Stochastic Volatility Model with an Exogenous Control Process of News Flow

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Brunel University,
the School of Information Systems, Computing and Mathematics

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Abstract

We consider different volatility models augmented with news analytics data to examine the impact of news intensity on stock volatility. We provides a description of the data used in the empirical analysis and defines the measures of news intensity. Results for the variance homogeneity tests for days with different news intensity are also given. We also show that abnormal returns occur more likely in days with high news intensity.

We propose the different modifications of the SV model. We proposed a way to test the hypothesis of a short-term impact of news intensity on volatility. The results show that news analytics data improves the quality of prediction of volatility of the SV model. For almost all FTSE100 companies, the hypothesis of a short-term impact of news on stock volatility is accepted. Negative news increase short-term stock volatility more likely than positive news.

Acknowledgements

I would like to express my gratitude to my supervisor Dr Keming Yu with whom I have the great pleasure of working, to my colleague Sergey Sidorov for generous assistance, and Prof Gautam Mitra for creative support and for the kindly provided opportunity to use Raven Pack news analytics data.

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Chapter 1

Introduction

The reactions of asset prices and market volatility to information concerning fundamental variables are of key interest for such financial and economic decisions as risk management, asset pricing, and portfolio allocation.

It is well-known that financial markets and investors react nervously to important news, economic crises, wars, political disorders or natural disasters. In such periods prices of financial assets may exhibit substantial fluctuations. It means that the conditional variance calculated for the price time series is not constant over time and the aforementioned process is conditionally heteroscedastic. It means that volatility changes over time. Fluctuations in returns and volatility are often interpreted as reactions of market participants to the new information. According to this view the most important stochastic process affecting price movement is the news arrival process. On the other hand news providers or agencies also react to the significant events in the economy. So we have two parallel processes which reflect the information sources available to the market participants.

We assume that conditional variance of returns depends on some hidden process that represents news arrival. To measure the effect of conditional variance of stock returns on the intencity of the news flow we investigate some probability distributions of stock returns.

Innovations of the stock returns process are often considered to be the latent stochastic process that represents the impact of news on the stock returns. We postulate that a latent process has two separate components which account for regular news and unexpected news events. It is possible that regular news has smaller impact on returns and expected volatility for individual stocks that unexpected news events.

It can be assumed that small volatility fluctuations are influenced by the regular news. Unexpected news causes bigger jumps in returns, and, consequently, in volatility. A potential source of jump-like innovations in the return process could be news about important of events.

The paper is organized as follows: Chapter 2 provides a description of the data used in the empirical analysis and defines the measures of news intensity. Results for the variance homogeneity tests for days with different news intensity are also given. We also show that abnormal returns occur more likely in days with high news intensity. Chapter 3 presents a review of the literature regarding the stochastic volatility model. Chapter 4 reports estimation results for different SV models. Chapter 5 provides summary and proposes directions for future work.

Chapter 2

News Data

2.1 News Data Structure

In this study, we will use daily stock returns for large UK companies. Daily price data for FTSE100 firms were obtained from Tompson Reuters Datastrim database. The sample period goes from June 6 2005 to December 31 2010. Several companies were excluded from consideration due to the large amount of missing data in their returns and news time series. Thus, we analyzed 92 companies.

Many investment companies in the U.S. and Europe have been using news analytics to improve the quality of their business. Interest in news analytics is related to its ability to predict change in prices, volatility and trading volume on the stock market.

News analytics can be described as a measurement, processing and interpretation of the following quantitative and qualitative characteristics of news:

The nature of news (describes the newsmaker - whether it is a rating agency, firm's own press release, or some news from conventional media)

The impact of news (it determines the impact of news (positive or negative), i.e. how news affects stock prices; it is believed that positive news about the company leads to a growth in the stock prices of its shares, and negative, on the contrary, can lead to decrease in prices);

The relevance (indicates how strongly related the company is to the underlying news story);

The novelty (shows the amount of new market information in the given news report and is usually inversely correlated with the number of references to the events in this news report from other news sources).

News analytics procedure could be described as follows:

Knowing the characteristics of news in numerical indices one can use them in mathematical and statistical models and automated trading systems. Currently, the news analytics tools have been increasingly used by traders in the U.S. and Europe.

The process of news analysis in information systems is automated and usually includes the following steps:

collecting news from different sources;

preliminary analysis of news;

analysis of news-related expectations (sentiments), taking into account the current market situation;

designing and using quantitative models.

News data can be obtained from various sources:

1. News sources of news agencies.

2. Pre-news

3. Social media (blogs, social networks, etc.).

In addition, the financial news can be classified in terms of their expectations. Expected news come out at a scheduled time and often their contents can be predicted on the basis of pre-news. They have a structured format and generally include numeric data. Macroeconomic reports have a strong influence on liquid markets (foreign exchange, futures, government bonds) and are widely used in the automatic trading. Reports of incomes and losses affect directly the change in stock prices and are widely used in trading strategies.

The most well-known providers of news analytics and data are:

1. RavenPack

2. Media Sentiment

3. Thomson Reuters News Analytics

We use the Raven Pack data.

RavenPack News Scores measure the news sentiment and news flow of the global equity market based on all major investable equity securities. News scores include analytics on more than 27,000 companies in 83 countries and covers over 98% of the investable global market. All relevant news items about companies are classified and quantified according to their sentiment, relevance, topic, novelty, and market impact; the result is a data product that can be segmented into many distinct benchmarks and used in various applications.

For every new instance a company is reported in the news, RavenPack produces a company level record.

Each record contains 16 fields such as a time stamp, company identifiers, scores for relevance, novelty and sentiment, and a unique identifier for each news story analyzed.

In the historical data files, each row in the file represents a company-level record.

2.2 Descriptive Statistics

The total number of records for which composite sentiment score was calculated is equal to 660351 (for all Companies listed on LSE). Event sentiment

TIMESTAMP_UTC	COMPANY	RELEVANCE	ESS	ENS	CSS	WLE	PCM	ECM	RCM	VCM	NIP
01.01.2005 14:00	US/BXS	100	49	100	52	50	50	100	50	50	36
02.01.2005 3:37	HK/2388	100	54	100	50	50	50	50	50	50	44
02.01.2005 13:55	GB/OOM	100	66	100	50	50	50	50	50	50	23
02.01.2005 15:15	CH/ROG	100	76	100	52	50	50	100	50	50	36
02.01.2005 15:15	DE/BAY	100	49	100	52	50	50	100	50	50	36
02.01.2005 15:30	CH/ROG	100	76	75	52	50	50	100	50	50	36
02.01.2005 15:30	DE/BAY	100	49	75	52	50	50	100	50	50	36
03.01.2005 0:58	KR/005380	100	50	100	50	50	50	50	50	50	52
03.01.2005 0:59	KR/005380	100	50	75	50	50	50	50	50	50	51
03.01.2005 1:00	TW/2330	100	50	100	53	100	50	100	50	50	57
03.01.2005 1:00	KR/005380	100	50	56	50	50	50	50	50	50	61
03.01.2005 1:18	KR/005380	100	50	42	50	50	50	50	50	50	52
03.01.2005 1:33	KR/005380	100	50	32	50	50	50	50	50	50	53
03.01.2005 1:45	CN/000898	100	63	100	50	50	50	50	50	50	41
03.01.2005 1:53	HK/0022	100	69	100	50	50	50	50	50	50	76

Figure 2.1: Extract from the Raven Pack Data Sheet

TIMESTAMP_UTC:	2010-01-21 21:20:08.297
COMPANY:	JP/7203 (Toyota Motor Corp.)
RP_COMPANY_ID:	CEC128
RELEVANCE:	100
EVENT CATEGORY:	product-recall
EVENT SENTIMENT (ESS):	29
NOVELTY (ENS):	100
NOVELTY ID (ENS_KEY):	D9592AD7D8E71803A6083E9A6B0395AE
COMPOSITE SENTIMENT (CSS):	50
WORD/PHRASE LEVEL (WLE):	50
PROJECTIONS BY COMPANY (PCM):	50
EDITORIALS & COMMENTARY (ECM):	50
REPORTS CORP ACTIONS (RCM):	50
VENTURE, CORPORATE, M& A (VCM):	50
NEWS IMPACT PROJECTION (NIP):	34
RP_STORY_ID:	D9592AD7D8E71803A6083E9A6B0395AE

scores are reported in 161486 items. For the FTSE100 companies our DataSet have 333189 and 76092 entries (329994 and 75408 in sample). The characteristics of this data sets are summarized in Appendix.

Figure 2.2 shows the histogram of relevance score. Relevance calculated as a score between 0-100 that indicates how strongly related the company is to the underlying news. A Story with a great index value has great relevance. In our investigation we consider news with relevance score more than 90.

Tables 2.2 shows the number of relevant news per year. It could be seen that the number of relevant news grows at 3-5% rate per year, which allows us to neglect this trend.

The Figure 2.3 presents the time plot of dynamics of number of news for all UK companies per day from January 2, 2005 to December 31, 2010.

