Big Data Analysis of Volatility Spillovers of Brands across Social Media and Stock Market Performance

Myrthe van Dieijen*, Abhishek Borah*, Gerard Tellis, Philip Hans Franses

Myrthe van Dieijen is a Doctoral Student, Department of Econometrics, Erasmus School of Economics (ESE), Erasmus University, Rotterdam, Netherlands. Tel: +31 10 4088945, E-mail: vandieijen@ese.eur.nl

Abhishek Borah is Assistant Professor of Marketing at INSEAD. INSEAD Boulevard de Constance, 77305 Fontainebleau, France, E-mail: abhishek.borah@insead.edu

Gerard J. Tellis is Professor of Marketing and Management & Organization, Director of the Center for Global Innovation and Neely Chair of American Enterprise at the Marshall School of Business, University of Southern California. Address: P.O. Box 90089-1421, Los Angeles, California, USA. Tel: +1.213.740.5031, fax: +1.213.740.7828, E-mail: tellis@usc.edu.

Philip Hans Franses is a Professor of applied econometrics and a Professor of marketing research at the Erasmus School of Economics (ESE), Erasmus University, Rotterdam, Netherlands. Tinbergen Building H11-34, Burgemeester Oudlaan 50, 3062 PA Rotterdam, Netherlands. Email: franses@ese.eur.nl

*The two authors contributed equally

Abstract

Volatility is an important metric of financial performance, indicating uncertainty or risk. So, predicting and managing volatility is of interest to both company managers and investors. This study investigates whether volatility in user-generated content (UGC) can spill over to volatility in stock returns and vice versa. Sources for user-generated content include tweets, blog posts, and Google searches. The authors test the presence of these spillover effects by a multivariate GARCH model. Further, the authors use multivariate regressions to reveal which type of company-related events increase volatility in user-generated content.

Results for two studies in different markets show significant volatility spillovers between the growth rates of user-generated content and stock returns. Further, specific marketing events drive the volatility in user-generated content. In particular, new product launches significantly increase the volatility in the growth rates of user-generated content, which in turn can spill over to volatility in stock returns. Moreover, the spillover effects differ in sign depending on the valence of the user-generated content in Twitter. The authors discuss the managerial implications.

Keywords: user-generated content, stock market performance, volatility, multivariate GARCH model, spillover effects, natural language processing.

Introduction

In September 2014, Apple released a highly anticipated new version of the iPhone. Soon after the release of the product, a consumer complained online that his iPhone got bent when he carried the iPhone tightly in his front pants' pocket for just a couple of hours. The complaint spread quickly through social media and technology blogs. Once it went viral, this design issue with the iPhone was dubbed as '*Bendgate*'. Immediately after this episode, Apple's stock price took a hit of approximately 3 percent, amounting to a drop in market value of 23 billion US Dollars.[1] The company tried to refute the complaints by stating that the product had undergone excessive testing procedures and that the total number of complaints was very small, but they were not able to stop the online storm of posts. The stock started to recover a bit, but up until mid-October 2014, the stock price experienced substantial fluctuations. These rapid changes in price in Apple's stock price reflected uncertainty about the value of the company largely driven by the 'Bendgate' controversy.

A measure such as stock price volatility captures uncertainty about a company's value. Firms are concerned about uncertainty because it could make it difficult for firms to raise capital or funding, attract talent, or collaborate with partners and distributors. Thus, in general, managers desire to minimize volatility in stock prices unless price trends up. Apart from managers, equity investors are also concerned with volatility, as it is often used as a proxy for financial risk (Franses and Van Dijk 2000). Indeed, during volatile periods, an external event can increase nervousness amongst traders, which could lead to big price drops. Thus, volatility in stock prices merits study, especially as it relates to marketing events such as new product introductions and consumer chatter about brands.

George Day mentions (2011) that the outside-in perspective focuses on market anticipation and adaptation (sensitivity to marketplace changes, customer engaging and partner-linking). There have been turbulent changes in the business landscape and managers now have to be mindful of how consumers perceive their firms. Indeed, UGC is one of the primary ways consumers connect with firms and firms can promote their products and services and subsequently extract value using UGC. In this increasingly open and complex market environment (Day 1994, 2011; Day and Moorman, 2010;

[1] Additional factors (a software glitch and iCloud security issues) may have contributed to this drop in market value as well.

Moorman and Day, 2016; Mu, 2015, Mu et al. 2018), UGC provides firms another tool to diagnose how consumers perceive their firms. Prior research has made strong and substantive attempts to understand how user-generated content affects firm performance in the form of sales and stock returns.

This study relates user-generated content to stock market volatility, a metric that has been scarcely studied in past research. User-generated content can be interpreted as a reflection of consumer sentiment (Bollen, Mao and Zeng 2011). It has been used to predict sales (Liu 2006, Chevalier and Mayzlin 2006, Duan, Gu and Whinston 2008, Moe and Trusov 2011, Onishi and Manchanda 2012, Gopinath, Thomas and Krishnamurthi 2014), media ratings (Godes and Mayzlin 2004), stock returns (Luo 2007, Tirunillai and Tellis 2012), and stock prices (Bollen et al. 2011, Luo 2009). This study contributes to the existing literature by investigating the relation between user-generated content and stock market volatility.

To model volatility, we adopt the (G)ARCH model, an acronym for the (Generalized) Autoregressive Conditional Heteroscedasticity model, which was pioneered by Robert Engle (Engle 1982). The G(ARCH) model assumes that volatility is a latent variable that can be estimated jointly with the model parameters. As we have more than one variable of interest, we estimate volatility spillover effects with the use of a multivariate GARCH model to incorporate multivariate high frequency data (Engle and Kroner 1995, Franses and Van Dijk 2000, Bauwens, Laurent and Rombouts 2006). We also investigate causality in these spillovers by means of a Granger causality in volatility test. No prior paper in marketing has either used a multivariate GARCH model or tested for Granger causality in volatilities.

In general, while modelling volatility, it is also important to explain its causes. Thus, this study examines two potential marketing related sources of volatility: user-generated content and marketing actions such as new product introductions, client announcements, business expansions, and product announcements. This paper explores the relative spillovers in volatility among these variables, the size of the effects, and the direction of causality.

Specifically, the goal of this study is to answer the following research questions:

1. Are there volatility spillovers between user-generated content and stock returns?
2. Do these spillovers differ depending on the type and valence of user-generated content?

3. What company-related events influence the volatility in user-generated content and what is the direction of effects?

We test the presence of volatility spillovers in two separate studies. The first study uses daily data on Apple's iPhone, from January 3, 2007 until March 30, 2010 (1183 days). As the effect of user-generated content can differ based on the platform (Schweidel and Moe 2014), we use user-generated content from a variety of online platforms.

In the first study the measures for user-generated content are: tweets and blog posts concerning the iPhone, and the daily search volume for the ticker symbol of Apple (AAPL) in Google. Moreover, because positive and negative user-generated content can have a different impact on firm performance (Luo 2007, Tirunillai and Tellis 2012), we use natural language processing techniques to classify positive and negative tweets about the iPhone. Apple markets one of the most popular consumer goods, i.e., the iPhone, is one of the most valued companies, and is highly discussed online. Thus, the firm is a good candidate for studying the relationship between UGC and stock market volatility. However, for the purpose of generalization, we perform a second study using a different industry.

The second study focuses on the airline industry, as both airlines and their customers are very active on social media. We use daily data on Delta, JetBlue, Southwest, and United airlines, from July 1, 2013 until June 30, 2014 (365 days). The source of our user-generated content is Twitter. Twitter is widely used by customers to post comments in the airline industry. The two studies provide an illustration of the method of studying volatility among stock prices, user-generated content, and marketing actions.

The results of the multivariate GARCH model confirm the presence of volatility spillovers between user-generated content and stock returns. We also find that volatility in the growth rates of user-generated content Granger causes volatility in stock returns. Further, marketing activities Granger cause volatility in user-generated content. In particular, new product launches have the biggest impact on volatility in user-generated content.

The results can be useful to managers. Knowing how specific volatility spillovers work can help managers deal with the company's user-generated content and influence consumer chatter in the desired direction. For example, quick replies to misunderstood messages may prevent a cascade of negative news. As such, managing consumer responses can be an important marketing instrument that has a strong link with financial performance. Moreover, once managers know which type of company-related events have the largest impact on the volatility in user-generated content, they can make informed decisions regarding the timing of certain events. For example, when a company wants to raise capital, it would be best to keep the volatility level of their stock low in order to signal stability. As certain marketing events can have a large impact on the volatility in user-generated content, which in turn can spill over to stock returns, managers can decide to postpone these type of events. Hence, knowing how volatility spillovers work and what the cause is, can help managers to stabilize the value of their company at the right time.

The rest of the paper is organized as follows. The second section presents a review of the literature and the third section explains the method and presents a preliminary analysis of various statistics. The fourth section explains the models. The fifth section describes the results. The paper ends with the discussion and some concluding remarks in section six.

Contribution to Literature

This section describes the contribution of this research to the literature on the influence of user-generated content on companies' performance. In addition, it provides a brief introduction to volatility estimation using GARCH models, and multivariate GARCH model to study volatility spillover effects.

The Influence of User-Generated Content on Companies' Performance

User-generated content is a reflection of consumer sentiment and can serve as a leading indicator of companies' financial performance. Prior research has shown that online chatter in blogs, reviews, and forums affects sales (Chevalier and Mayzlin 2006, Liu 2006, Dellarocas et al. 2007, Chintagunta et al. 2010, Trusov et al. 2009, Sonnier et al. 2011, Moe and Trusov 2011, Gopinath et al. 2014). Recently, three papers demonstrate the usefulness of Twitter to forecast movie revenues (Asur and Huberman 2010, Rui et al. 2013, Hennig-Thurau et al. 2014). But these authors do not examine the effects of online chatter on the stock market. We focus on stock market performance because it is of utmost importance to firms, is widely available at a disaggregate level, and reflects the consensus forecast of millions of investors about the financial health of a firm (Srinivasan and Hanssens 2009).

Several papers in marketing have explored the effects of traditional marketing variables such as advertising, distribution channel, product innovation, etc. on stock market returns (See Srinivasan and Hanssens 2009 for a thorough review). As investors continuously look for any novel information about the firm, marketing researchers have found that online chatter, which is daily, temporally disaggregate, and passionate, indeed affects stock prices (Luo 2009, McAlister et al. 2012, Tirunillai and Tellis 2012, Luo, Zhang, and Duan 2013, Nam and Kannan 2014). However, none of them examine the effect of Twitter and other user generated content on stock volatility.

Volatility is an important metric to consider because of the following reasons: First, in financial markets volatility is the canonical measure for uncertainty (Bloom 2009). Stock-market volatility has been previously used as a proxy for uncertainty at the firm level (e.g., Leahy and Whited 1996; Bloom, Bond, and Van Reenen 2007). For example, Bloom, Bond, and Van Reenen (2007) have shown that volatility is significantly correlated with a range of alternative uncertainty proxies, including real sales growth volatility and the cross-sectional distribution of financial analysts' forecasts. Thus, measuring volatility at the firm level provides a gauge of the uncertainty about a firm's prospects.

Second, volatility enables measuring risk for a firm in the stock market. In general, the higher the volatility, the riskier is the security. Investors might be wary of a security whose prices can change dramatically over a short time period in either direction and in general stock returns do not consider the range of possible values that a stock might take. Two stocks with different volatilities may have the same return. For example, a lower volatility stock may have an expected (average) return of 5%, with annual volatility of 5%. This would indicate returns from approximately negative 5% to positive 15% most of the time (19 times out of 20, or 95% via a two standard deviation rule). A higher volatility stock, with the same expected return of 5% but with annual volatility of 20%, would indicate returns from approximately negative 35% to positive 45% most of the time (19 times out of 20, or 95%).

Third, figuring out the range of likely outcomes for any future event is typically easier than predicting the event's actual outcome. One can use volatility to anticipate the most probable range of outcomes for a future event and to estimate the likelihood of outliers. The first type of analysis allows for making effective plans, while the second is the basis of proper contingency planning. Indeed, it is hard to predict what a stock's actual return will be tomorrow, even harder on a given day a few weeks from now. However, that stock's return will tend to be within a range that is consistent with the volatility exhibited over the past few months. Fourth, volatility is typically unobservable compared to stock returns. We use a model that enables us to estimate volatility.

Despite the size, regularity, and importance of volatility, there has been no prior research that has evaluated the effect of user generated content on stock market volatility. This is surprising given the literature on the impact of user generated content on stock performance. This is why we pose our research questions on the impact of user generated content, since these typically have both a first- and a second-moment component.

This study goes beyond prior studies in studying the relationship between marketing variables and stock market performance in 3 ways (see Table 1 for a review of prior papers examining effects on stock returns and online chatter's impact on firm performance). First, it analyses the effect of user-generated content on stock market volatility. Second, it contrasts the effect of different types of user-generated content such as Twitter versus Google Search versus Blogs on stock market volatility. Third, it analyses if firm announcements affect volatility in user-generated content.

Overall, using the outside-in perspective (Mu et al. 2018; Day 2011), we contribute to the literature by understanding how engaging in an outside-in perspective, i.e., by listening in social media can enable firms to gain a competitive advantage. Precisely, we show how user-generated content (UGC) can have effects on the second moment, i.e., firm's volatility in stock returns, which has been scarcely studied in prior research, and how UGC in different social media can affect firm's volatility. Moreover, we find that firms can affect stock market volatility by strategically making firm announcements.

Estimation of Volatility Using GARCH Models

We use the Generalized Autoregressive Conditional Heteroskedastic (GARCH) model to study the relationships between user-generated content and stock market volatility. As volatility is considered a strong proxy of risk, obtaining accurate estimates and forecasts of volatility has become an integral part of various financial topics, such as asset pricing, portfolio optimization, risk management, and option trading. Similar to stock prices, volatility varies over time, but unlike stock prices, volatility is not directly observable (Andersen and Bollerslev 1998a). Moreover, we often see periods of high and low volatility ('volatility clusters'), which is referred to as heteroscedasticity in volatility.

