Volatility spillovers across stock returns and user-generated content

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Abstract

This study examines the interdependence between a company's stock returns and user-generated content (UGC) concerning (the products of) that company. We investigate this interdependence by studying the presence of mean, shock and volatility spillover effects between returns and UGC. The number of positive and negative tweets, blog posts, forum posts and daily searches for ticker symbols in the Google search engine are used as measures of UGC. The UGC data is collected via multiple sources over a six month period. Using a multivariate generalised autoregressive conditional heteroscedasticity - Baba, Engle, Kraft and Kroner (GARCH-BEKK) model we identify the source, magnitude and significance of mean, shock and volatility spillover effects between UGC and returns. We estimate the BEKK model for 27 different combinations of variables and compute averages over those results. The (average) results confirm the presence of spillover effects and show that there is a stronger connection - both in magnitude and in significance - in terms of mean, shock and volatility spillovers from UGC to returns than from returns to UGC. There are significant spillover effects between the various UGC metrics as well and these are larger than the effects from returns to UGC. This indicates that online content is affected more by other online content than by stock returns. Positive and negative content exhibit different spillover effects. Moreover, new product launches explain part of the volatility dynamics in stock returns and UGC.

Keywords: *user-generated content; volatility; multivariate GARCH BEKK model; shock spillover effects; volatility spillover effects.*

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1. Introduction

Throughout the world online shopping has grown exponentially, characterized by strong consumer demands and an ongoing increase in the number and types of goods available. Apart from buying a product online, consumers use the internet as a way to search for and share information about products. Consumers actively share their experiences and questions about a product or service via product reviews, blogs, videos and social media. The range of possibilities to share your thoughts and comments on a product online with other (potential) consumers is unlimited. This online posting of information is also referred to as *User Generated Content*, hereafter "UGC". UGC can be interpreted as a reflection of consumers' sentiment. Large-scale Twitter feeds are used in several studies as a metric of consumer sentiment (Bollen et al., 2011; Pak and Paroubek, 2010). One individual tweet (which can only contain a maximum of 140 characters) does not provide much information, but millions of tweets combined can represent public sentiment (Bollen et al., 2011). Apart from Tweets, other sources of UGC can be used to extract indicators of the public mood state, such as blogs (Gilbert and Karahalios, 2010; Mishne and Glance, 2006; Liu et al., 2007). The continuing growth of the internet has contributed to the surge in available information on products. Online consumer reviews have altered the ways consumers shop and choose their products (Li and Hitt, 2008). Social networks can promote the consumer to share UGC (Goldenberg et al., 2012) and the growth in popularity of social networks can trigger an increase in the amount of UGC available. Due to the ease of use, the constant availability, the wide reach and low costs, online UGC sources – such as product reviews – can have a significant impact on the stock market performance of the firm that produces the product (Tellis and Johnsen, 2007; Tirunillai and Tellis, 2012). According to web consumers, consumer reviews are considered to be even more valuable than experts' reviews (Piller, 1999) and might form a substitute for other media sources such as advertising (Li and Hitt, 2008). Reviews posted by consumers are considered to be more trustworthy than descriptions (advertising, promotion, etcetera) that come from manufacturers (eMarketer, 2010). Furthermore, 83 per cent of consumers state that it would be important to read UGC before making a decision about banking or other financial services (Kelton Research, 2011).

UGC is not just created by individuals, but more and more through the collaborative efforts of multiple individuals or teams. The value of UGC is therefore not only determined by the sole creator of the content, but also by its embeddedness in the network ('the content-contributor network') in which it is enclosed (Ransbotham, Kane and Lurie, 2012). Hence, the relative influence of UGC depends on the characteristics of the content, the creators of the content and their interactions (Berger and Milkman, 2012).

With UGC serving as an indicator of consumer sentiment it might influence a company's performance, as the opinion of consumers is important to most companies. This leads us to believe that the influence of UGC might experience the same transition as the influence of marketing efforts. The initial goals of marketing have been formulated from a customer's perspective, but marketing has also proven to have an impact on sales, profits and shareholder value, which in turn has influenced marketing decision makers within companies (Joshi and Hanssens, 2010). The initial goals of creating UGC have mainly been formulated from a consumer's perspective as well; users inform other (potential) users by writing tweets, blogs, or forum posts. As the aforementioned studies show that UGC also has an impact on sales and the stock value of a firm, we suspect that the performance of a company (in terms of sales or the stock price) in turn can influence the UGC regarding that company as well. The connection between UGC and a company's performance might trigger that company to actively focus on the UGC regarding their products to influence their performance. There are studies which advocate that UGC might have more influence than marketing activities (Trusov et al., 2009). Hence, we will focus on both the influence of UGC on the stock market and vice versa.

Up until now the influence of UGC on stock market performance has been investigated through an assessment of the direct relation between the online content and the stock price, but not just the level of the stock price is of interest in the financial world, the risk associated with the stock is just as important. Our study adds to the previous literature by focussing on the volatility of a company's stock returns instead of focussing on sales, profits, earnings or trading volume. Volatility is seen as an indicator of risk and risk is of paramount importance in the financial world (Franses and Van Dijk, 2000). The current globalization trend of international financial markets, combined with the importance of volatility as a measure of risk in these markets, has led to an increase in literature regarding so-called shock and volatility spillover effects among financial markets. Given the interpretation of shocks as news and the fact that at least certain news items affect various assets simultaneously, it might be suggested that the volatility of different assets moves together over time (Franses and Van Dijk, 2000). If markets are integrated, an unforeseen event in one market would not only have consequences on that particular market, it would affect both the returns and the variance in the other markets as well (Joshi, 2011). Hence, shocks and volatility can *spill over* from one market to another. In this study we focus on possible spillover effects between stock returns and UGC, opposed to spillovers between stock markets, prices or exchange rates. If there are shock or volatility spillover effects from online content to stocks, investors might be able to react on that news by hedging their position. They could either foreclose a hedge on a volatile or less volatile movement, depending on how large the spillover effects are and how much the volatility in returns is affected. Apart from hedging, if a certain type of stock is sensitive to volatility spillovers from UGC, it might lead to a different risk profile of that stock. Investors who want to diversify their portfolio might decide to invest in either volatile (risky) or less volatile stocks. If stocks of companies in certain industries are more prone to volatility spillovers from online content than stocks of companies in other industries, it could lead to a diversification in terms of industry.

In short, in this paper we study the presence of shock and volatility spillover effects between UGC and stock returns. The metrics for UGC are a collection of daily tweets, blog posts and forum posts regarding the product iPhone and a collection of the daily search volume for the ticker symbol of Apple (AAPL) in Google Search Engine. The stock returns we investigate are from Apple, the company that produces iPhones. Furthermore, we take important events concerning Apple into account, such as new product launches, mergers, etc. Apart from detecting the presence of shock and volatility spillovers, this paper seeks to answer the following questions:

- Do the shock and volatility spillover effects between stock returns and UGC differ depending on the choice of UGC measure?
- Do the effects differ depending on whether the content of the UGC is negative or positive?
- Are there shock and volatility spillover effects between the different measures of UGC?
- What is the influence of new product launches and organizational events (mergers, law suits, strategic alliances, etc.) on the variance and covariance of stock returns and UGC metrics?

With the use of a multivariate GARCH BEKK model[1] we investigate the presence, magnitude, significance and sign of shock and spillover effects. By adding dummies to the model and by estimating a Volatility Impulse Response Function (VIRF) we study the influence of new product launches and organizational events. Our results confirm the presence of spillover effects, both between UGC and returns and among the various UGC sources. The spillover effects from UGC to returns is stronger – in terms of magnitude and significance of the spillovers – than vice versa. The effects differ for positive and negative content according to our results regarding positive and negative tweets. Furthermore, the results show that new product launches and organizational events influence the volatility dynamics of both stock returns and UGC. These events, especially the launch of new products, are popular topics on forums, blogs or Twitter.

The paper is organized as follows. The second section presents a review of the literature. The third section explains the data and presents a preliminary analysis of various statistics. The fourth section explains the methodology and the fifth section describes the results. The sixth section contains the discussion and the paper ends with some brief concluding remarks in section seven.

[1] We discuss the choice for a multivariate GARCH BEKK model opposed to other models in the methodology section (chapter 4) and the discussion (chapter 5).

2. Literature Review

This chapter presents a review of the literature on UGC and volatility. In order to build the theory on which our research question(s) are based, we discuss several topics: the influence of UGC on companies' performance, volatility as proxy of risk, heteroscedasticity and GARCH models, and the relevance of studying volatility spillover effects.

2.1 The influence of UGC on companies' performance

News events and public sentiment have a strong influence on stock market prices. This means that both information and emotions play an important role in financial decision making, which is affirmed by behavioural finance studies (Gilbert and Karahalios, 2010). Consumers' sentiment is heavily affected by unexpected economic news shocks (Starr, 2012). As UGC reflects consumer sentiment and can serve as an early indicator of unpredictable news events we can use it for investment decisions or to analyse companies' performance. The studies of Godes and Mayzlin (2004) and Chevalier and Mayzlin (2006) find a significant influence of online product reviews on sales. Product reviews influence consumer product choice, enhance sales forecast quality, affect product sales, and drive viewership. Gruhl et al. (2005) conclude that book sales can be predicted with online chat activity. Dhar and Chang (2009) use UGC to predict sales in the music industry. Liu et al. (2007) and Mishne and Glance (2006) study the predictive power of blogs on movie sales and emphasize that not the volume of the blogs is predictive, but the sentiment expressed in them is. This sentiment about movies is expressed on Twitter as well, which is why Asur and Huberman (2010) use tweets to predict box office receipts. Apart from tweets and blogs, Google search queries are a useful source of UGC. Choi and Varian (2011) for example show that these Google trends can serve as an early indicator of consumer spending.

The aforementioned studies confirm that consumer goods companies are heavily dependent upon the opinion of customers about their products. On the firm's side, acquiring data about the opinion of customers can be a source of inspiration to product innovation. Since the public's opinion is so important, shareholders of companies consider this information to be valuable to them as well. Investors claim that UGC has become an important determinant in their investment decision, as it uncovers feedback on products that may not be available in investigative reports or experts' reviews (Tirunillai and Tellis, 2012).

According to Tirunillai and Tellis (2012) two important dynamics should be kept in mind in studies on the influence of UGC. The first dynamic is the delay in response to UGC, which means that the information in UGC about products or a company's performance is not immediately reflected in the stock market performance. This can be caused by a lack of proper means to extract useful information at a high (daily) frequency. Our study takes this delay into account both in modelling (including lags) and interpreting the spillover effects between UGC and returns. The second dynamic is the asymmetric response across UGC metrics. As companies tend to send only positive messages about their products, investors or customers have the tendency to believe negative news more than positive news. This induces a *negativity bias* among consumers, which means that negative information might elicit a stronger reaction than positive information. It is because of this bias that in this study we distinguish between positive and negative tweets, in order to investigate whether negative content might have stronger (spillover) effects on returns than positive content.

2.2 Volatility as a proxy of risk

The econometric analysis of risk is an integral part of various financial fields, such as asset pricing, portfolio optimization, risk management and option pricing. Financial decisions within those fields are generally based upon the trade-off between risk and return. The conditional mean and conditional variance of financial time series represent the return and risk of financial assets, respectively. Volatility is the square root of the conditional variance (the standard deviation) and is usually used as the proxy of risk or uncertainty in financial applications.

In the field of asset pricing the Capital Asset Pricing Model of Sharpe (1964) and Lintner (1965) has been of major influence in the classification of risk. The CAPM is used to calculate a reasonable approximation of systematic risk. The beta coefficient represents this systematic risk and is a measure of the sensitivity of the returns of the asset to market returns. The idiosyncratic risk (non-systematic) risk of the firms is represented by the residuals of the CAPM. Idiosyncratic risk is company specific. This type of risk is considered to be diversifiable whereas systematic risk is not (Fama and French, 2004). Even though, theoretically, investors should be able to diversify their portfolio in such a way that they are only exposed to systematic risk, practice shows that many investors are still exposed to idiosyncratic risk. Various valuation experts have acknowledged the existence of significant idiosyncratic volatility in public stock prices, which explains the importance of company specific news for traders on the stock market (Conn, 2011). The CAPM model is a one factor model which defines only one source of systematic risk, whereas multifactor models such as the three-factor model of Fama and French (1993) and the four-factor model of Carhart (1997) imply multiple sources of systematic risk. The idiosyncratic risk is still represented by the error terms of these models.

In the field of portfolio optimization, the Markowitz approach of minimizing risk for a given level of expected returns has become a standard approach. An estimate of the variance-covariance matrix is required to measure the level of risk.

In risk management a large part of the work is measuring the potential future losses of (a portfolio of) assets, and in order to measure or hedge these potential losses, estimates must be made of future volatilities and correlations.

Perhaps the most challenging application of volatility forecasting, however, is to use it for developing a volatility trading strategy. Option traders often develop their own forecast of volatility, and based on this forecast they compare their estimated value of an option with its market price. Given the importance of volatility as a measure of risk in the aforementioned fields, we are interested in obtaining accurate forecasts of the volatility of financial assets. Unfortunately, the volatility of financial assets is not directly observable, which makes forecasting volatility a more challenging task as opposed to forecasting returns.

While stressing the importance of estimating and forecasting volatility, the main goal of volatility analysis must ultimately be to explain the causes of volatility. Volatility is a response to news events, which are considered to be unpredictable (Engle and Ng, 1993). In spite of the fact that these events are unpredictable, the timing in which they occur might not be a surprise. Via economic announcements for instance, we can somewhat predict the volatility, even though the news itself is still unknown. The mere presence of an announcement might boost volatility, quite apart from the size of the surprise associated with the announcement (Andersen et al., 2003). Depending on the type of market (stock, bond or exchange rate) and the phase of the business cycle (contraction or expansion) the impact of news can be positive or negative (Andersen et al., 2007). Schumaker and Chen (2009) investigate the relations between breaking financial news and stock price changes. The amplitude of return movements in a certain stock market might be caused by observed volatility in that same market earlier, or a different stock market. Engle, Ito and Lin (1990) call these 'heat wave' and 'meteor shower' effects.

2.3 Heteroscedasticity and GARCH models

Regression analysis investigates relationships (linear, nonlinear, simple or multiple) among variables. Forecasting is one of the main motivations for constructing a regression model. An observed time series can be written as the sum of a predictable and unpredictable part: $y_t = E[y_t|\Omega_{t-1}] + \varepsilon_t$, where Ω_{t-1} is the information set with all relevant information up to and including time *t-1* (Franses and Van Dijk, 2000). The variance of the error terms determines the accuracy of the predictions and – as mentioned in the previous paragraph – can be interpreted as a proxy of risk. The expected value of these error terms, when squared, is assumed to be the same at any given point. This assumption is called homoscedasticity. However, in practice we see a different phenomenon: one of the most characteristic features of financial time series is the existence of regimes within which returns and volatility display different dynamic behaviour. When the variances of error terms are not equal, but are larger for some points or ranges of the data, we state that the data suffers from heteroscedasticity. Consequently, the standard errors and confidence intervals of the regression coefficients of the ordinary least squares regression are too narrow and give a false sense of precision (Engle, 2001). Although 'variance stabilizing' transformations, like log-conversion take care of problems with differing variances, there still remain inexplicable differences among the segments of a data set. The existence of regimes of high or low volatility tells us that there is a degree of autocorrelation in the riskiness of financial returns. These periods of either high or low volatility are called 'volatility clusters'. The warnings about heteroscedasticity usually concern cross-section and time series models. Using exogenous variables (like income, population, etc.) to explain the variance is the standard solution for heteroscedasticity in cross-sectional models, but this is not the case with financial data. In finance, the forecast variance is of importance itself; a model where the variance changes based upon an exogenous regime will not be very helpful. The simplest approach to estimating volatility is to use the historical standard deviation. However, the presence of volatility clusters complicates this approach. Even if there appeared only a few variance clusters within the return series, there remains the problem in forecasting of not knowing which 'regime' would hold into the future.

Instead of considering volatility clustering as a problem to be corrected, ARCH (autoregressive conditional heteroscedasticity) and GARCH (*generalized* autoregressive conditional heteroscedasticity) models treat heteroscedasticity as a variance to be modelled (Engle, 2001). ARCH and GARCH models generate the type of variance clustering evident in financial data, but with the variance a closed form of the data, so it can be forecasted out-of-sample, which is of great importance to the aforementioned applications in finance (Engle, 2001). According to the GARCH specification, the error term (the unpredictable part or shock) of a time series regression[2], ε_t, has time-varying conditional variance, 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 $\sqrt{h_t}$, the square root of the conditional variance, is the volatility. To specify how the conditional variance of ε_t varies over time, various types of GARCH models can be used (Franses and Van Dijk, 2000). The most widely used GARCH specification asserts that the best predictor of the time-varying conditional variance h_t in the next period is a weighted average of the long-run average variance, the variance predicted for this period, and the new information in this period that is captured by the most recent squared residual. Since volatility is a proxy of risk, we could interpret the variable $\sqrt{h_t}$ as risk and z_t as idiosyncratic noise.

A wide range of 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. In the initial CAPM model the residuals are assumed to be identically independently distributed through time (CAPM-NORMAL), but in order to better capture the unsystematic or idiosyncratic risk in asset returns, a CAPM-GARCH model with GARCH effects is applied in several studies (Wang, Tzang, Wu, Hung, 2012; Najand, Lin and Fitzgerald, 2006) and the resulting estimates of systematic risk can be used in option pricing models (Wang, Tzang, Wu, Hung, 2012). Lin, Penm, Wu, and Chiu (2004)

[2] The error term of the aforementioned regression $y_t = E[y_t|\Omega_{t-1}] + \varepsilon_t$

studied the systematic risk and stock returns with GARCH effects in the banking industry of Taiwan, Hong Kong and Mainland China. Other studies jointly modelled the Fama French three factor model and a GARCH model to account for volatility clustering (Nath, 2012; Brooks, Li, and Miffre, 2009; Glabadanidis, 2009; Caldeira, Moura and Santos, 2012). Some studies applied a multivariate GARCH model to estimate systematic risk: the beta (Nieto, Orbe, Zarraga,2010; Bollerslev, Engle and Wooldrigde, 1988; Choudhry and Wu, 2008; Setiawan, 2012).

2.4 The relevance of studying shock and volatility 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 CAPM (Engle, 2001). Another interesting phenomenon is the possibility that the volatility of an asset might not only influence the amplitude of returns, the volatility of other assets as well. We can compare this to volatility 'spilling over' from one asset to another and refer to it as 'volatility spillover effects'. This can be studied using multivariate modelling, to investigate the (cross) influence of past shocks and past volatility on current volatility (Engle and Kroner, 1995; Bauwens et al., 2006). The current globalization trend of international financial markets, has sparked a surge in literature regarding shock and volatility spillovers among the financial markets. With volatility as an indicator or risk, investors want to study shock and volatility spillover effects in order to anticipate possible changes in the risk level of stocks, so they would be able to hedge positions or diversify portfolios. Some studies on spillovers find evidence of integration of Asian stock markets (Joshi, 2011), Eastern European markets (Li and Majerowska, 2008) or distinguish between spillovers from developed to emerging markets and vice versa (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). A Multivariate Generalized Autoregressive Conditional Heteroscedastic model (Multivariate GARCH model) is used in several of these studies, because it takes the time-varying nature of conditional volatility and correlation of stock markets into account. Furthermore, with this model future stock returns volatility can be predicted conditional on past volatilities and shocks (Bollerslev, 1992; Worthington and Higgs, 2004).

There are numerous types of multivariate GARCH models, such as the (diagonal) VECH model, the (diagonal) BEKK model, the CCC model, the DCC model and factor models. The choice for one of these models is based on outweighing the pros and cons of various factors such as the number of parameters (very large for the VECH model, smaller for the CCC and DCC model), the underlying assumptions (constant correlations in the CCC model), possible restrictions that need to be added (e.g. to guarantee positive definiteness of the covariance matrix), the estimation procedure (the number of steps and with which software it can be programmed) and whether 'interaction' between (co-)variances is allowed for (not the case with diagonal models). After outweighing these pros and cons we decided to use a multivariate GARCH BEKK model. We explain our choice more thoroughly in the methodology section and the discussion, as some advantages of the BEKK model are easier to explain when discussing the specific characteristics of the model (opposed to other models).

In the following chapters we explore the presence of shock and volatility spillover effects between UGC and stock returns, the next chapter will start with an outline of the data we use for our analysis.

3. Data and Preliminary Analysis

We use daily data on UGC and stock market performance from October 1, 2009 until March 30, 2010, in total 181 observations.[3] The UGC variables are Positive Tweets, Negative Tweets, Number of Blog Posts, Number of Forum Posts and Number of Google Search Tickers. Furthermore, we use data on new product launches and organizational events. Organizational events are all events which are not new product launches or financial events (announcements of earnings, dividends, etc.), such as mergers, client contracts, strategic alliances, lawsuits, reorganizations, corporate governance changes, changes in key executives and labour relations. The positive and negative tweets on Twitter are classified using a support vector machine algorithm. The number of daily blog posts are collected via Newstex, which enabled us to select blogs from news organizations, corporations, independent experts and thought leaders. The number of forum posts are collected via Google Groups. The Google search tickers, the daily number of searches for Apple's ticker symbol in the Google search engine, are obtained 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 (Luo et al. 2013) and to hide the actual search volume of the keyword in the Google search engine. The new product launches and organizational events are obtained from the Capital IQ's key developments database. A list of all the variables and their description is included in Table 1. Because the market is closed in weekends and during holidays, we use the average of the prior day (e.g., Friday) when the market is open and of the next day when the market is open (e.g., Monday) to impute the values for days when the market is closed.[4] The motivation to use daily data comes from the fact that at higher frequency levels (such as hourly) there is not much UGC data available and for the use of (multivariate) GARCH models, a sufficient amount of data is required. Furthermore, using lower frequency data (weekly or monthly) might lead to biased estimates (Tellis and Franses, 2006) and can conceal temporary reactions to unforeseen events or innovations which may only last for a few days (Elyasiani, Perera and Puri, 1998).

Figure 1 displays the graphs of the return and UGC data series and the series New Product Launch and Organizational Events. The spikes in some of the graphs indicate two important dates for Apple. On October 20th, 2009, the variable Returns reaches a maximum. On that same day there were 5 new product launches: Apple unveiled the new iMac, the Magic Mouse and several updates on the MacBook. The second important date 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. The spikes in the series Organizational Events are related to

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[3] Gathering the data has been a time-consuming and intricate task, which is why we have a rather small sample. We hope to collect more data for future research, which will be discussed in chapter 6.

[4] We understand that it is a rather unconventional approach to construct returns for Saturday and Sunday, but considering the fact that the dataset is small, omitting the UGC data in the weekends would make it too small to conduct our analysis. We recognize that other approaches would have been possible al well (such as aggregating the UGC data on weekends and Monday, although that would have made the sample smaller and would have caused an unnatural peak on Mondays), each coupled with pros and cons.

various mergers, client contracts, strategic alliances, lawsuits, reorganizations, corporate governance changes, changes in key executives and labour relations. In the graphs of the Number of Blog Posts and the Number of Google Search Tickers we can see a pattern; a seasonality. During weekends the number of blog posts and Google search tickers is lower than during weekdays.[5]

Apart from the aberrant observations, another interesting feature to explore in the graphs of Returns and the UGC variables of Figure 1 is heteroscedasticity. In the time series graphs of Returns, Positive Tweets, Negative Tweets and Forum Posts the variance of the (deviations from the trend of the) time series seems to change over time, which is a sign of heteroscedasticity. In the graphs of Blog Posts and Google Search Tickers this somewhat difficult to see. In order to check whether some of the time series exhibit time-varying volatility, we plotted time-varying estimates of the historical volatility, using a rolling window of 10 days.[6] Along with those estimates, we computed estimates of the exponentially-weighted average of each of the squared variables, which gives more weight to more recent data.[7] The graphs are presented in Figure 1 in the Appendix. The time series Returns, Positive Tweets, Negative Tweets and Forum Posts exhibit clear volatility clustering. The time series Blog Posts and Google Search Tickers have volatility clustering as well, but the volatility in these time series does not appear to be as time-varying as in the other four series.