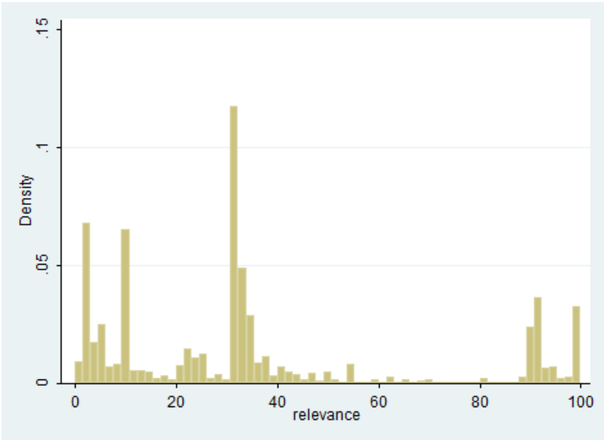

Figure 2.2: Histogram of Relevance index for GB Companies

Table 2.1: Number of Relevant News per Year

Year	Number of News
2005	97001
2006	106906
2007	111754
2008	102838
2009	118008
2011 (January)	8975

We can see that news intensity is stable. In some days the number of news was much bigger than the mean level. The increase of number of news in such days may be caused by important macro economical events.

RavnPack also calculates novelty of contents for some news (ENS field). A score between 0 and 100 that represents how new or novel a news story is within a 24 hour time window. The first story reporting a categorized event about one or more companies is considered to be the most novel and receives a score of 100. Subsequent stories within the 24 hour time window and about the same event for the same set of companies receive lower scores following a decay function whose values are (100 75 56 42 Unfortunately this field was reported for events records only (about 25% of total records number). This complicates the selection of repeated news records.

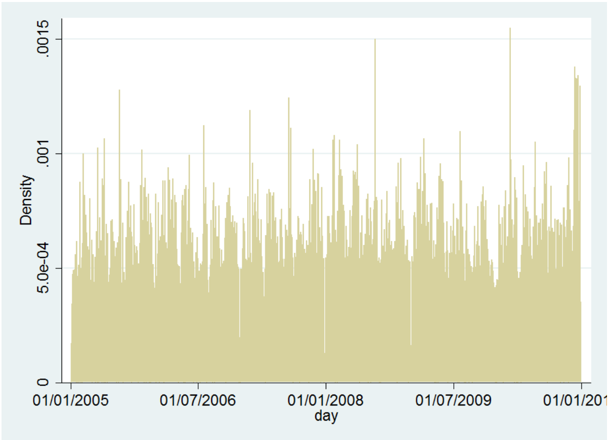

Figure 2.3: Total number of news for all UK companies per day (January 2, 2005 ñ December 31, 2010)

Table 2.2: Novelty Scores (ENS) for UK Companies

Novelty score	Percent
100	55
75	22
0-56	23

A preliminary analysis of RavenPack News historical dataset indicates strong seasonality on intrahourly, intradaily, intraweekly, intrayearly timescales (Fig. 2.4, 2.5).

Note that the seasonality is different for the news flow for different companies (Fig. 2.6, 2.7). For example, for HSHC PLC Mondays accumulate 26% of total number of news, while other days have 18% only. But for Vodafone Group PLC most of news comes on Wednesday.

Moreover, the news intensity in March, July and November is 50 per cent more than in other months.

The vast majority of news is generated by a few dozens of largest companies. We can see that 90% companies have less then 1 news item per day see (Fig. 2.8) and Appendix Table A.2.

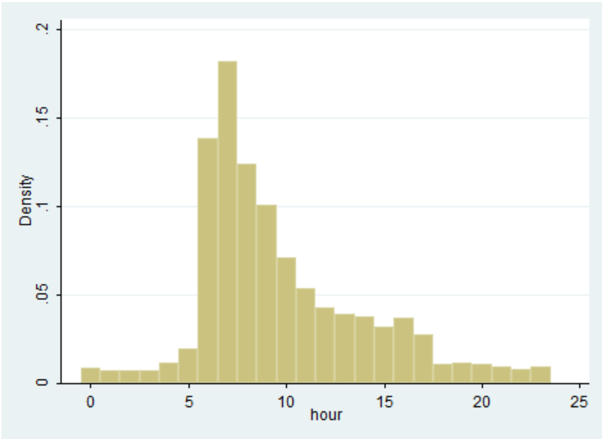

Figure 2.4: Intraday Arriving Time for Relevant News for UK Companies

We use two fields ESS and CSS for calculating number of positive and negative news for each companies. ESS is (Event sentiment sentiment) a score between 0 and 100 that represents the news sentiment for a given company by measuring various proxies sampled from the news. The score is determined by systematically matching stories typically categorized by financial experts as having short-term positive or negative share price impact. A score range between 0-100 where higher values indicate more positive sentiment while lower values below 50 show negative sentiment. The Figure 2.9 represent the histogram of event sentiment score for UK companies.

CSS (composite sentiment scores) is sentiment score between 0 and 100 that represents the news sentiment of a given story by combining various sentiment analysis techniques. RavenPack recommended, as example, such way of using CSS scores: If CSS $>$ 50 Then Positive Signal; If CSS $<$ 50 Then Negative Signal; If CSS = 50 Then Neutral Signal.

Figure 2.10 represents the histogram of composite sentiment score for UK companies.

The correlation coefficient between the indices is relatively small

$$cor(ESS, CSS) = 0.4643.$$

Therefore, we compared the results obtained using both measures. We count the number of negative, neutral and positive news for a given company for each day (Table A.3).

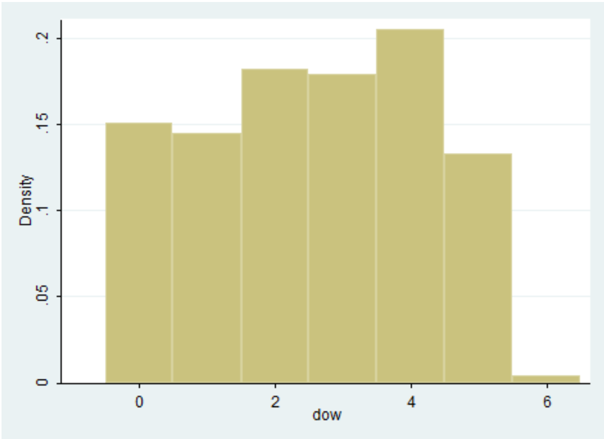

Figure 2.5: Seasonaity - Intra week Pattern for Relevant News for UK Companies

The numbers of positive and negative ESS and CSS records for all UK companies are shown on Figures 2.11 and 2.12.

Correlation Matrix

CSS positive	CSS negative	ESS positive	ESS negative
1			
0.85	1		
0.93	0.82	1	
0.82	0.90	0.79	1

The intensity of the flow of positive and negative news is strongly correlated. As a rule, positive and negative news comes in the same day. Perhaps this is due to inaccuracies in digitizing text messages.

Also we calculate day sentiment score as number of positive news record minus number of negative news records (Figures 2.13 and 2.14). In both cases there are a fall in the second half of 2008, and a gradual recovery in the first half of 2009.

The Figure 2.15 represents the histogram of positive ESS number per day. It is interesting to see, that distribution of number of news is not Poisson

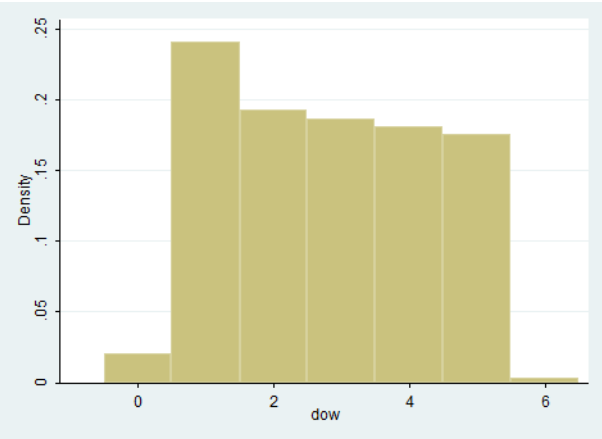

Figure 2.6: Number of Relevant News per Days of Week for HSBC Plc.

with constant intensities.We assume that intensity variate in the time or inhomogeneous Poisson process is more appropriate for modeling news time series.

2.3 High Volatility Levels and News Flow Intensity

Abrupt and significant changes in the prices of financial instruments are not very frequent, but constitute an important part of contemporary (modern) financial markets. Conventional financial markets' wisdom claims that these price jumps represent a reaction of the financial markets to the news flow (changes in companies' positions, important business desicions).

News could contain information about current events or disclose some hidden (and not obvious to the market) events in corporate business decisions. In other words, news can make business events accessible to public (traders, market analytics, etc.).

This could make financial market participants to change their views of the current market state (situation), and consequently, lead to stock price movements.