In general, many different models exist to model daily volatility. We can split these models in two categories (Andersen, Bollerslev and Diebold 2010). The first category of models estimates volatility using high-frequency data. In these models, the focus is on measuring *ex-post realized volatility* on a discrete time interval (e.g., day, week). The second category of models treats volatility as a latent variable and focusses on estimating *ex-ante expected volatility* as a point-in-time (instantaneous) measure. Because of the nature of our research design and data, we use the second category of models. We choose one of the most widely used models: the Generalized Autoregressive Conditional Heteroskedastic model (GARCH) model. GARCH models generate the type of variance clustering evident in financial data, but with the variance as a closed form of the data, so it can be forecasted out-of-sample (Engle 2001).

According to the GARCH specification, the error term of a time series regression (such as $y_t = E[y_t|\Omega_{t-1}] + \varepsilon_t$), has a time-varying conditional variance.[2] That is, $E[\varepsilon_t^2|\Omega_{t-1}] = h_t$, for some non-negative function $h_t \equiv h_t(\Omega_{t-1})$, which means that ε_t is conditionally heteroscedastic (Franses and Van Dijk 2000). Hence, ε_t can be represented as: $\varepsilon_t = \sqrt{h_t} z_t$, where the variable z_t can be assumed to follow a standard normal distribution (Engle 2001, Franses and Van Dijk 2000) and h_t is the conditional volatility. Various types of GARCH models can specify how volatility varies over time (Franses and Van Dijk 2000). The most widely used GARCH specification is the GARCH (1,1) process, where the current volatility depends upon the squared error terms from the previous period and the volatility from the previous period: $h_t = \varpi + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}$. A wide range of other GARCH models exists in order to estimate volatility as a proxy of risk (Christoffersen and Jacobs 2004). Bollerslev et al. (1992) provide a review of the theory and empirical evidence. The GARCH(1,1) model, however, is most often used in practice and the one we adopt.

[2] In our paper the time series regression is a Vector AutoRegressive (1) model.

Multivariate GARCH to Study Spillover Effects

The volatility of an individual stock is clearly influenced by the volatility of the market as a whole, which is implied by the structure of the Capital Asset Pricing Model (Engle 2001, Fama and French 2004). Another interesting phenomenon is the possibility that the volatility of an asset might not only influence the amplitude of returns, but also the volatility of other assets as well. We can compare this phenomenon to volatility 'spilling over' from one asset to another and refer to it as 'volatility spillover effects'. This can be studied using multivariate models, to investigate the (cross) influence of past volatility on current volatility (Engle and Kroner 1995, Bauwens et al. 2006). The globalization of international financial markets has sparked a surge in the literature concerning volatility spillovers among different financial markets, for instance among Asian stock markets (Joshi 2011), among Eastern European markets (Li and Majerowska 2008) and among developed and emerging markets (Worthington and Higgs 2004). In these scenarios, a Multivariate GARCH model is used, because it takes the time-varying nature of conditional volatility and correlation of stock markets into account. Furthermore, with the Multivariate GARCH model, future stock return volatility can be predicted conditional on past volatilities (Bollerslev 1992, Worthington and Higgs 2004). Apart from stock markets, the multivariate GARCH model has been applied to examine the cross country mean and volatility spillover effects of food prices (Alom, Ward and Hu 2011) and of exchange rates (Hafner and Herwartz 2006). We use the Multivariate GARCH model to estimate volatility spillover effects. As per our knowledge, this is the first paper in marketing to use the multivariate GARCH model to study volatility spillovers across user-generated content and stock markets.

Method

This section describes the rationale for the two studies of this paper, the data collection, the estimation framework, and the models.

Rationale for the Two Studies of this Paper

The purpose of this paper is to investigate whether volatility in user-generated content spills over to volatility in stock returns and vice versa. We estimate the spillover effects and test for Granger causality in volatility in two separate studies. Our two studies complement each other. In one study, we focus on one brand over a long time series of daily data spanning 4 years. In this study, we create metrics such as positive and negative sentiment in Twitter and collect Google Search and blog data. Because we focus on one brand in the first study and the results may not be generalizable, in the second study, we collect data for 4 airline brands spanning one year of data. Thus, one study gives breadth in the time series and while the other study gives breadth in the cross-section.

In the first study, we use data focusing on Apple's iPhone brand. Apart from estimating the spillover effects, we also investigate which type of company-related events lead to volatility in user-generated content, in order to detect the origin of the spillovers. In the second study, we use data from 4 airlines: Delta, JetBlue, Southwest and United Airlines.

Data Collection

This subsection describes the data collection for study 1 and study 2.

Study 1

We describe the data collection of the metrics: stock returns, user-generated content and company-related events. Moreover, we present a preliminary analysis of the data.

Metrics: Stock returns, user-generated content, and company-related events

We use daily data (excluding weekends and holidays) on user-generated content and stock market performance from January 3, 2007 until March 30, 2010, which total up to 816 observations. We use daily data for three specific reasons. First, using lower frequency data (weekly or monthly) might lead to biased estimates (Tellis and Franses 2006). Second, low frequency data can conceal temporary reactions to unforeseen events that last for only a few days (Elyasiani, Perera and Puri 1998). Third, we don't use data at a higher frequency level (such as hourly) than daily, because data is very sparse at that frequency. GARCH models require ample data and variation in the data at any chosen periodicity.

A list of all the variables used in the studies and their description is in Table 2. The stock returns are the daily normal returns based on Apple's stock price. The metrics of user-generated content are the volume of positive tweets, the volume of negative tweets, the volume of blog posts, and the volume of Google searches for Apple's ticker symbol (henceforth Google ticker search). We classify positive and negative tweets using the Support Vector Machine algorithm. The details of the Support Vector

Machine algorithm is in Appendix A. We collect the number of daily blog posts via Newstex, which enabled us to select blogs from news organizations, corporations, independent experts and thought leaders. We obtain the daily volume of Google ticker search via Google trends. Google normalizes and scales the actual search volume of the keyword – in this case the ticker symbol AAPL – to remove regional effects and to hide the actual search volume of the keyword in the Google search engine.

Table 3 displays the summary statistics of Apple's stock returns and the user-generated content variables. The average number of positive and negative tweets are very high, much higher than the average number of blog posts, which could be explained by both the popularity of Twitter and the fact that microblogs are less time-consuming to post than regular blogs. The average number of Google searches appear low because of the normalization procedure of Google. All variables have high standard deviations, skewness, and kurtosis. Thus, according to the Jarque-Bera test statistics, all the time series are not normally distributed.

Figure 1 displays the graphs of Apple's stock returns and the user-generated content data series. The graphs of the user-generated content variables on the left column of Figure 1 (1b-1e) display the actual number of tweets, blog posts and Google ticker searches. As tweeting and blogging have increased in popularity over the years of the sample, we see a huge rise in these series. As for Google ticker search, we see spikes on some specific dates. One such specific date for example is January 27th, 2010. On that day, Steve Jobs introduced the iPad, during a special product event. The number of positive tweets, negative tweets, blog posts and Google search tickers reached a maximum on that day. We also see some seasonality in the time series; on Tuesdays (and sometimes on Wednesdays as well) where the number of tweets, blog posts, and Google search tickers are somewhat larger than on the other days of the week.

For our analysis, we will use the first differences of the natural-logarithm transformed user-generated content variables, to remove the trend and get a stationary time series. The graphs of these log differences of the time series are displayed in the right column of Figure 1 (1f-1i). From now on we will refer to the log differences of the user-generated content variables as the "growth rates of user-generated content".

In order to test the stationarity conditions, the Augmented Dickey-Fuller (ADF) test is applied to the growth rates of user-generated content. The results in Table 4 show that all the time series of the growth rates are stationary.

Over the same time period, we collect data on the new product launches and organizational events of Apple. The new product launches and organizational events are obtained from Capital IQ's key developments database. For new product launches, we read each entry under the type of "Product-Related Announcements" within the Key Developments feature of Capital IQ to ascertain a new product announcement. We do this because "Product-Related Announcements" could include patent applications, product demonstration, etc. Organizational events are all events, which are not new product launches or financial events (announcements of earnings, dividends, etc.), such as mergers and acquisitions, product announcements, downsizings, client announcements, lawsuits and legal issues, executive changes, business expansions and strategic alliances.

Figure 2 displays the graphs of Apple's new product launches (2a) and various organizational events related to the company (2b-2i). There have been many new product launches from 2007 to 2010, on some days even up to 5. For instance on October 20th 2009, when Apple unveiled the new iMac, it also unveiled the Magic Mouse and made several updates on the MacBook. The graphs of the organizational events show quite a few business expansions and product and client announcements. Furthermore, there have been many lawsuits and legal issues, which is not surprising for a company like Apple. Downsizings and strategic alliances both occurred only twice in our sample period. Executive changes and mergers and acquisitions were more common in the later years of our sample period.

Preliminary analysis

Squared returns can be used as proxy for the volatility in returns (Alexander, 2008). Similarly, squaring the growth rates of a user-generated content series, allows one to get a proxy for the volatility of that series. These proxies give a noisy estimate of the volatility, but we can use them to get some preliminary insights into the relationship between the time series' of interest. Table 5 displays the correlation between the (squared) returns and (squared) user-generated content growth rates. The largest correlation between returns and a user-generated content growth rate time series is between Google ticker search and returns (0.07). Returns are positively correlated with the growth rates of positive tweets, but negatively correlated to the growth rates of negative tweets. The correlation between the volatility proxies in almost all combinations is larger than the correlation between the non-squared time series (please see lower panel of Table 5). The volatility of returns is positively correlated with all volatilities of the user-generated content growth rates, especially with the volatility of blog posts (0.10) and Google Ticker Search (0.19).

Apart from studying the correlation between the (squared) variables estimated over the entire sample, we plotted the correlation over a moving window of 10 days, as displayed in Figure 3 (3a-3h). These graphs show that the correlation is time-varying. Given the strong signs of volatility clustering and the time-varying nature of the correlation between the (volatility) of the time series, we investigate the relation between the growth rates of user-generated content and returns further using the multivariate GARCH model, which can handle these types of dynamics.

Study 2

We describe the data collection of the metrics for Study 2: stock returns and user-generated content.

Metrics: Stock returns and user-generated content

This second study uses data on four different airlines: Delta Airlines, JetBlue Airlines, Southwest Airlines and United Airlines. We use daily data on user-generated content and stock market performance from July 1, 2013 until June 30, 2014 (excluding weekends and holidays), which total 255 observations. For user-generated content data we use three Twitter metrics: Retweets, Replies, and Favorites. These metrics are collected through Twitter's Application Programming Interface (API). A description of the variables is given in Table 6 and the summary statistics are displayed in Table 7. We take the log differences of the user-generated content variables and all these log difference series are stationary, as confirmed by the results of the ADF test shown in Table 8. Note that we do not collect firm announcements for this study as the primary reason for this study is for robustness.

Estimation Framework for Studying Spillover Effects

Figure 4 displays the structure for how we empirically study spillover effects between user-generated content and stock returns. We measure both stock prices and user-generated content in terms of their growth rates and the volatility of these growth rates. First, we investigate the mean spillover effects between the growth rates in the volume of user-generated content and the growth rates in stock prices (i.e., stock returns) (see Label 1 in Figure 4, the two-pointed arrow indicates that these spillovers can be bidirectional). We estimate these mean spillovers by means of a VAR model, which delivers the ε_t. This is the error term which is needed to estimate h_t, the conditional volatility. From this model we compute the volatility of the growth rates in the volume of user-generated content and stock returns (see the two dotted arrows with Label 2 in Figure 4). Second, we estimate the volatility spillovers between the volatility of the growth rates of the volume of user-generated content and the volatility of stock returns (see Label 3 in Figure 4). We use a Multivariate GARCH BEKK model to estimate these volatility spillovers. We test for Granger causality in volatility in order to investigate whether the volatility spillovers are Granger casual from user-generated content to stock returns. Third, we explore the degree to which the volatility of the growth rates of the volume of user-generated content varies due to company-related events, such as new product launches, lawsuits or mergers (see Label 4 in Figure 4). We use a Multivariate regression analysis to study this relationship. Hence, the three bold arrows in Figure 4 highlight the models we use in this paper: Label 1 refers to the VAR model, Label 3 refers to the Multivariate GARCH BEKK model and Label 4 refers to the Multivariate regression.

Models

This subsection provides the specification of the Multivariate GARCH BEKK (Baba, Engle, Kraft and Kroner) model, the Granger causality in volatility test, and the Multivariate regression.