Both squared returns and absolute returns are used as proxies for the volatility in returns. Similarly, squaring the number of positive tweets, negative tweets, blog posts, forum posts or Google search tickers can form proxies for the volatility of those series. We use those proxies to get some preliminary insights into the relationship between the variables. Table 2 shows the correlation between the (squared) returns and (squared) UGC variables. The correlation between the UGC variables is bigger than the correlation between the UGC variables and returns. The largest (negative) correlation between returns and a UGC variable is between negative tweets and returns (-0.063), indicating a negative relationship between these series: when returns increase, the volume of negative tweets (slightly) decreases. The correlation between the squared variables (the volatility proxies) is in almost all combinations larger than the correlation between the variables. The volatility of returns is positively correlated with all volatilities of the UGC variables. The correlation between the volatility of returns and the volatility of positive tweets (0.129) is quite large and so is the correlation between the volatility of returns and the volatility of Google search tickers (0.277), indicating quite a strong connection between the volatilities of returns and positive tweets and the volatilities of returns and Google search tickers. Apart from studying the correlation between the (squared) variables estimated over the entire sample, we plotted the correlation between (squared) returns and (squared) UGC

[5] We will get back to that in the methodology in chapter 4.

[6] With the chosen window width W of 10 days, this is $\hat{\sigma}_t^2 = \frac{1}{W}\sum_{s=t-W+1}^{t} y(s)^2$, where y is the variable Returns, or one of the UGC variables.

[7] This volatility estimate is $\hat{\sigma}_t^2 = (1-\alpha)\hat{\sigma}_{t-1}^2 + \alpha y(t)^2$, which is a weighted sum of last period's volatility estimate and this period's squared variable $y(t)^2$ and y is the variable Returns, or one of the UGC variables. For α we use 1/(1+(W/2)), with W being the window width of 10 days (Doan, 2013).

variables with a moving window of 10 days, displayed in Figure 2. These graphs show that the correlation between these variables and their volatility is time-varying. In order to give an impression of the correlation using a different proxy, Figure 3 shows scatterplots of absolute returns with squared UGC variables. The plots confirm the previous findings: the volatility of returns is correlated with the volatility of positive tweets, blog posts, forum posts and Google search tickers. Finally, Table 3 shows the correlation between (squared) returns and new product launches and organizational events. Returns are more strongly correlated with new product launches than with organizational events and the volatility in returns is even stronger correlated with new product launches.

Given the strong signs of volatility clustering and the time-varying nature of the correlation between the (volatility) of the time series, we will investigate the relation between UGC variables and Returns further using a multivariate GARCH BEKK model, as this takes these type of dynamics into account. A multivariate GARCH model takes the time-varying nature of (co)variances into account and the BEKK specification is especially suited for estimating possible spillover effects. We will explain this model in more detail in the next chapter, but before proceeding to the methods, we present some summary statistics of the variables in Table 4 and 5. The Jarque Bera statistics and corresponding *p*-values indicate whether or not the series are normally distributed. For all series normality is rejected, except for Positive Tweets. The skewness and kurtosis of Negative Tweets, Blog Posts and Google Search Tickers are high, which is presumably caused by the spike in each of those series on January 27th, 2010 (the day the iPad was introduced). Hence, we will take the natural logarithm of those series before estimating the multivariate GARCH BEKK model.[8] In order to test the stationarity conditions the Augmented Dickey-Fuller (ADF) test is applied to the UGC variables and the results are displayed in Table 5. This unit root test is a statistical test to detect the presence of stationarity in time series used in autoregressive models. If a time series is stationary, it means that the mean, variance and covariance of this series remain unchanged by time shifts. If they are non-stationary, the mean and/or the variance are time-varying. In that case we can study only a limited period and results are not applicable to other periods. Moreover, the standard assumptions for asymptotic analysis are not valid for non-stationary time series, indicating that hypothesis tests about regression parameters (t-tests for instance) cannot be used in that case. The null hypothesis of the ADF-test states that there is a unit root and the *p*-values in Table 5 show whether or not this null hypothesis can be rejected. All UGC series are stationary.

We will now proceed with the methodology in the next chapter, taking the aforementioned findings into account.

[8] Since we have to match the scaling of the variables for our analysis (which will be explained in chapter 4), we will take the natural logarithm of Positive Tweets and Forum posts as well before estimating the BEKK model.

Table 1: Description of the variables

Variables	Description	Details about the variables
Returns	Stock returns of Apple	Stock return data of Apple
Positive Tweets	Volume of positive tweets about iPhone	e.g. I love the iPhone. Classified using a Support Vector Machine Algorithm.
Negative Tweets	Volume of negative tweets about iPhone	e.g. I hate the iPhone. Classified using a Support Vector Machine Algorithm.
Number of Blog Posts	Number of 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.
Number of Forum Posts	Number of posts by users in internet community forums about iPhone	Discussion Forums are the number of posts on internet community forums that mentioned the brand name in each day. An Internet community forum is an online discussion site where people hold conversations in the form of posted messages on topics that interest them. We collect the data for the discussion forums from Google Groups.
Number of Google Search Tickers	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. Google normalizes and scales the actual search volume of the keyword to remove regional effects (Luo et al. 2013) and to hide the actual search volume of the keyword in the Google search engine. 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 Search Tickers.
New Product Launch	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. We include events such as mergers, client contracts, strategic alliances, lawsuits, reorganizations, corporate governance changes, changes in key executives, and labour relations. We obtain the data from Capital IQ's key developments database

Table 2: Correlation between (squared) Returns (RTN) and (squared) UGC variables

Correlation	RTN	PT	NT	BP	FP	GST
RTN	1.000	0.010	-0.063	-0.023	-0.008	0.035
PT	0.010	1.000	0.814	0.234	-0.063	0.167
NT	-0.063	0.814	1.000	0.533	-0.102	0.419
BP	-0.023	0.234	0.533	1.000	-0.120	0.822
FP	-0.008	-0.063	-0.102	-0.120	1.000	-0.062
GST	0.035	0.167	0.419	0.822	-0.062	1.000
Correlation	**Squared RTN**	**Squared PT**	**Squared NT**	**Squared BP**	**Squared FP**	**Squared GST**
Squared RTN	1.000	0.129	0.079	0.081	0.070	0.277
Squared PT	0.129	1.000	0.693	0.329	-0.072	0.272
Squared NT	0.079	0.693	1.000	0.821	-0.136	0.691
Squared BP	0.081	0.329	0.821	1.000	-0.143	0.871
Squared FP	0.070	-0.072	-0.136	-0.143	1.000	-0.087
Squared GST	0.277	0.272	0.691	0.871	-0.087	1.000

Table 3: Correlation between (squared) Returns (RTN) and New Product Launches (NPL) and Organizational Events (OE)

Correlation	
RTN – NPL	0.173
RTN – OE	0.051
Squared RTN – NPL	0.264
Squared RTN – OE	0.063

Table 4: Summary statistics of the data: the mean, standard deviation, skewness, kurtosis, the Jarque Bera statistic (JB-stat) and the corresponding *p*-value of the Jarque Bera statistic (JB *p*-value)

Variables	Mean	Standard Deviation	Skewness	Kurtosis	*JB-stat*	*JB p-value*
Returns	0.279	1.571	-0.227	0.904	7.708	0.021
Positive Tweets	7450.834	2351.116	0.002	3.434	1.423	0.491
Negative Tweets	3355.564	1282.835	2.513	18.979	2116.016	0.000
Blog Posts	24.989	18.192	3.266	24.233	3721.756	0.000
Forum Posts	326011.000	22326.610	0.761	4.665	38.363	0.000
Google Search Tickers	18.426	12.282	2.868	16.228	1567.793	0.000

Table 5: The results of the ADF test for the UGC variables

UGC Variables	*ADF-statistic*	*ADF p-value*
Positive Tweets	-4.034	0.002
Negative Tweets	-6.790	0.000
Blog Posts	-3.156	0.024
Forum Posts	-13.247	0.000
Google Search Tickers	-4.285	0.001

Figure 1: Time Series Plot of Returns, Positive Tweets, Negative Tweets, Number of Blog Posts, Number of Forum Posts, Number of Google Search Tickers, New Product Launch and Organizational Events (October 2009 to March 2010)

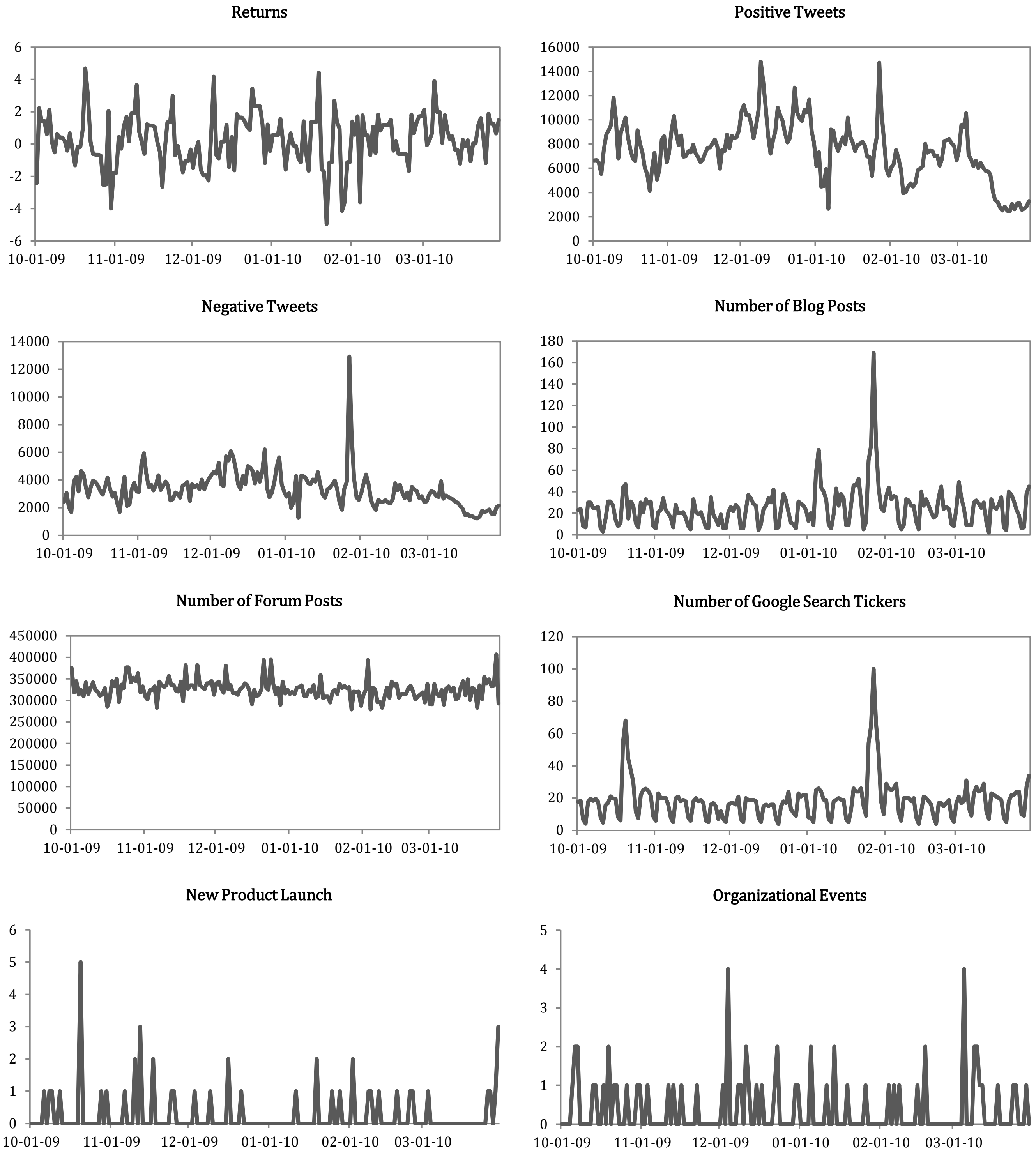


Figure 2: Correlation between (squared) Returns (RTN) and (squared) UGC variables Positive Tweets (PT), Negative Tweets (NT), Number of Blog Posts (BP), Number of Forum Posts (FP) and Number of Google Search Tickers (GST), plotted with a moving window of 10 days.

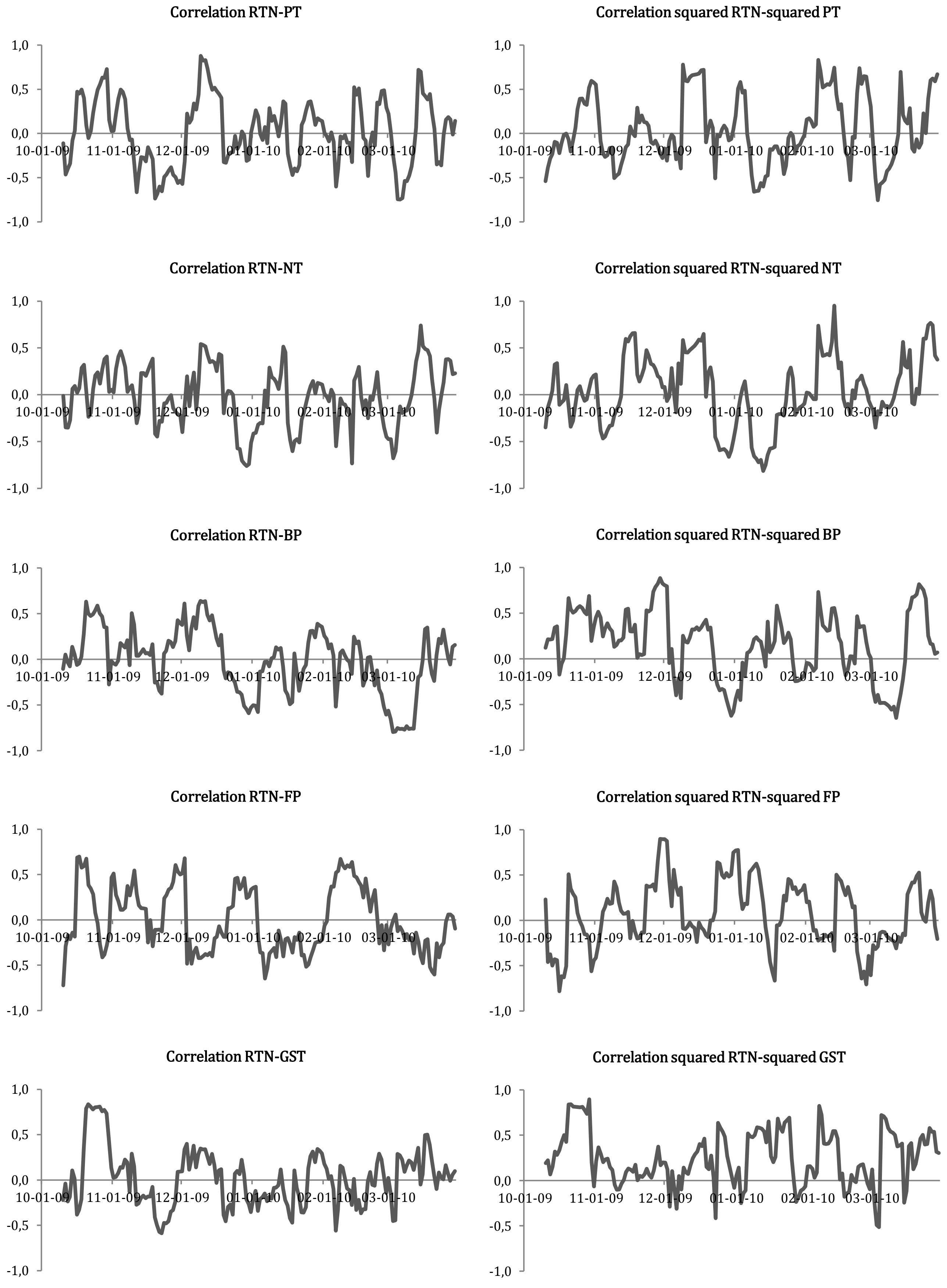
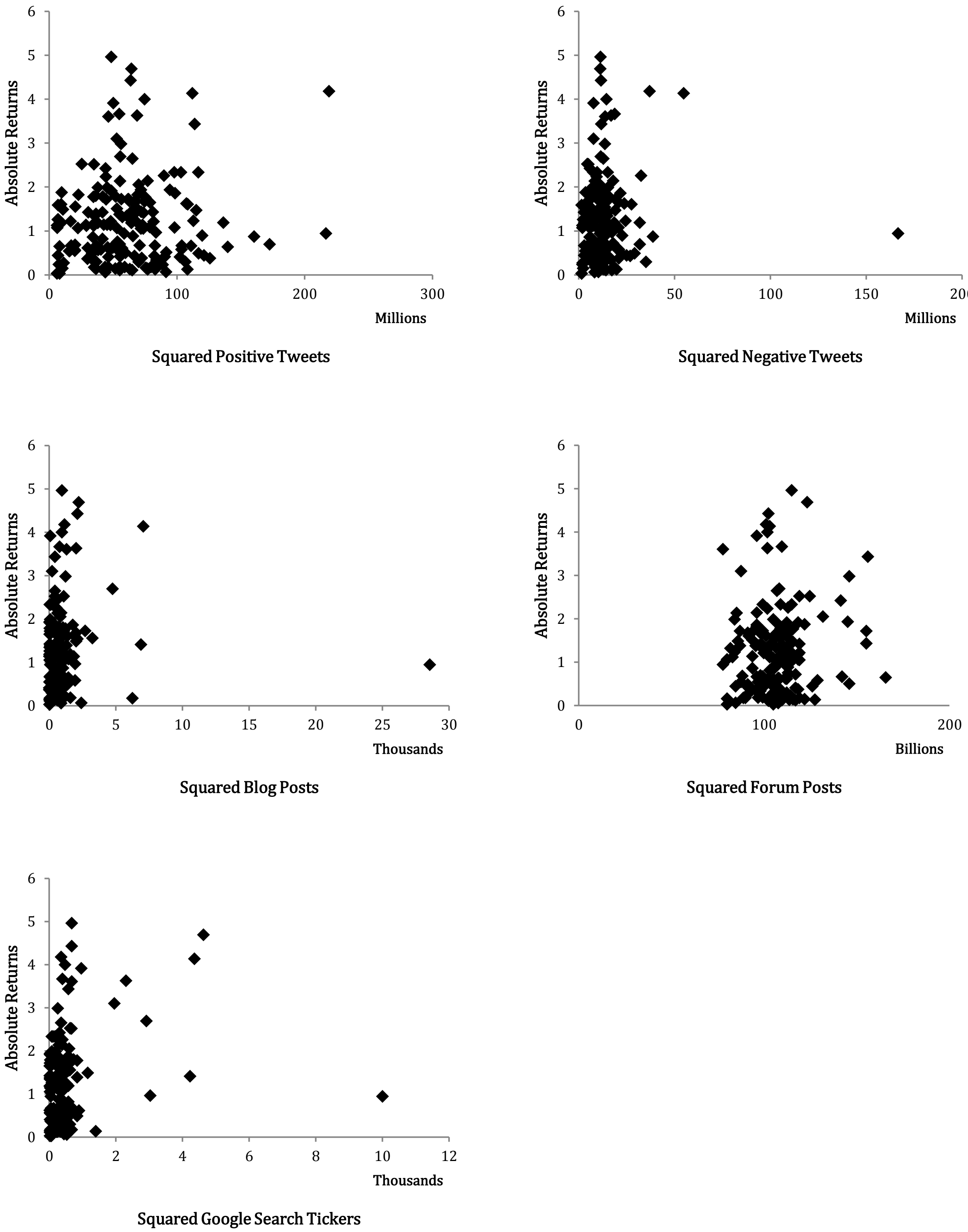


Figure 3: Scatter plots of Absolute Returns and squared UGC variables Positive Tweets, Negative Tweets, Number of Blog Posts, Number of Forum Posts and Number of Google Search Tickers.



4. Methods

To investigate the direct relation between stock returns and UGC we use a VAR(1) model. The specification of the VAR(1) model[9] is:

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

where Y_t and Y_{t-1} are n by 1 vectors at time t and t-1, respectively; n indicates the number of variables included in the model. We will elaborate on the choice of variables in the next section. The vector $\boldsymbol{\alpha}$ represents a n by 1 vector of constants and $\boldsymbol{\Gamma}$ is a n by n matrix for parameters associated with the lagged variables. The diagonal elements of the matrix $\boldsymbol{\Gamma}$, γ_{ij}, measure the own lagged mean spillover effects. The off-diagonal elements capture the cross mean spillover effects between the (lagged) variables. The n by 1 vector of random error, $\boldsymbol{\varepsilon}_t$, is the innovation for all n variables at time t and a general multivariate GARCH model for this n-dimensional process $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}, \ldots, \varepsilon_{nt})'$ is given by:

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

Where $\boldsymbol{z}_t$ is a n-dimensional 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 $E[\boldsymbol{\varepsilon}_t|\Omega_{t-1}] = \boldsymbol{0}$ 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 n by n conditional variance-covariance matrix $\boldsymbol{H}_t$ needs to be specified ($\boldsymbol{H}_t = f(\boldsymbol{H}_{t-1}, \boldsymbol{H}_{t-2}, \ldots, \boldsymbol{\varepsilon}_{t-1}, \boldsymbol{\varepsilon}_{t-2}, \ldots)$) (Franses and Van Dijk, 2000). The parameterization we choose is the multivariate GARCH BEKK model. With this type of multivariate GARCH model, combined with the VAR(1) model, we investigate the relation between the variance of UGC metrics and the variance of stock returns. The BEKK representation of the matrix $\boldsymbol{H}_t$ is:

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

where $\boldsymbol{A}$ and $\boldsymbol{B}$ are n by n matrices and $\boldsymbol{C}$ is a lower triangular matrix of constants. Engle and Kroner (1995) refer to this formulation as the BEKK (Baba, Engle, Kraft and Kroner) representation. 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 variable i to j. We refer to these effects as shock spillover effects. The diagonal elements in matrix $\boldsymbol{A}$ represent the ARCH effect (the effect of lagged shocks) and the off-diagonal elements the cross-spillover effects. Negative coefficients in the off-diagonals of matrix $\boldsymbol{A}$ mean that the variance 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

[9] The lag length in the VAR model is determined using the Schwarz Information Criterion. We estimate the VAR model for 27 different combinations of variables (as listed in Table 6) and according to the SIC, all 27 combinations should have lag length 1 in the VAR model.

variable *i* and *j*. 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. The guaranteed positive definiteness of $\boldsymbol{H}_t$ and the fact that all spillover effects are taken into account are the main advantages of the BEKK representation opposed to other multivariate GARCH representations (Doan, 2013). This has contributed to our decision to use the BEKK model, along with various drawbacks of other multivariate GARCH models. Diagonal models such as the Diagonal BEKK and Diagonal VECH do not take spillovers into account (matrices $\boldsymbol{A}$ and $\boldsymbol{B}$ are diagonal matrices), the full VECH model has more parameters than the BEKK model and needs restrictions to guarantee positive definiteness, the common factors employed in factor models (size, market-to-book, momentum) are not suitable for our dataset, the assumption of constant correlation in the CCC model is too strict (considering the results of our preliminary analysis in chapter 3) and the a drawback of the DCC model is the unrealistic assumption that all entries in the conditional correlation matrix are influenced by the same coefficients. Although some of these alternative models have some advantages over the BEKK model (some have fewer parameters), their disadvantages led us to favour the BEKK representation over the other models.

The aforementioned n variables are a combination of the UGC variables Positive Tweets, Negative Tweets, Number of Blog Posts, Number of Forum Posts and Number of Google Search Tickers and the variable Returns. The values of the coefficients of matrices $\boldsymbol{A}$ and $\boldsymbol{B}$ in the BEKK representation are sensitive to the scales of these variables, since 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). Figure 1 shows that there is a wide variety in the scaling of the series. In order to match the scaling we take the natural logarithm[10] of the UGC series Positive Tweets, Negative Tweets, Number of Blog Posts, Number of Forum Posts and Number of Google Search Tickers.

We perform a 'meta-analysis'[11] to study the shock and volatility spillover effects between UGC variables and Returns by estimating 27 multivariate GARCH BEKK models using various combinations of variables. Table 6 displays those 27 combinations. Since the total number of parameters in the GARCH BEKK equation differs depending on the number of variables included in the model, we also list the total number of parameters per model in Table 6. Certain shock and volatility spillover effects are estimated in all or a part of the 27 models and we compute the average of those effects. The purpose of estimating these different BEKK models is not just to average and generalize the results, it is also to investigate interesting combinations of variables. Since the BEKK model might suffer from

[10] Although in general taking the natural logarithm does not guarantee that the scaling of the variables is matched, it is sufficient for our dataset. We are aware of other options (e.g. subtracting the mean and then dividing by the unconditional sample standard deviation), but the advantage of the natural logarithm is that coefficients on the natural logarithm scale remain directly interpretable, which we prefer over advantages of other options.