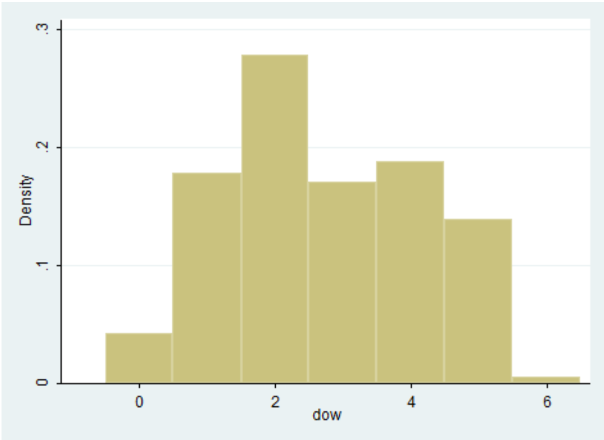

Figure 2.7: Number of Relevant News per Days of Week for Vodafone Group Plc.

It is hardly possible to construct an indicator capable of capturing the market significance of the particular news item. Nonetheless we believe that certain market state variables (for example, trading volume, Tauchen and Pitts [1983] could be used as latent factors capable of measuring the amount of relevant information flow.

Hereinafter we assume that the significance of the currents news and information disclosure for the particular company has a measurable impact on the news flow intensity. It means that more news comes to the market in the days when importance for the company under consideration events occurs or relevant information pertaining to the company is disclosed. And vice versa hight intensity of the news on particular company signifies that some importance for this company events take place on this day, which could increase the possibility of the stock price jumps (well above the mean average level for the past days) on this day. Absence of the news arrives a conclusion that there is no important events on this day, and, consequently, the probability of the price jump is small.

We will try to find empirical evidence to the fact that overall number of news items and the amount of good and bad news through the day could be used to identify (or mark) days with the highest probability of price jumps in stock prices.

If the above stated hypothesis is true, then the following statements are

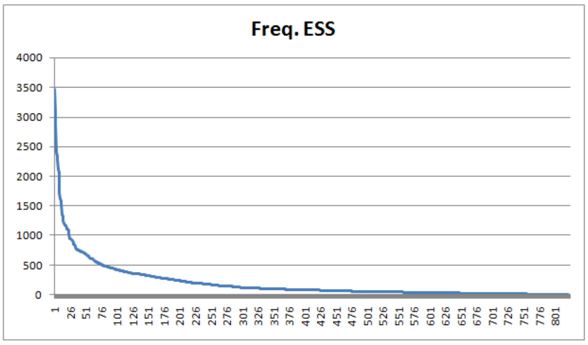

Figure 2.8: Number of News per Company

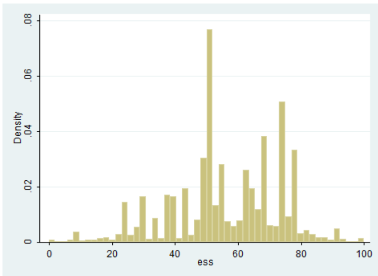

Figure 2.9: Event Sentiment Score

also true: probability of extremely low or high return in correlated with the news flow intensity, days with the higher news intensity are caracterised by higher volatility.

Our calculations support the proposed hypothesis.

It should be noted that due to substantial fluctuations in volatility during the 5 year period under consideration, a number of problems arise when we try to classify a particular trading day as a day with abnormally high or low return rate.

We used a T-day standard deviation of return rate as an estimate for the volatility(sw_{it}). All further calculations use T=5.

The following criteria were introduced: rate of return was considered abnormally (extremely) low ($Neg.Jump_{it} = 1$) if $r_{it} < 1.96 * sw_{it}$ and extremely

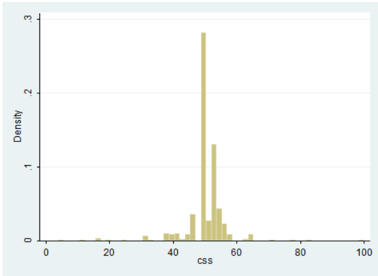

Figure 2.10: Composite Sentiment Score

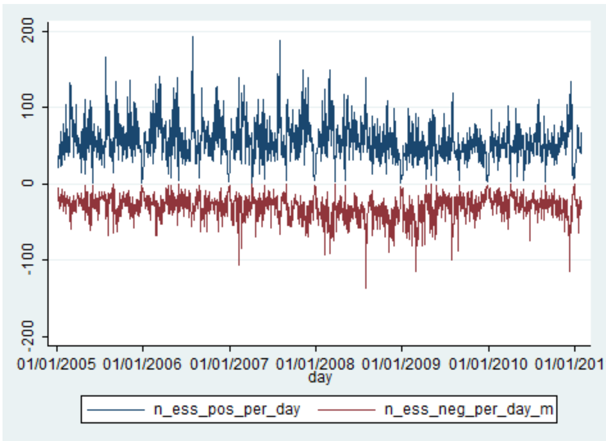

Figure 2.11: Number of Positive and Negative ESS News Items for All UK Company

high ($Pos.Jump_{it} = 1$) if $r(it) > 1.96 * sw_{it}$. To enable comparison between different companies we used logarithms of the relative numbers of positive and negative news for the i-th company in day t as regressors:

New variables

$$N_{it}^{+}(adjusted) = ln((N_{it}^{+} + 0.5)/\sum_{t} N_{it}^{+})$$

$$N_{it}^{-}(adjusted) = ln((N_{it}^{+} + 0.5)/\sum_{t} N_{it}^{-})$$

were used as independent variables in binary choice models (logit regression):

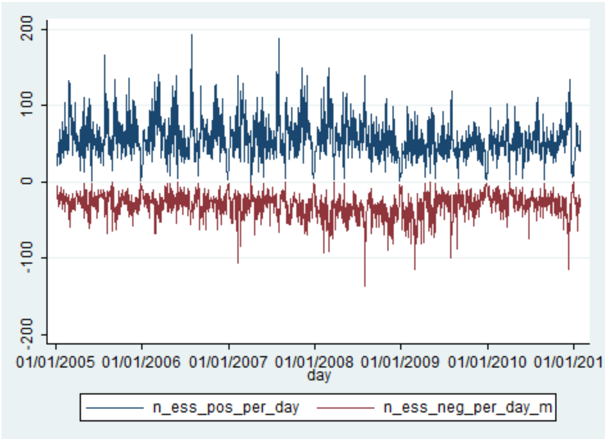

Figure 2.12: Number of Positive and Negative CSS News Items for All UK Company

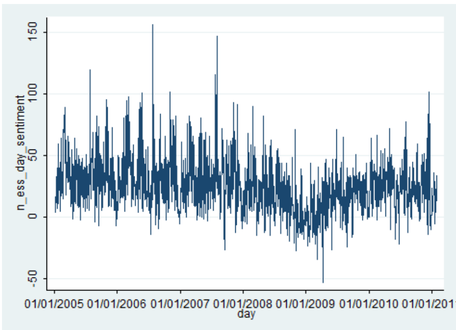

Figure 2.13: Daily ESS Sentiment Index for All UK Company

$$Prob(Pos.Jump_{it} = 1) = \Lambda(\beta_0 + \beta_1 N_{it}^{+} + \beta_2 N_{it}^{-}),$$
$$Prob(Neg.Jump_{it} = 1) = \Lambda(\gamma_0 + \gamma_1 N_{it}^{-} + \gamma_2 N_{it}^{-}),$$
where $\Lambda(X\beta) = e^{X\beta}/(1 + e^{X\beta})$.

Estimates of the logistic regression coefficient are given in Tables 2.3 and 2.4. Regression coefficients' significance proves the fact that high and low stock returns are more likely to occur on days with higher news intensity.

It should be also noted that the number of the positive news is the most significant predictor for the positive extremely high return (Table 2.3), and

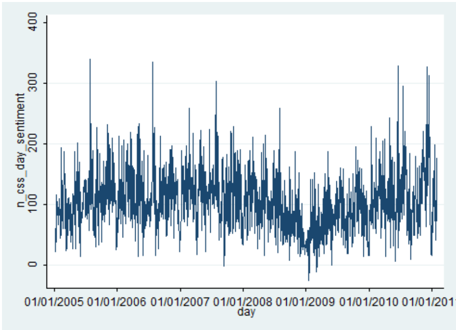

Figure 2.14: Daily CSS Sentiment Index for All UK Company

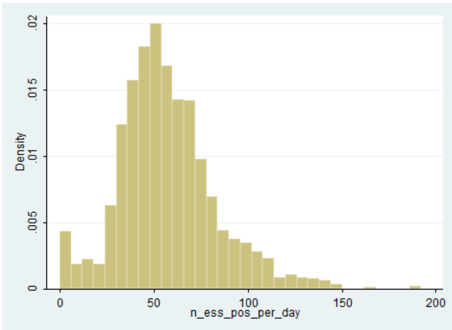

Figure 2.15: Number of Positive (CSS $>$ 50) News per Day

the number of the negative news - corresponds to the extreme loss (Table 2.4).