Multivariate GARCH BEKK Model

To investigate the direct relation between stock returns and user-generated content we use a VAR (1) model[3]. The specification of this conditional mean model is:

$$Y_t = \boldsymbol{\alpha} + \boldsymbol{\Gamma} Y_{t-1} + \boldsymbol{\varepsilon}_t \tag{1}$$

where Y_t and Y_{t-1} are K by 1 vectors, which contain K number of variables at time *t* and *t-1* respectively. The vector $\boldsymbol{\alpha}$ represents a K by 1 vector of constants and $\boldsymbol{\Gamma}$ is a K by K matrix for parameters associated

[3] The lag length in the VAR model is determined using the Schwarz Information Criterion.

with the lagged variables. In Study 1, the K variables are Returns, Positive Tweets, Negative Tweets, Blog Posts, and Google Ticker Search, (i.e., $K = 5$). In Study 2, the K variables are Returns, Retweets, Replies, and Favorites (i.e., $K = 4$). The diagonal elements of the matrix $\mathbf{\Gamma}$, γ_{ij}, measure the own lagged mean spillover effects. The off-diagonal elements capture the cross mean spillover effects between the variables. In the results section we report the estimated parameters in $\mathbf{\Gamma}$, but our main interest lies in the GARCH model for $\boldsymbol{\varepsilon}_t$. The K by 1 vector of random error, $\boldsymbol{\varepsilon}_t$, is the innovation for all K variables at time *t* and a general multivariate GARCH model for this K-dimensional process $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}, \dots, \varepsilon_{Kt})'$ is given by:

$$\boldsymbol{\varepsilon}_t = \boldsymbol{z}_t \boldsymbol{H}_t^{1/2} \tag{2}$$

where $\boldsymbol{z}_t$ is a K-dimensional independent and identically distributed (i. i. d.) process with mean zero and covariance matrix equal to the identity matrix $\boldsymbol{I}_n$. From these properties of $\boldsymbol{z}_t$ and Equation 2, it follows that $E[\boldsymbol{\varepsilon}_t|\Omega_{t-1}] = \mathbf{0}$ and $E[\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'|\Omega_{t-1}] = \boldsymbol{H}_t$, where Ω_{t-1} represents the market information available at time *t*-1. To complete the model, a parameterization for the K by K conditional variance-covariance matrix $\boldsymbol{H}_t$ needs to be specified ($\boldsymbol{H}_t = f(\boldsymbol{H}_{t-1}, \boldsymbol{H}_{t-2}, \dots, \boldsymbol{\varepsilon}_{t-1}, \boldsymbol{\varepsilon}_{t-2}, \dots)$) (Franses and Van Dijk 2000). The parameterization we choose is the multivariate GARCH BEKK (Baba, Engle, Kraft and Kroner) model.[4] With this type of multivariate GARCH model, combined with the VAR(1) model, we investigate the relation between the volatility of the growth rates of the volume of user-generated content and the volatility of stock returns. The BEKK representation of the matrix $\boldsymbol{H}_t$ is:

$$\boldsymbol{H}_t = \boldsymbol{C}\boldsymbol{C}' + \boldsymbol{A}\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}'\boldsymbol{A}' + \boldsymbol{B}\boldsymbol{H}_{t-1}\boldsymbol{B}' \tag{3}$$

[4] To investigate spillovers and Granger causality in volatility, the multivariate GARCH BEKK model is more suitable than other multivariate GARCH models such as the VECH model (which has too many parameters and needs constraints to ensure positive definiteness), the Diagonal BEKK and VECH model (which can only measure ARCH and GARCH effects; we would not be able to estimate Granger causality in volatility), the Constant Correlation model (which assumes that the covariances are generated with a constant - but unknown - correlation, which is too restrictive for our analysis), the Dynamic Correlation model (which applies the unrealistic assumption that all entries in the conditional correlation matrix are influenced by the same coefficients) and the factor model (which has the common factors size (SMB), market-to-book (HML) or momentum, which are not applicable to our data). We recognize that using 'model-free' realized volatility measures to study spillover effects would have been a possibility as well, but those estimates of volatility are much noisier than the estimates of the multivariate GARCH BEKK model. The advantage of the guaranteed positive definiteness of $\boldsymbol{H}_t$, the fact that all cross-spillovers are estimated and that Granger causality in volatility can be tested by means of the Wald test, have contributed to our decision to use the BEKK representation opposed to other multivariate GARCH representations.

where $\boldsymbol{A}$ and $\boldsymbol{B}$ are K by K matrices and $\boldsymbol{C}$ is a lower triangular matrix of constants. This formulation is referred to as the Baba, Engle, Kraft and Kroner (BEKK) representation (Engle and Kroner 1995). As the second and third term on the right-hand-side of equation 3 are expressed as quadratic forms, $\boldsymbol{H}_t$ is guaranteed to be positive definite without the need for imposing constraints on the parameter matrices $\boldsymbol{A}$ and $\boldsymbol{B}$. The elements of the matrix $\boldsymbol{A}$ measure the degree of lagged and cross innovation ('shocks') from one variable to the other. We refer to these effects as shock spillover effects and these have our focal interest, as they represent the effect of shocks (i.e., unpredictable information) on the volatility. The diagonal elements in matrix $\boldsymbol{A}$ represent the ARCH effect (the effect of lagged shocks) and the off-diagonal elements represent the cross-spillover effects. Negative coefficients in the off-diagonals of matrix $\boldsymbol{A}$ mean that the volatility is affected more when the shocks move in opposite directions than when they move in the same direction. The elements of the matrix $\boldsymbol{B}$ measure the spillover of conditional volatility between variables. Hence, we refer to these effects as volatility spillover effects. The diagonal elements in matrix $\boldsymbol{B}$ measure the GARCH effect (the effect of lagged volatility) and the off-diagonal elements measure the cross-volatility spillover effects, which is the effect of volatility in one variable on the volatility in another variable the following day.

The values of the coefficients of matrices $\boldsymbol{A}$ and $\boldsymbol{B}$ in the BEKK representation are sensitive to the scales of the variables, as there is no standardization to a common variance. This causes (relatively) higher variance series to have higher off-diagonal coefficients than lower variance series. Rescaling a variable keeps the diagonals of $\boldsymbol{A}$ and $\boldsymbol{B}$ the same, but forces a change in the scale of the off-diagonals (Doan 2013). As seen in the data section, the scales of the original user-generated content variables vary considerably. However, by taking the log differences we are able to match the scales of the variables.

The parameters in the VAR(1) model and multivariate BEKK model are estimated simultaneously by the Broyden, Fletcher, Goldfarb and Shanno (BFGS) maximum likelihood method (Broyden 1970, Fletcher 1970, Goldfarb 1970, Shanno 1970). The BFGS method is used to solve the nonlinear optimization problem and to produce the maximum likelihood parameter estimates and their corresponding asymptotic standard errors. BFGS estimates the curvature (and therefore the covariance matrix of the parameter estimates) using an update method, which gives a different answer for different initial guess values. A pre-estimation 'simplex' procedure is used before proceeding to the BFGS method. If we start the estimation with the BFGS method, the estimate of the curvature using the guess values can lead to inaccurate moves in the early iterations. Starting the estimation with a pre-estimation simplex procedure before proceeding to the BFGS method eliminates that problem. The first iterations using the simplex procedure move the parameter set off the guess values into what is likely to be the right direction. Thus, we use a pre-estimation simplex procedure.[5] We next use the BFGS method and the values from the simplex procedure as initial values instead of the guess values for obtaining the final estimates (Doan 2013). In order to correct for possible misspecification, we compute Bollerslev-Wooldridge standard errors (Bollerslev and Wooldridge 1992) in our final estimation.

Testing Granger Causality for Volatility

In order to investigate causality within the multivariate GARCH model, between the volatility in stock returns and the volatility in user-generated content, we test for Granger causality using the methods of Hafner and Herwartz (2004). This means that we test certain zero restrictions of the matrices $\boldsymbol{A}$ and $\boldsymbol{B}$ in equation 3 using a Wald statistic, which follows a chi-squared distribution. No prior research in marketing has tested for Granger causality in volatility. Technical details about this test are in the attached Online Appendix.

Multivariate Regression Analysis

As per our empirical framework in Figure 4, we investigate the relation between the volatility in user-generated content and new product launches and organizational events in Study 1 by performing a set of regressions. In each of these regressions, the dependent variable is the estimate of user-generated content volatility (components of the vector $\hat{h}_t$) as obtained from the multivariate GARCH model. The independent variables are dummy variables for new product launches, lawsuits and legal issues, downsizings, executive changes, mergers and acquisitions, strategic alliances, client announcements, business expansions, product announcements and the days of the week. To correct for autocorrelation we include one lag. For example, the regression we estimate for the volatility in the returns of positive tweets is:

[5] 30 iterations are used in the simplex procedure in study 1 and 10 iterations in study 2.

$$
\begin{aligned}
&\hat{h}_{t,positive\_tweets} \\
&\quad = \beta_0 + \beta_1 \hat{h}_{t-1,positive\_tweets} + \beta_2 New\ Product\ Launches_t \\
&\quad + \beta_3 Lawsuits\ \&\ Legal\ Issues_t + \beta_4 Downsizings_t \\
&\quad + \beta_5 Executive\ Changes_t + \beta_6 Mergers\ \&\ Acquisitions_t \\
&\quad + \beta_7 Strategic\ Alliances_t + \beta_8 Client\ Announcements_t \\
&\quad + \beta_9 Business\ Expansions_t + \beta_{10} Product\ Announcements_t \\
&\quad + \beta_{11} Monday_t + \beta_{12} Tuesday_t + \beta_{13} Wednesday_t \\
&\quad + \beta_{14} Thursday_t + e_t
\end{aligned} \tag{4}
$$

Where $\hat{h}_{t,positive\_tweets}$ and $\hat{h}_{t-1,positive\_tweets}$ are the volatility in the returns of positive tweets at time *t* and *t-1* respectively, followed by the dummies for new product launches, organizational events and the days of the week. e_t is the error term. The regressions for the volatility in the returns of negative tweets ($\hat{h}_{t,negative\_tweets}$), blog posts ($\hat{h}_{t,blog\_posts}$) and Google Ticker Search ($\hat{h}_{t,Google\_search\_tickers}$) are equivalent in their specifications to eq. (4) above.

Results

This section describes the results for study 1 and 2.

Study 1 – iPhone

This subsection provides the results of the multivariate GARCH BEKK model and the multivariate regression for Study 1.

Spillover Effects between User-Generated Content and Stock Returns

The estimated coefficients and standard errors for the conditional mean model (i.e., the VAR(1) model) are displayed in Table 9. The diagonal elements ($\gamma_{22}, \gamma_{33}, \gamma_{44}, \gamma_{55}$) of the user-generated content variables show that there are significant own past growth rates, indicating that the current growth rates of the user-generated content variables are dependent upon their own lag. Furthermore, stock returns significantly decrease the future growth rates of both positive and negative tweets, although these mean spillovers are small (-0.0087 and -0.0074, respectively). Only one user-generated content variable has a significant impact on stock returns: the growth rates of the number of Google ticker searches increases future stock returns (0.9147). Furthermore, there are significant mean spillover effects between the various user-generated content variables: growth rates of positive tweets and blog posts both increase the future growth rates of negative tweets (0.1721 and 0.0523, respectively), the growth rates of blog posts and Google ticker searches influence each other positively (0.2001 and 0.0266) and the growth rates of blog posts increase the future growth rates of positive tweets (0.0482).

Table 10 presents the estimated coefficients of the multivariate GARCH model. Matrix $\boldsymbol{A}$ (coefficients $a_{11}, a_{12}, a_{13}, \dots, a_{55}$) shows significant shock spillovers from user-generated content to stock returns: Past shocks in the growth rates of positive tweets decrease future volatility in stock returns (-0.2740), whereas past shocks in the growth rates of negative tweets and blog posts increase the future volatility in stock returns (with 0.2943 and 0.2365, respectively). Furthermore, positive shock spillovers from the growth rates of positive tweets to negative tweets (0.3853) are significant. The diagonal elements (a_{22}, a_{44}, a_{55}) show that there are significant own shock spillovers for the growth rates of positive tweets, blog posts and Google ticker searches.

Matrix $\boldsymbol{B}$ (coefficients $b_{11}, b_{12}, b_{13}, \dots, b_{55}$) show that all variables experience significant own volatility spillover effects: all the diagonal elements of the matrix ($b_{11}, b_{22}, b_{33}, b_{44}, b_{55}$) are significant. Furthermore, there are significant bidirectional volatility spillovers between stock returns and the growth rates of blog posts, showing that past volatility in the growth rates of blog posts decreases future volatility in stock returns (-0.2021), whereas past volatility in stock returns increases future volatility in the growth rates of blog posts (0.0141). The first spillover effect is much larger than the second. Moreover, past volatility in the growth rates of positive tweets leads to a significant decrease (-0.1076) of the future volatility in the growth rates of negative tweets. Inspection of the residuals did not indicate serious misspecification of the model.

All in all, the significant parameters in matrix $\boldsymbol{A}$ and $\boldsymbol{B}$ show that most of the spillover effects are unidirectional and that the size of the effect varies. There are more spillovers from the growth rates of user-generated content volume to stock returns than vice versa, and they are larger. Finally, Table 11 shows that volatility in the growth rates of user-generated content “Granger causes” the volatility in stock returns.

The Effect of Company-Related Events on the Volatility in the Growth Rates of User-Generated Content

Table 12 presents the results of the multivariate egression, where the volatility of the growth rates of the volume of positive tweets is the dependent variable. The results show that Apple's launch of a new product or involvement in a lawsuit or other legal issue has a positive and significant effect on the volatility (0.034 and 0.044, respectively). None of the other organizational events have a significant effect on the volatility of positive tweets. Seasonality is significant with volatility higher on Tuesdays (0.037).

Table 13 presents the results of the second regression with the volatility of the growth rates of the volume of negative tweets as the dependent variable. Consistent with prior results, new product launches of Apple and Apple's lawsuits and legal issues have a significant and positive effect on the volatility of the growth rates of the volume of negative tweets (0.039 and 0.047, respectively). Seasonality is significant as well with the volatility high on Tuesdays (0.086). Thus, new product launches increases volatility of the growth rates for both positive and negative tweets.

Table 14 presents the results of the regression with the volatility of the growth rates of the volume of blog posts as the dependent variable. New product launches have a significant positive impact on the volatility (0.01). None of the other organizational events have a significant effect and neither does seasonality.

Table 15 shows the results of the fourth and final regression, with the volatility of the growth rates of the volume of Google ticker searches as the dependent variable. None of the other organizational events have a significant effect on the volatility. However, seasonality is significant, with the volatility high on Tuesdays (0.005).

Study 2 – Airline Industry

This subsection provides the results of the multivariate GARCH BEKK model for study 2.

Spillover Effects between User-Generated Content and Stock Returns

Table 16 shows the shock and volatility spillovers between returns and the growth rates of the volume of user-generated content for the 4 airlines. The complete output of all the mean, shock, and volatility spillovers among the time series are Table B1 to B8 in Appendix B. These results confirm the presence of significant shock and volatility spillover effects between the growth rates of the volume of user-generated content and stock returns for a different industry. Especially Delta and United airlines exhibit many significant shock and volatility spillovers. Moreover, these results confirm our previous finding that spillovers are larger from the growth rates of the volume of user-generated content to stock returns than vice versa. Table 17 shows that volatility in the growth rates of user-generated content Granger causes the volatility in stock returns.

Discussion

This final section summarizes the main findings from the study, lists the contributions, discusses key issues, draws implications, and lists limitations.

Summary of Findings

The main findings of this study are the following:

- Mean shock and volatility spillovers are significant between the growth rates of the volume of user-generated content and stock returns.
- Spillovers from the growth rates of volume of user-generated content to stock returns are more frequent and larger than vice versa.
- Spillovers differ depending on the valence of user-generated content: Past shocks in the growth rates of positive tweets decrease future volatility in stock returns, whereas past shocks in the growth rates of negative tweets increase future volatility in stock returns.
- New product launches and – to a lesser extent – lawsuits and legal issues increase the volatility in the growth rates of user-generated content.