[11] The term meta-analysis is usually used to indicate combined results from different studies. In this case not different studies, but different models are combined. The term is therefore mainly used out of convenience opposed to alternatives as 'an analysis of the summarized results of 27 models with various combinations of variables'.

the so-called 'curse of dimensionality' and our dataset is rather small, we decided to estimate the model for different combinations of time series. The possible consequences of this curse of dimensionality are not clear beforehand and could vary from overfitting to numerical instabilities. Hence, including all variables might not guarantee a 'better' model opposed to a smaller version (Verleysen et al., 2005), which is why we choose to model different combinations of variables.[12] To be able to discuss and compare all these results (reviewing whether effects are large/ small or significant/insignificant in most models), we summarized them and refer to this as a 'meta-analysis'.[13]

Table 6 also shows that we add a dummy variable to the BEKK equation in some of these models. The dummy variables are Dummy New Product Launch and Dummy Organizational Events and they are computed using the series New Product Launch and Organizational Events and they are used to study the possible influence of these launches or events on the (co)variances of returns and UGC variables. If one or more new product launches occur on a specific date in the series New Product Launch, the variable Dummy New Product Launch lists a 1 on that date, and if there are no launches a 0 is listed. The same procedure is used to compute the variable Dummy Organizational Events, where a 1 indicates one or more organizational events on a certain date and 0 indicates no events on that date. Adding one of these dummies to the BEKK equation adjusts the $\boldsymbol{C}$ term. Due to the fact that there are sign restrictions in the BEKK recursion because of the desire to enforce positive-definiteness, adding a dummy in the recursion comes down to replacing $\boldsymbol{C}'\boldsymbol{C}$ with:

$$(\boldsymbol{C} + \boldsymbol{E}d_t)'(\boldsymbol{C} + \boldsymbol{E}d_t) \tag{4}$$

Where $\boldsymbol{E}$ is, like $\boldsymbol{C}$, a lower triangular matrix. Adding the dummy, d_t, this way enforces positive definiteness and guarantees that the model is not sensitive to the choice of representation of the dummy, due to the fact that adjustments to matrix $\boldsymbol{C}$ are made before squaring. In chapter 2 we described the seasonality present in the number of blog posts and the number of Google search tickers. This could be taken into account by creating a dummy, but that would increase the number of parameters in each model and considering the large number of parameters we have in the BEKK recursions (see Table 6), we decided not to create a dummy for the weekends as well. As it might be a possibility to explore in future research, we get back to that in the discussion in chapter 5.

The mean equation 1 and the BEKK equation 3 (or the BEKK equation 3 with $\boldsymbol{C}'\boldsymbol{C}$ replaced by equation 4) are estimated simultaneously by the BFGS maximum likelihood method. The BFGS (Broyden, Fletcher, Goldfarb and Shanno) 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)

[12] This approach is rather unconventional opposed to other studies using multivariate GARCH models, where usually one model is chosen and presented. Due to our small dataset we preferred estimating BEKK models using multiple combinations of variables over choosing one model with the risk of that one model suffering from overfitting or numerical instabilities.
[13] We understand that merely providing these summarized results might not be the ideal approach to discussing results of a multivariate GARCH BEKK model, which is why we will discuss one model separately.

using an update method which will give a different answer for different initial guess values. A pre-estimation 'simplex' procedure is used with approximately 20 iterations 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. The BFGS method uses those values as initial values instead of the guess values for doing the final estimates (Doan, 2013). In order to correct for possible misspecification we compute Bollerslev-Wooldridge standard errors in this final estimation.

The fit of the BEKK model is exactly the same if you change the sign of the entire $\boldsymbol{A}$ or $\boldsymbol{B}$ matrix, as the model is not globally identified. This means that the sign of the coefficients should be interpreted with caution, although in most cases the sign will be steered in the right direction by the initial guess values (Doan, 2013).

To test the adequacy of the models we perform a multivariate ARCH test on the residuals of the BEKK recursion, to check the possible presence of remaining arch effects.

Impulse response functions describe the dynamics of a VAR model. To describe the dynamics of a multivariate GARCH BEKK model, we use a similar model: a volatility impulse response function (hereafter: VIRF) (Hafner and Herwartz, 2006). With IRFs, the impulses are responses to a standardized set of shocks, which can be rescaled to get responses to any other set of shocks. These type of shocks are not possible in VIRFs, as the $\boldsymbol{\varepsilon}_t$ enters as a square in the recursion. The standardized shocks may therefore be out of scale, so we need to calculate the VIRFs as the responses to a complete vector of shocks (Doan, 2013). The shocks we include in the recursion are characteristic for the data (Hafner and Herwartz, 2006). We choose to use two important dates for Apple: the October 20th, 2009 and January 27th, 2010. As explained in chapter 3: on October 20th, 2009, the variable Returns reaches a maximum and on that day 5 new products were launched. On January 27th, 2010 Steve Jobs launched the iPad and the number of positive tweets, negative tweets, blog posts and Google search tickers reached a maximum. To compute the VIRF, we need to convert the BEKK estimates into VECH estimates (Doan, 2013). The BEKK model is a restriction of the VECH model. A VECH(1,1) model is written as:

$$vech(\boldsymbol{H}_t) = \boldsymbol{C}^* + \boldsymbol{A}^* vech(\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1}) + \boldsymbol{B}^* vech(\boldsymbol{H}_{t-1}) \tag{5}$$

The *vech* operator converts a n by n symmetric matrix into a $n(n+1)/2$ vector by eliminating the duplicated entries. $\boldsymbol{A}^*$ and $\boldsymbol{B}^*$ are full $(n(n+1)/2 \text{ x } n(n+1)/2)$ matrices and $\boldsymbol{C}^*$ is a $n(n+1)/2$ x 1 vector which is the *vech* of a positive semi-definite matrix. The VECH model is rarely used, because it contains a very large number of free parameters. Even though it is not very useful for estimation, it is useful for forecasting and similar calculations, such as computing a VIRF (Doan, 2013). Forecasts of recursion 5 can be generated via:

$$vech(\widehat{\boldsymbol{H}}_{t+1}) = \boldsymbol{C}^* + \boldsymbol{A}^* vech(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t') + \boldsymbol{B}^* vech(\boldsymbol{H}_t)$$
$$vech(\widehat{\boldsymbol{H}}_{t+k}) = \boldsymbol{C}^* + (\boldsymbol{A}^* + \boldsymbol{B}^*) vech(\widehat{\boldsymbol{H}}_{t+k-1}) \tag{6}$$

To create shocks for the VIRF we pick either $\boldsymbol{\varepsilon}_t$ and transform to $\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'$ or pick $\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'$ directly (Doan, 2013). Computing volatility forecasts with a shock (with $\varepsilon_t \neq 0$) is different compared to equation 6:

$$vech(\mathbf{v}_{t+1}) = \boldsymbol{A}^* vech(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t')$$
$$vech(\mathbf{v}_{t+k}) = (\boldsymbol{A}^* + \boldsymbol{B}^*) vech(\mathbf{v}_{t+k-1}) \tag{7}$$

Hafner and Herwartz (2006) refer to this function of the model coefficients and the shock (not the data) as the conditional volatility profile. In the standard IRF, we compute the revision in the forecast by observing the given shock. For the analogous idea in the volatility equation, we use a formula similar to equation 7 for the VIRF, with a slightly different input (Doan, 2013):

$$vech(\mathbf{V}_{t+1}) = \boldsymbol{A}^* vech(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t' - \boldsymbol{H}_t)$$
$$vech(\mathbf{V}_{t+k}) = (\boldsymbol{A}^* + \boldsymbol{B}^*) vech(\mathbf{V}_{t+k-1}) \tag{8}$$

Where $\boldsymbol{H}_t$ is the variance-covariance matrix for time *t*. The VIRF depends upon the data now through $\boldsymbol{H}_t$ – the 'shock' to the variance is the amount by which the $\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'$ exceeds its expected value (Doan, 2013). As with other types of impulse responses, constants ($\boldsymbol{C}^*$) drop out, because it is the difference in the behaviour with and without the added shocks that matters. In the VIRFs and conditional volatility profiles we estimate we take k=10 days.

All of the above is programmed using the software of WinRATS, which is suitable for computing multivariate GARCH models, especially the BEKK specification (Brooks, Burke and Persand, 2003).

Table 6: The list of 27 models with varying combinations of the variables Returns (RTN), Positive Tweets (PT), Negative Tweets (NT), Number of Blog Posts (BP), Number of Forum Posts (FP), Number of Google Search Tickers (GST) and dummy variables New Product Launch (NPL) and Organizational Events (OE).

	Variables (n)						Dummies		
Model	**RTN**	**PT**	**NT**	**BP**	**FP**	**GST**	**NPL**	**OE**	**# parameters BEKK model**
1	X	X	X						24
2	X	X	X				X		30
3	X	X	X					X	30
4	X	X	X	X					42
5	X	X	X	X			X		52
6	X	X	X	X				X	52
7	X	X	X		X				42
8	X	X	X		X		X		52
9	X	X	X		X			X	52
10	X	X	X			X			42
11	X	X	X			X	X		52
12	X	X	X			X		X	52
13	X	X	X	X	X	X			93
14	X	X	X	X	X	X	X		114
15	X	X	X	X	X	X		X	114
16	X			X	X	X			42
17	X			X	X	X	X		52
18	X			X	X	X		X	52
19	X	X	X	X	X				65
20	X	X	X	X	X		X		80
21	X	X	X	X	X			X	80
22	X	X	X		X	X			65
23	X	X	X		X	X	X		80
24	X	X	X		X	X		X	80
25	X	X	X	X		X			65
26	X	X	X	X		X	X		80
27	X	X	X	X		X		X	80

5. Results

In this chapter we report the results of mean, shock and volatility spillover effects estimated over 27 different models. Table 1 in the appendix displays the estimated results per model and in this chapter we report the meta-analysis of those 27 models. Certain mean, shock and volatility spillover effects are estimated in a selection of the 27 models (see Table 6, where the variables included in each model are listed) and we study the overall effect by computing averages. For instance, spillover effects between Returns and Positive Tweets are estimated in 24 models, (1-15 and 19-27) so we compute the average mean, shock and spillover effects over these 24 models. The coefficients that represent a spillover effect can either be significant or insignificant, depending on whether their *p*-value is below 10 percent. For each (average) spillover effect we report the 'percentage significant', expressing the significant estimated coefficients as a percentage of the total estimates of the spillover effect. We discuss one model separately, to give an indication of how each model individually should be discussed opposed to the summarized results. Furthermore, we discuss the volatility impulse response functions.

5.1 Mean Spillover Effects

Table 7 shows the average mean spillover effects estimated over all 27 models. The matrix Γ in the mean equation, with parameters γ_{ij} captures the relationship between Returns (RTN), Positive Tweets (PT), Negative Tweets (NT), Number of Blog Posts (BP), Number of Forum Posts (FP) and Number of Google Search Tickers (GST). For example, γ_{13} represents the mean spillover effect from Negative Tweets on Returns. The average of all coefficients, the average of all significant coefficients (coefficients with a *p*-value below 10 percent) and the average of all coefficients in absolute numbers are calculated, including the percentage of the coefficients that turn out to be significant. For example, Table 7 shows that γ_{13} corresponds to a percentage of 41.67, indicating that the effect, which was estimated in 24 models, was significant in 41.67 percent of the 24 estimates. We focus the discussion of our results on effects that are significant in at least 50 percent of the estimates and on the magnitude, sign and meaning of the effects.

Table 7 displays high percentages for the diagonal parameters γ_{11}, γ_{22}, γ_{33}, γ_{44} and γ_{66}, which means that Returns, Positive Tweets, Negative Tweets, Blog Posts and Google Search Tickers (positively) depend on their first lag in 100, 100, 100, 100 and 80 percent of the estimates.

The mean spillovers between the UGC variables and returns are represented by the off-diagonal parameters γ_{ij}. The off-diagonal parameters γ_{26} and γ_{62}, γ_{34} and γ_{43}, γ_{36} and γ_{63} are all statistically significant (*p*-values below 10 percent) in at least 50 per cent of the estimates, indicating that there are bidirectional spillovers from Google search tickers to Positive Tweets, from Blog Posts to Negative Tweets and from Google Search Tickers to Negative Tweets, respectively. The bidirectional spillovers between the number of Google search tickers and positive tweets (γ_{26} and γ_{62}) are negative, implying that the past number of Google search tickers decreases the future volume of negative tweets and that the past volume of negative tweets decreases the future number of Google search tickers. The effect from the number of blog posts on the volume of negative tweets is small and negative (γ_{34}), whereas the counterpart (γ_{43}) is larger and positive. Hence, the past number of blog posts slightly decreases the future volume of negative tweets whereas the past volume of negative tweets slightly increases the future number of blog posts.

The off-diagonal parameters γ_{32}, γ_{42}, γ_{45} and γ_{46} are statistically significant (*p*-values below 10 percent) in more than 50 percent of the estimates, whereas their counterparts are not, indicating that there are unidirectional linkages from the volume of positive tweets to negative tweets (which is a positive spillover) and from the volume of positive tweets, the number of forum posts and the number of Google search tickers to the number of blog posts (all three are negative spillovers).

The results of the mean spillover effects indicate a strong connection between the various UGC metrics, whereas the link between returns and the UGC metrics is much weaker. The next subsection proceeds with studying the relationship between returns and UGC variables in terms of shock and spillover effects.

5.2 Shock and volatility spillover effects

Table 8 displays the average shock spillover effects between Returns (RTN), Positive Tweets (PT), Negative Tweets (NT), Number of Blog Posts (BP), Number of Forum Posts (FP) and Number of Google Search Tickers (GST). For example, 'PT(-1) -> RTN' indicates the shock spillover effects from the volume of positive tweets to returns. 'Average coefficients' refers to the average shock spillover effect as measured over all the models in which this effect is estimated, 'Average significant coefficients' is the average of the *significant* shock spillover effects and 'Average absolute coefficients' is the average of all the spillover effects expressed in *absolute* values. The column 'Percentage significant' displays the percentage of the estimated coefficients that are significant (have a *p*-value below 10 percent). For example, the percentage 51.85 in the first row of Table 8 indicates that of the 27 models in which this effect was estimated, 51.85 percent of the effects are statistically significant (p-value < 0.10). Table 9 displays the results on volatility spillover effects in a similar way as the shock spillover effects presented in Table 8. The discussion of the results is focussed on spillover effects that are significant in at least 50 percent of the estimates and on the sign and magnitude and meaning of the effects.

The ARCH effects (the effect of lagged shocks) are captured by the diagonal elements of the $\boldsymbol{A}$ matrix and the GARCH effects (the effect of past volatility) are captured by the diagonal elements of the $\boldsymbol{B}$ matrix of the multivariate GARCH BEKK model. Table 8 shows that the average ARCH effect is significant in more than 50 percent of the estimates for Returns, Negative Tweets, Forum Posts and

Google Search Tickers, implying presence of ARCH effects in those three UGC variables and the stock returns of Apple. The magnitude of the ARCH effect is highest for Negative Tweets (0.376), followed by Forum Posts (-0.230). Table 9 shows that the average GARCH effect is significant in more than 50 percent of the estimates for Returns, Negative Tweets and Forum Posts, implying that own past volatility largely affects the conditional variance of those series. The magnitude of the GARCH effect is highest for Negative Tweets (0.697), followed by Forum Posts (0.628).

The off-diagonal elements of matrices $\boldsymbol{A}$ and $\boldsymbol{B}$ capture the cross-linkages, such as shock spillover and volatility spillover, among UGC variables and returns. Table 8 shows evidence of bidirectional shock spillovers (shock transmissions) between the number of Google search tickers and the volume of positive tweets and the number of Google search tickers and the volume of negative tweets, which indicates a strong connection between these UGC metrics. Past shocks in the volume of positive tweets *decrease* the future volatility in the number of Google search tickers and past shocks in the number of Google search tickers *decrease* the future volatility in the volume of positive tweets, although the magnitude of both effects is small. Past shocks in the number of Google search tickers slightly *decrease* the volatility in the volume of negative tweets and shocks in the volume of negative tweets *increase* the volatility in the number of Google search tickers.

Table 8 also shows evidence of unidirectional shock spillovers from Blog Posts to Returns, from Negative Tweets to Positive Tweets, from Returns to Negative Tweets, from Blog Posts to Negative Tweets and from Google search tickers to Blog Posts. Past shocks in the number of blog posts decrease volatility in returns. The number of blog posts is the only UGC metric with a significant (negative) shock spillover effect on stock returns in at least 50 percent of the estimates. For investors this could mean that by reviewing the presence of shocks in the number of blog posts an increase in the volatility of stock returns could be anticipated, which in turn could be used for hedging or portfolio strategies. The volume of negative tweets is the only UGC metric whose volatility is (positively) affected by past shocks in stock returns in at least 50 percent of the estimates, but the effect is small. The remaining unidirectional shock spillovers indicate that shocks in the volume of negative tweets *increase* the future volatility in the volume of positive tweets, that shocks in the number of blog posts *decrease* the future volatility of the volume of negative tweets and that shocks in the number of Google search tickers *increase* the future volatility of the number of blog posts.

Table 9 shows no evidence of bidirectional volatility spillover effects, merely of unidirectional effects. Past volatility in the number of Google search tickers *decreases* the future volatility of the volume of positive tweets, the volume of negative tweets and the number of blog posts. Past volatility in the number of blog posts *decreases* the future volatility in the volume of negative tweets. The future volatility of the number of forum posts *decreases* due to past volatility in the volume of positive tweets decreases and it *increases* due to past volatility in the volume of negative tweets. The only UGC metric of which the future volatility is affected by past volatility in stock returns (among the effects that are significant in at least 50 percent of the estimates) is the number of Google search tickers, but the magnitude is small (0.044), indicating a weak integration between the time series.

Figures 4 and 6 display the plots of the (significant) shock spillover effects between the variables, of which the average values are presented in Table 8. Figures 5 and 7 display plots of the (significant) volatility spillover effects, corresponding to the averages in Table 9. The plots show that the effects can vary widely between models, both in magnitude and in sign. As mentioned in the methodology section: the fit of the BEKK model is exactly the same if you change the sign of the entire $\boldsymbol{A}$ or $\boldsymbol{B}$ matrix, as the model is not globally identified. This means that the sign of the coefficients should be interpreted with caution, although in most cases the sign will be steered in the right direction by the initial guess values (Doan, 2013). The plots show that the sign of an effect is the same in most cases, but sometimes it differs.

The multivariate ARCH test is used to test for any remaining arch effects and the results are displayed in Table 10. If the p-value indicates no significance (value above 10 percent), there is no remaining series dependence in the residuals of that model. In 13 of the 27 models the test statistics are insignificant, indicating the appropriateness of the fitted variance-covariance equations by the multivariate GARCH BEKK model.

Some of the models contain a dummy variable in the GARCH BEKK recursion, either the dummy New Product Launch, or Organizational Events. As displayed in equation 4, adding a dummy adds coefficients to the $\boldsymbol{C}$ coefficients. Coefficient c_{11} is the variance intercept, and all the other $\boldsymbol{C}$ coefficients are factors of that variance intercept (Doan, 2013). This means that the coefficients do not have simple interpretations, opposed to the coefficients in the $\boldsymbol{A}$ and $\boldsymbol{B}$ matrices. The $\boldsymbol{E}$ coefficients, which are added to the $\boldsymbol{C}$ coefficients, are therefore not easy to interpret either. However, what we can see from the results of the multivariate ARCH tests is that adding a dummy can lead to a better fit of the multivariate GARCH BEKK model. Some of the models had remaining series dependence when there was no dummy in the BEKK model, but when a dummy was added, the ARCH test showed no proof of remaining series dependence, indicating that adding that dummy had led to a better fit. This was the case for model 5 (opposed to model 4 without a dummy), models 11 and 12 (opposed to model 10 without a dummy) and models 23 and 24 (opposed to model 22 without a dummy).

In the next subsection we discuss the results of one of the 27 models separately.

5.3 Discussion of one model

To give an impression of how each of the 27 results of the BEKK models should be discussed individually we describe the results of one model, number 5. This model contains the variables Returns, Positive Tweets, Negative Tweets and Blog Posts. The results are listed in the appendix in Table 1, model 5. As the diagonal elements γ_{11}, γ_{22}, γ_{33} and γ_{44} are statistically significant with p-values below 5 percent, all four variables depend on their first lag. The values of past returns, volume of positive tweets, volume of negative tweets and number of blog posts positively affect the values of the returns, the volume of positive and negative tweets and the number of blog posts the following day. The cross-linkages are represented by the off-diagonal elements, of which γ_{32}, γ_{42} and γ_{43} are statistically significant. The past volume of positive tweets increases the future volume of negative tweets and decreases the future number of blog posts. The past volume of negative tweets on the other hand increases the future number of blog posts. The difference in influence of the volume of positive and negative tweets on the number of blog posts might be due to the *negativity bias*. As people are more inclined to respond to (and believe) negative news, they might pay more attention to it, resulting in more blog posts. The link between positive and negative tweets is probably due to the fact that topics on Twitter are indicated with a hashtag (e.g. '#iPhone'), which makes it likely that the number of positive and negative tweets regarding the same subject, in this case the iPhone, move closely together.

The diagonal elements of the $\boldsymbol{A}$ matrix show that there are statistically significant (at a 5 percent level) ARCH effects in the volume of negative tweets and the number of blog posts, implying that own past shocks largely affect the conditional variance of these two series. The conditional variance of negative tweets decreases due to own past shocks and the conditional variance of the number of blog posts increases due to own past shocks. The off-diagonal elements of the $\boldsymbol{A}$ matrix show that there are unidirectional shock spillover effects between some of the UGC variables. Past shocks in positive tweets *increase* the future volatility of the number of blog posts, whereas past shocks in negative tweets *decrease* the future volatility of the number of blog posts. The size of these two shock spillovers is similar (around 1.5). Furthermore, past shocks in the volume of negative tweets *decreases* future volatility in the volume of positive tweets.

The diagonal elements of the $\boldsymbol{B}$ matrix show that the returns have a significant GARCH effect, indicating that the volatility in returns is negatively affected by own past volatility. The off-diagonal elements capture some statistically significant volatility spillovers. Past volatility in the volume positive tweets increases the future volatility in the volume of negative tweets, whereas past volatility in the number of blog posts decreases the future volatility in the volume of negative tweets. Past volatility in the volume of negative tweets increases future volatility in the stock returns and this effect is the largest volatility spillover effect in this model (3.009). This means that investors can anticipate a possible future increase in the volatility of the Apple stock by studying the volatility in negative tweets.

The dummy New Product Launches is added to the model and some of the elements of the $\boldsymbol{E}$ matrix are statistically significant. As mentioned earlier, the constant and dummies are difficult to interpret. However, what we can see if we compare the multivariate ARCH test results in Table 10 of model 5 with model 4, is that adding this dummy enhances the fit of the multivariate GARCH BEKK model. The results of the multivariate ARCH test indicate the appropriateness of the fitted variance-covariance equation by the multivariate GARCH BEKK model.

5.4 Volatility Impulse Response Functions

Figure 8 displays the volatility impulse response functions (VIRFs) and conditional volatility profiles for model 1 containing the three variables Returns, Positive Tweets and Negative Tweets. This means that the VIRFs and conditional volatility profiles are plotted for 6 (co)variances: the variance of Returns, the covariance between Returns and Positive Tweets, the variance of Positive Tweets, the covariance between Returns and Negative Tweets, the covariance between Positive Tweets and Negative Tweets and the variance of Negative Tweets. The two historical shocks which we used to compute the VIRFs and conditional volatility profiles are characteristic for our data: October 20th, 2009, when 5 new products were launched, and January 27th, 2010, when Steve Jobs first introduced the iPad. Both of these dates concern new products of Apple, but on January 27th the product was introduced via a big keynote speech and was not made available to the public yet, whereas on October 20th the introductions were done via smaller press releases and most of the products were instantly available to the public.

The left column shows that the variance of Returns displays the biggest positive shock, the other shocks in that column are closer to zero or negative. The impulse response in the covariance between Returns and Positive Tweets is smaller and positive as well. The other four impulse responses in the column are all negative, slowly moving to zero. The conditional volatility profiles of the variance of Returns, the covariance of Returns and Positive Tweets and the covariance of Returns and Negative Tweets are close to the corresponding impulse responses. The conditional volatility profiles are just slightly above the impulse responses, which can be explained by the way these functions were constructed (see equations 7 and 8 in chapter 3). The conditional volatility profile is a function of the model coefficients and the shock (the baseline is set to zero), whereas the VIRF depends upon the data as well through the variance-covariance matrix. A shock in the VIRF is the amount by which it exceeds the expected value. Hence, the conditional volatility profile and the VIRF have a positive difference if the expected value is close to the shock (in that case the VIRF is close to zero and the corresponding conditional volatility profile is positive) (Hafner and Herwartz, 2006). This is visible in the three remaining plots of the left column: the conditional volatility profiles indeed have positive values, are located above the VIRFs and the VIRFs are negative. In these plots the conditional volatility profiles could lead to the misbelief that the effect of the shock on the (co)variance of (between) Positive and Negative Tweets is positive, while it is not given the data.