Let's discuss some ways of verifying that volatility in marked days is really above the average. We are going to mark days when the registered number of the news was above the average. We have tried three different approaches to mark these days:

- The day is marked when there was at least one news on this day ($N_{it} > 0$);

Table 2.3: Parameter estimates for panel logit model for positive abnormal returns

Pos.Jump	Coef.	Std. Err.	z	$Prob > \|z\|$	$95\% Conf.$	Interval
N^+	0.4787247	0.0242572	19.74	0.00	0.4311814	0.5262679
N^-	-0.1594172	0.027533	-5.79	0.00	-0.2133809	-0.1054535
cons	-1.22819	0.1582066	-7.76	0.00	-1.538269	-0.9181104
$lnsig2u$	-3.151898	0.2323829			-3.607361	-2.696436
$sigma(u)$	0.0979406	0.0236241			0.0610444	0.1571373
rho	0.0029073	0.0013984			0.0011314	0.0074496

Table 2.4: Parameter estimates for panel logit model for negative abnormal returns

Neg.Jump	Coef.	Std. Err.	z	$Prob > \|z\|$	$95\% Conf.$	Interval
N^+	-0.0264089	0.03089	-0.85	0.393	-0.0869523	0.0341345
N^-	0.4555	0.0479	9.50	0.00	0.3616	0.5495
cons	-1.4076	0.2502	-5.63	0.00	-1.8980	-0.9173
$lnsig2u$	-1.7830	0.2346			-2.2428	-1.3232
$sigmau$	0.4100	0.0481			0.3258	0.5160
rho	0.0486	0.0109			0.0313	0.0749

- The day is marked when the relative number of news is bigger than certain threshold level c, i.e. $N_{it}/\sum_t N_{it} > c$;
- The day is marked when the number of the news items was greater than the upper bound for the confidence interval of the Poisson regression ($N_{it} > C_{it}$). We used dummy variables for days of the week, months of the year, certain years and periods with the maximum number of regular news per day as regressors (see Figure 2.16).

Remark. In weeks 17-18, 30-31, 44-45 of every year the number of the news items is generally above the average, which could be explained by the fact corporate financial reports are published on these days.

The first method has an obvious drawback. Having applied it, we usually end up with more than 50% days marked for some companies. Method 3 can take into account seasonal factor in the news flow. Our own investigations have shown that methods 2 and 3 usually give similar results (similar days were marked).

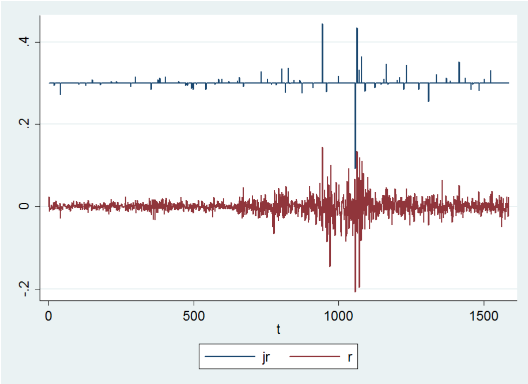

Figure 2.16: Historical movement of log returns of the HSBC Holding PLC stock market closing daily prices and log returns occurred in jump days predicted by Poisson regression (January 2, 2005 - December 31, 2010)

If volatility levels in marked and not marked days are the same, then there is no evidence to the interdependence of the news flow intensity and price jumps in these days.

If volatility levels in marked and not marked days are different, we can explore another hypothesis, namely, that current volatility level consists of two components: smooth (or regular) and jumps.

The histograms (Figures 2.17, 2.18) show that the yield spread greater in labeled days than in unlabeled days.

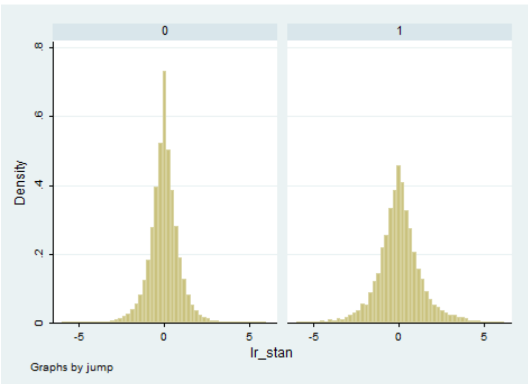

Figure 2.17: Density plot for returns for all FTSE100 companies for days with high level and low level news intensity

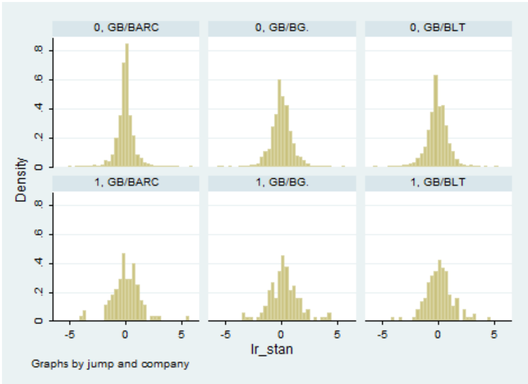

Figure 2.18: Density plot for returns for companies GB/BARC, GB/BG, GB/BLT for days with high level and low level news intensity

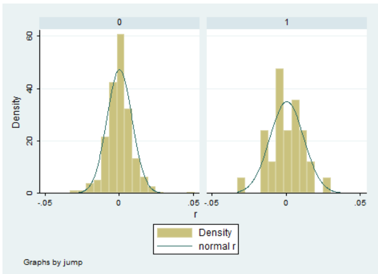

Figure 2.19: Histogram of log returns for HSBC Plc. for labeled and unlabeled days

We use variance homogeneity test for hypothesis

$$\begin{cases} H_0 : \sigma_U^2 = \sigma_L^2, \\ H_1 : \sigma_U^2 < \sigma_L^2. \end{cases} \tag{2.1}$$

The results is given in Table A.4 of Appendix. As an example we show the results of F-test for the homogeneity of variance for HSBC Plc. in Table 2.5.

$$F_{obs} = \frac{s_U^2}{s_L^2} = \frac{0.018^2}{0.058^2} = 0.138 < F(0.95, 42, 1521) = 0.67$$

The null–hypothesis was rejected. So the volatility was significantly higher in days with high news flow intensity.

Table 2.5: F-test for the homogeneity of variance for HSBC Plc.

Group	Obs	Mean	Std. Dev.
1 (Labeled)	43	0.004	0.058
0 (Unlabeled)	1522	0.000	0.018
All	1565	0.000	0.020

For most of the companies the variance levels in the marked days are significantly higher then in the not marked days (see table of Appendix A.4-A.6 and Figure 2.20). Stock return jumps were also seen on the days when extremely huge number of news arrived to the market. But the effect of the news number on the volatility is for a short term. For the days that follow the days with high news levels variance levels for marked and not marked days are the same (the required hypothesis was tested).

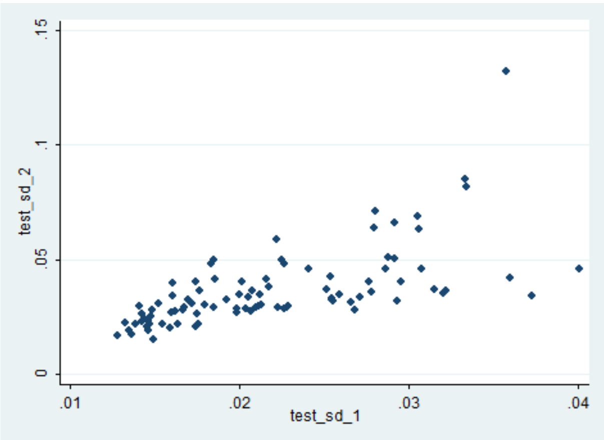

Figure 2.20: St. Dev. for labeled day and control groups

Note that this result is not a coincidence. The standard test does not detect difference in volatility in days before or follow the marked days. If we mark the days preceding the outliers in news intensity, the hypothesis of homogeneity of variances taken 59 cases out of 91. The day after outliers hypothesis not rejected in 35 cases out of 91.

Thus, it can be argued that during high-intensity news flow volatility was above average. Perhaps it can explain the volatility jumps.

Analysis of the market data for several companies allows to consider some additional aspects for the 2 component (smooth and jumps) volatility representation.

Firstly, we will investigate relative time evolution of smooth and jump-like volatility components for different companies.

Secondly, we will investigate whether regular and jump volatility are correlated or not. It is obvious that smooth component changes over time (ARCH effects are present). It is interesting to see whether jump component also has such behavioural patterns. We considere two extreme cases: jump-like volatility does not depend on the regular volatility component; jump-like volatility is 100% correlated with the regular volatility component. Thirdly, we are going to investigate whether the news effect on the stock prices is long-term or not. To explore this proposition, we will test, whether there is high volatility only in the days with the high news intensity, or there are also such volatility effect in the previous and past days also. If this effect of the news intensity on the volatility propagates in the time, this would contradict the hypothesis of smooth and jump-like volatility components.

It is also interesting to investigate whether volatility jumps depend on the news intensity in particular day.

Let us consider the following simplified data generation process. We will divide our data into 2 groups.