Contributions

This study makes three main contributions. First, this is the first study to investigate the presence of shock and volatility spillovers between user generated content and stock returns. With volatility being an important proxy of risk in the stock market, influences on the volatility of stocks can present important insights in the fields of asset pricing, portfolio optimization, risk management, and option pricing. The direct relationship between user-generated content and stock market performance has been investigated by Tirunillai and Tellis (2012) and Luo (2007, 2009). Our study adds to this existing literature by not only investigating the direct connection between the growth rates of the volume of user-generated content and returns, but by investigating the link in terms of volatility spillovers as well.

Second, we investigate whether the volatility in the growth rates of the volume of user-generated content is influenced by new product launches or other organizational events regarding the company. Hence, our findings on both the spillovers and the origin of these spillovers contribute to unravelling the dynamics between user-generated content and stock market performance.

Third, as far as we know, ours is the first paper in marketing that utilizes a Multivariate GARCH BEKK model to study volatility. Models such as these can be used to infer many marketing questions especially for metrics related to the second moment, such as volatility. We encourage future researchers to utilize such models.

Overall, UGC is one of the primary ways firms consumers connect with firms. In this increasingly open and complex market environment (Day 1994, 2011; Day and Moorman, 2010; Moorman and Day, 2016; Mu, 2015, Mu et al. 2018), UGC provides firms a means to diagnose how consumers perceive their firms. Prior research has made strong and substantive attempts to understand how UGC affects firm performance in the form of sales and stock returns. We contribute to the literature in outside-in marketing and UGC by understanding how UGC can affect stock market volatility.

Implications

This study has four implications for marketing, PR, investing, and strategy. First, as volatile stocks are risky stocks that reflect instability about a company, it is best to keep volatility low. We show that volatility is Granger caused by user-generated content. So, managers need to monitor and control user-generated content constantly.

Second, this study also investigates the Granger causes of user-generated content. Foremost among these are negative content, which can increase volatility. So, marketing and communication managers need to focus specifically on monitoring and responding to negative user comments. The findings of this study can help them develop strategies that tackle the effects of negative user comments, either by engaging with complaining customers or by hedging the estimated effect on the volatility. For example, the Airlines Industry has already started this practice by using Twitter as a customer service tool to listen and pacify customer problems.

Third, by means of the multivariate GARCH model, we can use UGC t to predict the volatility of stocks, which can be useful in hedging strategies for both the company itself as well as for external investors.

Fourth, knowing which type of events are the source of the volatility spillovers can help managers make an informed decision about the timing of these events. They could for example decide to postpone a new product launch if a capital raise is planned, in an effort to keep the stock return volatility level low at that time.

Questions

These results raise the following questions: Why is the effect asymmetric? Why are there spillover effects between the various metrics of user-generated content? Why do new product launches increase volatility of user generated content?

Why is the Effect Asymmetric?

The impact of shocks in negative user-generated content on stock return volatility is bigger than the impact of shocks in positive user-generated content. This difference may be due to negativity bias or loss aversion. Consumer response to negative and positive news is asymmetric (Kahneman and Tversky 1979). In general, prospect theory (Kahneman and Tversky 1979) suggests that the damage in sales due to negative content is higher than the increase in sales due to the same amount of positive content. Second, negative information is more diagnostic than positive information. Hence, investors find the negative information more useful than positive information.

Why are there Spillover Effects between the Various User-Generated Content Measures?

The results show that the spillovers are larger among measures of user-generated content than between user-generated content and stock returns. This means that online content is influenced more by other online content than by stock returns. As there is a lot of interaction between the various user-generated content measures (for example, people refer to blogs based on what they read in tweets), shocks in one measure of user-generated content are likely to spillover to another. For example, the strong connection between negative tweets and positive tweets in our results is most likely due to the fact that Twitter uses hashtags for topics, to which tweets are linked (after each tweet follows '#topic'). Shocks in the growth rates of negative tweets are therefore likely to be linked to shocks in the growth rates of positive tweets, as people tend to have various opinions about a topic.

Why do New Product Launches Increase Volatility of User Generated Content?

We find that new product launches increase the volatility in the growth rates of volume of user-generated content. This effect may be due to the high level of market uncertainty surrounding new product launches. Prior research suggests that new products often fail and that failure rates are especially high in innovation-driven industries (e.g., Urbig et al. 2013). For example, in the pharmaceutical industry failure rates can be as high as 80% (Urbig et al. 2013). Thus, the prior history of new product failures and the inherent uncertainty in new product launches may increase the volatility of user generated content as consumers express doubts about the performance of new products.

Limitations and Future Research

This study suffers from several limitations that could be the focus of future research. First, we recommend to investigate the presence of spillovers for companies other than Apple and the airline industry. Preferably research could be conducted for companies in various industries, to investigate the generalizability of our results and to study differences in spillover effects between industries.

Second, to keep the research manageable, we only derived the valence of tweets. In future research, it would be insightful to incorporate the valence of other user-generated content measures such as blog posts as well.

Third, it would be useful to explore how tweets affect volatility in sales. We are unable to obtain sales data at the daily level.

Fourth, our results can only assure causality in the sense of Granger causality. Field experiments such as by Aral and Walker 2012 can be a fertile direction for assessing causality.

Finally, some of the described analyses are computationally intensive and time consuming. To implement this research in managerial settings, practitioners would have to scale up and implement efficient, computational procedures, especially in real-time monitoring of user-generated content.

Figure 1: Time series plots of Apple's stock returns (in US Dollars), the volume of user-generated content variables Positive tweets, Negative tweets, Blog posts and Google Ticker Search, and the log differences (i.e., the growth rates) of the volume of user-generated content variables (January 2007 to March 2010).

Figure 1a: Apple's stock returns

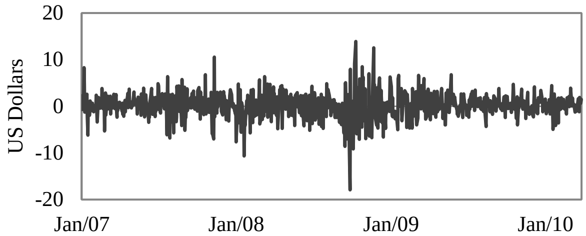

Figure 1b: Volume of Positive Tweets about the iPhone

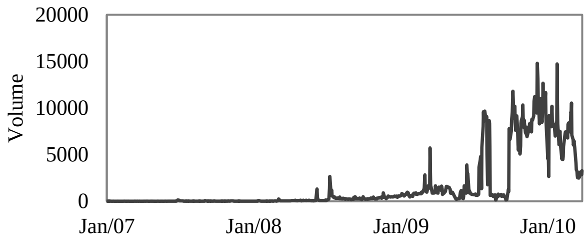

Figure 1c: Volume of Negative Tweets about the iPhone

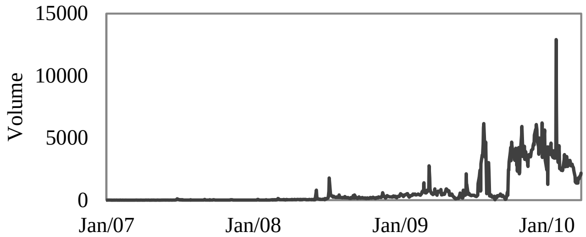

Figure 1d: Volume of Blog Posts about the iPhone

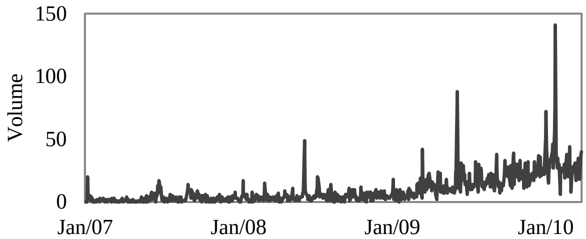

Figure 1e: Volume of Google Searches for Apple's Ticker Symbol

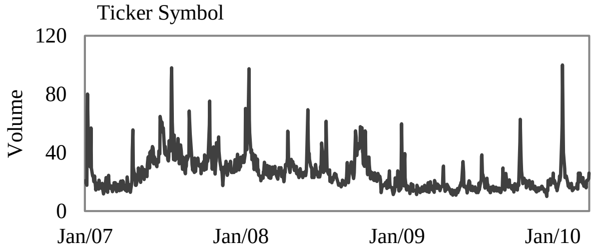

Figure 1f: Growth rates of the Volume of Positive Tweets about the iPhone

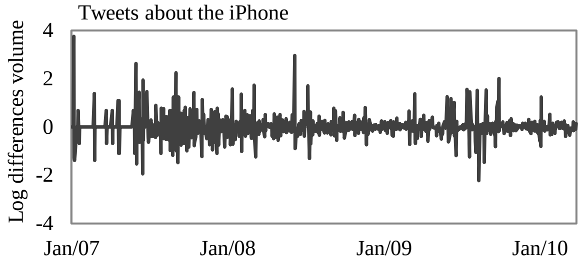

Figure 1g: Growth rates of the Volume of Negative Tweets about the iPhone

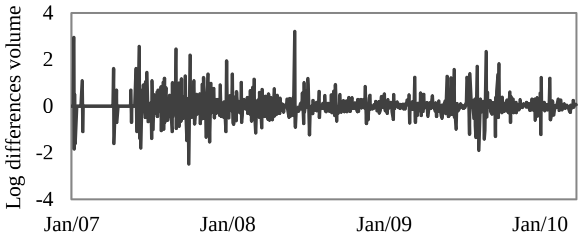

Figure 1h: Growth rates of the Volume of Blog Posts about the iPhone

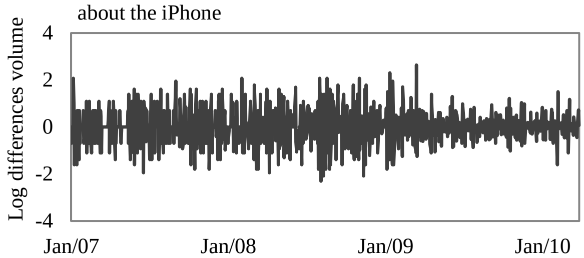

Figure 1i: Growth rates of the Volume of Google Searches for Apple's Ticker Symbol

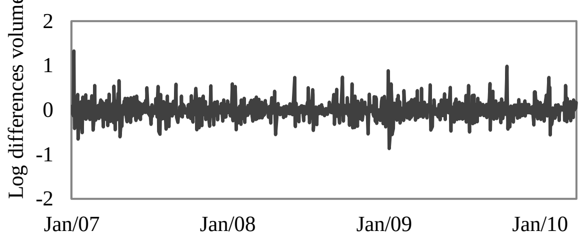

Figure 2: Time series plots of Apple's New product launches and the eight categories of Apple's Organizational events: mergers and acquisitions, product announcements, downsizings, client announcements, lawsuits and legal issues, executive changes, business expansions and strategic alliances (January 2007 to March 2010)

Figure 2a: New Product Launches

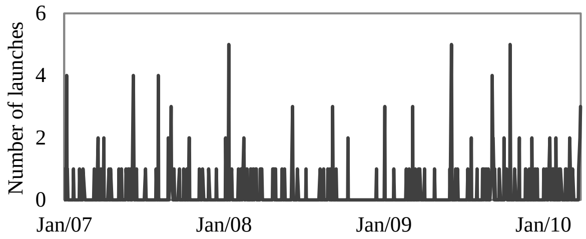

Figure 2b: Organizational Events - Business Expansions

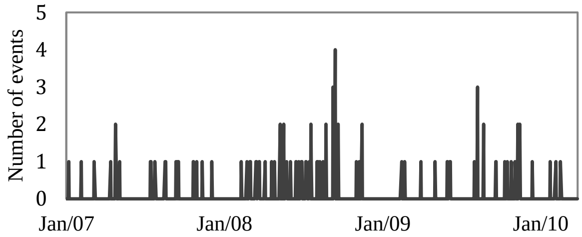

Figure 2f: Organizational Events - Lawsuits & Legal Issues

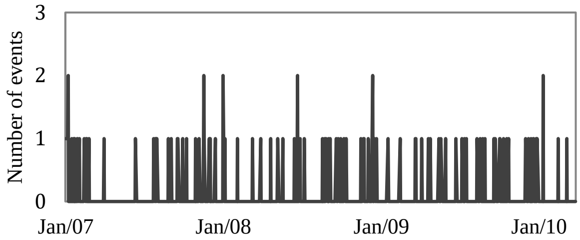

Figure 2c: Organizational Events - Client Announcements

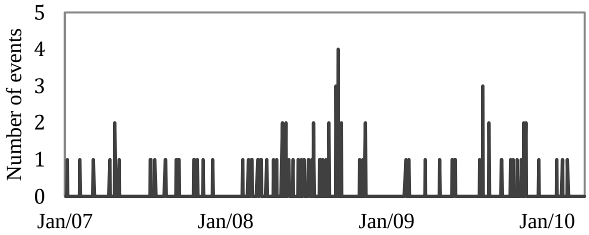

Figure 2g: Organizational Events - Downsizings

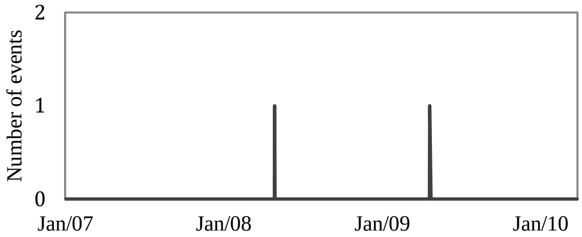

Figure 2d: Organizational Events - Executive Changes

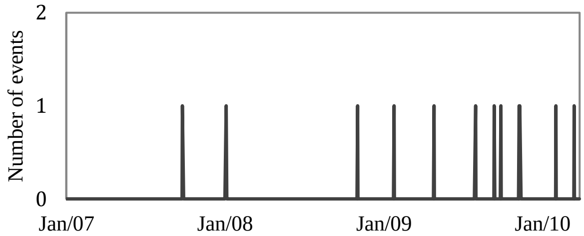

Figure 2h: Organizational Events - Mergers & Acquisitions

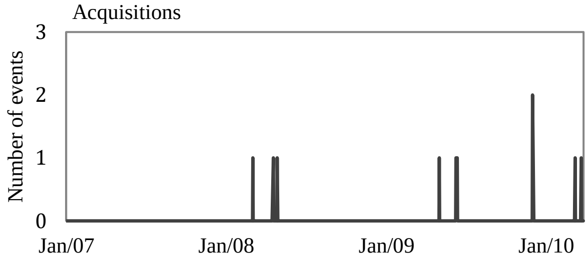

Figure 2e: Organizational Events - Product Announcements

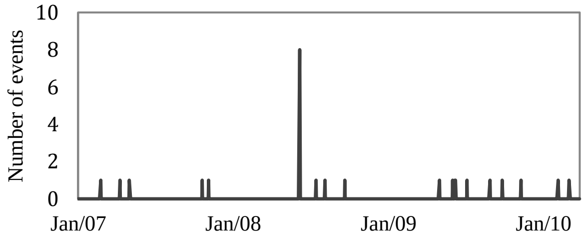

Figure 2i: Organizational Events - Strategic Alliances

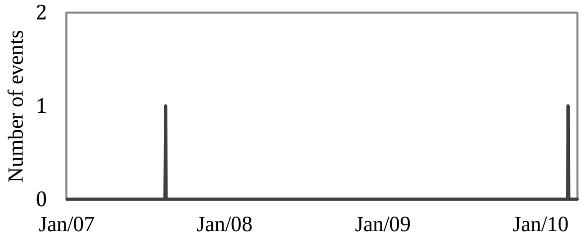

Figure 3: Correlation between (squared) Returns and (squared) growth rates of the volume of Positive tweets, Negative tweets, Blog posts and Google Ticker Search, plotted over a moving window of 10 days.