The right column in Figure 8 shows that the shocks are strongly positive in the variances of Positive Tweets, Negative Tweets, and that effect appears in the 3 covariances as well. The conditional volatility profiles are all just slightly above the impulse responses, indicating that the shocks differ from the expected value. The difference in the effects in the two columns indicates that the announcement of the iPad had a much bigger effect than the launch of the 5 new products. Even though most of those 5 products were instantly available, those 5 product launches led to smaller shocks than the introduction of the iPad. This could imply that those products were perhaps not as innovative as the iPad, leading to smaller responses in stock returns and the volume of tweets. Hence, new product launches can cause shocks in volatilities of UGC and stock returns, but the magnitude of the impact depends on the product being launched.

Table 7: The averages of the estimated coefficients of the conditional mean VAR equations in all 27 models. The matrix Γ in the mean equation, with parameters γ_{ij} captures the relationship between Returns (RTN), Positive Tweets (PT), Negative Tweets (NT), Number of Blog Posts (BP), Number of Forum Posts (FP) and Number of Google Search Tickers (GST).

Average of all coefficients

	RTN(i=1)	PT(i=2)	NT(i=3)	BP(i=4)	FP(i=5)	GST(i=6)
c	17.148	0.497	1.426	9.572	12.629	3.485
γi1	0.317	0.002	0.003	0.027	-0.001	0.025
γi2	0.675	0.840	0.229	-0.707	-0.046	-0.578
γi3	-1.013	0.085	0.593	0.618	0.049	0.523
γi4	-0.006	0.017	-0.020	0.424	-0.015	0.123
γi5	-2.056	0.049	0.000	-0.847	0.007	-0.147
γi6	-0.361	-0.083	-0.121	-0.233	0.004	0.319

Average of all significant coefficients

	RTN(i=1)	PT(i=2)	NT(i=3)	BP(i=4)	FP(i=5)	GST(i=6)
c	24.327	0.553	1.620	10.299	12.629	3.333
γi1	0.317	-	-	-	-	0.054
γi2	1.091	0.840	0.263	-0.788	-0.064	-0.650
γi3	-1.661	0.143	0.593	0.722	0.069	0.599
γi4	0.267	0.069	-0.063	0.424	-0.025	0.166
γi5	-3.087	0.169	0.163	-1.091	0.091	-0.246
γi6	-0.578	-0.088	-0.124	-0.332	0.030	0.367

Average of all coefficients in absolute values

	RTN(i=1)	PT(i=2)	NT(i=3)	BP(i=4)	FP(i=5)	GST(i=6)
c	17.227	0.954	1.667	9.652	12.629	4.510
γi1	0.317	0.004	0.006	0.029	0.002	0.026
γi2	0.783	0.840	0.229	0.707	0.047	0.578
γi3	1.054	0.086	0.593	0.619	0.049	0.524
γi4	0.174	0.030	0.047	0.424	0.015	0.129
γi5	2.078	0.116	0.127	0.894	0.051	0.420
γi6	0.365	0.083	0.121	0.247	0.009	0.319

Percentage significant coefficients[1]

	RTN(i=1)	PT(i=2)	NT(i=3)	BP(i=4)	FP(i=5)	GST(i=6)
c	40.74	54.17	54.17	93.33	100.00	60.00
γi1	100.00	0.00	0.00	0.00	0.00	6.67
γi2	37.50	100.00	79.17	75.00	41.67	83.33
γi3	41.67	29.17	100.00	75.00	41.67	83.33
γi4	13.33	16.67	50.00	100.00	44.44	44.44
γi5	40.00	16.67	16.67	66.67	13.33	33.33
γi6	33.33	91.67	91.67	66.67	11.11	80.00

[1] A coefficient is significant if the corresponding *p*-value is below 10 percent. An effect is estimated over various models and the 'percentage significant coefficients' expresses how many of those coefficients are significant. For instance, the mean spillovers from Positive Tweets to Returns are estimated in 24 of the 27 models, and are significant in 37.50 of those 24 estimates.

Table 8: Average shock spillover effects between Returns (RTN), Positive Tweets (PT), Negative Tweets (NT), Number of Blog Posts (BP), Number of Forum Posts (FP) and Number of Google Search Tickers (GST).

Shock spillover effects	Average coefficients	Average significant coefficients	Average absolute coefficients	Percentage significant
RTN(-1) -> RTN*	-0.042	-0.090	0.217	51.85
PT(-1) -> RTN	-0.621	-1.067	1.955	41.67
NT(-1) -> RTN	0.182	-0.219	1.418	25.00
BP(-1) -> RTN***	-0.261	-0.306	0.563	60.00
FP(-1) -> RTN	1.188	0.513	5.241	46.67
GST(-1) -> RTN	0.209	0.457	0.723	46.67
RTN(-1) -> PT	0.011	0.023	0.017	37.50
PT(-1) -> PT	0.172	0.367	0.269	37.50
NT(-1) -> PT***	0.182	0.208	0.399	87.50
BP(-1) -> PT	-0.045	-0.091	0.059	41.67
FP(-1) -> PT	-0.148	-0.179	0.231	16.67
GST(-1) -> PT**	-0.025	-0.026	0.089	66.67
RTN(-1) -> NT***	0.026	0.036	0.040	75.00
PT(-1) -> NT	0.040	0.176	0.320	33.33
NT (-1) -> NT*	0.286	0.376	0.509	75.00
BP(-1) -> NT***	-0.076	-0.136	0.093	58.33
FP(-1) -> NT	-0.122	-0.405	0.275	8.33
GST(-1) -> NT**	-0.001	-0.011	0.134	58.33
RTN(-1) -> BP	0.053	0.105	0.096	46.67
PT(-1) -> BP	-0.162	-0.269	0.694	33.33
NT(-1) -> BP	0.152	0.333	0.635	25.00
BP(-1) -> BP	0.047	0.175	0.284	46.67
FP(-1) -> BP	-0.998	-1.880	1.300	44.44
GST(-1) -> BP***	0.143	0.274	0.413	55.56
RTN(-1) -> FP	-0.001	-0.005	0.006	33.33
PT(-1) -> FP	-0.005	0.026	0.062	25.00
NT(-1) -> FP	-0.008	-0.028	0.050	25.00
BP(-1) -> FP	-0.011	-0.011	0.026	44.44
FP(-1) -> FP*	-0.159	-0.230	0.239	73.33
GST(-1) -> FP	-0.001	-0.011	0.026	33.33
RTN(-1) -> GST	0.011	0.015	0.042	40.00
PT(-1) -> GST**	-0.129	-0.096	0.569	50.00
NT(-1) -> GST**	0.068	0.109	0.484	66.67
BP(-1) -> GST	0.000	0.104	0.194	44.44
FP(-1) -> GST	-0.648	-1.621	0.811	33.33
GST(-1) -> GST*	0.104	0.048	0.437	60.00

* ARCH effects (percentage of significant coefficients above 50 percent)

** Bidirectional shock spillover effects (percentage of significant coefficients above 50 percent)

*** Unidirectional shock spillover effects (percentage of significant coefficients above 50 percent)

Table 9: : Average volatility spillover effects between Returns (RTN), Positive Tweets (PT), Negative Tweets (NT), Number of Blog Posts (BP), Number of Forum Posts (FP) and Number of Google Search Tickers (GST).

Volatility spillover effects	Average coefficients	Average significant coefficients	Average absolute coefficients	Percentage significant
RTN(-1) -> RTN*	0.215	0.287	0.500	62.96
PT(-1) -> RTN	2.171	3.851	3.812	41.67
NT(-1) -> RTN	-1.324	-2.918	3.319	41.67
BP(-1) -> RTN	-0.188	0.307	0.755	40.00
FP(-1) -> RTN	0.913	1.867	3.283	20.00
GST(-1) -> RTN	0.176	0.063	1.207	46.67
RTN(-1) -> PT	0.009	0.025	0.024	20.83
PT(-1) -> PT	0.403	0.680	0.431	41.67
NT(-1) -> PT	0.119	0.160	0.234	41.67
BP(-1) -> PT	-0.036	-0.092	0.084	33.33
FP(-1) -> PT	0.298	0.309	0.530	41.67
GST(-1) -> PT***	-0.041	-0.110	0.126	50.00
RTN(-1) -> NT	0.011	0.013	0.042	45.83
PT(-1) -> NT	0.094	0.177	0.388	41.67
NT (-1) -> NT*	0.494	0.697	0.517	66.67
BP(-1) -> NT***	-0.066	-0.135	0.129	50.00
FP(-1) -> NT	0.365	0.454	0.551	25.00
GST(-1) -> NT***	-0.037	-0.098	0.191	58.33
RTN(-1) -> BP	0.041	0.049	0.102	33.33
PT(-1) -> BP	-0.124	-0.788	0.717	8.33
NT(-1) -> BP	0.285	0.776	0.780	33.33
BP(-1) -> BP	0.053	0.200	0.568	46.67
FP(-1) -> BP	-1.381	-3.699	2.243	44.44
GST(-1) -> BP***	-0.057	-0.169	0.632	66.67
RTN(-1) -> FP	0.004	0.015	0.009	33.33
PT(-1) -> FP***	-0.012	-0.021	0.127	50.00
NT(-1) -> FP***	0.009	0.020	0.114	66.67
BP(-1) -> FP	0.043	0.047	0.055	44.44
FP(-1) -> FP*	0.608	0.628	0.645	86.67
GST(-1) -> FP	-0.025	-0.045	0.056	33.33
RTN(-1) -> GST***	0.034	0.044	0.106	66.67
PT(-1) -> GST	-0.365	-0.854	0.785	33.33
NT(-1) -> GST	0.353	1.216	0.792	41.67
BP(-1) -> GST	-0.023	-0.019	0.379	44.44
FP(-1) -> GST	0.064	-2.170	1.277	22.22
GST(-1) -> GST	0.181	0.053	0.399	40.00

* GARCH effects (percentage of significant coefficients above 50 percent)

** Bidirectional shock spillover effects (percentage of significant coefficients above 50 percent)

*** Unidirectional shock spillover effects (percentage of significant coefficients above 50 percent)

Figure 4: Plots of shock spillover effects on Returns (RTN), Positive Tweets (PT), Negative Tweets (NT), Number of Blog Posts (BP), Number of Forum Posts (FP) and Number of Google Search Tickers (GST). For example, 'RTN(-1) -> RTN' indicates the shock spillover effects of lagged returns on current returns. The model numbers are listed on the horizontal axis.

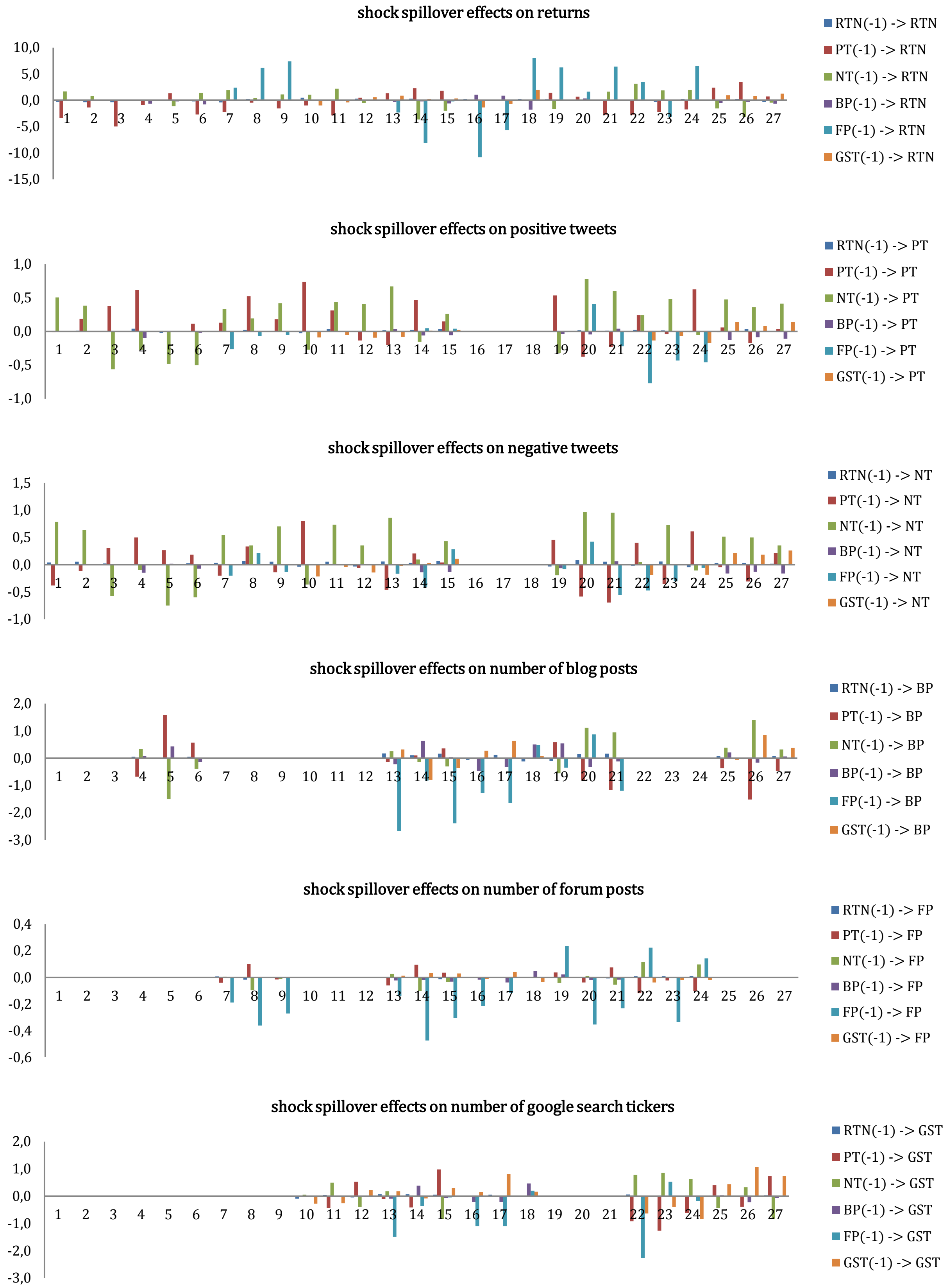


Figure 5: Plots of volatility spillover effects on Returns (RTN), Positive Tweets (PT), Negative Tweets (NT), Number of Blog Posts (BP), Number of Forum Posts (FP) and Number of Google Search Tickers (GST). For example, 'RTN(-1) -> RTN' indicates the volatility spillover effects of lagged returns on current returns. The model numbers are listed on the horizontal axis.

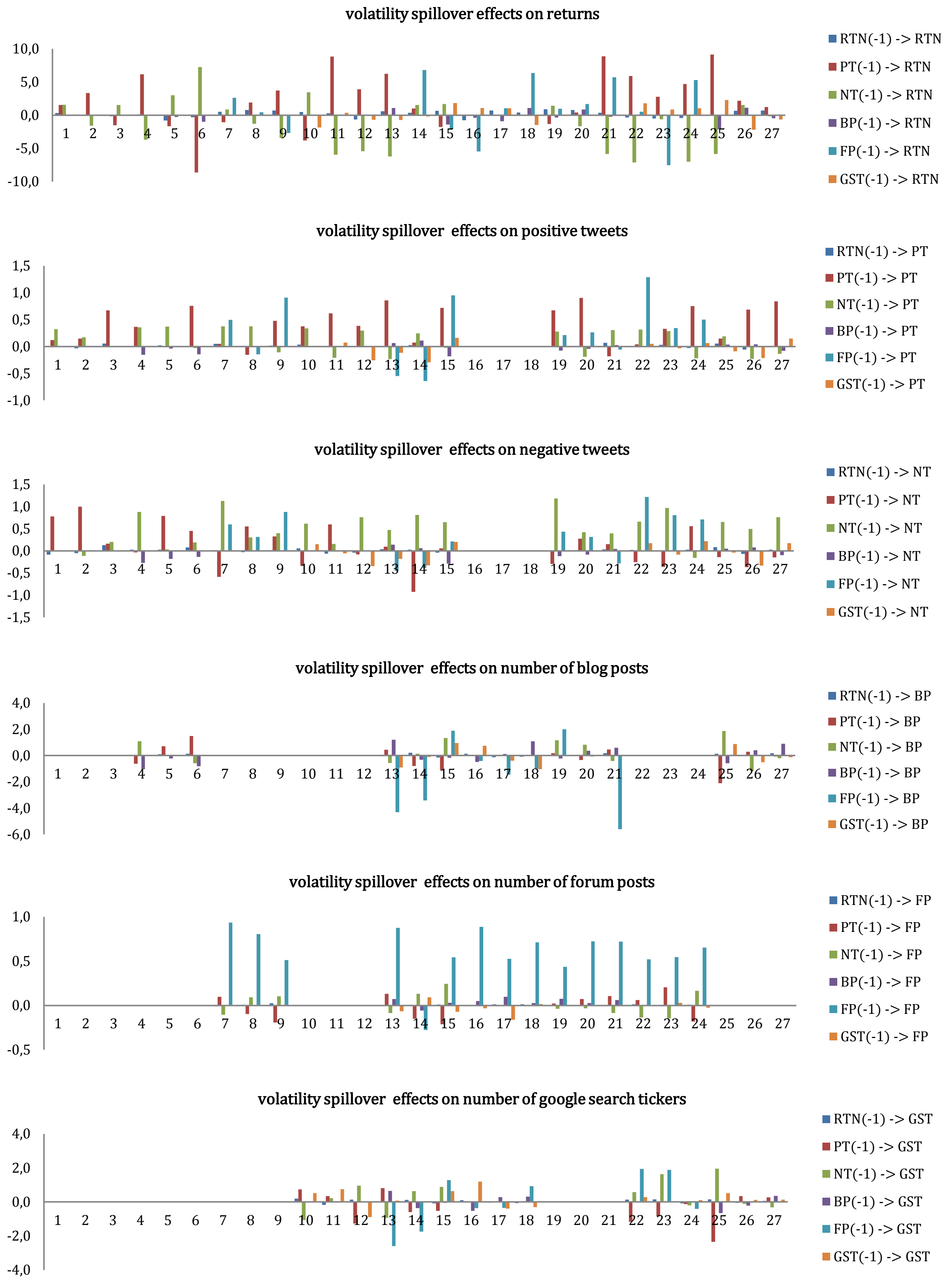


Figure 6: Plots of significant (p-value < 0.10) shock spillover effects on Returns (RTN), Positive Tweets (PT), Negative Tweets (NT), Number of Blog Posts (BP), Number of Forum Posts (FP) and Number of Google Search Tickers (GST). For example, 'RTN(-1) -> RTN' indicates the shock spillover effects of lagged returns on current returns. The model numbers are listed on the horizontal axis.

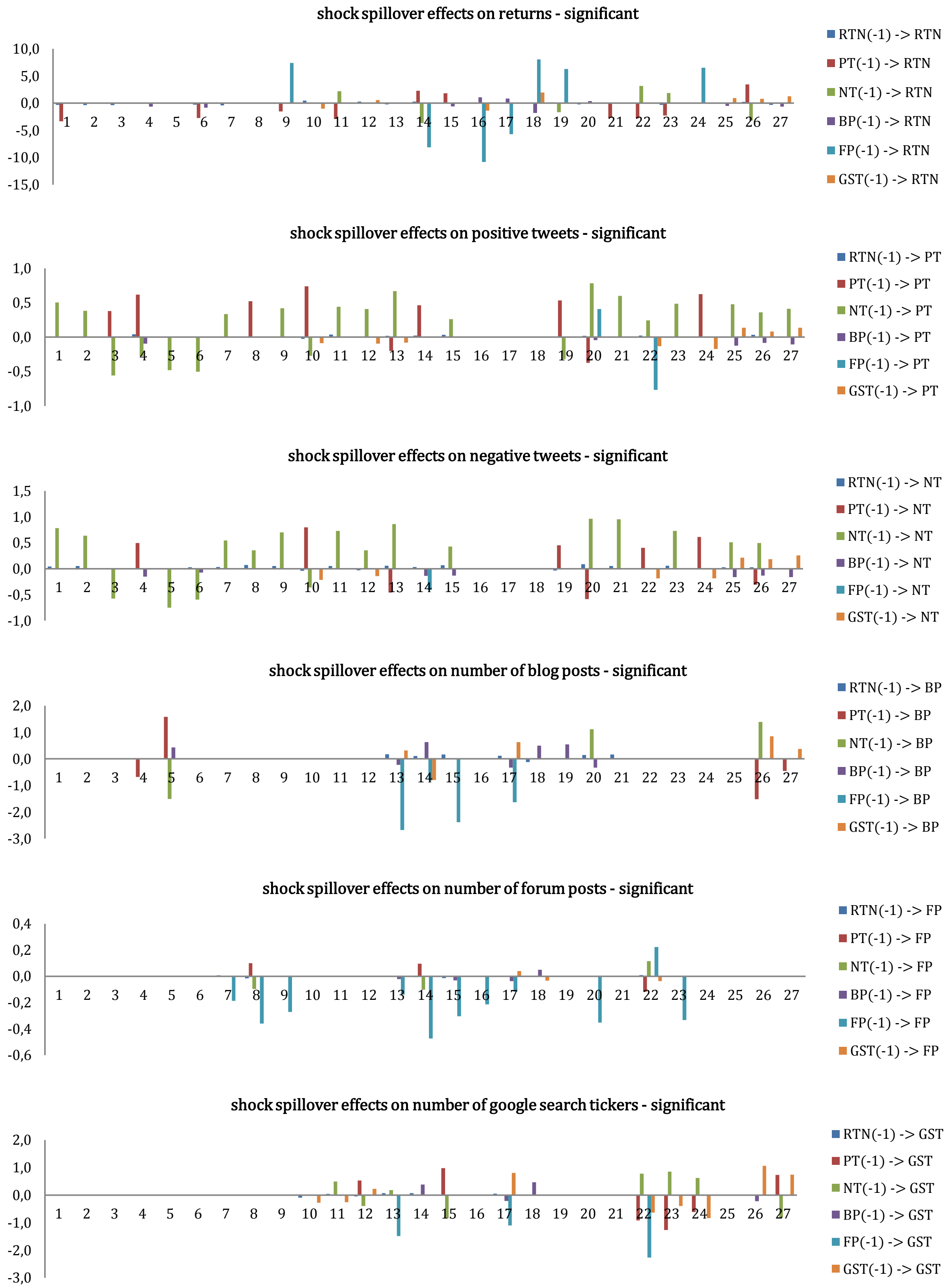


Figure 7: Plots of significant (*p*-value < 0.10) volatility spillover effects on Returns (RTN), Positive Tweets (PT), Negative Tweets (NT), Number of Blog Posts (BP), Number of Forum Posts (FP) and Number of Google Search Tickers (GST). For example, 'RTN(-1) -> RTN' indicates the volatility spillover effects of lagged returns on current returns. The model numbers are listed on the horizontal axis.