In ordinary days variable J_t is equal to 0 and data could be generated as independent identically distributed variables with density with zero mean and variance σ_R^2.

$$r_t = R_t, R_t \sim iid(0, \sigma_R^2).$$

In the second data group $J_t = 1$ and our data could be represented as a sum of two random variables (regular component and jump)

$$r_t = R_t + V_t, R_t \sim iid(0, \sigma_R^2), V_t \sim iid(0, \sigma_J^2).$$

Consider the following relations for the expected value of observed values r_t^2. Assume that correlation coefficient of R and V is equal to ρ. First case: jump and regular component are independent. For the first group of data we will get

$$E(r_t^2 | J_t = 0) = \sigma_R^2$$

while for the second

$$E(r_t^2 | J_t = 1) = \sigma_R^2 + \sigma_J^2.$$

or, written in another form

$$E(r_t^2|J_t) = \sigma_R^2 + \sigma_J^2 J_t.$$

The last equation could be treated as regression model. Adding an error term, we get a standard regression model

$$r_t^2 = \sigma_R^2 + \sigma_J^2 J_t + u_t$$

or

$$r_t^2 = \beta_0 + \beta_1 J_t + u_t.$$

If we are to analyze data for several companies, we could write this model in the form of panel regression

$$r_{it}^2 = \beta_{0i} + \beta_{1i} J_{it} + u_{it},$$

where $i = 1, \ldots, N$ is a company's number, β_{0i} - effect of the regular component, β_{1i} - effect of jumps. This notation brings certain advantages: it is easy to expand the model and there are standard procedures for hypothesis testing. For example, if hypothesis $H_0 : \beta_{11} = \beta_{12} = \ldots = \beta_{1N} = \beta_1$ (variance of jumps for all firms is the same) is true, our model will take the form

$$r_{it}^2 = \beta_{0i} + \beta_1 J_{it} + u_{it}.$$

To test this hypothesis we could employ a standard F-test. It is also possible to propose a model under assumption that variance of the jumps and regular component are on the same level. Dividing our initial equation

$$r_{it}^2 = \sigma_{Ri}^2 + \sigma_{Ji}^2 J_{it} + u_{it}$$

by the variance of the regular component s_{Ri}^2, we get

$$r_{it}^2/s_{Ri}^2 = 1 + \sigma_{Ji}^2/s_{Ri}^2 J_{it} + v_{it},$$

or

$$r_{it}^2/\sigma_{Ri}^2 = \beta_{0i} + \beta_{1i} J_{it} + v_{it}.$$

Hypothesis for our assumption will take the form

$$H_0 : \beta_{01} = \beta_{02} = \ldots = \beta_{0N} = 1; \beta_{10} = \beta_{12} = \ldots = \beta_{1N}$$

If we assume that variance of jumps is a linear function of some exogenous variable (for example, of the number of the news items N_{it},), then we could write our model as

$$r_{it}^2 = \beta_{0i} + \beta_1 J_{it} N_{it} + u_{it}.$$

Hereafter we will give estimation results for some of these models. Finally, the model under consideration allows for autoregressive processes. Such dynamic models will be treated in the chapters devoted to stochastic volatility. Consider also the case when jumps and regular components are fully correlated ($\rho = 1$). In this case

$$E(r_t^2|J_t = 0) = \sigma_R^2,$$

$$E(r_t^2|J_t = 1) = (\sigma_R + \sigma_J)^2 = \sigma_R^2(1 + \sigma_J/\sigma_R)^2 = \sigma_R^2(1 + \sigma_J/\sigma_R)^2 = \sigma_R^2\delta.$$

Combining both equations, we get

$$E(r_t^2|J_t) = \sigma_R^2\delta^{J_t},$$

and, applying logarithmic transformation for both sides and introducing error term, we get the regression model

$$log(r_t^2) = \beta_0 + \beta_1 J_t + u_{it}.$$

In the case of several firms we will use panel data notation

$$log(r_{it}^2) = \beta_{0i} + \beta_{1i} J_{it} + u_{it}.$$

Consider that unconditional volatility in unlabeled days σ_U^2 is equal to regular volatility) $\sigma_U^2 = \sigma_R^2$, and volatility in labeled days σ_L^2 is equal the sum of regular and jump components $\sigma_L^2 = \sigma_R^2 + \sigma_J^2$, where σ^2 - unconditional volatility for stocks *i* at day *t*; σ_R^2 - regular volatility for stocks *i* at day *t*; σ_J^2 - jump variance stocks *i* at day *t*;

Table A.7 in Appendix presents estimates of parameters for fixed and random effect models when days are marked if at least one news come. We use Hausman test with the null hypothesis as that the preferred model is random effects vs. the alternative the fixed effects. Because reported value of Chi-square is significant, we conclude that random effects is not appropriate and choose fixed effect estimators:

$$\log(r_{it}^2) = \alpha_i + 0.47 J_{it}.$$

The elasticity volatility on dummy variables for jumps is equal 0.47. Therefore, the volatility in the days with at least one news is 1.5 times higher than that in other days.

Consider how quickly faded effect of volatility shock in time. Let $J^P_{it} = J_{it-1}$, $J^N_{it} = J_{it+1}$ be dummy variables. We consider the following model:

$$\log(r^2_{it}) = \alpha_i + \beta_1 J^P_{it} + \beta_2 J_{it} + \beta_3 J^N_{it} + \varepsilon_{it}$$

and obtain the estimation results:

$$\log(s^2_{it}) = \alpha_i + 0.19 J^P_{it} + 0.45 J_{it} + 0.12 J^N_{it}$$

The results for fixed, random effect model, Hausman and LM (Breusch-Pagan) test reported in Table A.8 in Appendix.

Although the coefficients on the dummy variables for the previous and next days are significant, they are relatively small. Effect of news shocks is short-lived. It could be explained by the fact that arriving times and trading sessions do not coincide. The news arrive continuously, while the the trading session is limited in time, so errors may occur.

Positive news occur more often than negative ones in our data set. In addition it is possible that the market reacts differently to positive and negative news. Therefore, we include in the modelling number of positive and negative news:

$$\log(r^2_{it}) = \alpha_i + \beta_1 J_{it} + (\beta_2 E^-_{it} + \beta_3 E^+_{it}) J_{it} + \varepsilon_{it},$$

$$\log(r^2_{it}) = \alpha_i + \gamma_1 J_{it} + (\gamma_2 R^-_{it} + \gamma_3 R^+_{it}) J_{it} + \varepsilon_{it},$$

E^-_{it}, E^+_{it}, R^-_{it}, R^+_{it} are logarithms of numbers negative (positive) event news and logarithms of numbers of negative (positive) relevant news for day t.

The estimation result, shown in Table A.9, indicates that there is no difference between coefficients for negative and positive event news. But the number of negative relevant news has little influence on volatility than the number of positive news:

$$\log(s^2_{it}) = \alpha_i + 0.28 J_{it} + (0.33 E^-_{it} + 0.39 E^+_{it}) J_{it},$$

$$\log(s_{it}^2) = \alpha_i + 0.28J_{it} + (0.38R_{it}^- + 0.17R_{it}^+)J_{it}.$$

This result allows us to suggest that the news information can be useful for predicting not only jump days but also the size of the volatility jumps.

Let us compare this results with other method of labeling days with high news intensity. If day is marked when the relative number of news is bigger than certain threshold level c, i.e. $N_{it}/\sum_t N_{it} > c$, then the estimated equation for additive model is

$$\log(r_{it}^2) = \alpha_i + 0.68J_{it}.$$

For multiplicative model we have

$$\log(s_{it}^2) = \alpha_i + 0.17J_{it}^P + 0.65J_{it} + 0.14J_{it}^N.$$

that there is no long-lived impact of jumps to volatility.

Also the impact of the number of negative relevant news on volatility is more significant then impact of positive ones. It follows from equation

$$\log(s_{it}^2) = \alpha_i - 0.22J_{it} + (0.44R_{it}^- + 0.34R_{it}^+)J_{it}.$$

Estimation results presented in this sections let us to conclude that time jumps may be predicted on the basis news information. Nevertheless, we do not take into account the dynamic nature of volatility process. In the next section we will apply stochastic volatility approach.

Chapter 3

Stochastic Volatility Models

3.1 Stochastic Volatility Models

In recent years, there has been an increasing interest in the modelling of the dynamic evolution of the volatility for the financial time series in the framework of stochastic volatility (SV) models. In these models the volatility is modeled as an unobserved latent variable. SV models are attractive because:

1. they represent the behavior of financial prices rather well.

2. their statistical properties are easy to derive

3. Compared with the more popular GARCH models, they capture the main empirical properties of financial time series in a more appropriate way.