Figure 3a: Returns - Growth rates Positive Tweets

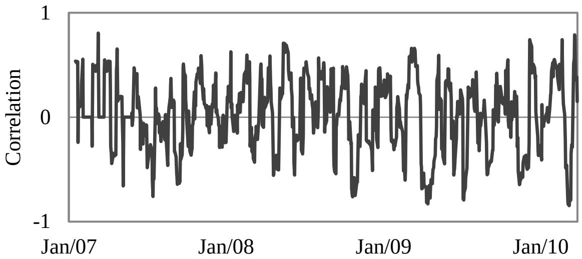

Figure 3b: Returns - Growth rates Negative Tweets

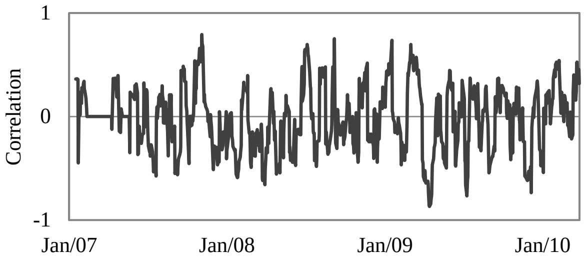

Figure 3c: Returns - Growth rates Blog Posts

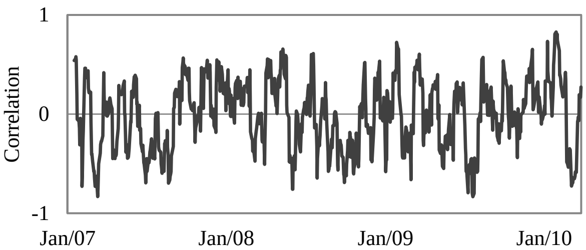

Figure 3d: Returns - Growth rates Google Search Tickers

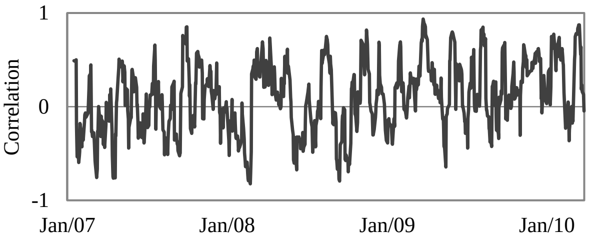

Figure 3e: Squared: Returns - Growth rates Positive Tweets

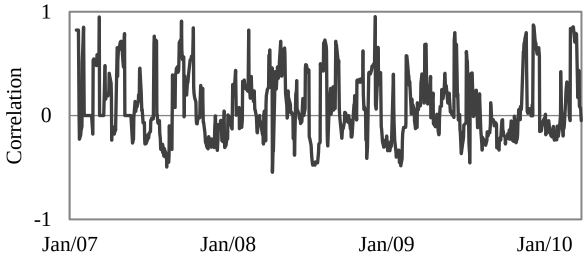

Figure 3f: Squared: Returns - Growth rates Negative Tweets

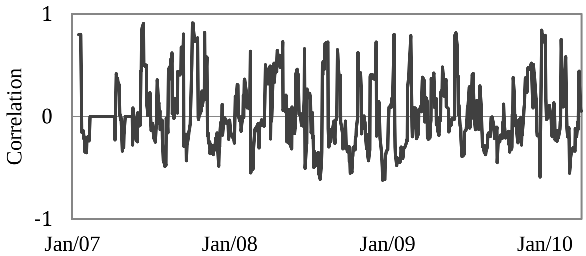

Figure 3g: Squared: Returns - Growth rates Blog Posts

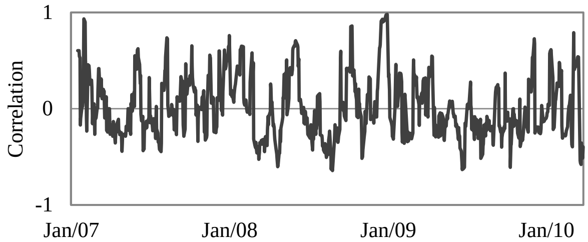

Figure 3h: Squared: Returns - Growth rates Google Search Tickers

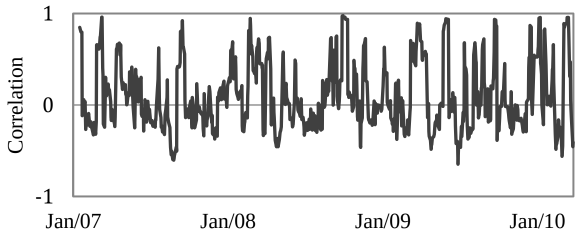

Figure 4: Estimation framework of studying the spillover effects between user-generated content and stock returns

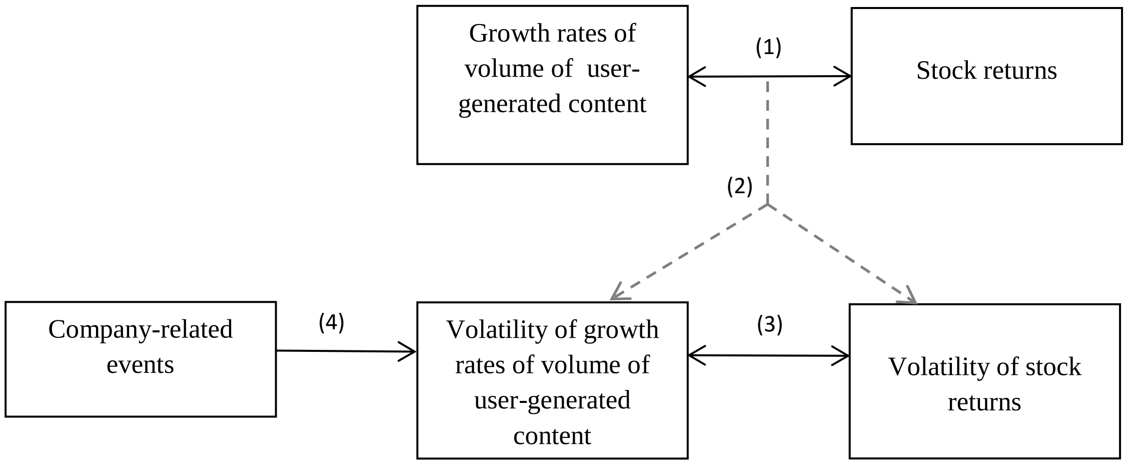

Table 1: Literature on effects of UGC and marketing information on firm performance

Type of Study	Representative Publications	Contrasts Twitter vs. Google Search vs. Blogs	Analyses Effect of Firm Announcement on Volatility in UGC	Includes Twitter	Evaluates Effect on Stock Volatility
UGC on Sales	Chevalier and Mayzlin (2006)	No	No	No	No
	Gopinath et al. (2014)	No	No	No	No
	Rui et al. (2013)	No	No	Yes	No
Marketing Information on Stock Returns	Mizik and Jacobson (2003)	No	No	No	No
	Pauwels et al. (2004)	No	No	No	No
	McAlister et al. (2007)	No	No	No	No
UGC on Stock Returns	Luo (2009)	No	No	No	No
	Bollen et al. (2011)	No	No	Yes	No
	McAlister et al. (2012)	No	No	No	No
	Tirunillai and Tellis (2012)	No	No	No	No
	Luo et al. (2013)	No	No	No	No
	This Study	**Yes**	**Yes**	**Yes**	**Yes**

Table 2: Description of the variables of study 1 concerning Apple

Variables	Description	Details about the variables
Returns	Stock returns of Apple	Normal returns of Apple
Positive tweets	Volume of positive tweets about iPhone	e.g. I love the iPhone. Classified using the Support Vector Machine Algorithm.
Negative tweets	Volume of negative tweets about iPhone	e.g. I think the iPhone is too heavy. Classified using the Support Vector Machine Algorithm.
Blog posts	Number of blog posts by influential bloggers about iPhone	We collect the data for blogs about the brands from Newstex. Newstex's Authoritative Content feature enables us to select blogs from news organizations and corporate blogs, as well as respected independent experts and thought leader blogs, which include blogging sites such as Gawker.com, Mashable.com, b5media.com, and consumerist.com.
Google Ticker Search	Search volume for AAPL in Google Search Engine	Daily search volume for the ticker symbol "AAPL". We obtain the daily search volume from Google Trends (http://www.google.com/trends/) provided by Google Search, which is the most popular search engine on the World Wide Web. The actual search volume is normalized by Google using a common variable over a certain period, in this case it is the maximum number of searches for the term "AAPL". Since Google Trends does not give daily number of searches for a period of more than 90 days we collected daily searches from October to December 2009, November 2009 to January 2010, December 2009 to February 2010, and January 2010 to March 2010. Hence, the actual daily search volume is divided by the maximum search volume over a period of 90 days. We mapped the common dates and synchronized the values across these months to get the normalized values over our sample period. Since the actual daily search volume is not available, we use this normalized daily search volume as the variable: Number of Google Ticker Search.
New product launches	Number of new product launches for Apple	We measure new product announcements by the number of new product launches made by the firm. We rely on the Capital IQ database for this particular variable. We read each entry under the category of "Product-Related Announcements" within the Key Developments feature of Capital IQ to ascertain a new product launch.
Organizational events	Number of organizational related events for Apple	We measure organizational events by counting and aggregating all key firm events excluding new product announcements and financial events (announcements of earnings, dividends, etc.). Organizational events are all events which are not new product launches or financial events. We categorized the organizational events into: mergers and acquisitions, product announcements, downsizings, client announcements, lawsuits and legal issues, executive changes, business expansions and strategic alliances.

Table 3: Summary statistics of the data (816 observations): the mean, standard deviation, skewness, kurtosis, the Jarque Bera statistic and the corresponding *p*-value

Variables	**Mean**	**Standard Deviation**	**Skewness**	**Kurtosis**	**Jarque Bera-statistic**	***p*-value**
Returns	0.164	2.757	-0.234	6.995	549.967	0.000
Positive tweets	1622.900	3021.475	2.024	5.843	832.048	0.000
Negative tweets	772.110	1424.498	2.556	11.774	3505.724	0.000
Blog posts	9.634	11.964	3.327	25.473	18676.438	0.000
Google Ticker Search	26.015	12.491	1.918	8.668	1592.506	0.000

Table 4: Results of the ADF test for the log differences of the user-generated content variables (no trend or intercept)

User-generated content variables	**ADF-statistic**	**ADF *p*-value**
Growth rates Positive tweets	-20.156	0.000
Growth rates Negative tweets	-15.582	0.000
Growth rates Blog posts	-14.726	0.000
Growth rates Google Ticker Search	-22.974	0.000

Table 5: Correlation between (squared) returns and (squared) growth rates of user-generated content

Correlation	Returns	Growth rates Positive tweets	Growth rates Negative tweets	Growth rates Blog posts	Growth rates Google Ticker Search
Returns	1.000	0.0370	-0.0141	-0.0038	0.0692
Growth rates Positive tweets	0.0370	1.000	0.6410	0.1484	0.1868
Growth rates Negative tweets	-0.0141	0.6410	1.000	0.1688	0.1656
Growth rates Blog posts	-0.0038	0.1484	0.1688	1.000	0.2393
Growth rates Google Ticker Search	0.0692	0.1868	0.1656	0.2393	1.000
Correlation (squared variables)	Returns	Growth rates Positive tweets	Growth rates Negative tweets	Growth rates Blog posts	Growth rates Google Ticker Search
Returns	1.000	0.0661	0.0356	0.1030	0.1912
Growth rates Positive tweets	0.0661	1.000	0.7092	0.1457	0.4485
Growth rates Negative tweets	0.0356	0.7092	1.000	0.1028	0.3248
Growth rates Blog posts	0.1030	0.1457	0.1028	1.000	0.2017
Growth rates Google Ticker Search	0.1912	0.4485	0.3248	0.2017	1.000

Table 6: Description of the variables of study 2 concerning Delta, JetBlue, Southwest and United Airlines

Variables	**Description**
Returns	Stock returns of the airline
Retweets	Number of user retweets about the airline brand
Replies	Number of user replies about the airline brand
Favorites	Number of users *favoriting* tweets regarding the airline brand

Table 7: Summary statistics of the data (251 observations): the mean, standard deviation, skewness, kurtosis, the Jarque Bera statistic (JB-stat) and the corresponding *p*-value of the Jarque Bera statistic

Variables	**Mean**	**Standard Deviation**	**Skewness**	**Kurtosis**	**JB-stat**	***p*-value**
Delta Airlines						
Returns	0.299	2.099	0.125	4.672	29.904	0.000
Retweets	71.976	98.486	8.718	106.747	115746.228	0.000
Replies	151.896	100.549	2.659	21.425	3846.185	0.000
Favorites	85.928	94.453	2.739	14.854	1783.470	0.000
JetBlue Airlines						
Returns	0.231	1.950	0.293	3.603	7.401	0.025
Retweets	70.582	48.857	2.941	15.946	2114.708	0.000
Replies	203.299	118.068	4.163	27.309	6905.350	0.000
Favorites	77.434	86.973	2.167	10.975	861.589	0.000
Southwest Airlines						
Returns	0.297	1.415	-0.070	4.067	12.120	0.002
Retweets	70.124	107.342	5.009	34.849	11658.186	0.000
Replies	137.132	92.175	1.867	10.643	756.744	0.000
Favorites	85.825	119.767	3.464	18.443	2996.147	0.000
United Airlines						
Returns	0.127	2.637	-0.120	4.414	21.499	0.000
Retweets	95.418	227.936	13.662	204.746	433479.385	0.000
Replies	506.291	221.486	1.105	4.261	67.747	0.000
Favorites	102.721	115.462	4.812	41.323	16328.153	0.000