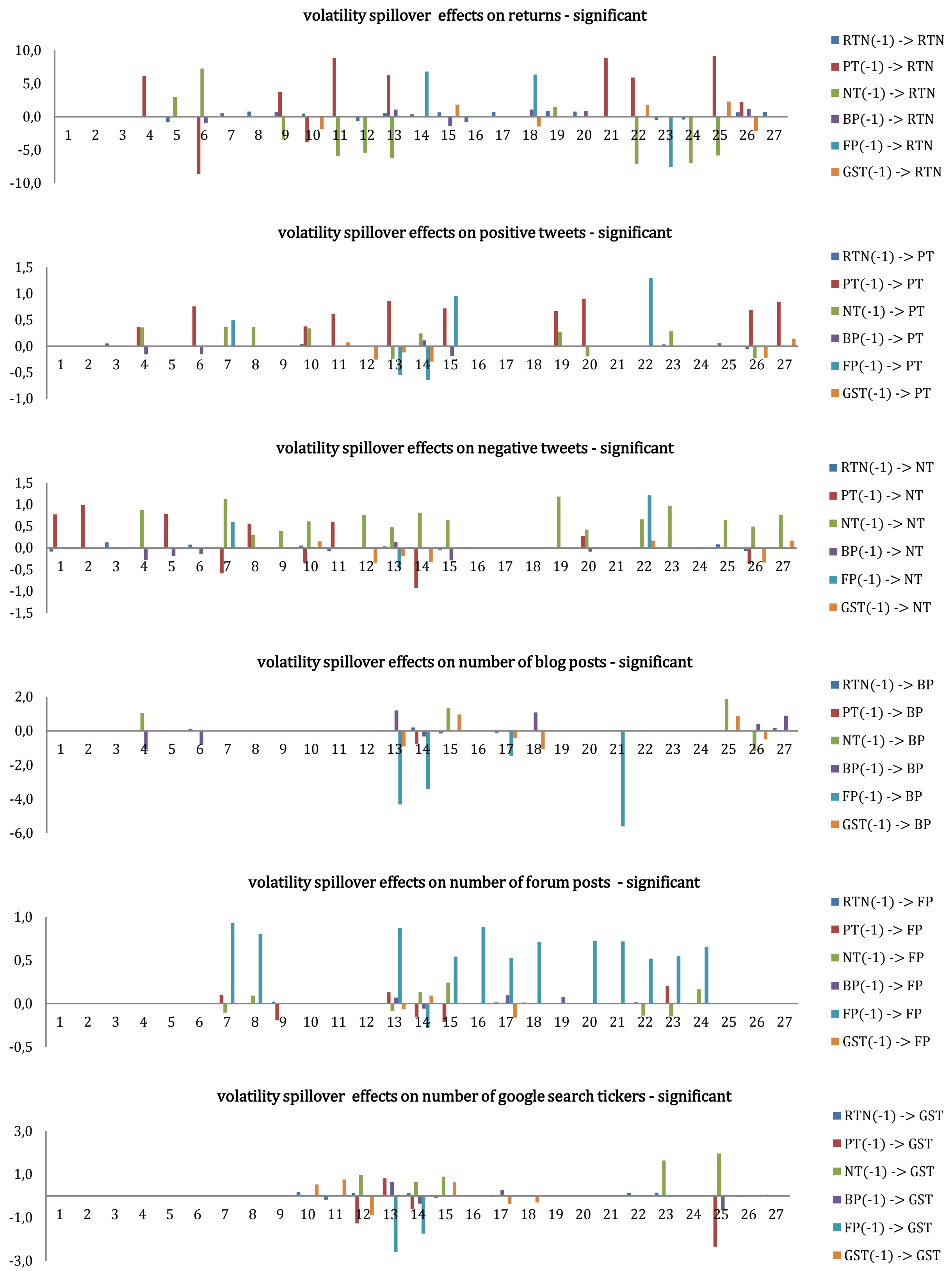
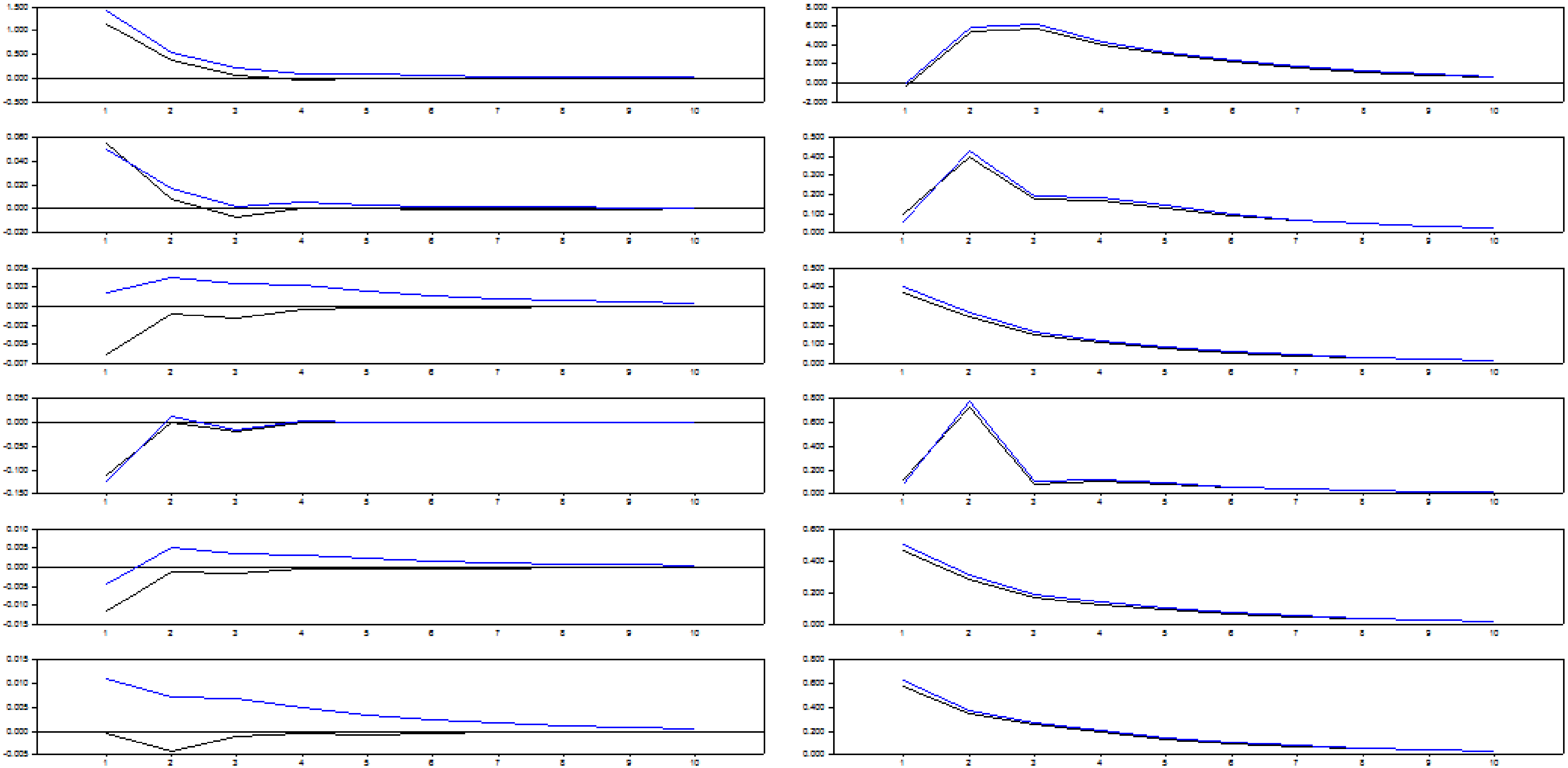


Table 10: Results of the multivariate arch test (one lag) for all 27 models.

	MVARCH test (lags=1)		
	Statistic	**Degrees**	***p*-value**
1	43.440	36	0.184
2	37.370	36	0.406
3	48.320	36	0.082
4	151.270	100	0.001
5	113.52	100	0.168
6	135.810	100	0.010
7	108.160	100	0.271
8	105.940	100	0.323
9	110.790	100	0.216
10	135.100	100	0.011
11	105.780	100	0.327
12	101.450	100	0.441
13	683.820	441	0.000
14	637.070	441	0.000
15	671.840	441	0.000
16	93.530	100	0.663
17	108.970	100	0.254
18	77.740	100	0.952
19	324.360	225	0.000
20	282.310	225	0.006
21	274.640	225	0.013
22	308.790	225	0.000
23	237.620	225	0.269
24	247.380	225	0.146
25	305.130	225	0.000
26	283.860	225	0.005
27	274.920	225	0.013

Figure 8: Volatility impulse response functions (black) and conditional volatility profiles (blue) for model 1, for two historical shocks. Left column: shock on October 20, 2009. Right column: shock on January 27, 2010. Rows from top to bottom: Return variance, Return Positive Tweets covariance, Positive Tweets variance, Returns Negative Tweets covariance , Positive Tweets Negative Tweets covariance and Negative Tweets variance.



6. Discussion

This is the first study to investigate the presence of shock and volatility spillover effects 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 UGC and stock market performance has been investigated by Tirunillai and Tellis(2012) and Luo (2007, 2009). Those studies were the first to examine the dynamics between UGC and stock market performance; previous studies had merely focussed on examining the dynamics between UGC and sales. Our study adds to the existing literature by not only investigating the direct connection between UGC metrics and returns, but by investigating the connection between the volatilities of UGC metrics and returns as well. Hence, our findings of spillovers between UGC and returns contribute to unravelling the dynamics between UGC and stock market performance. According to these findings there are more significant shock and volatility spillover effects from UGC sources to returns than vice versa. The impact on the volatility of returns depends on the type of UGC source, some exhibit more spillover effects than others. With these findings in mind, investors could be able to anticipate possible changes in the volatility of a company's stock by reviewing the volatility in UGC regarding that company.

The multivariate GARCH BEKK model we used for our analysis is certainly the most suitable for investigating shock and volatility spillover effects within our data, opposed to other multivariate GARCH models such as the VECH model (too many parameters and the need to impose constraints to ensure positive definiteness), the Diagonal BEKK and VECH model (can only measure ARCH and GARCH effects, spillovers are not estimated in those models), the Constant Correlation model (assumes that the covariances are generated with a constant, but unknown, correlation and therefore might be too restrictive for our analysis), the Dynamic Correlation model (unrealistic assumption that all entries in the conditional correlation matrix are influenced by the same coefficients) and the factor model (the common factors size (SMB), market-to-book (HML) or momentum are not applicable to our dataset).[14]

One aspect of the BEKK model we should be alert to is the fact that the model assumes that positive and negative shocks have an equal impact. If that is not considered to be a realistic assumption, the asymmetric BEKK model can be used, which takes into account whether shocks are positive or negative. The asymmetric BEKK model has a larger number of parameters than the 'regular' BEKK model we use in our study. Considering the small dataset we use we decided not to increase the number of parameters to be estimated by employing an asymmetric version of the BEKK model. If in

[14] We recognize that using 'model-free' realized volatility measures to study spillover effects would have been a possibility as well, but the advantages of the multivariate GARCH BEKK model to study spillover effects were crucial for our decision to use a multivariate GARCH model. Other options could be explored in further research.

time more data can be collected this would be worthwhile to explore. The same applies to incorporating seasonality effects: with a larger sample it should not be a problem to add extra dummies to the BEKK model. With our current relatively small sample this is not preferable. The curse of dimensionality associated with estimating a BEKK model with a small sample might lead to problems as overfitting or numerical instabilities (Verleysen and François, 2005). Correcting for this curse of dimensionality can be quite cumbersome and would be a new study in itself, which is why for our study we choose to estimate 27 models with both small and larger combinations of variables, of which we presented the summarized results (the 'meta-analysis'). A risk we take with our analysis is the possibility that some of the smaller models may be misspecified, as other (important) variables are omitted.

A drawback of our meta-analysis is that the averages of the effects are calculated of different totals. For instance, the shock and volatility spillover effects between returns and the volume of positive tweets are estimated in 24 models and the average of those spillovers are computed over the 24 estimates. The shock and volatility spillover effects between the number of blog posts and the number of Google search tickers are estimated in only 9 models and the averages are therefore computed over just 9 estimates. When the average is calculated over fewer models, one estimate can have relatively more influence. Not only can one value have a bigger impact on the value of the coefficient, the percentage of significant coefficients is affected as well. In the previous chapter we mainly focussed on the results that are significant in at least 50 percent of the estimates, but 50 percent over 9 estimates is of course different than 50 percent over 24 estimates. When an effect is estimated in 15, 24 or 27 models and the percentage of significant coefficients is high, we can state that with greater certainty that this particular effect is significant (on average) than when it would have been estimated over just 9 models. Hence, average effects that are significant in at least 75 percent of the estimates and are estimated in at least 15 models allow us to draw conclusions with bigger empirical certainty. There are four effects present in our results that match these criteria: the shock spillover effect from negative tweets to positive tweets; the shock spillover effect from returns to negative tweets, the ARCH effect in the volume negative tweets and the GARCH effect in the number of forum posts. The strong connection between negative tweets and positive tweets makes sense, as Twitter uses hashtags for topics, to which tweets are linked (after each tweet follows '#topic'). Shocks in the volume of negative tweets are therefore likely to be linked to shocks in positive tweets, as people tend to have various opinions about a topic. The shock spillovers from returns to negative tweets might be explained by the fact that shocks in stock returns are associated with higher risk, and therefore might trigger negative responses rather than positive responses on Twitter. The effect is small, which is probably due to the fact that the negative tweets in our dataset are about the product iPhone of Apple, not about the company Apple in general.

With time, the analysis could be extended in various ways. One approach would be to collect similar data and perform a similar analysis for companies other than Apple. This paper is a case-study of Apple and performing our analysis on other companies could serve to verify whether the linkages between stock returns and UGC extend to other companies as well. Furthermore, if the analysis could be performed for companies in different industries, we could investigate whether the stocks of companies in certain industries are more prone to shock and volatility spillovers from online content than stocks of companies in different industries. Another approach would be to collect new UGC data regarding Apple, but not just content about the iPhone, but about all products of Apple, among which the computers and iPad. The iPad had been launched, but was not available to the public in the period of our dataset. We assume that there will be much UGC about this product as well after it was made available to the public, as it has now grown out to be one of the most iconic product of Apple. Since the wide range of products of Apple all contribute to the performance of the company and all influence the way consumers view the company, we might find stronger linkages between stock returns and UGC when more of Apple's product are taken into account in the dataset. All of the aforementioned approaches would allow us to get greater empirical certainty on the nature and significance of the mean, shock and volatility spillovers between stock returns and UGC.

7. Conclusion

This study examines the dynamics between user-generated content (UGC) and stock returns by investigating the presence of mean, shock and volatility spillover effects between UGC and returns related to the company Apple. The volume of positive and negative tweets, the number of blog posts and forum posts and the number of searches for the Apple ticker symbol in the Google search engine are used as metrics of UGC. We collected the UGC data over a six month period (from October 2009 until March 2010), using various online sources. The multivariate GARCH BEKK model is used to study the source, significance and magnitude of the mean, shock and volatility spillover. We perform a meta-analysis to study the spillover effects between UGC variables and Returns by estimating 27 multivariate GARCH BEKK models using various combinations of variables and computed averages over the results of those 27 models. These results confirm the presence of the mean, shock and volatility spillover effects and show that the spillovers from UGC to returns are bigger (and are significant in more of the estimates) than from returns to UGC. There are spillovers between the various UGC sources as well and these effects are bigger (and are significant in more of the estimates) than the effect of returns on UGC. Hence, online content is influenced more by other online content than by stock returns. Furthermore, the results show that both the magnitude and sign of the shock and volatility spillover effects between stock returns and UGC and among UGC sources differ per UGC measure. The effects of positive tweets versus the effects of negative tweets show us that the spillovers differ in magnitude, significance and sign depending on whether online content is positive or negative. Negative tweets have a slightly bigger impact (and are significant in more of the estimates) than positive tweets in most cases, which might be due to the fact that people are more inclined to focus on negative than on positive news (*negativity bias*). New product launches and organizational events partly explain the variance and covariance between UGC and stock returns and the Volatility Impulse Response Functions and conditional volatility profiles show that new product launches can cause a shock in (co)variances of stock returns and UGC. The impact of the shock depends on the product being launched, judging from the different responses in our results.

Considering that this is the first study to examine the dynamics between UGC and stock returns in terms of mean, shock and volatility spillovers, we recommend to perform a similar study to a different company, preferably in a different industry, in order to obtain greater empirical certainty about these spillover effects.

8. References

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. and Vega, C. (2003) Micro effects of macro announcements: real-time price discovery in foreign exchange. *The American Economic Review*, 93(1):38-62.

Andersen, T.G., Bollerslev, T., Diebold, F.X. and Vega, C. (2007) Real-time price discovery in global stock, bond and foreign exchange markets. *Journal of International Economics*, 73:251-277.

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.

Berger, J. and Milkman, K.L. (2012) What makes online content viral? *Journal of Marketing Research*, 49(1):192-206.

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., Engle, R. and Woolridge, J. (1988) A Capital Asset Pricing Model with Time-varying Covariances. *Journal of Political Economy*, 96:116-131.

Brooks, C., Burke, S. and Persand, G. (2003) Multivariate GARCH Models: Software Choice and Estimation Issues. *ISMA Centre Discussion Papers in Finance DP2003-07*.

Brooks, C., Li, X. and Miffre, J. (2009) Time-Varying Volatility and the Cross-Section of Equity Returns. *ICMA Centre Discussion Papers in Finance DP2009-01.*

Caldeira, J., Moura, G. and Santos, A.A.P. (2012) Portfolio optimization using a parsimonious multivariate GARCH model: application to the Brazilian stock market. *Economics Bulletin*, 32(3):1848-1857.

Carhart, M.M. (1997) On Persistence in Mutual Fund Performance. *Journal of Finance*, 52(1):57-82.

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.

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

Choudhry, T. and Wu, H. (2008) Forecasting Ability of GARCH vs Kalman Filter Method: Evidence from Daily UK Time-Varying Beta. *Journal of Forecasting*, 27:670-689.

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

Conn, R.R. (2011) A Primer on the Nature of Idiosyncratic Risk and Volatility. *The value examiner September/October 2011,* 13-19.

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.

eMarketer (2010) http://www.bazaarvoice.com/research-and-insight/social-commerce-statistics

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., Ito, T. and Lin, W. (1990) Meteor Showers or Heat Waves? Heteroskedastic Intra- Daily Volatility in the Foreign Exchange Market, *Econometrica*, 58:525-542.

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. (1993) Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33: 3-56.

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

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

Gilbert, E., Karahalios, K. (2010) Widespread worry and the stock market. *Proceedings of the 4th International AAAI (Association for the Advancement of Artificial Intelligence) Conference on Weblogs and Social Media, ICWSM.*

Glabadanidis, P. (2009) A Dynamic Asset Pricing Model with Time-Varying Factor and Idiosyncratic Risk. *Journal of Financial Econometrics*, 7(3):247-264.

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

Goldenberg, J., Oestreicher-Singer, G. and Reichman, S. (2012) The Quest for Content: How User-Generated Links Can Facilitate Online Exploration. *Journal of Marketing Research*, 49:452-468.

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

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

Joshi, A., Hanssens, D.M. (2010) The Direct and Indirect Effects of Advertising Spending on Firm Value. *Journal of Marketing*, 74:20-33.

Kelton Research (2011) http://www.bazaarvoice.com/research-and-insight/social-commerce-statistics

Li, X., Hitt, L. (2008) Self-Selection and Information Role of Online Product Reviews. *Information Systems Research*, 19:456-474.

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.

Lin, S.L., Penm, J., Wu, S., Chiu, W.J. (2004) A Factor-GARCH approach to conditional risk and return in banking stocks: comparison of industry effect in Taiwan, Hong Kong, and Mainland China. Working paper, *SSRN eLibrary*.

Lintner, J. (1965) The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics*, 47:13-37.

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.

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.*

Najand, M., Lin, C.Y. and Fitzgerald, E. (2006) The Conditional CAPM and Time Varying Risk Premium for Equity REITs. *Journal of Real Estate Portfolio Management*, 12(2):167-175.

Nath, H.B. (2012) An empirical investigation of idiosyncratic risk and stock returns relation in heteroscedasticity corrected predictive models. *In:* http://www.efmaefm.org/0EFMAMEETINGS/EFMA%20ANNUAL%20MEETINGS/2012-Barcelona/papers/EFMA2012_0202_fullpaper.pdf

Nieto, B., Orbe, S. and Zarraga, A. (2010) Time-Varying Market Beta: Does the estimation methodology matter? *Working paper:* http://web.ua.es/es/researchgroupmffe/investigadores/documentos/nietodomenech/betas2.pdf

Pak, A., Paroubek, P. (2010) Twitter as a Corpus for Sentiment Analysis and Opinion Mining. *In: Calzolari, N., Choukri, K., Maegaard, B., Mar- iani, J., Odijk, J., Piperidis, S., Rosner, M., Tapias, D. (Eds.), Proceedings of the Seventh conference on International Language Resources and Evaluation (LREC'10). European Language Resources Association (ELRA), Valletta, Malta*, May 19–21.

Piller, Charles (1999), "Everyone Is A Critic in Cyberspace," *Los Angeles Times*, (December 3rd), A1.

Ransbotham, S., Kane, G.C., Lurie, N.H. (2012) Network Characteristics and the Value of Collaborative User-Generated Content. *Marketing Science*, 31(3):387-405.

Setiawan, K. (2012) Reexamination of Dynamic Beta International CAPM: a SUR with GARCH Approach. *Review of Economic and Business Studies*, 5(2):105-127.

Sharpe, W. (1964) Capital asset prices: a theory of market equilibrium under conditions of risk. *Journal of Finance*, 19:425-442.

Starr, M.A. (2012) Consumption, sentiment and economic news. *Economic Inquiry*, 50(4):1097-1111.

Schumaker, R.P., Chen, H. (2009) Textual Analysis of Stock Market Prediction Using Breaking Financial News: The AZFinText System. *ACM Transactions on Information Systems,* 27(2):Article 12.

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

Tellis, G.J. and Johnson, J. (2007) The value of quality. *Marketing Science*, 26(6):758-773.

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. and Pauwels, K. (2009) Effects of word-of-mouth versus traditional marketing: finding from an internet social networking site. *Journal of Marketing*, 73:90-102.

Verleysen, M. and François, D. (2005) The Curse of Dimensionality in Data Mining and Time Series Prediction. *Computational Intelligence and Bioinspired Systems, Lecture Notes in Computer Science*, 3512:758-770.

Wang, C.W., Tzang, S.W., Wu, C.W. and Hung C.H. (2012) Systematic Risk in GARCH Option Pricing: A Theoretical and Empirical Perspective. *In:* http://www.researchgate.net/publication/228693018_Systematic_Risk_in_GARCH_Option_Pricing_A_Theoretical_and_Empirical_Perspectives

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

Table 1: The following 27 tables contain the results per model for all 27 models, with various combinations of the variables Returns (RTN), Positive Tweets (PT), Negative Tweets (NT), Number of Blog Posts (BP), Number of Forum Posts (FP) and Google Search Tickers (GST) and dummy variables New Product Launch (NPL) and Organizational Events(OE).