There are two main classes of models used to explain time-varying volatility: GARCH and SV. In both of them, volatility is a random process. The stochastic volatility (SV) model provides an alternative to the ARCH-type models of Engle (1982). In GARCH models, the link between the data and this volatility process is deterministic, whereas in SV models the volatility process incorporates an additional source of noise. Given a model, Bayes' rule can be used to infer the distribution of the volatility variable conditional on the data. In GARCH models, this distribution is singular (up to an initial condition). The deterministic link between the data and the volatility process posited by GARCH models is difficult to justify, either theoretically or empirically. However, it makes estimation and analysis of such models much simpler, justifying their widespread use. SV models are closely related to financial models often used to represent stock price. Stochastic volatility (SV) models may be used as a way to model the time-varying volatility of asset returns. Time series of asset returns feature some stylized facts, the most important being volatility clustering, which produces a slowly decreasing positive autocorrelation function of the squared returns. Another stylized fact is excess kurtosis of the distribution (with respect to the Gaussian distribution). In the context of Financial Econometrics they were first introduced by Taylor Taylor [1986].

3.1.1 Canonical SV model

First we consider the case of a constant volatility. We will assume that the derivative's underlying price follows a standard model for geometric a Brownian motion:

$$dS_t = \mu S_t dt + \sigma S_t dW_t,$$

where

- μ is the constant drift (i.e. expected return) of the security price,
- σ is the constant volatility,
- dW_t is a Wiener process.

In the stochastic volatility model we replace the constant volatility σ with a function V_t, that models the variance of S_t. This variance function can also be modeled as brownian motion. It should be noted that the form of V_t is determined by the particular SV model under consideration.

The SV models includes two random processes, the first one for observations, and the second one for latent volatilities. Stochastic volatility asset price dynamics results in the movements of the price of an asset S_t and its stochastic volatility V_t via a continuous time diffusion by a Brownian motion:

$$dS_t = \mu_S dt + \sigma_S exp(V_t/2) dW_{1t}, \tag{3.1}$$
$$V_t = \omega + \psi V_t dt + \sigma_V dW_{2t} \tag{3.2}$$

where

- S_t represents log price,
- V_t is the latent volatility process,
- W_{1t} and W_{2t} are (possibly correlated) Brownian motions.

Data arise in discrete time so it is natural to take Euler discretization of equation (3.1) and (3.2).

The simplest version of a SV model is given by

$$y_t = exp(h_{t-1}/2)\epsilon_t, \tag{3.3}$$
$$h_t = \omega + \phi h_{t-1} + \sigma_h \eta_t, \tag{3.4}$$

where

- y_t is a return measured as $y_t = ln(S_t/S_{t-1})$,
- h_t is the unobserved log-volatility of y_t,
- $\mu = \mu_S$,
- $\sigma_Y = \sigma_S$,
- $\phi = \psi + 1$,
- and ϵ_t and η_t are iid standard normal variables with $N(0,1)$ and are mutually independent,
- μ, ϕ, σ are parameters to be estimated, jointly denoted as θ.

The parameter ϕ is the persistence of the volatility process that also allows for the volatility clustering feature. The strict stationarity of y_t is ensured by the restriction on ϕ. Estimates of ϕ are usually quite close to 1.

The unconditional mean of log volatility h_t is equal to $\mu = \omega/(1-\phi)$. Thus the second equation may be parameterized using μ. Then

$$y_t = exp(h_{t-1}/2)\epsilon_t,$$
$$h_t = \mu + \phi(h_{t-1} - \mu) + \sigma_h \eta_t$$

or

$$y_t = exp(h_{t-1}/2)\epsilon_t,$$
$$h_t = \mu(1-\phi) + \phi h_{t-1} + \sigma_h \eta_t.$$

It is convenient to remove ω from second equation. In this case the model will take the form

$$y_t = \delta exp(h_{t-1}/2)\epsilon_t,$$
$$h_t = \phi h_{t-1} + \sigma_h \eta_t,$$

where $\delta = exp(\omega/2)$.

All of these parameterizations are equivalent. Which one to choose is mainly a matter of convenience.

3.1.2 Other univariate SV models

SV model with leverage effect

The financial leverage effect is an essential and well-known empirical fact observed in many financial time series. Many studies and research papers were devoted to the relationship between volatility and price/return. It is evident that bad news decrease the price and hence increase the debt-to-equity ratio (i.e. financial leverage). Therefore, bad news lead the firm to be riskier and push to increase future expected volatility. This phenomena describe the relationship between returns and conditional variances. It is plausible to think that bad news in the markets simultaneously leads price decrease and to an increase in the variance. On the other hand, periods of high volatility produce expectations of lower future returns, hence the negative correlation between these shocks. Leverage effect also plays an important part in the explanation of some of the characteristics of the data on the financial derivatives' markets.

Usually, the leverage effect manifests in a negative relationship between volatility and price/return. Nelson (1991) developed the framework for analysis of the leverage effect in the GARCH setting. Based on this empirical feature, Harvey et al. [1994] introduced a SV model with leverage effect. The model is referred as the asymmetric SV (ASV1) model. This model is the Euler approximation to the continuous time asymmetric SV model, which is well-known in the devoted to option price papers Hull and White [1987], Wiggins [1987], and Chesney and Scott [1989]. Harvey and Shephard (1996) treat the filtered volatility as a predictor of the return rate. Another approach also exists, in which the leverage effect is defined as a negative relationship between expected volatility and the return at period t. In the paper (Harvey and Shephard) the model is fitted to stock data using a quasi-maximum likelihood method. Jacquier et al. [2004] Jaquuier, Polson and Rossi (2004) provide an MCMC algorithm for the leverage stochastic volatility (SVL) model. Stochastic volatility framework has also been presented in Yu [2004]. Thus SV model is extended by including non-zero correlation ρ between ϵ_t and η_t from equations 3.3, 3.4. The model is specified as follows:

$$y_t = exp(h_{t-1}/2)\epsilon_t, \tag{3.5}$$

$$h_t = \omega + \phi h_{t-1} + \varphi\epsilon_t + \sigma_\eta\eta_t, \tag{3.6}$$

- $\varphi = \tau\rho$
- $\sigma_\eta^2 = \tau(1-\rho^2)$
- ϵ_t, η_t are iid standard normal errors,
- $y_t = ln(S_t/S_{t-1})$ is the continuously compounded return,
- $\epsilon_t = W_1(t) - W_1(t-1)$,
- $\eta_t = W_2(t) - W_2(t-1)$.

Hence, ϵ_t and η_t are iid $N(0,1)$ and $cor(\epsilon_t, \eta_t) = \rho$. Compared with the basic SV model, a contemporaneous dependence is allowed in the ASV1 model. While $\rho < 0$ characterizes a leverage effect, negative shocks in observation

y_t are associated with higher $h_{t+k}, k \geq 0$ and positive shock in y_t is associated with lower h_t. We assume that the initial state h_0, i.e. the volatility at time 0, is distributed according $N(\frac{\omega}{1-\phi}, \frac{\omega}{\sigma_\eta^2-\phi^2})$, that is the invariant law of the autoregressive model, equal to the first two marginal moments of the underlying volatility process.

Fat-tailed distribution of error term

Since daily asset returns are leptokurtic, some researchers model stock returns as independent and identically distributed draws from fat-tailed distributions. On the other hand volatility changes over time. Therefore, the unconditional distribution of returns is leptokurtic even if the conditional distribution is normal. Changes on volatility cannot completely explain leptokurtosis of assets returns. The SV model with fat-tailed error can describe a wide range of kurtosis. This is important when we are dealing with outliers in the financial series. The SV model with fat-tailed error can be represented as

$$y_t = exp(h_{t-1}/2)\epsilon_t, \tag{3.7}$$

$$h_t = \omega + \phi h_{t-1} + \varphi U_t + \sigma_\eta \eta_t, \tag{3.8}$$

$$\epsilon_t = \sqrt{\lambda_t} z_t, \tag{3.9}$$

$$\lambda_t \sim IG(\nu/2, \nu/2) \tag{3.10}$$

so that $\epsilon_t \sim t_k(0,1)$ is a standard Student's t distribution with k degrees o freedom. Further particulars can be found in Griffin and Steel [2010], Omori et al. [2007], Asai [2008], Nakajima and Omori [2009], and Abanto-Valle et al. [2010] .

Long memory SV models.

Such models explain how persistent the volatility is, or how quickly financial markets forget large volatility shocks.

A observed property of many financial data series is that they appear to have long memory, either in mean or in variance. This means that the results of shocks on financial time series take a very long time to pass. The long memory property is well documented for various volatility measures (such as absolute returns, squared returns, an realized volatility for stock prices, foreign exchange rates) (see. Taylor [1986] Taylor (1986), Ding, Granger, and Engle (1993), Dacorogna et al. [1993] , and Andersen et al. [2007] One way to model such behavior is through fractionally integrated time series processes. Long memory in the conditional variance of financial data series is even more prevalent than long memory in the mean. This has led to the development of fractionally integrated versions of both the GARCH and the stochastic volatility model. Models of conditional volatility lead to fractionally integrated GARCH and fractionally integrated stochastic volatility models. The stationary stochastic processes such as LMSV are long-memory models for volatility. Jensen [2004] proposed a long-memory SV model where the log-volatilities exhibit long memory properties (LMSV)

$$y_t = exp(h_{t-1}/2)\epsilon_t, \tag{3.11}$$

$$(1-L)^d h_t = \sigma_\eta \eta_t, \tag{3.12}$$

where L is the lag operator.