Table 8: Results of the ADF test for the log differences of the user-generated content variables (no trend or intercept)

User-generated content variables	ADF-statistic	ADF *p*-value
Delta Airlines		
Growth rates Retweets	-13.998	0.000
Growth rates Replies	-12.081	0.000
Growth rates Favorites	-14.339	0.000
JetBlue Airlines		
Growth rates Retweets	-10.915	0.000
Growth rates Replies	-13.975	0.000
Growth rates Favorites	-18.571	0.000
Southwest Airlines		
Growth rates Retweets	-10.660	0.000
Growth rates Replies	-18.311	0.000
Growth rates Favorites	-13.249	0.000
United Airlines		
Growth rates Retweets	-10.887	0.000
Growth rates Replies	-11.962	0.000
Growth rates Favorites	-21.238	0.000

Table 9: Estimation Results of the VAR(1) model for Study 1 – iPhone

	Returns (i =1)		**Positive Tweets (i =2)**		**Negative Tweets (i =3)**		**Blog Posts (i =4)**		**Google Ticker Search (i =5)**	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
α	***0.2574	0.0935	**0.0194	0.0095	**0.0217	0.0105	0.0187	0.0227	-0.0006	0.0064
γ_{1i}	-0.0113	0.0346	***-0.0087	0.0033	**-0.0074	0.0034	-0.0057	0.0083	-0.0020	0.0026
γ_{2i}	0.1717	0.2208	***-0.3167	0.0660	**0.1721	0.0693	-0.0126	0.0622	0.0245	0.0175
γ_{3i}	-0.2567	0.1980	0.0061	0.0416	***-0.4386	0.0483	-0.0193	0.0576	-0.0013	0.0146
γ_{4i}	-0.0315	0.1062	***0.0482	0.0177	***0.0523	0.0196	***-0.4179	0.0328	**0.0266	0.0112
γ_{5i}	**0.9147	0.3674	-0.0494	0.0545	-0.0545	0.0616	*0.2001	0.1091	***-0.2006	0.0389

*,**,*** indicates significance at the 0.10 (*), 0.05 (**) and 0.01 (***) level.

Table 10: Estimation Results of the multivariate GARCH BEKK model for Study 1 – iPhone

	Returns (i =1)		**Positive Tweets (i =2)**		**Negative Tweets (i =3)**		**Blog Posts (i =4)**		**Google Ticker Search (i =5)**	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
c_{1i}	***0.3557	0.1020								
c_{2i}	0.0381	0.0533	*0.1350	0.0781						
c_{3i}	0.0561	0.0626	0.1446	0.0895	0.0039	0.0103				
c_{4i}	**0.0668	0.0314	0.0135	0.0357	0.0052	0.0298	-0.0001	0.0115		
c_{5i}	***0.1213	0.0334	-0.0003	0.0244	**0.0741	0.0341	-0.0006	0.0088	-0.0001	0.0775
a_{1i}	0.1008	0.0625	0.0053	0.0076	0.0044	0.0088	*-0.0163	0.0094	-0.0081	0.0066
a_{2i}	*-0.2740	0.1649	***0.5175	0.1161	***0.3853	0.1340	0.0811	0.1021	-0.0143	0.0558
a_{3i}	*0.2943	0.1612	-0.0069	0.1123	0.1644	0.1275	-0.0422	0.0684	-0.0149	0.0369
a_{4i}	**0.2365	0.1182	-0.0031	0.0249	-0.0057	0.0274	***0.1704	0.0458	-0.0271	0.0286
a_{5i}	0.2997	0.7958	-0.1068	0.2266	-0.1199	0.2563	0.0858	0.1173	***0.3963	0.0943
b_{1i}	***0.9802	0.0070	0.0002	0.0021	0.0006	0.0024	***0.0141	0.0023	-0.0001	0.0024
b_{2i}	0.0871	0.0756	***0.8863	0.0407	**-0.1076	0.0420	-0.0077	0.0277	0.0242	0.0344
b_{3i}	-0.1040	0.0835	-0.0657	0.0535	***0.9066	0.0635	-0.0042	0.0185	-0.0072	0.0203
b_{4i}	***-0.2021	0.0474	0.0067	0.0257	0.0106	0.0287	***0.9920	0.0131	0.0218	0.0133
b_{5i}	-0.5828	0.7277	0.0425	0.3345	0.0102	0.3855	-0.1742	0.1154	***0.6191	0.1629

*,**,*** indicates significance at the 0.10 (*), 0.05 (**) and 0.01 (***) level.

Table 11: Test for Granger causality in volatility from user-generated content to Returns for Study 1 – iPhone

Wald test causality in volatility	
$\chi^2(8)$	96.210
p-value	0.000

Table 12: Estimation Results for Volatility of the growth rates of the volume of Positive Tweets for Study 1 – iPhone

Dependent Variable: Volatility of the growth rates of Positive Tweets

Variable	**Coefficient**	**Standard Error**
Constant	*0.031	0.016
Volatility growth rates Positive Tweets (-1)	***0.786	0.022
New Product Launches Dummy	*0.034	0.018
Lawsuits and Legal issues Dummy	**0.044	0.020
Downsizing Dummy	-0.041	0.132
Executive changes Dummy	-0.032	0.054
Mergers and Acquisitions Dummy	-0.045	0.062
Strategic Alliances Dummy	-0.008	0.133
Client Announcements Dummy	-0.005	0.018
Business Expansions Dummy	-0.010	0.022
Product Announcements Dummy	0.028	0.042
Monday	0.015	0.021
Tuesday	*0.037	0.021
Wednesday	0.017	0.021
Thursday	0.006	0.021
Centered R-squared	0.625	
R-Bar squared	0.618	
Uncentered R-squared	0.785	
Log likelihood	221.942	
Durbin-Watson statistic	2.155	
Mean of Dependent Variable	0.260	
Std Error of Dependent Variable	0.301	
Standard Error of Estimate	0.186	
Sum of Squared Residuals	27.574	
Regression F(14,798)	94.822	
Significance Level of F	0.000	

Included observations: 813 after adjustments

*.**.*** indicates significance at the 0.10 (*). 0.05 (**) and 0.01 (***) level.

Table 13: Estimation Results for Volatility of the growth rates of the volume of Negative Tweets for Study 1 – iPhone

Dependent Variable: Volatility of the growth rates of Negative Tweets

Variable	Coefficient	Standard Error
Constant	**0.039	0.017
Volatility growth rates Negative Tweets (-1)	***0.746	0.023
New Product Launches Dummy	**0.039	0.018
Lawsuits and Legal issues Dummy	**0.047	0.021
Downsizing Dummy	-0.043	0.136
Executive changes Dummy	-0.022	0.056
Mergers and Acquisitions Dummy	-0.043	0.064
Strategic Alliances Dummy	-0.015	0.136
Client Announcements Dummy	-0.002	0.018
Business Expansions Dummy	-0.009	0.023
Product Announcements Dummy	0.041	0.044
Monday	0.021	0.022
Tuesday	*0.041	0.022
Wednesday	0.015	0.021
Thursday	0.008	0.021
Centered R-squared	0.567	
R-Bar squared	0.559	
Uncentered R-squared	0.766	
Log likelihood	199.608	
Durbin-Watson statistic	2.146	
Mean of Dependent Variable	0.265	
Std Error of Dependent Variable	0.288	
Standard Error of Estimate	0.191	
Sum of Squared Residuals	29.131	
Regression F(14,798)	74.613	
Significance Level of F	0.000	
Included observations: 813 after adjustments		

*.**.*** indicates significance at the 0.10 (*). 0.05 (**) and 0.01 (***) level.

Table 14: Estimation Results for Volatility of the growth rates of the volume of Blog Posts for Study 1 – iPhone

Dependent Variable: Volatility of the growth rates of Blog Posts		
Variable	**Coefficient**	**Standard Error**
Constant	0.004	0.004
Volatility growth rates Blog Posts (-1)	***0.989	0.006
New Product Launches Dummy	***0.010	0.003
Lawsuits and Legal issues Dummy	0.005	0.004
Downsizing Dummy	0.016	0.026
Executive changes Dummy	-0.005	0.011
Mergers and Acquisitions Dummy	-0.002	0.012
Strategic Alliances Dummy	-0.012	0.026
Client Announcements Dummy	-0.002	0.003
Business Expansions Dummy	-0.003	0.004
Product Announcements Dummy	-0.002	0.008
Monday	-0.003	0.004
Tuesday	0.006	0.004
Wednesday	0.001	0.004
Thursday	-0.002	0.004
Centered R-squared	0.973	
R-Bar squared	0.972	
Uncentered R-squared	0.996	
Log likelihood	1555.025	
Durbin-Watson statistic	2.048	
Mean of Dependent Variable	0.493	
Std Error of Dependent Variable	0.217	
Standard Error of Estimate	0.036	
Sum of Squared Residuals	1.038	
Regression F(14,798)	2032.854	
Significance Level of F	0.000	
Included observations: 813 after adjustments		

*.**.*** indicates significance at the 0.10 (*). 0.05 (**) and 0.01 (***) level.

Table 15: Estimation Results for Volatility of the growth rates of the volume of Google Ticker Search for Study 1 – iPhone

Dependent Variable: Volatility of the growth rates of Google Ticker Search

Variable	**Coefficient**	**Standard Error**
Constant	***0.016	0.002
Volatility growth rates Google Ticker Search (-1)	***0.610	0.028
New Product Launches Dummy	0.001	0.001
Lawsuits and Legal issues Dummy	0.000	0.001
Downsizing Dummy	-0.005	0.009
Executive changes Dummy	0.001	0.004
Mergers and Acquisitions Dummy	-0.007	0.004
Strategic Alliances Dummy	-0.004	0.009
Client Announcements Dummy	0.000	0.001
Business Expansions Dummy	-0.001	0.002
Product Announcements Dummy	0.003	0.003
Monday	0.002	0.001
Tuesday	***0.005	0.002
Wednesday	0.001	0.001
Thursday	0.002	0.001
Centered R-squared	0.376	
R-Bar squared	0.366	
Uncentered R-squared	0.931	
Log likelihood	2369.242	
Durbin-Watson statistic	2.026	
Mean of Dependent Variable	0.047	
Std Error of Dependent Variable	0.017	
Standard Error of Estimate	0.013	
Sum of Squared Residuals	0.140	
Regression F(14.798)	34.415	
Significance Level of F	0.000	

Included observations: 813 after adjustments

*.**.*** indicates significance at the 0.10 (*). 0.05 (**) and 0.01 (***) level.

Table 16: Cross spillover effects of the multivariate GARCH BEKK model for Study 2 – Airlines

Returns (i=1) Retweets (i=2) Replies (i=3) Favorites (i=4)

	Delta Airlines		**JetBlue Airlines**		**Southwest Airlines**		**United Airlines**	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
a_{21}	***0.680	0.230	-0.157	0.334	-0.257	0.222	-0.286	0.332
a_{31}	-0.270	0.182	**0.803	0.338	0.396	0.344	**-0.943	0.434
a_{41}	**-0.344	0.155	**-0.474	0.207	0.191	0.144	0.330	0.241
a_{12}	***0.099	0.030	0.001	0.022	0.053	0.057	***0.097	0.027
a_{13}	***0.037	0.014	0.030	0.018	***0.098	0.037	**-0.024	0.012
a_{14}	-0.002	0.048	*0.078	0.041	-0.034	0.066	***0.101	0.031
b_{21}	***-2.211	0.317	-0.511	1.191	***-1.286	0.248	**-0.457	0.233
b_{31}	***1.174	0.186	**3.027	1.193	*0.523	0.299	0.326	0.432
b_{41}	**0.728	0.321	-0.151	0.185	***0.880	0.168	*-0.245	0.148
b_{12}	***0.209	0.035	***-0.182	0.067	*-0.186	0.096	***0.090	0.022
b_{13}	***-0.030	0.011	***-0.174	0.033	***-0.078	0.027	***0.073	0.014
b_{14}	0.087	0.080	**-0.186	0.079	*-0.153	0.084	***0.078	0.025

*,**,*** indicates significance at the 0.10 (*), 0.05 (**) and 0.01 (***) level.

Table 17: Test for Granger causality in volatility from user-generated content to Returns for Study 2 – Airlines

	Wald test causality in volatility	
Delta	$\chi^2(6)$	244.359
	p-value	0.000
JetBlue	$\chi^2(6)$	36.766
	p-value	0.000
Southwest	$\chi^2(6)$	52.940
	p-value	0.000
United	$\chi^2(6)$	17.724
	p-value	0.000

References

Alexander, C. (2008) Market Risk Analysis, Volume II, Practical Financial Econometrics. *Wiley*.

Alom, F., Ward, B.D. and Hu, B. (2011) Cross country mean and volatility spillover effects of food prices: multivariate GARCH analysis. *Economics Bulletin*, 31(2):1439-1450.

Andersen, T.G., Bollerslev, T., Diebold, F.X. (2010) Parametric and Nonparametric Volatility Measurement. *Handbook of Financial Econometrics* by L.P. Hansen and Y. Ait-Sahalia, Elsevier: 67-138.

Andersen, T.G. and Bollerslev, T., (1998a) Answering the Skeptics: Yes, Standard Volatility Models Do Provide Accurate Forecasts. *International Economic Review*, 39:885-905.

Asur, S., Huberman, B.A. (2010) Predicting the Future with Social Media. *Working paper: arXiv:1003.5699v1*

Bauwens, L., Laurent, S. and Rombouts, J.V.K. (2006) Multivariate GARCH Models: A Survey. *Journal of Applied Econometrics*, 21:79-109.

Bollen, J., Mao, H., Zeng, X.J. (2011) Twitter mood predicts the stock market. *Journal of Computational Science*, 2:1-8.