Model 1																		
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	3,621	2,042	0,076	0,680	0,332	0,040	1,253	0,416	0,003									
γi1	0,299	0,062	0,000	0,000	0,007	0,983	-0,003	0,012	0,825									
γi2	1,039	0,685	0,129	0,828	0,088	0,000	0,256	0,125	0,041									
γi3	-1,564	0,837	0,062	0,103	0,105	0,324	0,561	0,158	0,000									
ci1	1,046	0,163	0,000	-0,018	0,044	0,674	0,003	0,030	0,933									
ci2				-0,097	0,023	0,000	-0,058	0,045	0,190									
ci3							0,000	0,011	1,000									
ai1	-0,297	0,119	0,012	-3,328	1,592	0,037	1,655	1,557	0,288									
ai2	0,007	0,012	0,563	-0,011	0,297	0,971	0,503	0,179	0,005									
ai3	0,042	0,014	0,003	-0,384	0,292	0,188	0,783	0,199	0,000									
bi1	0,333	0,214	0,119	1,537	4,572	0,737	1,593	4,080	0,696									
bi2	-0,010	0,020	0,608	0,122	0,335	0,715	0,326	0,262	0,213									
bi3	-0,085	0,018	0,000	0,779	0,404	0,054	-0,002	0,368	0,996									

Model 2	Dummy NPL																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	3,437	2,113	0,104	0,518	0,292	0,076	1,019	0,385	0,008									
γi1	0,311	0,073	0,000	0,004	0,006	0,471	0,004	0,011	0,698									
γi2	1,478	0,707	0,037	0,851	0,066	0,000	0,227	0,082	0,006									
γi3	-2,030	0,785	0,010	0,098	0,080	0,220	0,622	0,112	0,000									
ci1	-1,144	0,208	0,000	-0,008	0,027	0,759	0,018	0,042	0,660									
ci2				-0,110	0,018	0,000	-0,065	0,034	0,056									
ci3							-0,046	0,054	0,394									
ai1	-0,354	0,138	0,010	-1,373	1,567	0,381	0,822	1,259	0,514									
ai2	0,010	0,019	0,593	0,190	0,281	0,500	0,383	0,198	0,053									
ai3	0,051	0,018	0,005	-0,120	0,291	0,679	0,636	0,222	0,004									
bi1	0,068	0,292	0,816	3,336	4,801	0,487	-1,590	2,873	0,580									
bi2	-0,035	0,026	0,185	0,147	0,207	0,478	0,174	0,169	0,304									
bi3	-0,049	0,031	0,114	0,995	0,381	0,009	-0,114	0,266	0,668									
ei1	2,946	0,513	0,000	0,072	0,042	0,087	0,006	0,066	0,933									
ei2				0,039	0,023	0,086	0,077	0,044	0,077									
ei3							0,046	0,054	0,393									

Model 3	Dummy OE																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	4,340	2,667	0,104	0,713	0,245	0,004	1,172	0,383	0,002									
γi1	0,338	0,094	0,000	-0,006	0,011	0,611	-0,006	0,012	0,655									
γi2	-0,031	1,019	0,976	0,935	0,071	0,000	0,462	0,123	0,000									
γi3	-0,478	1,082	0,659	-0,019	0,075	0,806	0,345	0,128	0,007									
ci1	1,078	0,108	0,000	0,014	0,063	0,826	0,022	0,054	0,685									
ci2				-0,044	0,035	0,206	0,032	0,061	0,595									
ci3							0,000	0,043	1,000									
ai1	-0,347	0,128	0,007	-4,986	3,151	0,114	-0,187	1,767	0,916									
ai2	0,007	0,022	0,766	0,379	0,211	0,073	-0,559	0,109	0,000									
ai3	0,020	0,016	0,204	0,300	0,235	0,201	-0,574	0,162	0,000									
bi1	-0,151	0,144	0,295	-1,509	2,990	0,614	1,540	2,849	0,589									
bi2	0,056	0,022	0,013	0,672	0,704	0,340	-0,006	0,894	0,995									
bi3	0,132	0,021	0,000	0,161	0,659	0,806	0,201	0,644	0,755									
ei1	-0,059	0,262	0,821	-0,014	0,027	0,617	-0,045	0,037	0,225									
ei2				-0,015	0,139	0,915	-0,089	0,162	0,584									
ei3							0,000	0,043	1,000									

Model 4																		
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	2,682	2,393	0,262	0,984	0,270	0,000	1,756	0,269	0,000	3,016	0,873	0,001						
γi1	0,288	0,065	0,000	-0,003	0,005	0,612	0,001	0,009	0,916	0,040	0,026	0,119						
γi2	-0,316	0,452	0,484	0,867	0,049	0,000	0,225	0,060	0,000	-0,969	0,180	0,000						
γi3	0,099	0,453	0,827	0,030	0,061	0,624	0,561	0,080	0,000	0,949	0,197	0,000						
γi4	-0,144	0,133	0,279	-0,019	0,017	0,274	-0,078	0,021	0,000	0,271	0,060	0,000						
ci1	-1,101	0,273	0,000	0,013	0,022	0,547	0,028	0,030	0,349	-0,051	0,133	0,700						
ci2				0,059	0,013	0,000	-0,026	0,021	0,207	0,119	0,094	0,205						
ci3							0,001	0,017	0,944	0,007	0,113	0,948						
ci4										0,001	0,039	0,981						
ai1	-0,133	0,165	0,419	-0,893	1,847	0,629	-0,099	1,203	0,934	-0,647	0,281	0,021						
ai2	0,040	0,012	0,001	0,619	0,095	0,000	-0,275	0,065	0,000	-0,097	0,020	0,000						
ai3	0,007	0,015	0,624	0,497	0,086	0,000	-0,092	0,109	0,395	-0,150	0,026	0,000						
ai4	0,049	0,038	0,197	-0,678	0,403	0,093	0,324	0,242	0,182	0,084	0,113	0,460						
bi1	0,128	0,230	0,579	6,158	2,724	0,024	-3,697	2,709	0,172	-0,021	0,378	0,955						
bi2	0,001	0,019	0,963	0,365	0,134	0,007	0,356	0,101	0,000	-0,156	0,032	0,000						
bi3	0,030	0,022	0,178	-0,037	0,123	0,764	0,878	0,087	0,000	-0,270	0,038	0,000						
bi4	-0,004	0,112	0,975	-0,622	0,795	0,434	1,079	0,440	0,014	-1,046	0,040	0,000						

Model 5	Dummy NPL																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	1,388	2,024	0,493	0,684	0,328	0,037	1,087	0,377	0,004	3,766	1,581	0,017						
γi1	0,320	0,077	0,000	0,002	0,008	0,832	0,004	0,012	0,744	0,023	0,032	0,475						
γi2	0,775	0,783	0,322	0,856	0,058	0,000	0,296	0,084	0,000	-0,824	0,283	0,004						
γi3	-0,925	0,840	0,271	0,076	0,073	0,300	0,555	0,104	0,000	0,667	0,301	0,027						
γi4	-0,202	0,131	0,123	-0,009	0,018	0,623	-0,044	0,023	0,055	0,388	0,072	0,000						
ci1	-0,294	0,146	0,045	-0,003	0,067	0,965	-0,023	0,062	0,712	-0,499	0,169	0,003						
ci2				-0,115	0,017	0,000	-0,105	0,033	0,001	-0,320	0,292	0,272						
ci3							0,000	0,006	1,000	0,000	0,077	1,000						
ci4										0,000	0,067	1,000						
ai1	-0,124	0,125	0,322	1,362	0,899	0,130	-1,128	0,734	0,124	-0,228	0,172	0,184						
ai2	-0,023	0,025	0,356	-0,005	0,201	0,981	-0,482	0,174	0,006	0,008	0,034	0,804						
ai3	0,000	0,027	0,992	0,266	0,181	0,140	-0,750	0,141	0,000	0,017	0,032	0,587						
ai4	-0,020	0,107	0,854	1,579	0,501	0,002	-1,508	0,369	0,000	0,431	0,112	0,000						
bi1	-0,780	0,071	0,000	-1,639	1,797	0,362	3,009	1,603	0,061	-0,264	0,569	0,642						
bi2	0,024	0,025	0,340	0,006	0,286	0,985	0,369	0,244	0,131	-0,036	0,063	0,570						
bi3	0,026	0,017	0,121	0,787	0,260	0,003	0,034	0,186	0,856	-0,182	0,044	0,000						
bi4	0,103	0,068	0,130	0,711	1,327	0,592	-0,015	1,075	0,989	-0,217	0,177	0,221						
ei1	1,840	0,321	0,000	0,012	0,073	0,868	0,010	0,056	0,860	0,605	0,200	0,002						
ei2				0,073	0,033	0,025	0,145	0,060	0,016	0,175	0,388	0,653						
ei3							-0,017	0,056	0,761	-0,312	0,117	0,008						
ei4										0,000	0,181	1,000						

Model 6	Dummy OE																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	1,014	2,302	0,660	0,654	0,274	0,017	1,396	0,380	0,000	3,153	1,110	0,005						
γi1	0,364	0,064	0,000	-0,004	0,007	0,567	-0,008	0,011	0,478	0,013	0,033	0,699						
γi2	0,669	0,710	0,347	0,911	0,062	0,000	0,313	0,079	0,000	-0,619	0,240	0,010						
γi3	-0,771	0,829	0,352	0,021	0,072	0,769	0,506	0,097	0,000	0,543	0,281	0,053						
γi4	-0,222	0,166	0,181	-0,014	0,016	0,392	-0,060	0,019	0,002	0,309	0,063	0,000						
ci1	-0,271	0,199	0,173	-0,015	0,032	0,644	-0,066	0,033	0,048	-0,154	0,160	0,336						
ci2				-0,048	0,031	0,123	-0,023	0,057	0,686	0,317	0,246	0,198						
ci3							0,000	0,012	1,000	0,000	0,064	1,000						
ci4										0,000	0,027	1,000						
ai1	-0,249	0,146	0,088	-2,718	1,516	0,073	1,394	0,922	0,130	-0,807	0,294	0,006						
ai2	0,008	0,010	0,414	0,115	0,295	0,697	-0,502	0,175	0,004	-0,018	0,024	0,455						
ai3	0,027	0,015	0,065	0,182	0,309	0,555	-0,596	0,186	0,001	-0,073	0,034	0,031						
ai4	0,051	0,034	0,139	0,569	0,599	0,342	-0,385	0,326	0,238	-0,134	0,146	0,359						
bi1	-0,303	0,278	0,275	-8,618	3,167	0,007	7,265	1,513	0,000	-0,962	0,367	0,009						
bi2	0,002	0,019	0,926	0,756	0,296	0,011	-0,030	0,211	0,888	-0,144	0,057	0,011						
bi3	0,080	0,020	0,000	0,452	0,413	0,273	0,194	0,300	0,519	-0,133	0,070	0,058						
bi4	0,130	0,058	0,024	1,490	0,926	0,107	-0,576	0,753	0,444	-0,813	0,103	0,000						
ei1	-0,107	0,551	0,846	-0,033	0,064	0,604	0,058	0,094	0,539	-0,013	0,236	0,955						
ei2				-0,023	0,050	0,650	-0,065	0,063	0,296	-0,403	0,283	0,154						
ei3							0,000	0,016	1,000	0,000	0,070	1,000						
ei4										0,000	0,029	1,000						

Model 7																		
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	51,316	21,920	0,019	-0,234	1,806	0,897	1,062	2,110	0,615				12,408	0,834	0,000			
γi1	0,271	0,064	0,000	-0,004	0,006	0,560	-0,005	0,009	0,579				-0,002	0,003	0,488			
γi2	1,376	0,587	0,019	0,846	0,096	0,000	0,245	0,111	0,027				-0,048	0,034	0,152			
γi3	-1,954	0,748	0,009	0,086	0,104	0,407	0,568	0,121	0,000				0,033	0,028	0,237			
γi5	-3,746	1,723	0,030	0,070	0,139	0,617	0,017	0,163	0,915				0,035	0,068	0,602			
ci1	1,033	0,260	0,000	-0,049	0,058	0,393	-0,026	0,033	0,429				0,005	0,012	0,679			
ci2				0,044	0,133	0,743	0,020	0,062	0,744				-0,004	0,017	0,812			
ci3							0,000	0,002	1,000				0,000	0,002	1,000			
ci5													0,000	0,002	1,000			
ai1	-0,400	0,237	0,091	-2,214	1,804	0,220	1,926	1,234	0,119				2,393	2,249	0,287			
ai2	0,000	0,017	0,989	0,130	0,314	0,678	0,333	0,174	0,055				-0,262	0,218	0,229			
ai3	0,035	0,010	0,000	-0,204	0,273	0,453	0,543	0,184	0,003				-0,201	0,168	0,230			
ai5	0,007	0,003	0,051	-0,039	0,035	0,265	0,004	0,024	0,854				-0,188	0,074	0,011			
bi1	0,529	0,253	0,036	-1,040	1,840	0,572	0,868	1,003	0,387				2,619	1,699	0,123			
bi2	0,053	0,035	0,131	0,049	0,178	0,785	0,374	0,112	0,001				0,496	0,300	0,098			
bi3	0,017	0,025	0,500	-0,587	0,167	0,000	1,127	0,087	0,000				0,599	0,169	0,000			
bi5	-0,009	0,006	0,108	0,099	0,046	0,032	-0,104	0,029	0,000				0,934	0,042	0,000			

Model 8	Dummy NPL																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	21,402	23,505	0,363	0,458	1,881	0,808	1,460	2,447	0,551				11,916	0,900	0,000			
γi1	0,258	0,067	0,000	0,008	0,006	0,211	0,012	0,010	0,227				-0,005	0,003	0,124			
γi2	1,147	0,441	0,009	0,836	0,055	0,000	0,241	0,074	0,001				0,005	0,026	0,849			
γi3	-1,328	0,530	0,012	0,099	0,056	0,078	0,622	0,084	0,000				0,003	0,024	0,894			
γi5	-1,628	1,876	0,386	0,014	0,145	0,921	-0,044	0,188	0,816				0,056	0,070	0,425			
ci1	0,315	0,149	0,034	0,035	0,105	0,740	0,047	0,066	0,479				-0,004	0,016	0,813			
ci2				-0,100	0,036	0,006	-0,072	0,057	0,205				-0,011	0,014	0,446			
ci3							0,013	0,043	0,763				0,010	0,029	0,728			
ci5													0,000	0,006	1,000			
ai1	0,187	0,185	0,311	-0,451	0,743	0,544	0,415	0,620	0,503				6,117	4,255	0,151			
ai2	0,022	0,015	0,157	0,523	0,191	0,006	0,193	0,121	0,112				-0,067	0,221	0,762			
ai3	0,071	0,018	0,000	0,332	0,234	0,157	0,354	0,178	0,046				0,210	0,222	0,342			
ai5	-0,017	0,005	0,000	0,100	0,046	0,031	-0,096	0,039	0,014				-0,361	0,092	0,000			
bi1	0,787	0,116	0,000	1,898	3,134	0,545	-1,275	2,112	0,546				0,457	2,633	0,862			
bi2	0,007	0,011	0,535	-0,155	0,134	0,247	0,375	0,140	0,008				-0,145	0,301	0,631			
bi3	-0,027	0,013	0,037	0,551	0,223	0,014	0,304	0,178	0,088				0,317	0,198	0,109			
bi5	0,007	0,004	0,056	-0,098	0,081	0,226	0,092	0,041	0,026				0,806	0,072	0,000			
ei1	1,394	0,205	0,000	-0,022	0,114	0,846	-0,048	0,087	0,582				0,017	0,018	0,346			
ei2				0,012	0,042	0,782	0,062	0,061	0,306				0,038	0,015	0,014			
ei3							-0,013	0,051	0,798				-0,010	0,027	0,704			
ei5													0,000	0,005	1,000			

Model 9	Dummy OE																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	34,108	24,446	0,163	0,425	2,079	0,838	1,316	2,264	0,561				13,253	0,758	0,000			
γi1	0,284	0,085	0,001	-0,002	0,006	0,730	-0,008	0,011	0,444				-0,002	0,003	0,542			
γi2	1,448	0,681	0,033	0,900	0,062	0,000	0,277	0,095	0,003				-0,021	0,028	0,459			
γi3	-2,005	0,935	0,032	0,054	0,070	0,438	0,583	0,117	0,000				0,021	0,027	0,447			
γi5	-2,405	1,955	0,218	0,001	0,161	0,997	-0,034	0,177	0,846				-0,043	0,058	0,456			
ci1	0,475	0,207	0,022	0,012	0,089	0,890	0,074	0,046	0,104				-0,027	0,038	0,480			
ci2				0,076	0,056	0,175	0,026	0,102	0,795				-0,029	0,020	0,137			
ci3							0,000	0,008	1,000				0,000	0,002	1,000			
ci5													0,000	0,002	1,000			
ai1	-0,027	0,221	0,901	-1,538	0,893	0,085	1,097	0,955	0,251				7,396	3,552	0,037			
ai2	0,007	0,030	0,820	0,182	0,219	0,405	0,420	0,112	0,000				-0,050	0,230	0,827			
ai3	0,052	0,025	0,039	-0,137	0,202	0,497	0,702	0,112	0,000				-0,133	0,335	0,691			
ai5	-0,002	0,005	0,687	-0,015	0,082	0,854	-0,009	0,065	0,884				-0,272	0,097	0,005			
bi1	0,723	0,093	0,000	3,701	1,642	0,024	-3,411	0,851	0,000				-2,681	3,236	0,407			
bi2	0,016	0,026	0,534	0,477	0,349	0,171	-0,105	0,301	0,726				0,910	1,260	0,470			
bi3	0,019	0,016	0,229	0,325	0,314	0,300	0,398	0,242	0,100				0,881	0,546	0,107			
bi5	0,023	0,004	0,000	-0,193	0,104	0,064	0,104	0,077	0,175				0,511	0,437	0,242			
ei1	0,413	0,324	0,202	-0,078	0,079	0,326	-0,177	0,050	0,000				0,007	0,027	0,800			
ei2				-0,184	0,102	0,072	-0,079	0,145	0,585				0,041	0,032	0,198			
ei3							0,000	0,017	1,000				0,000	0,010	1,000			
ei5													0,000	0,003	1,000			

Model 10																		
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	2,223	2,120	0,294	0,902	0,265	0,001	1,690	0,274	0,000							2,211	0,595	0,000
γi1	0,250	0,073	0,001	-0,005	0,007	0,405	-0,006	0,009	0,534							-0,003	0,022	0,893
γi2	1,723	0,447	0,000	0,821	0,050	0,000	0,286	0,074	0,000							-0,491	0,196	0,012
γi3	-2,033	0,522	0,000	0,098	0,059	0,097	0,502	0,087	0,000							0,453	0,195	0,020
γi6	-0,312	0,144	0,030	-0,042	0,020	0,035	-0,086	0,025	0,001							0,420	0,069	0,000
ci1	-0,453	0,374	0,226	-0,016	0,019	0,402	0,039	0,023	0,092							-0,266	0,122	0,030
ci2				0,000	0,015	1,000	0,000	0,008	1,000							0,000	0,195	1,000
ci3							0,000	0,005	1,000							0,000	0,037	1,000
ci6																0,000	0,048	1,000
ai1	0,477	0,139	0,001	-1,006	1,328	0,449	1,072	1,125	0,341							-1,010	0,409	0,013
ai2	-0,026	0,008	0,001	0,737	0,114	0,000	-0,269	0,098	0,006							-0,089	0,024	0,000
ai3	-0,039	0,013	0,003	0,799	0,138	0,000	-0,362	0,079	0,000							-0,217	0,053	0,000
ai6	-0,097	0,035	0,005	-0,032	0,366	0,930	0,050	0,311	0,873							-0,276	0,104	0,008
bi1	0,485	0,126	0,000	-3,804	1,718	0,027	3,460	2,171	0,111							-1,848	0,332	0,000
bi2	0,039	0,007	0,000	0,377	0,106	0,000	0,339	0,102	0,001							0,016	0,043	0,711
bi3	0,056	0,014	0,000	-0,336	0,166	0,044	0,614	0,125	0,000							0,153	0,044	0,000
bi6	0,190	0,037	0,000	0,733	1,218	0,547	-1,073	0,988	0,278							0,522	0,139	0,000

Model 11	Dummy NPL																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	3,625	2,030	0,074	0,426	0,222	0,055	1,253	0,240	0,000							2,498	0,716	0,000
γi1	0,358	0,069	0,000	0,004	0,006	0,577	0,008	0,008	0,327							0,031	0,019	0,115
γi2	-0,089	0,485	0,854	0,777	0,051	0,000	0,069	0,059	0,240							-0,726	0,213	0,001
γi3	-0,285	0,554	0,608	0,205	0,057	0,000	0,804	0,064	0,000							0,703	0,213	0,001
γi6	-0,198	0,137	0,148	-0,041	0,016	0,012	-0,111	0,022	0,000							0,376	0,084	0,000
ci1	0,591	0,169	0,000	-0,081	0,025	0,001	-0,030	0,034	0,378							0,038	0,080	0,634
ci2				-0,015	0,053	0,773	-0,020	0,073	0,780							0,080	0,115	0,489
ci3							0,000	0,007	1,000							0,000	0,110	0,999
ci6																0,000	0,083	0,998
ai1	-0,137	0,128	0,284	-2,887	0,952	0,002	2,175	0,691	0,002							-0,399	0,246	0,104
ai2	0,038	0,018	0,037	0,310	0,264	0,240	0,440	0,081	0,000							-0,051	0,032	0,109
ai3	0,055	0,013	0,000	0,012	0,298	0,968	0,731	0,100	0,000							-0,041	0,039	0,291
ai6	0,039	0,024	0,100	-0,430	0,314	0,171	0,495	0,266	0,063							-0,259	0,094	0,006
bi1	0,299	0,191	0,117	8,814	1,064	0,000	-5,927	1,041	0,000							0,372	0,565	0,511
bi2	-0,009	0,016	0,550	0,617	0,212	0,004	-0,209	0,160	0,193							0,072	0,030	0,015
bi3	-0,063	0,015	0,000	0,599	0,216	0,006	0,155	0,183	0,395							-0,057	0,070	0,418
bi6	-0,177	0,043	0,000	0,346	0,833	0,678	0,219	0,477	0,646							0,758	0,158	0,000
ei1	0,563	0,204	0,006	0,082	0,020	0,000	0,093	0,028	0,001							0,067	0,077	0,385
ei2				0,005	0,071	0,949	0,031	0,074	0,681							-0,078	0,127	0,536
ei3							0,000	0,014	1,000							0,000	0,109	0,999
ei6																0,000	0,086	0,998

Model 12	Dummy OE																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	2,182	1,701	0,200	0,402	0,245	0,100	1,151	0,311	0,000							2,019	0,767	0,008
γi1	0,393	0,070	0,000	0,006	0,007	0,438	0,009	0,009	0,344							0,017	0,017	0,325
γi2	0,510	0,523	0,329	0,879	0,088	0,000	0,280	0,126	0,027							-0,385	0,159	0,016
γi3	-0,761	0,641	0,235	0,093	0,110	0,398	0,570	0,161	0,000							0,341	0,194	0,078
γi6	-0,237	0,188	0,207	-0,029	0,023	0,197	-0,063	0,033	0,053							0,509	0,079	0,000
ci1	-0,260	0,418	0,535	-0,065	0,042	0,119	0,012	0,044	0,781							0,021	0,046	0,646
ci2				0,000	0,009	1,000	0,000	0,006	1,000							0,000	0,010	1,000
ci3							0,000	0,005	1,000							0,000	0,008	1,000
ci6																0,000	0,009	1,000
ai1	0,281	0,123	0,022	0,492	0,799	0,538	-0,509	0,679	0,453							0,585	0,152	0,000
ai2	0,008	0,012	0,482	-0,134	0,116	0,248	0,407	0,076	0,000							-0,093	0,031	0,003
ai3	-0,032	0,016	0,040	-0,061	0,139	0,661	0,354	0,154	0,022							-0,144	0,041	0,000
ai6	-0,049	0,022	0,025	0,527	0,159	0,001	-0,398	0,125	0,001							0,230	0,044	0,000
bi1	-0,640	0,214	0,003	3,921	7,765	0,614	-5,409	3,104	0,081							-0,671	0,516	0,193
bi2	0,001	0,048	0,980	0,385	0,538	0,474	0,297	0,412	0,471							-0,254	0,073	0,000
bi3	-0,039	0,026	0,133	-0,077	0,132	0,558	0,760	0,049	0,000							-0,342	0,044	0,000
bi6	0,134	0,038	0,000	-1,276	0,691	0,065	0,961	0,551	0,081							-0,896	0,055	0,000
ei1	0,780	0,429	0,069	0,084	0,086	0,329	-0,045	0,064	0,478							0,007	0,073	0,925
ei2				0,046	0,040	0,254	-0,001	0,056	0,982							-0,044	0,071	0,535
ei3							0,000	0,014	1,000							0,000	0,015	1,000
ei6																0,000	0,009	1,000

Model 13																		
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	41,879	7,147	0,000	-0,684	0,771	0,375	-0,828	1,106	0,454	15,028	2,910	0,000	12,293	0,547	0,000	2,192	2,477	0,376
γi1	0,329	0,061	0,000	0,003	0,006	0,563	0,003	0,007	0,686	0,039	0,024	0,101	-0,002	0,003	0,467	0,034	0,023	0,149
γi2	0,787	0,472	0,095	0,768	0,058	0,000	0,094	0,077	0,223	-0,970	0,232	0,000	-0,057	0,024	0,018	-0,822	0,195	0,000
γi3	-0,658	0,495	0,184	0,173	0,056	0,002	0,758	0,078	0,000	0,846	0,255	0,001	0,058	0,025	0,019	0,764	0,232	0,001
γi4	0,209	0,322	0,516	0,032	0,024	0,190	-0,016	0,033	0,627	0,513	0,097	0,000	-0,012	0,010	0,240	0,170	0,083	0,041
γi5	-3,352	0,594	0,000	0,117	0,056	0,035	0,177	0,082	0,032	-0,870	0,248	0,000	0,036	0,042	0,393	0,040	0,198	0,841
γi6	-0,594	0,414	0,151	-0,090	0,037	0,015	-0,100	0,054	0,066	-0,299	0,130	0,022	0,005	0,013	0,691	0,220	0,123	0,074
ci1	0,577	0,143	0,000	-0,048	0,014	0,001	-0,063	0,016	0,000	-0,107	0,115	0,351	-0,005	0,009	0,524	-0,140	0,121	0,246
ci2				0,000	0,005	0,999	0,000	0,006	0,994	0,000	0,013	0,992	0,000	0,001	0,995	0,000	0,017	0,995
ci3							0,000	0,004	0,993	0,000	0,008	0,996	0,000	0,001	0,998	0,000	0,007	0,997
ci4										0,000	0,011	0,995	0,000	0,001	0,996	0,000	0,011	0,995
ci5													0,000	0,002	0,995	0,000	0,012	0,993
ci6																0,000	0,004	0,997
ai1	-0,200	0,080	0,013	1,346	0,952	0,157	-0,197	0,842	0,815	-0,304	0,488	0,534	-2,323	2,511	0,355	0,845	0,571	0,139
ai2	0,020	0,011	0,061	-0,200	0,090	0,027	0,668	0,113	0,000	0,033	0,026	0,204	-0,006	0,211	0,978	-0,080	0,043	0,064
ai3	0,059	0,017	0,000	-0,459	0,123	0,000	0,861	0,144	0,000	0,014	0,035	0,700	-0,168	0,353	0,634	-0,023	0,067	0,725
ai4	0,170	0,034	0,000	-0,133	0,232	0,565	0,257	0,248	0,301	-0,222	0,117	0,058	-2,680	0,544	0,000	0,318	0,169	0,060
ai5	0,000	0,004	0,955	-0,061	0,046	0,190	0,027	0,029	0,361	-0,022	0,013	0,083	-0,139	0,051	0,006	0,012	0,017	0,489
ai6	0,074	0,030	0,013	-0,113	0,091	0,212	0,180	0,099	0,070	-0,093	0,090	0,301	-1,490	0,568	0,009	0,179	0,130	0,168
bi1	0,607	0,101	0,000	6,230	0,653	0,000	-6,192	0,869	0,000	1,105	0,614	0,072	0,020	3,995	0,996	-0,709	0,575	0,218
bi2	-0,006	0,008	0,488	0,861	0,052	0,000	-0,234	0,091	0,010	0,065	0,041	0,117	-0,549	0,161	0,001	-0,117	0,040	0,004
bi3	0,041	0,010	0,000	0,098	0,077	0,205	0,475	0,117	0,000	0,143	0,051	0,005	-0,452	0,240	0,059	-0,182	0,083	0,028
bi4	-0,050	0,053	0,340	0,448	0,294	0,128	-0,559	0,485	0,249	1,205	0,135	0,000	-4,311	0,700	0,000	-0,907	0,161	0,000
bi5	-0,006	0,006	0,331	0,131	0,045	0,003	-0,085	0,043	0,051	0,071	0,016	0,000	0,874	0,052	0,000	-0,065	0,021	0,002
bi6	-0,030	0,049	0,549	0,815	0,455	0,073	-0,931	0,593	0,116	0,656	0,123	0,000	-2,593	0,507	0,000	0,081	0,195	0,679

