.

Park, B. J. (2010). Surprising information, the mdh, and the relationship between volatility and trading volume. *Journal of Financial Markets*, *13*, 344–366.

Reher, G., & Wilfling, B. (2015). A nesting framework for Markov-switching garch modelling with an application to the german stock market. *Quantitative Finance*, *1–16*.

Sharma, S. S., Narayan, P. K., & Zheng, X. (2014). An analysis of firm and market volatility. *Economic Systems*, *38*, 205–220.

Smith, L. V., & Yamagata, T. (2011). Firm level return–volatility analysis using dynamic panels. *Journal of Empirical Finance*, *18*, 847–867.

Susmel, R., & Engle, R. F. (1994). Hourly volatility spillovers between international equity markets. *Journal of International Money and Finance*, *13*, 3–25.

Tauchen, G. E., & Pitts, M. (1983). The price variability-volume relationship on speculative markets. *Econometrica*, *51*, 485–505.

Veronesi, P. (1999). Stock market overreactions to bad news in good times: A rational expectations equilibrium model. *Review of Financial Studies*, *12*, 975–1007.