SV model with jumps in returns

In the recent econometric literature, the basic SV model was extended in order to take into account a jump's dynamic to describe extreme and rare events such as crashes on the market. It is useful to introduce a jump component in the return and in the volatility equations. Similar to the basic SV model, the Euler discretization of continuous time jump (SVJ) process leads to a specification of the form

$$y_t = exp(h_{t-1}/2)\epsilon_t + J_t z_t, \tag{3.13}$$

$$h_{t+1} = h_t + \phi h_{t-1} + \eta_t, \eta_t \sim N(0, \sigma_\eta^2), \tag{3.14}$$

$$J_t \sim Ber(\lambda), \tag{3.15}$$

$$z_t \sim N(\mu_z, \sigma_z^2), \tag{3.16}$$

where J_t is the indicator of a jump and Z_t the jump size. For the jump specification, one can conditionally conjugate prior structure for parameters $(\lambda, \mu_z, \sigma_z,^2)$, where $\lambda \sim Beta(a,b)$, $\mu_z \sim N(c,d)$ and $\sigma_z^2 \sim IG(\nu/2, \nu\sigma_z^2)$, respectively. Lopes and Polson [2010] discusses the choice $c = -3, d = 0.01$

and $a = 2, b = 100$. In that case the prior mean of standard deviation of λ is around 0.02. This prior specification predicts about five large negative jumps per year (250 trading days), whose magnitude is around -3 percent.

SV with jumps in volatility

Empirical evidence suggests that conditional volatility of returns demonstrates a number of visible jumps in a year. Duffie et al. [2000] provides evidence of positive jumps in volatility. The SV model with fat-tailed error can be represented as

$$y_t = exp(h_{t-1}/2)\epsilon_t, \tag{3.17}$$

$$h_{t+1} = h_t + \phi h_{t-1} + J_t z_t + \eta_t, \eta_t \sim N(0, \sigma_\eta^2), \tag{3.18}$$

$$J_t \sim Ber(\lambda), \tag{3.19}$$

$$z_t \sim N(\mu_z, \sigma_z^2), \tag{3.20}$$

where J_t is the indicator of jump and Z_t the jump size. For the jump specification, one can conditionally conjugate prior structure for parameters $(\lambda, \mu_z, \sigma_z,^2)$, where $\lambda \sim Beta(a, b)$, $\mu_z \sim N^+(0, d)$ (truncated normal distribution) and $\sigma_z^2 \sim IG(\nu/2, \nu\sigma_z^2)$, respectively.

Markov switch stochastic volatility

One of the most popular nonlinear time series models in the literature is the Markov switching or regime switching model (see Hamilton (1989)). This model can characterize the time series behaviors in different regimes or states by postulating multiple equations for each states. This model is able to capture more complex dynamic patterns by permitting switching between these states. An important aspect of the Markov switching model is that the switching mechanism is controlled by an unobservable state variable. The Markovian property postulates that the current value of the state variable depends on its immediate past value. It is assumed that state variables follow a first-order Markov chain.

In 1998, So So et al. [1998] introduces Markov switching to the stochastic volatility model. Time varying parameters could be incorporated in the SV model in the dynamics of the log volatility. Model becomes:

$$y_t = exp(h_t/2) + e_t, e_t \sim N(0, \sigma_e^2), \tag{3.21}$$

$$h_{t+1} = \mu_{s,t} + \phi h_{t-1} + \eta_t, \eta_t \sim N(0, \sigma_\eta^2), \tag{3.22}$$

$$p_{ij} = Pr(s_t = j|s_{t-1} = i), i, j = 1, ..., k \tag{3.23}$$

$$\mu_{st} = \gamma_1 + \sum_{j=1}^{k} \gamma_j I_{ji}, \tag{3.24}$$

and regime variables s_t follow a k-state first order Markov process. $I_{jt} = 1$ if $s_t \geq j$ and zero otherwise, $\gamma_i >= 0$ for $i > 1$.

3.1.3 Adding News to the SV Model

The canonical SV model is too restrictive, but makes it easy to include additional regressors. The mean of y_t is not necessarily equal to zero and may be a function of explanatory variables x_t:

$$y_t = exp(h_t/2)\epsilon_t + x_t^T \beta, \epsilon_t \sim N(0, 1), \tag{3.25}$$

Exactly the same h_t may be a function of observable variables z_t in addition to its own lags:

$$h_{t+1} = \mu + \phi h_{t-1} + z_t^T \gamma + \eta_t, \tag{3.26}$$

The impact of exogenous explanatory variables on volatility has been examined in the context of the GARCH model by several authors Baillie and Bollerslev [1989]; Lamoureux and Lastrapes [1990].

Such explanatory variables could be intervention dummies, seasonal components, or regressors like option implied volatility, trade volume data, etc.

The empirical validity of the SV model with explanatory variables has been examined elsewhere (Ghysels and Jasiak [1995], Hubalek and Posedel

[2008]). Therefore, we considered models including the number of news as the first and the second equation.

SV Model with Exogenous Jump Process

$$Y_t = \epsilon_t \exp(h_t/2) + \delta_t J_t$$

$$h_{t+1} = \mu(1-\phi) + \phi h_t + \sigma_h \eta_t$$

μ is drift in the state equation; σ^2 - variance of the error term; ϕ - persistence parameter; δ_t jump size; $J_t \in \{0,1\}$ - an exogenous binary variable based on news flow; $\epsilon_t \sim \mathcal{N}(0, \sigma_Y^2)$, $\eta_t \sim \mathcal{N}(0,1)$

SV Model with Exogenous Jumps in Return depends on Positive and Negative News Intensity

Let us assume that the size of the particular jump is proportional to the number of positive or negative news.

$$y_t = exp(h_t/2)\epsilon_t + \beta_1 N_t^+ + \beta_2 N_t^-, \epsilon_t \sim N(0, \sigma_e^2), \tag{3.27}$$

$$h_{t+1} = \mu + \phi h_{t-1} + \eta_t, \tag{3.28}$$

SV model with exogenous control process of news flow

$$Y_t = \epsilon_t \exp(h_t/2)$$

$$h_{t+1} = \mu(1-\phi) + \phi h_t + \gamma \log N_t + \sigma_h \eta_t$$

μ - drift in the state equation; σ^2 - variance of the error term; ϕ - persistence parameter; N_t - index of news intensity; $\epsilon_t \sim \mathcal{N}(0, \sigma_Y^2)$, $\eta_t \sim \mathcal{N}(0,1)$

Positive and Negative News Intensity in State Equation

Previous model could be elaborated by adding two separate variables for the number of positive and negative news:

$$y_t = exp(h_t/2)e_t, e_t \sim N(0, \sigma_e^2), \tag{3.29}$$

$$h_{t+1} = \mu + \phi h_{t-1} + \gamma_1 N_t^+ + \gamma_2 N_t^- + \eta_t, \tag{3.30}$$

3.2 Estimation

Stochastic volatility model belongs to a class of nonlinear non-Gaussian state space models. The returns y_t is an observed variable and logarithmic volatility h_t is a latent state of the system at time t. Likelihood function $L(\theta; \mathbf{y})$ for stochastic volatility models can not be expressed explicitly. The likelihood is a T-dimensional integration with respect to unknown latent volatilities and its analytical form is, in general, unknown. The parameter estimation of the SV model is not straight-forward due the intractable form of likelihood. Several estimation methods have been proposed, including the generalised method of moments, quasi-maximum likelihood, efficient method of moments and simulation likelihood. Estimation of the parameters of the canonical SV model may be done by the maximum likelihood (ML) method or by Bayesian inference. ML and, in principle, Bayesian estimation require to compute the likelihood function of an observed sample, which is a difficult task.

Canonical SV Model

The standard univariate SV model proposed by Taylor(1986) is

$$y_t = exp(h_{t-1}/2)\epsilon_t, \epsilon_t \sim NID(0,1)$$
$$h_t = \omega + \phi h_{t-1} + \sigma_h \eta_t, \eta_t \sim N(0,1)$$
$$h_0 \sim N(\frac{\omega}{1-\phi}, \frac{\sigma_\eta^2}{1-\phi^2}),$$

where y_t is the observation at time t, h_t - logarithmic volatility is assumed to follow a stationary AR(1) process. It is assumed that the parameter σ_η is positive and the persistent parameter $|\phi| < 1$ (is close to one for application). The observation errors $\epsilon_t \sim N(0,1)$ captures the measurement and sampling errors, whereas the process error $\eta_t \sim N(0,1)$ assesses the variation in the underlying volatility dynamics.