Model 14	Dummy NPL																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	7,939	3,538	0,025	-1,536	0,886	0,083	0,123	0,208	0,553	6,376	2,122	0,003	11,289	0,301	0,000	0,879	0,294	0,003
γi1	0,313	0,085	0,000	0,004	0,007	0,622	0,010	0,011	0,374	0,037	0,030	0,218	0,002	0,003	0,602	0,032	0,023	0,163
γi2	-0,863	0,408	0,034	0,762	0,045	0,000	0,203	0,038	0,000	-0,519	0,107	0,000	-0,082	0,018	0,000	-0,477	0,062	0,000
γi3	0,394	0,524	0,452	0,122	0,030	0,000	0,557	0,044	0,000	0,486	0,151	0,001	0,093	0,017	0,000	0,256	0,086	0,003
γi4	0,011	0,213	0,959	0,038	0,025	0,128	-0,005	0,031	0,881	0,494	0,084	0,000	-0,020	0,010	0,044	0,162	0,071	0,023
γi5	-0,211	0,210	0,314	0,220	0,059	0,000	0,150	0,019	0,000	-0,310	0,195	0,111	0,114	0,023	0,000	0,210	0,022	0,000
γi6	-0,199	0,253	0,432	-0,097	0,035	0,006	-0,096	0,040	0,018	-0,111	0,078	0,157	0,002	0,011	0,873	0,312	0,082	0,000
ci1	0,678	0,140	0,000	-0,043	0,031	0,171	-0,079	0,029	0,007	-0,085	0,114	0,454	-0,010	0,009	0,269	0,005	0,112	0,964
ci2				-0,087	0,025	0,001	-0,061	0,027	0,024	-0,132	0,127	0,299	-0,025	0,009	0,003	-0,196	0,083	0,018
ci3							0,026	0,018	0,155	0,376	0,072	0,000	-0,028	0,006	0,000	0,371	0,070	0,000
ci4										-0,109	0,146	0,455	0,004	0,013	0,772	0,100	0,105	0,341
ci5													0,000	0,006	0,983	0,007	0,162	0,965
ci6																-0,020	0,126	0,871
ai1	0,280	0,097	0,004	2,269	0,896	0,011	-3,649	0,873	0,000	-0,241	0,395	0,541	-8,115	3,306	0,014	0,229	0,766	0,765
ai2	0,024	0,009	0,007	0,463	0,123	0,000	-0,153	0,105	0,146	-0,061	0,046	0,184	0,050	0,176	0,776	0,012	0,072	0,871
ai3	0,034	0,014	0,014	0,204	0,188	0,279	0,097	0,147	0,511	-0,137	0,052	0,008	-0,405	0,200	0,043	0,032	0,079	0,687
ai4	0,110	0,041	0,008	0,102	0,616	0,868	-0,143	0,459	0,755	0,627	0,171	0,000	-0,820	0,475	0,084	-0,795	0,215	0,000
ai5	-0,007	0,004	0,087	0,096	0,044	0,028	-0,102	0,039	0,009	-0,019	0,014	0,168	-0,474	0,102	0,000	0,033	0,021	0,124
ai6	0,071	0,027	0,010	-0,417	0,303	0,169	0,004	0,245	0,987	0,385	0,091	0,000	-0,371	0,349	0,288	-0,083	0,152	0,584
bi1	0,386	0,100	0,000	1,030	0,746	0,167	1,537	1,011	0,128	0,055	0,447	0,902	6,791	1,802	0,000	-0,201	0,409	0,623
bi2	0,026	0,021	0,225	0,073	0,080	0,360	0,245	0,084	0,004	0,113	0,050	0,022	-0,643	0,167	0,000	-0,292	0,054	0,000
bi3	0,028	0,025	0,252	-0,923	0,125	0,000	0,813	0,140	0,000	0,064	0,071	0,362	-0,384	0,289	0,183	-0,328	0,069	0,000
bi4	0,204	0,090	0,023	-0,788	0,338	0,020	0,129	0,307	0,674	-0,324	0,150	0,030	-3,415	0,821	0,000	-0,118	0,209	0,574
bi5	0,008	0,005	0,114	-0,152	0,050	0,003	0,130	0,049	0,008	-0,057	0,019	0,002	-0,278	0,066	0,000	0,093	0,017	0,000
bi6	0,126	0,053	0,018	-0,603	0,239	0,012	0,640	0,186	0,001	-0,360	0,101	0,000	-1,748	0,745	0,019	-0,029	0,148	0,847
ei1	0,375	0,427	0,380	0,092	0,035	0,008	0,174	0,050	0,001	0,260	0,162	0,109	-0,016	0,025	0,529	0,073	0,140	0,604
ei2				0,146	0,028	0,000	0,117	0,044	0,007	0,000	0,153	0,999	-0,027	0,013	0,038	0,083	0,103	0,420

ei3	-0,026	0,020	0,198	-0,379	0,078	0,000	0,028	0,008	0,001	-0,373	0,081	0,000
ei4				0,110	0,126	0,386	-0,004	0,013	0,763	-0,099	0,099	0,317
ei5							0,000	0,006	0,986	-0,007	0,164	0,965
ei6										0,020	0,126	0,872

Model 15	Dummy OE																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	35,066	21,512	0,103	-1,358	3,070	0,658	-1,883	3,755	0,616	23,314	8,785	0,008	14,302	1,326	0,000	7,377	9,553	0,440
γi1	0,306	0,088	0,000	0,009	0,008	0,279	0,013	0,011	0,216	0,063	0,051	0,216	-0,001	0,003	0,660	0,054	0,034	0,108
γi2	0,421	0,543	0,438	0,889	0,083	0,000	0,258	0,092	0,005	-0,780	0,242	0,001	-0,056	0,031	0,070	-0,581	0,175	0,001
γi3	-0,986	0,578	0,088	0,030	0,108	0,783	0,579	0,124	0,000	0,764	0,238	0,001	0,065	0,030	0,028	0,571	0,216	0,008
γi4	0,112	0,244	0,644	0,043	0,028	0,128	0,048	0,040	0,229	0,478	0,145	0,001	-0,044	0,011	0,000	0,093	0,097	0,336
γi5	-2,255	1,669	0,177	0,180	0,259	0,486	0,264	0,321	0,410	-1,583	0,699	0,024	-0,125	0,097	0,197	-0,400	0,799	0,616
γi6	-0,910	0,346	0,009	-0,121	0,035	0,001	-0,195	0,052	0,000	-0,337	0,185	0,069	0,030	0,011	0,010	0,251	0,127	0,047
ci1	-0,328	0,195	0,091	0,000	0,055	0,999	-0,013	0,074	0,862	-0,035	0,138	0,803	0,029	0,019	0,124	0,020	0,169	0,904
ci2				0,031	0,022	0,162	0,038	0,025	0,126	0,180	0,161	0,263	0,000	0,015	0,976	0,319	0,134	0,017
ci3							0,000	0,004	1,000	0,000	0,025	1,000	0,000	0,003	1,000	0,000	0,052	1,000
ci4										0,000	0,021	1,000	0,000	0,003	1,000	0,000	0,043	1,000
ci5													0,000	0,003	1,000	0,000	0,020	1,000
ci6																0,000	0,016	1,000
ai1	-0,123	0,106	0,244	1,837	1,042	0,078	-2,008	1,293	0,120	-0,615	0,355	0,083	-0,211	2,681	0,937	0,338	0,399	0,398
ai2	0,034	0,016	0,031	0,148	0,144	0,302	0,261	0,127	0,040	-0,056	0,060	0,350	0,040	0,423	0,924	0,021	0,079	0,793
ai3	0,068	0,018	0,000	0,039	0,138	0,777	0,428	0,126	0,001	-0,132	0,063	0,036	0,285	0,364	0,434	0,109	0,087	0,211
ai4	0,165	0,069	0,017	0,351	0,503	0,485	-0,305	0,490	0,533	0,035	0,138	0,801	-2,385	1,331	0,073	-0,363	0,291	0,211
ai5	-0,015	0,005	0,005	0,035	0,033	0,291	-0,035	0,043	0,419	-0,032	0,017	0,068	-0,305	0,116	0,008	0,029	0,028	0,287
ai6	0,054	0,051	0,296	0,977	0,396	0,013	-0,836	0,309	0,007	-0,071	0,137	0,603	-0,048	1,323	0,971	0,290	0,238	0,223
bi1	0,677	0,100	0,000	-1,764	2,212	0,425	1,688	1,881	0,369	-1,390	0,591	0,019	-2,096	3,821	0,583	1,827	0,707	0,010
bi2	-0,008	0,015	0,608	0,719	0,123	0,000	-0,024	0,153	0,875	-0,183	0,105	0,080	0,950	0,503	0,059	0,161	0,153	0,294
bi3	-0,041	0,015	0,008	0,058	0,180	0,749	0,646	0,152	0,000	-0,285	0,095	0,003	0,215	0,914	0,814	0,203	0,141	0,149
bi4	-0,145	0,050	0,004	-1,117	0,977	0,253	1,333	0,610	0,029	-0,164	0,279	0,557	1,886	1,564	0,228	0,964	0,289	0,001
bi5	0,009	0,006	0,148	-0,212	0,062	0,001	0,243	0,056	0,000	0,031	0,043	0,464	0,544	0,165	0,001	-0,073	0,044	0,100
bi6	-0,086	0,041	0,035	-0,524	0,650	0,420	0,882	0,467	0,059	-0,055	0,224	0,805	1,275	1,010	0,207	0,628	0,247	0,011
ei1	1,555	0,393	0,000	0,000	0,074	0,998	0,010	0,075	0,893	0,063	0,175	0,717	-0,029	0,021	0,162	0,146	0,176	0,405
ei2				-0,079	0,040	0,048	-0,038	0,064	0,550	-0,371	0,222	0,095	0,009	0,024	0,721	-0,302	0,245	0,218

ei3							0,000	0,010	1,000	0,000	0,031	1,000	0,000	0,003	1,000	0,000	0,057	1,000
ei4										0,000	0,026	1,000	0,000	0,003	1,000	0,000	0,045	1,000
ei5													0,000	0,003	1,000	0,000	0,020	1,000
ei6																0,000	0,018	1,000

Model 16																		
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	-1,069	24,200	0,965							-0,601	18,492	0,974	12,744	0,787	0,000	-3,946	8,782	0,653
γi1	0,332	0,088	0,000							0,051	0,060	0,395	0,000	0,003	0,903	0,041	0,036	0,253
γi4	-0,199	0,204	0,329							0,580	0,239	0,015	-0,005	0,015	0,761	0,206	0,202	0,308
γi5	0,162	1,868	0,931							0,210	1,434	0,883	-0,003	0,062	0,957	0,426	0,679	0,530
γi6	-0,094	0,223	0,673							-0,304	0,155	0,050	0,001	0,015	0,956	0,239	0,156	0,126
ci1	0,246	0,499	0,622							0,547	0,105	0,000	0,002	0,010	0,818	0,278	0,096	0,004
ci4										0,000	0,119	1,000	0,000	0,004	1,000	0,000	0,070	1,000
ci5													0,000	0,002	1,000	0,000	0,007	1,000
ci6																0,000	0,006	1,000
ai1	0,188	0,439	0,669							1,064	0,358	0,003	-10,813	1,776	0,000	-1,371	0,691	0,047
ai4	-0,062	0,530	0,907							-0,473	0,310	0,127	-1,275	3,560	0,720	0,268	0,790	0,734
ai5	0,003	0,022	0,900							-0,017	0,033	0,603	-0,214	0,123	0,081	-0,010	0,057	0,858
ai6	-0,012	0,240	0,960							-0,211	0,200	0,291	-1,107	1,974	0,575	0,143	0,435	0,742
bi1	-0,736	0,320	0,021							-0,388	2,955	0,896	-5,466	11,941	0,647	1,101	1,767	0,533
bi4	0,132	0,157	0,397							-0,489	2,272	0,830	-0,414	2,752	0,880	0,753	1,628	0,644
bi5	-0,002	0,013	0,891							0,051	0,077	0,508	0,888	0,121	0,000	-0,033	0,056	0,557
bi6	0,109	0,167	0,515							-0,519	1,311	0,692	-0,367	0,780	0,638	1,194	0,951	0,209

Model 17	Dummy NPL																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	14,666	0,247	0,000							8,430	0,081	0,000	11,817	0,061	0,000	-3,739	0,071	0,000
γi1	0,339	0,061	0,000							-0,010	0,026	0,705	0,001	0,002	0,691	0,002	0,025	0,922
γi4	-0,192	0,219	0,382							0,335	0,109	0,002	-0,002	0,007	0,824	0,009	0,078	0,903
γi5	-1,021	0,032	0,000							-0,517	0,009	0,000	0,068	0,005	0,000	0,411	0,004	0,000
γi6	-0,350	0,179	0,050							0,064	0,125	0,611	0,002	0,009	0,793	0,465	0,110	0,000
ci1	0,304	0,097	0,002							0,603	0,099	0,000	-0,014	0,007	0,044	0,444	0,084	0,000
ci4										0,132	0,316	0,677	0,008	0,007	0,241	-0,124	0,213	0,561
ci5													-0,005	0,005	0,315	0,109	0,086	0,205
ci6																0,000	0,082	0,996
ai1	0,044	0,097	0,649							0,844	0,314	0,007	-5,696	1,028	0,000	-0,680	0,556	0,221
ai4	0,113	0,039	0,004							-0,326	0,092	0,000	-1,634	0,463	0,000	0,630	0,162	0,000
ai5	-0,005	0,003	0,130							-0,037	0,013	0,003	-0,117	0,055	0,032	0,040	0,013	0,003
ai6	0,049	0,018	0,007							-0,214	0,072	0,003	-1,108	0,394	0,005	0,809	0,110	0,000
bi1	0,696	0,098	0,000							-0,906	0,612	0,138	1,048	2,643	0,692	1,051	0,865	0,224
bi4	-0,127	0,032	0,000							0,110	0,112	0,328	-1,462	0,588	0,013	-0,404	0,214	0,059
bi5	0,014	0,005	0,003							0,097	0,017	0,000	0,526	0,073	0,000	-0,162	0,021	0,000
bi6	-0,035	0,017	0,038							0,283	0,074	0,000	-0,345	0,397	0,385	-0,387	0,124	0,002
ei1	1,553	0,310	0,000							-0,452	0,116	0,000	0,026	0,013	0,048	-0,347	0,083	0,000
ei4										-0,133	0,304	0,662	-0,008	0,027	0,769	0,124	0,212	0,558
ei5													0,005	0,010	0,587	-0,109	0,089	0,222
ei6																0,000	0,084	0,995

Model 18	Dummy OE																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	15,738	20,170	0,435							17,426	5,522	0,002	12,902	0,817	0,000	0,151	4,340	0,972
γi1	0,326	0,082	0,000							0,035	0,025	0,154	-0,002	0,003	0,429	0,041	0,025	0,109
γi4	0,535	0,210	0,011							0,373	0,079	0,000	-0,022	0,009	0,011	0,115	0,067	0,086
γi5	-1,137	1,592	0,475							-1,171	0,434	0,007	-0,015	0,064	0,811	0,140	0,342	0,681
γi6	-1,032	0,250	0,000							-0,171	0,104	0,098	0,017	0,012	0,144	0,220	0,098	0,024
ci1	0,753	0,188	0,000							0,091	0,100	0,365	-0,022	0,016	0,156	0,091	0,101	0,369
ci4										-0,422	0,090	0,000	0,011	0,015	0,469	-0,452	0,045	0,000
ci5													0,000	0,001	1,000	0,000	0,007	1,000
ci6																0,000	0,005	1,000
ai1	0,243	0,203	0,230							-1,790	0,490	0,000	8,036	2,510	0,001	1,982	0,483	0,000
ai4	-0,125	0,027	0,000							0,498	0,173	0,004	0,488	0,624	0,435	0,068	0,149	0,647
ai5	-0,003	0,004	0,437							0,049	0,013	0,000	-0,003	0,060	0,962	-0,034	0,014	0,019
ai6	-0,037	0,026	0,159							0,464	0,127	0,000	0,201	0,643	0,754	0,161	0,151	0,287
bi1	0,405	0,345	0,242							1,093	0,247	0,000	6,341	2,191	0,004	-1,473	0,599	0,014
bi4	-0,083	0,064	0,189							1,089	0,252	0,000	-1,019	1,117	0,362	-1,036	0,144	0,000
bi5	0,013	0,005	0,010							0,027	0,033	0,418	0,713	0,239	0,003	0,017	0,067	0,796
bi6	-0,077	0,082	0,344							0,315	0,313	0,315	0,929	1,069	0,385	-0,306	0,185	0,098
ei1	0,329	0,258	0,201							-0,154	0,118	0,193	0,010	0,014	0,490	0,007	0,118	0,953
ei4										0,479	0,098	0,000	0,009	0,017	0,593	0,354	0,121	0,003
ei5													0,000	0,014	1,000	0,000	0,073	1,000
ei6																0,000	0,018	1,000

Model 19																		
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	55,993	27,823	0,044	-1,182	1,785	0,508	-0,174	2,692	0,948	16,710	8,774	0,057	13,049	1,186	0,000			
γi1	0,260	0,066	0,000	0,002	0,009	0,785	0,008	0,012	0,507	0,023	0,033	0,483	-0,003	0,003	0,312			
γi2	0,181	0,651	0,781	0,798	0,094	0,000	0,243	0,130	0,061	-0,427	0,525	0,416	-0,044	0,046	0,343			
γi3	-0,431	0,731	0,556	0,064	0,079	0,414	0,523	0,125	0,000	0,162	0,552	0,769	0,048	0,044	0,268			
γi4	-0,089	0,119	0,454	0,000	0,019	0,993	-0,042	0,025	0,099	0,404	0,054	0,000	-0,014	0,008	0,068			
γi5	-4,237	2,248	0,059	0,193	0,152	0,202	0,157	0,222	0,480	-0,983	0,699	0,159	-0,025	0,090	0,783			
ci1	0,369	0,493	0,454	0,028	0,022	0,204	-0,006	0,031	0,848	-0,100	0,312	0,747	-0,014	0,024	0,552			
ci2				0,031	0,035	0,384	0,044	0,039	0,256	0,488	0,106	0,000	-0,016	0,019	0,394			
ci3							0,000	0,009	1,000	0,000	0,143	1,000	0,000	0,004	1,000			
ci4										0,000	0,046	1,000	0,000	0,003	1,000			
ci5													0,000	0,003	1,000			
ai1	0,152	0,086	0,078	1,448	0,903	0,109	-1,676	0,725	0,021	-0,026	0,199	0,896	6,257	2,314	0,007			
ai2	0,002	0,010	0,860	0,534	0,228	0,019	-0,319	0,151	0,035	-0,038	0,061	0,535	-0,010	0,261	0,970			
ai3	-0,035	0,015	0,025	0,453	0,211	0,032	-0,194	0,159	0,222	-0,066	0,074	0,375	-0,083	0,375	0,826			
ai4	-0,110	0,076	0,147	0,589	0,616	0,339	-0,556	0,569	0,328	0,539	0,235	0,022	-0,352	0,860	0,682			
ai5	0,000	0,004	0,991	0,037	0,107	0,730	-0,041	0,097	0,670	0,021	0,014	0,125	0,235	0,219	0,283			
bi1	0,885	0,144	0,000	-1,317	0,817	0,107	1,437	0,827	0,082	-0,349	0,729	0,632	0,968	8,598	0,910			
bi2	-0,012	0,023	0,614	0,671	0,141	0,000	0,279	0,099	0,005	-0,076	0,111	0,493	0,215	0,708	0,761			
bi3	-0,011	0,024	0,637	-0,294	0,210	0,162	1,184	0,093	0,000	-0,117	0,139	0,398	0,435	0,630	0,490			
bi4	0,022	0,101	0,827	0,167	1,190	0,888	1,162	1,101	0,291	-0,230	0,291	0,430	1,993	2,900	0,492			
bi5	0,005	0,010	0,646	0,023	0,117	0,847	-0,037	0,119	0,752	0,076	0,023	0,001	0,437	0,481	0,364			

Model 20	Dummy NPL																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	36,313	19,680	0,065	-0,487	1,854	0,793	1,495	2,093	0,475	19,200	6,332	0,002	13,387	1,456	0,000			
γi1	0,317	0,071	0,000	-0,001	0,006	0,869	-0,005	0,009	0,551	0,031	0,034	0,369	-0,003	0,003	0,208			
γi2	1,608	0,564	0,004	0,789	0,070	0,000	0,128	0,085	0,130	-1,162	0,229	0,000	-0,064	0,030	0,031			
γi3	-1,608	0,620	0,010	0,136	0,077	0,075	0,729	0,097	0,000	0,971	0,238	0,000	0,061	0,029	0,036			
γi4	-0,179	0,123	0,145	-0,014	0,020	0,471	-0,078	0,023	0,001	0,377	0,055	0,000	-0,009	0,011	0,430			
γi5	-2,917	1,586	0,066	0,102	0,141	0,468	-0,017	0,163	0,916	-1,176	0,493	0,017	-0,047	0,115	0,684			
ci1	0,128	0,525	0,808	-0,002	0,147	0,989	-0,063	0,189	0,740	-0,187	1,787	0,917	-0,014	0,073	0,853			
ci2				-0,043	0,033	0,184	-0,055	0,187	0,769	-0,496	0,774	0,521	0,020	0,035	0,568			
ci3							0,000	0,020	1,000	0,000	0,086	1,000	0,000	0,007	1,000			
ci4										0,000	0,037	1,000	0,000	0,002	1,000			
ci5													0,000	0,001	1,000			
ai1	-0,204	0,091	0,024	0,698	0,720	0,332	-0,168	0,571	0,769	0,361	0,150	0,016	1,622	2,126	0,446			
ai2	0,020	0,008	0,015	-0,375	0,129	0,004	0,781	0,131	0,000	-0,044	0,025	0,087	0,408	0,185	0,028			
ai3	0,085	0,013	0,000	-0,584	0,175	0,001	0,961	0,179	0,000	0,011	0,030	0,718	0,421	0,328	0,198			
ai4	0,141	0,049	0,004	-0,810	0,533	0,129	1,117	0,550	0,042	-0,326	0,128	0,011	0,873	1,339	0,515			
ai5	0,001	0,003	0,745	-0,037	0,064	0,559	0,011	0,052	0,833	-0,021	0,013	0,102	-0,353	0,104	0,001			
bi1	0,778	0,058	0,000	0,427	1,660	0,797	-1,670	1,365	0,221	0,866	0,277	0,002	1,700	3,051	0,577			
bi2	0,003	0,008	0,728	0,904	0,128	0,000	-0,191	0,110	0,082	-0,044	0,040	0,280	0,264	0,282	0,349			
bi3	0,019	0,012	0,113	0,273	0,141	0,052	0,424	0,091	0,000	-0,085	0,038	0,027	0,315	0,365	0,388			
bi4	-0,025	0,037	0,500	-0,338	0,566	0,550	0,818	0,560	0,144	0,364	0,368	0,322	-0,077	2,432	0,975			
bi5	-0,003	0,005	0,478	0,073	0,072	0,313	-0,032	0,094	0,734	0,026	0,050	0,600	0,722	0,282	0,010			
ei1	1,493	0,515	0,004	0,019	0,142	0,892	0,088	0,210	0,674	0,313	1,678	0,852	0,010	0,067	0,882			
ei2				0,092	0,057	0,104	0,051	0,168	0,762	0,682	0,858	0,427	-0,063	0,038	0,094			
ei3							-0,069	0,035	0,049	0,156	0,114	0,171	0,007	0,018	0,714			
ei4										0,000	0,042	1,000	0,000	0,004	1,000			
ei5													0,000	0,003	1,000			