Bollerslev, T., Chou, R. and Kroner, K. (1992) ARCH modelling in finance: A review of the theory and empirical evidence. *Journal of Econometrics*, 52:5-59.

Bollerslev, T. and Wooldridge, J.M. (1992) Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariances. *Econometric Reviews*, 11(2):143-172.

Bloom, N. (2009) The Impact of Uncertainty Shocks. *Econometrica*, 77(3):623-685.

Bloom, N., Bond, S., and Van Reenen, J. (2007) Uncertainty and Investment Dynamics. *Review of Economic Studies*, 74:391-415.

Broyden, C.G. (1970) The Convergence of a Class of Double-rank Minimization Algorithms. *Journal of the Institute of Mathematics and Its Applications*, 6:76–90.

Chevalier, J.A. and Mayzlin, D. (2006) The Effect of Word-of-Mouth on Sales: Online Book Reviews. *Journal of Marketing Research*, 43:345-354.

Chintagunta, P.K., Gonipath, S., and Venkataraman, S. (2010) The effects of online user reviews on movie box office performance: Accounting for sequential rollout and aggregation across local markets. *Marketing Science*, 29(5):944-957.

Choi, H. and Varian, H. (2011) Predicting the Present with Google Trends. *Google Inc. Technical Report*.

Christoffersen, P. and Jacobs, K. (2004) Which GARCH Model for Option Valuation? *Management Science*, 50(9):1204-1221.

Comte, F., and Lieberman, O. (2003) Asymptotic theory for multivariate GARCH processes. *Journal of Multivariate Analysis*, 84(1):61-84.

Day, G. S. (1994). The capabilities of market-driven organizations. *Journal of Marketing*, 58(October), 37 – 52.

Day, G. S. (2011). Closing the marketing capabilities gap. *Journal of Marketing*, 75(July), 183 – 195.

Day, G. S. & Moorman, C. (2010). *Strategy from the Outside-In: Profiting from Customer Value*. New York: McGraw-Hill.

Dellarocas, C., Zhang, X., and Awad, N.F. (2007) Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive Marketing*, 21(4): 23-45.

Dhar, V., Chang, E.A. (2009) Does Chatter Matter? The Impact of User-Generated Content on Music Sales. *Journal of Interactive Marketing*, 23:300-307.

Doan, T.A. (2013) RATS Handbook for ARCH/GARCH and Volatility Models. Estima WINRATS.

Duan, W., Gu, B., and Whinston, A.B. (2008) The dynamics of online word-of-mouth and product sales, an empirical investigation of the movie industry. *Journal of Retailing*, 84(2):233-242.

Elyasiani, E., Perera, P. and Puri, T.N. (1998) Interdependence and dynamic linkages between stock markets of Sri Lanka and its trading partners. *Journal of Multinational Financial Management*, 8:89-101.

Engle, R.F. (2001) GARCH 101: The Use of ARCH/GARCH Models in Applied Econometrics. *Journal of Economic Perspectives*, 15(4):157-168.

Engle, R.F. and Ng, V.K. (1993) Measuring and Testing the Impact of News on Volatility. *The Journal of Finance*, 48(5):1749-1778.

Engle, R.F. and Kroner, K.F. (1995) Multivariate simultaneous generalized ARCH. *Economic Theory*, 11:122-150.

Fama, E.F. and French, K.R. (2004) The Capital Asset Pricing Model: Theory and Evidence. *Journal of Economic Perspectives*, 18(3):25-46.

Fletcher, R. (1970): A New Approach to Variable Metric Algorithms. *Computer Journal*, 13:317– 322.

Franses, P.H. and Van Dijk, D. (2000) Nonlinear Time Series Models in Empirical Finance. *Cambridge University Press.*

Godes, D. and Mayzlin, D. (2004) Using Online Conversations to Study Word-of-Mouth Communication. *Marketing Science*, 23(4):545-560.

Goldfarb, D. (1970): A Family of Variable Metric Updates Derived by Variational Means. *Mathematics of Computation*, 24:23–26.

Gruhl, D., Guha, R., Kumar, R., Novak, J., Tomkins, A. (2005) The predictive power of online chatter. *ACM, New York, NY, USA*, 78-87.

Hafner, C.M., and Herwartz, H. (2004) Testing for Causality in Variance using Multivariate GARCH Models. *Working paper.*

Hafner, C.M., and Herwartz, H. (2006) Volatility impulse responses for multivariate GARCH models: An exchange rate illustration. *Journal of International Money and Finance*, 25(5):719-740.

Hennig-Thurau T., Wiertz, C., and Feldhaus, F. (2014) Does Twitter matter? The impact of microblogging word of mouth on consumers' adoption of new movies. *Journal of the Academy of Marketing Science*, 43(3):375-394.

Joshi, P. (2011) Return and Volatility Spillovers among Asian stock markets. *SAGE Open*, 1:1-8.

Kahneman, D., and Tversky, A. (1979) Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, 47(2):263-292.

Leahy, J.V., and Whited, T.M., (1996) The Effect of Uncertainty on Investment: Some Stylized Facts. *Journal of Money, Credit, and Banking*, 28(1):64-83.

Li, H. and Majerowska, E. (2008) Testing stock market linkages for Poland and Hungary: A multivariate GARCH approach. *Research in International Business and Finance*, 22(3):247-266.

Liu, Y. (2006) Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing*, 70(3):75-88.

Liu, Y., Huang, X., An, A., Yu, X. (2007) ARSA: a sentiment-aware model for predicting sales performance using blogs. *ACM, New York, NY, USA*, 607-614.

Luo, X. (2007) Consumer negative voice and firm-idiosyncratic stock returns. *Journal of Marketing*, 71(3): 75-88.

Luo, X. (2009) Quantifying the long-term impact of negative word-of-mouth on cash flows and stock prices. *Marketing Science*, 28(1):148-165.

Luo, X., Zhang, J., and Duan, W. (2013) Social Media and Firm Equity Value. *Information Systems Research*, 24(1):146-163.

McAlister, L., Sonnier, G., and Shively, T. (2012) The relationship between online chatter and firm value. *Marketing Letters*, 23(1):1-12.

Mishne, G., Glance, N. (2006) Predicting Movie Sales from Blogger Sentiment. *AAAI (Association for the Advancement of Artificial Intelligence) 2006 Spring Symposium on Computational Approaches to Analysing Weblogs.*

Mizik, N., and Jacobson, R. (*2003*) Trading Off Between Value Creation and Value Appropriation: The Financial Implications of Shifts in Strategic Emphasis. *Journal of Marketing*: 67(1):63-76.

Moe, W.W., and Trusov, M. (2011) The value of social dynamics in online product ratings forums. *Journal of Marketing Research*, 48(June):444-456.

Moorman, C., & Day, G. S. (2016). Organizing for marketing excellence. *Journal of Marketing*, 80(6), 6-35.

Mu, J. (2015). Marketing capability, organizational adaptation and new product development performance. *Industrial Marketing Management*, 49, 151–166.

Mu, J., Bao, K., Sekhon, T., Qi, J., & Love, E. (2018). Outside-in marketing capability and firm performance, *Industrial Marketing Management*, in press.

Nam, H. and Kannan, P.K. (2014) The Informational Value of Social Tagging Networks. *Journal of Marketing*, 78(4):21-40.

Onishi, N., and Manchanda, P. (2012) Marketing activity, blogging and sales. *International Journal of Research in Marketing*, 29(3):221-234.

Rui, H., Liu, Y., and Whinston, A. (2013) Whose and what chatter matters? The effect of tweets on movie sales. *Decision Support Systems*, 55:863-870.

Schweidel, D.A., and Moe, W.W. (2014) Listening in on social media: A joint model of sentiment and venue format choice. *Journal of Marketing Research*, LI(August):387-402.

Shanno, D.F. (1970): Conditioning of Quasi-Newton Methods for Function Minimization, *Mathematics of Computation*, 24:647–656.

Sonnier, G.P., McAlister, L., and Rutz, O.J. (2011) A Dynamic Model of the Effect of Online Communications on Firm Sales. *Marketing Science*, 30(4):702–716.

Srinivasan, S. and Hanssens, D.M. (2009) Marketing and firm value: Metrics, methods, findings, and future directions. *Journal of Marketing Research*, 46(3):293-312.

Tellis, G.J. and Franses, P.H. (2006) Optimal data interval for estimating advertising response. *Marketing Science*, 25(3):217-229.

Tirunillai, S. and Tellis, G.J. (2012) Does Chatter Really Matter? Dynamics of UGC and Stock Performance. *Marketing Science*, 31(2):198-215.

Trusov, M., Bucklin, R.E., and Pauwels, K. (2009) Effects of Word-of-Mouth Versus Traditional Marketing: Findings from an Internet Social Networking Site. *Journal of Marketing*, 73(5): 90-102.

Urbig, D., Bürger, R., Patzelt, H., and Schweizer, L. (2013) Investor Reactions to New Product Development Failures: The Moderating Role of Product Development Stage. *Journal of Management*, 39(4): 985-1015.

Worthington, A. and Higgs, H. (2004). Transmission of Equity Returns And Volatility In Asian Developed And Emerging Markets: A Multivariate GARCH Analysis. *International Journal of Finance and Economics*, 9(1):71

Appendix A: Technical details of the Support Vector Machine Algorithm

We used the Support Vector Machine (SVM) classification algorithm, a semi-parametric classification technique, to classify the tweets as positive, negative, or neutral.

Table A1 details the eight steps we used to prepare the Twitter dataset. This approach has been shown to be highly reliable for text classification by computer science scholars, especially where predictive validity is important (Cui and Curry, 2005; Joachims, 2002) and researchers across the management sciences have used similar techniques (e.g., Das and Chen, 2007; Rui, Liu, and Whinston, 2013; Tirunillai and Tellis, 2012). We compiled a dictionary that categorizes words used in tweets comprising 1739 words into positive, neutral, and negative. This dictionary includes words from tweets and various dictionaries such as Urban dictionary, Harvard's General Inquirer, Roget's Thesaurus, Miriam-Webster, and Twictionary. We manually classified 13,781 tweets into positive, negative and neutral. 12,781 of the 13,781 tweets formed the training set and the remaining 1,000 tweets the test set. The test set was then used to evaluate how well the SVM algorithm classified the tweets. We find a classification accuracy of 78% when we test the SVM algorithm based model, built on this training dataset of 12,781 tweets, on the test dataset of 1000 tweets. In other words, 78% of the tweets were classified as positive, negative, and neutral to match the manually classified tweets.

The SVM algorithm model can be described as follows. Given a training set of instance-label pairs (x_i, y_i) where x_i is the instance and y_i is the valence category (positive, negative and neutral); $i = 1,2,.........l$ where $x_i \varepsilon R^n$ and $y \varepsilon \{1,\ 1\}^l$, Support Vector Machines requires the solution to the following optimization problem (Boser, Guyon, and Vapnik, 1992; Cortes and Vapnik, 1995):

$$\begin{aligned} &\min_{w,b,\xi} \frac{1}{2} w^T w + C \sum_{i=1}^{l} \xi_i \\ &\text{subject to } \ y_i(w^T \varphi(x_i) + b) \geq 1 - \xi_i , \quad \text{(A1)} \\ &\xi_i \geq 0. \end{aligned}$$

Here, training vectors x_i are mapped into a higher (perhaps infinite) dimensional space by the function φ. The SVM algorithm finds a separating hyperplane with the maximal margin in this higher dimensional space. In this case, C > 0 is the penalty parameter of the error term, and

$K(x_i, x_j) = \varphi(x_i)^T \varphi(x_j)$ represents the kernel function.

We used the "Libsvm" package created by Chang and Lin (2001) via Matlab statistical software, our dictionary, and the SVM algorithm model described above for classifying the sentiment of iPhone tweets in our Twitter dataset.

Table A1: Steps for Creation of Twitter Sentiment

Data Processing Step	Description of Step
Creation of dictionary	Create a dictionary, which forms the basis for the valence classification. We create the dictionary using a combination of tweets and various dictionaries. We use a subset of tweets from our corpus (13,781 tweets) and dictionaries such as Urban dictionary, Harvard's General Inquirer, Twictionary, Roget's Thesaurus and Miriam-Webster
Formation of training and test Sample	Pre-process 13,781 tweets into positive, negative and neutral. Two human coders manually classify the tweets intro positive, negative, and neutral. There is 87% agreement. The differences between coders were resolved through discussion and mutual agreement. 12,781 tweets used for training and 1,000 tweets used for testing.
Removal of urls and user-ids	Remove universal resource locator (URLs) and user-ids in the tweets
Conversion of Emoticons and Internet Words	Convert the emoticons into their meanings (e.g. ☺ as happy, ☹ as sad). 7,383 Internet acronyms/slang/words were converted into their actual meanings. The list is available from the authors. We consult various online sources to convert the various types of emoticons and the 7383 Internet acronyms/slang/words.
Removal of punctuation and numeric characters	Remove punctuation and numeric characters except exclamation and question marks. These exclamation and question marks were replaced by EXM and QSM respectively
Tokenization of Tweets	Tokenize tweets to individual words or phrases
Removal of Stop-Words	Remove stop-words (e.g. I, or, etc.)
Stemming of words	Stem words (convert to base form: e.g., love, loved, loving, etc. stemmed to "love")
Classification of Valence	Classify the tweets using Support Vector Machine

Appendix B: Detailed estimation results for the airlines

Table B1: Estimated coefficients of the VAR(1) model for Study 2 – Delta Airlines

	Returns (i=1)		**Retweets (i=2)**		**Replies (i=3)**		**Favorites (i=4)**	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
α	*0.236	0.131	-0.021	0.050	-0.003	0.023	-0.069	0.066
γ_{1i}	**0.117	0.058	0.043	0.027	***0.048	0.010	0.056	0.035
γ_{2i}	-0.162	0.211	***-0.452	0.073	-0.008	0.031	-0.149	0.097
γ_{3i}	0.151	0.155	-0.094	0.077	***-0.491	0.049	-0.055	0.111
γ_{4i}	0.071	0.138	0.032	0.050	0.016	0.019	***-0.433	0.072

*.**.*** indicates significance at the 0.10 (*). 0.05 (**) and 0.01 (***) level.