Model 21	Dummy OE																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	49,620	64,310	0,440	0,338	7,357	0,963	1,949	8,135	0,811	19,783	8,391	0,018	12,508	0,767	0,000			
γi1	0,293	0,068	0,000	0,001	0,020	0,977	0,001	0,040	0,972	0,020	0,075	0,792	0,000	0,004	0,971			
γi2	1,118	0,615	0,069	0,833	0,096	0,000	0,111	0,198	0,573	-0,946	0,864	0,274	-0,064	0,066	0,339			
γi3	-1,611	0,912	0,077	0,046	0,103	0,654	0,708	0,275	0,010	0,765	1,108	0,490	0,074	0,057	0,197			
γi4	-0,043	0,458	0,925	-0,020	0,022	0,370	-0,076	0,030	0,012	0,314	0,074	0,000	-0,007	0,011	0,518			
γi5	-3,636	4,700	0,439	0,064	0,614	0,917	-0,030	0,675	0,964	-1,227	0,708	0,083	0,014	0,056	0,801			
ci1	0,458	0,524	0,382	-0,006	0,036	0,860	0,058	0,063	0,354	0,095	0,616	0,878	-0,011	0,056	0,841			
ci2				0,051	0,178	0,776	0,037	0,143	0,797	-0,113	0,135	0,401	-0,008	0,061	0,890			
ci3							0,000	0,016	1,000	0,000	0,062	1,000	0,000	0,006	1,000			
ci4										0,000	0,088	1,000	0,000	0,009	1,000			
ci5													0,000	0,001	1,000			
ai1	-0,140	0,249	0,575	-2,752	1,059	0,009	1,649	1,439	0,252	-0,094	0,406	0,816	6,394	8,350	0,444			
ai2	0,013	0,013	0,335	-0,232	0,330	0,483	0,599	0,195	0,002	0,041	0,053	0,449	-0,220	0,395	0,578			
ai3	0,054	0,023	0,019	-0,696	0,461	0,131	0,953	0,287	0,001	0,065	0,159	0,686	-0,557	0,425	0,190			
ai4	0,162	0,036	0,000	-1,167	1,368	0,394	0,942	1,445	0,515	-0,125	0,201	0,534	-1,197	2,856	0,675			
ai5	-0,008	0,011	0,438	0,075	0,047	0,109	-0,055	0,073	0,451	-0,017	0,014	0,234	-0,231	0,310	0,457			
bi1	0,389	0,302	0,198	8,850	5,048	0,080	-5,821	6,248	0,352	-0,215	0,980	0,826	5,720	14,766	0,698			
bi2	0,070	0,088	0,425	-0,183	0,749	0,807	0,306	0,993	0,758	0,028	0,311	0,929	-0,054	1,352	0,968			
bi3	0,032	0,109	0,772	0,149	0,853	0,861	0,394	0,658	0,549	0,043	0,164	0,794	-0,280	0,345	0,417			
bi4	0,166	0,316	0,599	0,454	4,275	0,915	-0,422	4,146	0,919	0,593	0,528	0,261	-5,611	2,306	0,015			
bi5	-0,005	0,005	0,308	0,106	0,143	0,460	-0,087	0,256	0,736	0,062	0,067	0,354	0,720	0,106	0,000			
ei1	0,289	1,144	0,801	-0,022	0,095	0,819	-0,142	0,183	0,437	-0,179	0,502	0,722	0,001	0,050	0,982			
ei2				-0,131	0,286	0,646	-0,070	0,167	0,675	0,018	0,460	0,969	0,009	0,051	0,860			
ei3							0,000	0,034	1,000	0,000	0,068	1,000	0,000	0,013	1,000			
ei4										0,000	0,091	1,000	0,000	0,009	1,000			
ei5													0,000	0,001	1,000			

Model 22																		
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	11,966	33,910	0,724	4,535	3,289	0,168	6,249	4,814	0,194				13,547	0,876	0,000	19,031	7,355	0,010
γi1	0,312	0,089	0,000	0,011	0,008	0,160	0,007	0,011	0,489				-0,001	0,003	0,604	0,054	0,022	0,015
γi2	0,019	0,615	0,975	0,802	0,076	0,000	0,184	0,105	0,080				-0,060	0,035	0,091	-0,884	0,209	0,000
γi3	-0,162	0,686	0,814	0,165	0,089	0,063	0,623	0,117	0,000				0,067	0,040	0,097	0,982	0,247	0,000
γi5	-0,779	2,714	0,774	-0,306	0,258	0,236	-0,355	0,373	0,342				-0,066	0,070	0,346	-1,358	0,604	0,024
γi6	-0,288	0,165	0,081	-0,089	0,029	0,002	-0,135	0,029	0,000				-0,011	0,009	0,221	0,282	0,092	0,002
ci1	-0,306	0,266	0,250	0,020	0,090	0,822	0,016	0,034	0,642				0,027	0,021	0,206	-0,254	0,217	0,241
ci2				0,063	0,039	0,107	0,000	0,032	0,991				-0,022	0,027	0,421	0,186	0,185	0,314
ci3							0,000	0,004	1,000				0,000	0,005	1,000	0,000	0,038	1,000
ci5													0,000	0,003	1,000	0,000	0,033	1,000
ci6																0,000	0,008	1,000
ai1	0,043	0,157	0,784	-2,754	1,400	0,049	3,145	1,149	0,006				3,475	3,757	0,355	-0,175	0,407	0,668
ai2	0,021	0,010	0,042	0,242	0,185	0,192	0,243	0,145	0,093				-0,767	0,319	0,016	-0,133	0,039	0,001
ai3	-0,018	0,013	0,157	0,401	0,198	0,042	0,044	0,142	0,756				-0,475	0,416	0,254	-0,188	0,045	0,000
ai5	0,009	0,005	0,084	-0,118	0,055	0,032	0,114	0,042	0,007				0,223	0,133	0,093	-0,038	0,017	0,030
ai6	0,057	0,050	0,255	-0,923	0,411	0,025	0,778	0,342	0,023				-2,266	0,975	0,020	-0,640	0,123	0,000
bi1	-0,344	0,232	0,137	5,895	2,955	0,046	-7,120	1,687	0,000				0,509	4,315	0,906	1,804	0,517	0,000
bi2	-0,014	0,025	0,583	0,042	0,192	0,827	0,315	0,229	0,168				1,292	0,769	0,093	0,051	0,099	0,608
bi3	0,020	0,027	0,463	-0,253	0,289	0,382	0,659	0,254	0,010				1,216	0,449	0,007	0,172	0,082	0,035
bi5	0,014	0,008	0,084	0,061	0,096	0,526	-0,137	0,069	0,046				0,521	0,270	0,054	-0,008	0,024	0,738
bi6	0,136	0,081	0,093	-1,169	0,885	0,187	0,573	0,804	0,476				1,943	1,930	0,314	0,280	0,358	0,433

Model 23	Dummy NPL																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	40,967	24,119	0,089	0,508	2,196	0,817	4,503	2,321	0,052				11,830	1,030	0,000	11,150	8,968	0,214
γi1	0,298	0,063	0,000	0,006	0,008	0,467	0,009	0,011	0,404				-0,001	0,003	0,678	0,026	0,024	0,287
γi2	0,833	0,699	0,233	0,757	0,087	0,000	0,099	0,092	0,284				-0,051	0,035	0,142	-0,840	0,207	0,000
γi3	-0,799	0,940	0,396	0,174	0,116	0,134	0,749	0,122	0,000				0,039	0,029	0,174	0,665	0,210	0,002
γi5	-3,251	1,921	0,091	0,030	0,183	0,868	-0,242	0,191	0,205				0,080	0,078	0,306	-0,589	0,683	0,389
γi6	-0,207	0,146	0,156	-0,056	0,025	0,024	-0,111	0,032	0,001				-0,006	0,011	0,568	0,427	0,071	0,000
ci1	0,494	0,149	0,001	0,009	0,033	0,781	0,004	0,034	0,916				-0,023	0,009	0,011	0,227	0,073	0,002
ci2				0,069	0,021	0,001	0,036	0,037	0,335				-0,004	0,014	0,789	-0,161	0,094	0,087
ci3							-0,014	0,024	0,573				-0,020	0,010	0,051	-0,162	0,094	0,084
ci5													0,000	0,008	1,000	0,000	0,053	1,000
ci6																0,000	0,020	1,000
ai1	-0,331	0,188	0,079	-2,262	0,989	0,022	1,883	0,626	0,003				-3,245	4,113	0,430	-0,045	0,290	0,878
ai2	0,017	0,019	0,367	-0,042	0,353	0,906	0,484	0,175	0,006				-0,430	0,485	0,375	-0,068	0,046	0,141
ai3	0,057	0,018	0,002	-0,356	0,293	0,225	0,728	0,147	0,000				-0,306	0,333	0,358	-0,010	0,073	0,891
ai5	0,008	0,008	0,293	-0,023	0,059	0,690	-0,004	0,043	0,924				-0,333	0,166	0,045	-0,019	0,025	0,441
ai6	-0,009	0,079	0,908	-1,270	0,523	0,015	0,853	0,274	0,002				0,532	0,993	0,592	-0,400	0,212	0,059
bi1	-0,491	0,267	0,066	2,797	2,820	0,321	-0,597	2,310	0,796				-7,532	3,050	0,014	0,853	0,678	0,208
bi2	0,033	0,020	0,091	0,329	0,379	0,384	0,287	0,162	0,076				0,345	0,537	0,521	-0,035	0,101	0,733
bi3	0,001	0,033	0,985	-0,360	0,240	0,134	0,968	0,136	0,000				0,808	0,541	0,136	-0,085	0,114	0,457
bi5	-0,010	0,008	0,213	0,203	0,089	0,023	-0,146	0,056	0,010				0,546	0,142	0,000	0,031	0,023	0,182
bi6	0,144	0,051	0,005	-0,846	0,807	0,294	1,633	0,517	0,002				1,888	2,008	0,347	-0,019	0,304	0,949
ei1	1,195	0,441	0,007	0,010	0,057	0,861	0,006	0,040	0,872				0,031	0,011	0,007	-0,225	0,115	0,051
ei2				0,011	0,036	0,764	-0,034	0,045	0,458				-0,034	0,022	0,116	0,213	0,130	0,102
ei3							0,060	0,039	0,128				-0,009	0,020	0,659	0,036	0,097	0,711
ei5													0,000	0,010	1,000	0,000	0,062	1,000
ei6																0,000	0,022	1,000

Model 24	Dummy OE																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	8,544	24,183	0,724	2,419	6,811	0,722	2,401	6,442	0,709				12,193	1,423	0,000	5,353	12,628	0,672
γi1	0,361	0,076	0,000	0,004	0,016	0,781	0,002	0,014	0,882				0,000	0,004	0,944	0,031	0,026	0,236
γi2	0,875	1,147	0,445	0,848	0,143	0,000	0,322	0,163	0,049				-0,008	0,031	0,796	-0,409	0,268	0,126
γi3	-1,231	1,455	0,398	0,043	0,167	0,796	0,447	0,157	0,004				0,022	0,043	0,618	0,300	0,244	0,219
γi5	-0,424	1,739	0,807	-0,094	0,549	0,864	-0,040	0,493	0,935				0,032	0,120	0,791	-0,202	0,974	0,836
γi6	-0,324	0,211	0,124	-0,082	0,036	0,023	-0,102	0,035	0,003				-0,004	0,010	0,723	0,426	0,109	0,000
ci1	0,421	0,201	0,036	-0,049	0,032	0,121	-0,045	0,039	0,248				0,023	0,030	0,447	-0,213	0,360	0,555
ci2				0,052	0,050	0,297	0,039	0,051	0,448				0,031	0,026	0,230	0,086	0,348	0,805
ci3							-0,061	0,019	0,001				-0,003	0,039	0,949	-0,332	0,209	0,112
ci5													0,000	0,012	1,000	0,000	0,034	1,000
ci6																0,000	0,024	1,000
ai1	0,195	0,350	0,577	-1,762	1,415	0,213	1,960	2,135	0,359				6,527	3,628	0,072	-0,175	0,382	0,647
ai2	-0,012	0,033	0,720	0,623	0,168	0,000	-0,049	0,320	0,879				-0,458	0,626	0,465	-0,171	0,040	0,000
ai3	-0,046	0,030	0,118	0,611	0,219	0,005	-0,108	0,208	0,604				-0,057	0,745	0,939	-0,187	0,104	0,073
ai5	0,010	0,007	0,125	-0,104	0,074	0,161	0,097	0,062	0,120				0,143	0,243	0,557	-0,018	0,030	0,539
ai6	-0,025	0,102	0,807	-0,617	0,276	0,025	0,624	0,316	0,049				-0,176	1,076	0,870	-0,841	0,127	0,000
bi1	-0,406	0,169	0,016	4,693	3,854	0,223	-7,009	2,409	0,004				5,293	5,630	0,347	1,060	0,736	0,150
bi2	-0,029	0,055	0,601	0,754	0,681	0,268	-0,221	0,769	0,774				0,499	0,732	0,495	0,064	0,104	0,538
bi3	0,025	0,051	0,622	0,555	0,625	0,375	-0,156	0,665	0,814				0,710	1,271	0,576	0,220	0,147	0,133
bi5	0,007	0,010	0,456	-0,181	0,136	0,183	0,165	0,099	0,094				0,653	0,177	0,000	-0,026	0,056	0,644
bi6	-0,088	0,091	0,334	-0,132	0,952	0,890	-0,200	0,598	0,739				-0,405	2,006	0,840	0,107	0,220	0,627
ei1	-0,870	0,420	0,038	0,091	0,166	0,585	0,083	0,132	0,530				-0,024	0,036	0,494	0,438	0,381	0,250
ei2				0,026	0,109	0,811	0,069	0,146	0,637				-0,024	0,016	0,132	-0,067	0,531	0,899
ei3							0,061	0,025	0,013				0,003	0,040	0,949	0,332	0,222	0,134
ei5													0,000	0,012	1,000	0,000	0,036	1,000
ei6																0,000	0,025	1,000

Model 25																		
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	2,770	2,338	0,236	0,892	0,355	0,012	1,727	0,489	0,000	2,813	1,503	0,061				2,682	1,421	0,059
γi1	0,253	0,086	0,003	0,004	0,009	0,692	-0,002	0,010	0,832	0,015	0,033	0,641				0,008	0,027	0,755
γi2	0,712	0,709	0,315	0,832	0,067	0,000	0,159	0,082	0,053	-0,776	0,253	0,002				-0,733	0,213	0,001
γi3	-1,098	0,875	0,209	0,095	0,076	0,210	0,653	0,114	0,000	0,802	0,247	0,001				0,711	0,206	0,001
γi4	-0,076	0,289	0,793	0,062	0,033	0,063	0,052	0,045	0,250	0,542	0,134	0,000				0,161	0,117	0,170
γi6	0,028	0,308	0,927	-0,133	0,041	0,001	-0,188	0,058	0,001	-0,391	0,162	0,016				0,116	0,146	0,428
ci1	0,173	0,368	0,638	-0,072	0,063	0,253	0,007	0,036	0,846	-0,002	0,934	0,999				0,003	0,441	0,995
ci2				0,040	0,139	0,774	0,023	0,032	0,474	0,463	0,078	0,000				0,231	0,132	0,080
ci3							0,000	0,056	1,000	0,000	0,787	1,000				0,000	0,425	1,000
ci4										0,000	0,066	1,000				0,000	0,043	1,000
ci6																0,000	0,024	1,000
ai1	-0,102	0,150	0,494	2,385	2,278	0,295	-1,560	2,218	0,482	-0,517	0,210	0,014				0,952	0,440	0,030
ai2	-0,011	0,013	0,431	0,058	0,107	0,588	0,477	0,144	0,001	-0,124	0,044	0,005				0,137	0,080	0,087
ai3	0,030	0,012	0,017	-0,048	0,112	0,665	0,512	0,216	0,018	-0,162	0,045	0,000				0,214	0,070	0,002
ai4	0,079	0,105	0,453	-0,373	0,476	0,433	0,379	0,260	0,144	0,212	0,212	0,318				-0,056	0,416	0,894
ai6	0,018	0,059	0,757	0,405	0,482	0,401	-0,433	0,281	0,123	0,024	0,155	0,874				0,442	0,286	0,122
bi1	0,090	0,245	0,714	9,110	3,315	0,006	-5,824	3,422	0,089	-2,110	1,324	0,111				2,304	1,237	0,062
bi2	0,057	0,024	0,015	0,146	0,446	0,743	0,192	0,318	0,546	0,039	0,070	0,581				-0,088	0,107	0,411
bi3	0,086	0,015	0,000	-0,144	0,434	0,741	0,652	0,320	0,041	0,052	0,085	0,539				-0,039	0,124	0,755
bi4	0,137	0,096	0,154	-2,103	1,351	0,120	1,871	0,862	0,030	-0,581	0,384	0,131				0,871	0,335	0,009
bi6	0,152	0,098	0,122	-2,351	1,078	0,029	1,962	0,518	0,000	-0,653	0,356	0,067				0,517	0,368	0,160

Model 26	Dummy NPL																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	4,333	1,709	0,011	1,012	0,213	0,000	1,640	0,271	0,000	2,398	0,612	0,000				1,787	0,599	0,003
γi1	0,400	0,085	0,000	0,007	0,008	0,337	0,017	0,012	0,158	0,020	0,042	0,626				0,015	0,032	0,632
γi2	0,092	0,477	0,847	0,867	0,037	0,000	0,247	0,036	0,000	-0,019	0,073	0,795				-0,030	0,027	0,262
γi3	-0,603	0,637	0,344	0,031	0,034	0,370	0,557	0,028	0,000	-0,007	0,113	0,948				-0,007	0,074	0,921
γi4	0,327	0,261	0,210	0,033	0,027	0,217	-0,008	0,038	0,831	0,324	0,103	0,002				-0,025	0,065	0,700
γi6	-0,349	0,276	0,205	-0,072	0,033	0,029	-0,087	0,054	0,106	-0,061	0,123	0,622				0,493	0,113	0,000
ci1	-0,134	0,247	0,588	0,000	0,037	0,996	-0,002	0,070	0,972	-0,179	0,374	0,632				-0,229	0,247	0,354
ci2				0,036	0,017	0,040	0,074	0,024	0,002	0,576	0,151	0,000				0,385	0,159	0,015
ci3							0,000	0,017	0,992	-0,002	0,180	0,992				0,000	0,153	0,998
ci4										-0,001	0,078	0,987				-0,002	0,130	0,987
ci6																0,000	0,155	0,998
ai1	0,263	0,094	0,005	3,466	0,899	0,000	-3,193	0,887	0,000	-0,263	0,206	0,200				0,812	0,399	0,042
ai2	0,035	0,011	0,001	-0,170	0,129	0,188	0,359	0,113	0,002	-0,084	0,032	0,008				0,081	0,047	0,087
ai3	0,028	0,013	0,032	-0,308	0,122	0,012	0,497	0,107	0,000	-0,131	0,041	0,002				0,182	0,051	0,000
ai4	-0,004	0,032	0,910	-1,519	0,435	0,000	1,390	0,391	0,000	-0,169	0,134	0,210				0,848	0,286	0,003
ai6	0,006	0,018	0,722	-0,384	0,277	0,165	0,331	0,284	0,243	-0,219	0,095	0,021				1,062	0,212	0,000
bi1	0,685	0,111	0,000	2,174	1,108	0,050	1,543	0,986	0,118	1,129	0,495	0,022				-2,176	0,473	0,000
bi2	-0,058	0,012	0,000	0,686	0,097	0,000	-0,229	0,082	0,005	0,043	0,082	0,604				-0,216	0,076	0,004
bi3	-0,067	0,017	0,000	-0,365	0,150	0,015	0,495	0,114	0,000	0,079	0,108	0,466				-0,335	0,099	0,001
bi4	-0,022	0,037	0,543	0,286	0,447	0,522	-1,180	0,416	0,005	0,398	0,238	0,095				-0,502	0,199	0,012
bi6	-0,050	0,029	0,083	0,347	0,250	0,166	-0,109	0,254	0,668	-0,221	0,150	0,140				0,119	0,154	0,439
ei1	0,295	0,443	0,504	-0,041	0,044	0,349	0,047	0,079	0,553	0,142	0,361	0,695				0,197	0,250	0,431
ei2				-0,032	0,057	0,574	-0,076	0,043	0,079	-0,576	0,147	0,000				-0,383	0,151	0,011
ei3							0,000	0,022	0,994	0,002	0,179	0,992				0,000	0,152	0,998
ei4										0,001	0,081	0,988				0,002	0,131	0,987
ei6																0,000	0,155	0,998

Model 27	Dummy OE																	
	RTN(i=1)			PT(i=2)			NT(i=3)			BP(i=4)			FP(i=5)			GST(i=6)		
	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif	Coeff	Std Error	Signif
α	6,943	2,457	0,005	0,861	0,254	0,001	1,415	0,311	0,000	2,773	1,010	0,006				2,630	0,625	0,000
γi1	0,385	0,065	0,000	-0,002	0,009	0,818	0,002	0,012	0,882	0,009	0,035	0,796				-0,003	0,025	0,893
γi2	0,689	0,455	0,129	0,912	0,088	0,000	0,276	0,084	0,001	-0,475	0,237	0,045				-0,559	0,217	0,010
γi3	-1,490	0,658	0,023	0,009	0,098	0,926	0,552	0,108	0,000	0,470	0,276	0,089				0,540	0,301	0,073
γi4	0,065	0,236	0,784	0,075	0,029	0,010	0,062	0,041	0,127	0,662	0,129	0,000				0,219	0,121	0,071
γi6	-0,354	0,317	0,263	-0,146	0,053	0,006	-0,172	0,066	0,009	-0,490	0,190	0,010				0,022	0,222	0,920
ci1	0,235	0,148	0,112	0,015	0,048	0,755	0,014	0,032	0,675	0,259	0,109	0,018				0,383	0,066	0,000
ci2				-0,003	0,026	0,911	-0,027	0,055	0,627	-0,032	0,190	0,866				-0,052	0,242	0,829
ci3							0,000	0,142	0,999	0,000	0,156	0,999				0,000	0,266	0,999
ci4										0,000	0,033	1,000				0,000	0,040	1,000
ci6																0,000	0,011	1,000
ai1	-0,326	0,067	0,000	0,705	0,702	0,315	-0,455	0,609	0,455	-0,645	0,154	0,000				1,247	0,243	0,000
ai2	0,005	0,010	0,606	0,037	0,128	0,771	0,414	0,168	0,014	-0,107	0,035	0,002				0,138	0,078	0,077
ai3	0,017	0,016	0,285	0,216	0,135	0,111	0,354	0,244	0,147	-0,163	0,039	0,000				0,259	0,082	0,001
ai4	0,076	0,054	0,159	-0,458	0,231	0,048	0,317	0,195	0,105	0,058	0,105	0,583				0,369	0,155	0,017
ai6	0,028	0,029	0,334	0,730	0,213	0,001	-0,828	0,256	0,001	-0,066	0,093	0,479				0,744	0,166	0,000
bi1	0,702	0,052	0,000	1,229	1,277	0,336	-0,164	1,039	0,875	-0,467	0,465	0,315				-0,656	0,805	0,415
bi2	0,008	0,008	0,347	0,841	0,124	0,000	-0,137	0,171	0,422	-0,080	0,060	0,185				0,146	0,046	0,002
bi3	0,025	0,007	0,001	-0,146	0,209	0,484	0,759	0,231	0,001	-0,095	0,076	0,211				0,174	0,103	0,090
bi4	0,181	0,038	0,000	-0,076	0,716	0,915	-0,214	0,463	0,645	0,895	0,190	0,000				-0,134	0,290	0,645
bi6	0,056	0,033	0,085	0,274	0,888	0,758	-0,324	0,694	0,640	0,350	0,281	0,212				0,140	0,398	0,726
ei1	0,941	0,284	0,001	-0,057	0,049	0,251	-0,092	0,057	0,109	-0,458	0,093	0,000				-0,442	0,084	0,000
ei2				-0,044	0,044	0,319	-0,004	0,071	0,954	0,061	0,238	0,796				0,154	0,254	0,543
ei3							0,000	0,142	0,999	0,000	0,155	0,999				0,000	0,266	0,999
ei4										0,000	0,035	1,000				0,000	0,047	1,000
ei6																0,000	0,021	1,000

Figure 1: Time varying estimates of historical volatility for Returns and UGC variables using a rolling window of 10 days and exponentially weighted estimates. Left column (from top to bottom): Returns, Positive Tweets, Negative Tweets. Right column (from top to bottom): Blog Posts, Forum Posts, Google Search Tickers.