Table B2: Estimated coefficients of the multivariate GARCH BEKK model for Study 2 – Delta Airlines

	Returns (i=1)		**Retweets (i=2)**		**Replies (i=3)**		**Favorites (i=4)**	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
c_{1i}	0.208	0.208						
c_{2i}	***0.499	0.099	-0.001	0.099				
c_{3i}	**0.077	0.030	0.000	0.060	0.000	0.028		
c_{4i}	***1.108	0.082	-0.003	0.232	0.000	0.040	0.000	0.067
a_{1i}	***0.187	0.059	***0.099	0.030	***0.037	0.014	-0.002	0.048
a_{2i}	***0.680	0.230	***0.330	0.088	***0.198	0.073	***0.646	0.157
a_{3i}	-0.270	0.182	***0.771	0.109	***0.926	0.106	***0.685	0.157
a_{4i}	**-0.344	0.155	**-0.097	0.043	0.076	0.049	***-0.423	0.085
b_{1i}	***0.669	0.042	***0.209	0.035	***-0.030	0.011	0.087	0.080
b_{2i}	***-2.211	0.317	***0.697	0.034	***-0.241	0.037	***0.891	0.012
b_{3i}	***1.174	0.186	-0.072	0.054	***0.425	0.052	0.051	0.069
b_{4i}	**0.728	0.321	***-0.116	0.040	***0.192	0.039	***-0.541	0.085

*.**.*** indicates significance at the 0.10 (*). 0.05 (**) and 0.01 (***) level.

Table B3: Estimated coefficients of the VAR(1) model for Study 2 – JetBlue Airlines

	Returns (i=1)		Retweets (i=2)		Replies (i=3)		Favorites (i=4)	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
α	0.204	0.134	-0.002	0.033	0.007	0.024	-0.011	0.066
γ_{1i}	-0.010	0.064	-0.012	0.016	-0.008	0.012	-0.029	0.027
γ_{2i}	-0.049	0.191	***-0.453	0.068	-0.048	0.064	-0.168	0.142
γ_{3i}	0.232	0.267	0.111	0.091	***-0.311	0.097	0.116	0.229
γ_{4i}	0.037	0.121	0.006	0.028	-0.026	0.024	**-0.210	0.106

*.**.*** indicates significance at the 0.10 (*). 0.05 (**) and 0.01 (***) level.

Table B4: Estimated coefficients of the multivariate GARCH BEKK model for Study 2 – JetBlue Airlines

	Returns (i=1)		Retweets (i=2)		Replies (i=3)		Favorites (i=4)	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
c_{1i}	***1.247	0.462						
c_{2i}	-0.143	0.109	0.000	0.053				
c_{3i}	-0.171	0.119	0.000	0.043	0.000	0.021		
c_{4i}	-0.190	0.162	0.000	0.058	0.000	0.018	0.000	0.017
a_{1i}	***0.424	0.114	0.001	0.022	0.030	0.018	*0.078	0.041
a_{2i}	-0.157	0.334	0.038	0.096	-0.115	0.080	-0.225	0.223
a_{3i}	**0.803	0.338	***0.312	0.106	***0.341	0.094	***-1.215	0.376
a_{4i}	**-0.474	0.207	0.028	0.030	0.010	0.041	***0.647	0.160
b_{1i}	*-0.262	0.138	***-0.182	0.067	***-0.174	0.033	**-0.186	0.079
b_{2i}	-0.511	1.191	***0.800	0.159	-0.171	0.167	-0.022	0.159
b_{3i}	**3.027	1.193	-0.113	0.279	0.143	0.191	0.472	0.595
b_{4i}	-0.151	0.185	-0.046	0.050	-0.003	0.059	***0.653	0.155

*.**.*** indicates significance at the 0.10 (*). 0.05 (**) and 0.01 (***) level.

Table B5: Estimated coefficients of the VAR(1) model for Study 2 – Southwest Airlines

	Returns (i=1)		**Retweets (i=2)**		**Replies (i=3)**		**Favorites (i=4)**	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
α	***0.351	0.093	-0.023	0.070	0.005	0.023	-0.006	0.082
γ_{1i}	-0.070	0.063	**-0.109	0.050	-0.028	0.023	*-0.120	0.062
γ_{2i}	***0.325	0.103	***-0.579	0.090	0.014	0.035	-0.108	0.099
γ_{3i}	0.087	0.113	0.118	0.109	***-0.359	0.063	-0.014	0.115
γ_{4i}	***-0.237	0.084	*0.158	0.085	-0.005	0.032	***-0.363	0.094

*.**.*** indicates significance at the 0.10 (*). 0.05 (**) and 0.01 (***) level.

Table B6: Estimated coefficients of the multivariate GARCH BEKK model for Study 2 – Southwest Airlines

	Returns (i=1)		**Retweets (i=2)**		**Replies (i=3)**		**Favorites (i=4)**	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
c_{1i}	***0.747	0.145						
c_{2i}	***0.886	0.139	***0.459	0.175				
c_{3i}	0.042	0.038	**0.084	0.042	0.000	0.067		
c_{4i}	***0.809	0.228	***0.933	0.192	0.000	0.393	0.000	0.155
a_{1i}	***-0.438	0.127	0.053	0.057	***0.098	0.037	-0.034	0.066
a_{2i}	-0.257	0.222	***0.444	0.143	-0.023	0.039	0.310	0.218
a_{3i}	0.396	0.344	0.257	0.157	***0.542	0.096	0.270	0.209
a_{4i}	0.191	0.144	-0.153	0.129	-0.001	0.036	0.013	0.160
b_{1i}	***0.412	0.081	*-0.186	0.096	***-0.078	0.027	*-0.153	0.084
b_{2i}	***-1.286	0.248	***0.696	0.034	**-0.158	0.069	***0.708	0.059
b_{3i}	*0.523	0.299	***0.612	0.110	***0.885	0.052	**0.175	0.085
b_{4i}	***0.880	0.168	***-0.654	0.049	0.073	0.068	**-0.282	0.110

*.**.*** indicates significance at the 0.10 (*). 0.05 (**) and 0.01 (***) level.

Table B7: Estimated coefficients of the VAR(1) model for Study 2 – United Airlines

	Returns (i=1)		**Retweets (i=2)**		**Replies (i=3)**		**Favorites (i=4)**	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
α	0.148	0.171	-0.005	0.038	-0.019	0.018	**-0.075	0.033
γ_{1i}	0.103	0.066	*-0.028	0.016	-0.006	0.006	***-0.041	0.015
γ_{2i}	-0.005	0.225	***-0.356	0.063	0.012	0.035	-0.053	0.077
γ_{3i}	**-0.849	0.374	0.194	0.119	***-0.240	0.067	-0.341	0.208
γ_{4i}	0.278	0.176	-0.063	0.041	-0.074	0.048	***-0.311	0.056

*.**.*** indicates significance at the 0.10 (*). 0.05 (**) and 0.01 (***) level.

Table B8: Estimated coefficients of the multivariate GARCH BEKK model for Study 2 – United Airlines

	Returns (i=1)		**Retweets (i=2)**		**Replies (i=3)**		**Favorites (i=4)**	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
c_{1i}	***2.359	0.227						
c_{2i}	0.054	0.109	0.000	0.067				
c_{3i}	-0.066	0.049	0.000	0.046	0.000	0.015		
c_{4i}	0.053	0.099	0.000	0.058	0.000	0.010	0.000	0.013
a_{1i}	0.142	0.133	***0.097	0.027	**-0.024	0.012	***0.101	0.031
a_{2i}	-0.286	0.332	**-0.218	0.094	***-0.300	0.092	-0.204	0.126
a_{3i}	**-0.943	0.434	***0.404	0.117	***0.313	0.084	-0.284	0.223
a_{4i}	0.330	0.241	**0.258	0.108	***0.613	0.139	*0.332	0.200
b_{1i}	0.356	0.242	***0.090	0.022	***0.073	0.014	***0.078	0.025
b_{2i}	**-0.457	0.233	***0.797	0.039	*-0.094	0.051	**-0.106	0.048
b_{3i}	0.326	0.432	***-0.506	0.086	-0.006	0.069	0.084	0.237
b_{4i}	*-0.245	0.148	*0.056	0.029	***0.079	0.022	***0.908	0.036

*.**.*** indicates significance at the 0.10 (*). 0.05 (**) and 0.01 (***) level.

Online Appendix: Technical details Granger causality in volatility test

We split the variables in two groups, for which we define two index sets: $I = (i_1, \dots, i_k)$ and $\mathcal{J} = (j_1, \dots, j_{K-k})$, where $I \cup \mathcal{J} = (1, \dots, K)$ and $I \cap \mathcal{J} = \emptyset$. In the study using Apple data the number of variables is $K = 5$, so group $I = \{Returns\} = \{1\}$ and group $\mathcal{J} = \{Positive\ Tweets, Negative\ Tweets, Blog\ Posts, Google\ Search\ Tickers\} = \{2, 3, 4, 5\}$. We will investigate the issue whether the variance of the variables indexed by $\mathcal{J}$ cause the variance of the variables indexed by I. We define the sub-vectors of $\boldsymbol{\varepsilon}_t$ by $\boldsymbol{\varepsilon}_t^I = (\varepsilon_{t,i_1}, \dots, \varepsilon_{t,i_k})'$ and $\boldsymbol{\varepsilon}_t^{\mathcal{J}} = (\varepsilon_{t,j_1}, \dots, \varepsilon_{t,j_{K-k}})'$. The σ-algebras generated by $\boldsymbol{\varepsilon}_s^I$ and $\boldsymbol{\varepsilon}_s^{\mathcal{J}}$, $s \leq t$, are denoted by $\mathcal{F}_t^I$ and $\mathcal{F}_t^{\mathcal{J}}$, respectively. We say that $\boldsymbol{\varepsilon}_t^{\mathcal{J}}$ does not cause $\boldsymbol{\varepsilon}_t^I$ in variance, denoted by $\boldsymbol{\varepsilon}_t^{\mathcal{J}} \overset{V}{\nrightarrow} \boldsymbol{\varepsilon}_t^I$, if:

$$Var(\boldsymbol{\varepsilon}_t^I | \mathcal{F}_{t-1}) = Var(\boldsymbol{\varepsilon}_t^I | \mathcal{F}_{t-1}^I) \tag{1}$$

Noncausality in variance amounts to certain zero restrictions of the matrices $\boldsymbol{A}$ and $\boldsymbol{B}$. We need to define a test statistic that tests the zero restrictions in these matrices. Let us first define the restriction matrix $\tilde{Q}$ associated with the BEKK model. Let $\tilde{Q}$ be a matrix of dimension $k(K-k)$ x $(K)^2$, of rank $k(K-k)$. The (r, τ) element of $\tilde{Q}$ is defined by

$$\tilde{Q}_{r,\tau} = \begin{cases} 1, & \tau = s_{mn} \\ 0, & \tau \neq s_{mn} \end{cases} \tag{2}$$

where $r = m + (n-1)k$, $s_{mn} = i_m + (j_n - 1)K$, $i_m \in I$, $j_n \in J$, and $m = 1, \dots, k$, $n = 1, \dots, K-k$.

Each row of $\tilde{Q}$ contains a 1 at the $i + (j-1)K$-th position, where $i \in I$ and $j \in J$ and zeros elsewhere. So the 4 by 25 matrix $\tilde{Q}$ is:

$$\tilde{Q} = \begin{bmatrix} 0&0&0&0&0&1&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&1&0&0&0&0&0&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&0&0&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&0&1&0&0&0&0 \end{bmatrix}$$

For the BEKK model the $K(5K+1)/2$-dimensional parameter vector is:

$$\vartheta = (vech(\boldsymbol{C})', vec(\boldsymbol{A})', vec(\boldsymbol{B})')' \tag{2}$$

The null hypothesis of noncausality (H_0: $\varepsilon_t^{\mathcal{J}} \overset{V}{\nrightarrow} \varepsilon_t^I$) can now be written as:

$$H_0: Q\vartheta = 0, \tag{3}$$

where

$$Q = [0_{(k(K-k)\text{ x }K}, \tilde{Q}, \tilde{Q}] \tag{4}$$

Similar to Comte and Lieberman (2003) we assume that for T observations, a consistent estimator, $\hat{\vartheta}$, of the true parameter vector ϑ_0 has the following asymptotic distribution:

$$\sqrt{T}\big(\hat{\vartheta} - \vartheta_0\big) \overset{\mathcal{L}}{\to} N(0, \Sigma_{\vartheta}), \tag{5}$$

with some positive definite and symmetric matrix Σ_{ϑ}. We also assume that a consistent estimate for Σ_{ϑ} is given by $\hat{\Sigma}_{\vartheta}$. If QML estimation is used, then (5) holds under the regularity conditions listed by Comte and Lieberman (2003), and Σ_{ϑ} is given by

$$\Sigma_{\vartheta} = \mathcal{S}^{-1}\mathcal{D}\mathcal{S}^{-1}, \tag{6}$$

where

$$\mathcal{D} = E\left[\frac{\partial l_t(\vartheta)}{\partial \vartheta}\frac{\partial l_t(\vartheta)}{\partial \vartheta'}\bigg|_{\vartheta_0}\right], \quad \mathcal{S} = -E\left[\frac{\partial^2 l_t(\vartheta)}{\partial \vartheta \partial \vartheta'}\bigg|_{\vartheta_0}\right], \tag{7}$$

with

$$l_t(\vartheta) = -\frac{K}{2}\ln(2\pi) - \frac{1}{2}\ln|\boldsymbol{H}_t(\vartheta)| - \frac{1}{2}\varepsilon_t'\boldsymbol{H}_t^{-1}(\vartheta)\boldsymbol{\varepsilon}_t. \tag{8}$$

We use the following standard Wald statistic for testing the hypothesis (3):

$$W_T = T(Q\hat{\vartheta})'\big(Q\hat{\Sigma}_{\vartheta}Q'\big)^{-1}(Q\hat{\vartheta}) \tag{9}$$

The asymptotic distribution of this Wald statistic is a chi-squared distribution with $k(K-k)$ degrees of freedom (Hafner and Herwartz, 2004):

$$W_T \overset{\mathcal{L}}{\to} \chi^2_{k(K-k)} \tag{10}$$

In study 2 the groups are $I = \{Returns\} = \{1\}$ and $\mathcal{J} = \{Retweets, Replies, Favorites\} = \{2, 3, 4\}$.