Let us assume $\mathbf{y} = (y_1, ..., y_T)$ to be the vector of observed log-returns, $\mathbf{h} = (h_1, ..., h_T)$ to be the vector of unobserved volatilities,$\Omega_t = (y_1, ..., y_t, h_1, ..., h_t)$, $\theta = (\sigma_\epsilon, \phi, \sigma_\eta)$ to be the set of parameters. The SV model can be regarded as a nonlinear state space model. So to evaluate the likelihood, we have to integrate out the latent log volatilities.

$$f(\mathbf{y}|\theta) = \int f(\mathbf{y}, \mathbf{h}|\theta) d\mathbf{h} = \int f(\mathbf{y}|\mathbf{h}, \theta) f(\mathbf{h}|\theta) d\mathbf{h} \quad (3.31)$$

$$f(\mathbf{h}|\theta) = \frac{f(\mathbf{y}, \mathbf{h}|\theta)}{f(\mathbf{y}|\theta)} \tag{3.32}$$

The log volatility h_t is specified by the AR(1) process with Gaussian innovation noise. The density functions of y_t given h_t and of h_t given h_{t-1} are

$$f(y_t|h_t) = \frac{1}{\sqrt{2\pi}} exp(-\frac{y_t^2}{2} exp(-h_t) - \frac{h_t^2}{2}), \tag{3.33}$$

$$f(h_t|h_{t-1}) = \frac{1}{\sqrt{2\pi}} exp(-\frac{h_t - \omega - \phi h_{t-1}}{2\sigma_\eta^2}), \tag{3.34}$$

respectively.

$$log f(y_t, h_t|\theta) = -\frac{1}{2} log(2\pi) - \frac{h_t}{2} - \frac{y_t^2}{2exp(h_t)} \tag{3.35}$$

The multistep procedure for likelihood evaluation takes the following form.
(i) one step ahead prediction of y_t

$$\begin{aligned} f(y_t|\mathbf{y}_{t-1}) &= \int_{-\infty}^{\infty} f(y_t, h_t|\mathbf{y}_{t-1}) dh_t = \\ &= \int_{-\infty}^{\infty} f(y_t|h_t) f(h_t|\mathbf{y}_{t-1}) dh_t \end{aligned} \tag{3.36}$$

(ii) updating of h_t

$$\begin{aligned} f(h_t|\mathbf{y}_t) &= f(h_t|y_t, \mathbf{y}_{t-1}) = \\ &= \frac{f(y_t, h_t|\mathbf{y}_{t-1})}{f(y_t|\mathbf{y}_{t-1})} = \\ &= \frac{f(y_t, h_t) f(h_t|\mathbf{y}_{t-1})}{f(y_t|\mathbf{y}_{t-1})} \end{aligned} \tag{3.37}$$

(iii) one step ahead prediction of h_t:

$$f(h_{t+1}|\mathbf{y}_t) = \int_{-\infty}^{\infty} f(h_{t+1}, h_t|\mathbf{y}_t)dh_t = \\ = \int_{-\infty}^{\infty} f(h_{t+1}|h_t)f(h_t|\mathbf{y}_t)dh_t \tag{3.38}$$

If we have $f(y_t|\mathbf{y}_{t-1}), t = 1, ..., T$, we can calculate the log likelihood

$$L(\theta|\mathbf{y}_t) = \sum_{t=1}^{T} logf(y_t|\mathbf{y}_{t-1}) \tag{3.39}$$

The logarithms of the densities of the components are given

$$logf(y_t|h_t, \theta) = -\frac{1}{2}log(2\pi) - \frac{h_t}{2} - \frac{y_t^2}{2\sigma_\eta^2 exp(h_t)} \tag{3.40}$$

$$logf(h_t|h_t - 1, \theta) = -\frac{1}{2}log(2\pi\sigma_\eta^2) + \frac{\omega}{2\sigma_\eta^2} - \frac{1}{2\sigma_\eta^2}(h_t - h_{t-1})^2 \tag{3.41}$$

$$logf(h_1|\theta) = -\frac{1}{2}log(2\pi\sigma_\eta^2) + \frac{1}{2}log(1 - \phi^2) - (\frac{h_1 - \frac{\omega}{1-\phi}}{\frac{\sigma_\eta^2}{1-\phi^2}})^2 \tag{3.42}$$

It is difficult to solve the integrations in equations (3.37) and (3.39) analytically, because the SV model is not a linear Gaussian state space model.

An analytical solution to the integration problem is not available. Simulation methods are therefore used. Two methods directly approximate (3.39): efficient importance sampling (EIS), and Monte Carlo maximum likelihood (MCML). In this study we will use QML estimation, while other methods (MCML and EIS) are to be used in later investigations to enable us to compare results.

3.2.1 Linear Filtering and QML Estimation

Despite a very simple representation, standard SV model captures most of the empirical regularities found in financial time series.

An attractive feature of specification is the possibility of linearizing the model. By taking logarithms of the squared mean adjusted returns one obtains:

$$log(y_t^2) = \mu + h_t + \xi_t, \tag{3.43}$$

$$h_t^2 = \omega + \phi h_{t-1} + \epsilon_t, \tag{3.44}$$

where $\mu = log(y_t^2) + E(log(\epsilon_t^2))$, $h_t = log(\sigma_t^2)$, $\xi_t = log(\epsilon_t^2) - E(log(\epsilon_t^2))$. Model (3.43), (3.44), is non-Gaussian linear state space model. The property of measurement error ξ_t depend on the distribution of ϵ_t. If the original mean equation disturbance, ϵ_t, is standard normal, ξ_t follows the $\log \chi_1^2$ distribution whose mean and variance are known to be -1.27 and $\pi^2/2$, respectively Broto and Ruiz [2004]. However the approximating model replaces this with a Gaussian distribution (defined below), keeping the state equation unchanged. Therefore, the whole machinery of the Kalman filter is applicable to the approximating model, which is a Gaussian linear state space model.

Harvey et al. (1994) suggested a Quasi-Maximum Likelihood (QML) method of estimating the model based on the Kalman filter.

Assuming joint conditional normality of (ξ_t, η_t) in equations (3.43), (3.44) represents the measurement and transition equations of the general linear state space model.

Once the model is in the state space form, the advantages of this approach become evident:

(i) explanatory variables can be easily incorporated into the variance equation,

(ii) more general ARMA processes can be assumed for the evolution of the latent variable,

(iii) missing or irregularly spaced observations can be handled,

(iv) it is be possible to examine the impact of exogenous explanatory variables and

(v) generalisations to the multivariate case are straightforward.

The disadvantages

- ξ_t is far from being Gaussian;
- the QML estimator is likely to have poor small sample properties even though it is consistent.

When returns y_t are very close to zero, the log-squared transformation yields large negative numbers. To solve this problem the following modification of log-squared transformation may be used

$$y_t^* = log(y_t^2 + \tau s^2) - \frac{\tau s^2}{y_t^2 + \tau s^2}, \tag{3.45}$$

where s^2 is the sample variance of y_t and τ is a small constant Bollerslev and Wright. [2001]. To increase conversion speed of the estimation procedure, we subtracted the mean value from the our variable $\widetilde{y_t^*} = y_t^* - \overline{y}^*$, because in this case significantly fewer iterations are needed to find a solution, and estimates practically coincide with the case when centering was not carried out.

The Stata code for the SV model is given below

```
gen tau=0.02
egen sd=sd(lr)
gen sd2=sd*sd
gen z=ln(lr*lr + tau*sd2) - tau*sd2 / (lr*lr + tau*sd2)
egen zmean=mean(z)
gen y=z-zmean
constraint 1 [z] h=0.5
sspace (h L.h, state)(y h ,noconst ), constraints(1)
predict eqst,st
matrix B=e(b)
svmat B
gen hst=sqrt(exp(eqst)*exp(B2[1])*exp(zmean))
drop sd sd2 z zmean y
```

Even though this method is not perfect, the QML procedure is very flexible and has been successfully implemented for empirical analysis of stock price returns and other financial data. In addition, is is easy to add more explanatory variables to the model and then apply QML.

Chapter 4

Empirical Results

4.1 Empirical Results for Canonical SV Model

We examine the following stochastic volatility model with uncorrelated measurement errors and state equation with exogenous control process of news flow ((3.43), (3.44), (3.45)):

$$y_t = \mu + h_t + \delta_t,$$
$$h_{t+1} = \omega + \phi h_t + \sigma_h \eta_t$$
$$y_t^* = log(y_t^2 + \tau s^2) - \frac{\tau s^2}{y_t^2 + \tau s^2},$$

where s^2 is the sample variance of y_t and $\tau = 0.02$. Also, we apply a preliminary transformation as described in the previous section (3.2).

The data series consists of 1450 daily contionously compounded return, $lr_{it} = logp_t - logp_{t-1}$ from July 6, 2005 to December 31, 2010 for 92 company from FTSE100. The estimates of SV model for all 92 company are presented in Table C.1. (see Appendix)

As an example, we briefly discuss the results for GB/ABF (Associated British Foods PLC). The time series plot is presented on Figure 4.1. The annualized mean and annualized standard deviation of the data are 0.018%

and 1.406%, respectively. The data exhibits the negative skewness with value -0.165, and kurtosis is 7.555. Skewness/Kurtosis test rejects hypothesis of normality.

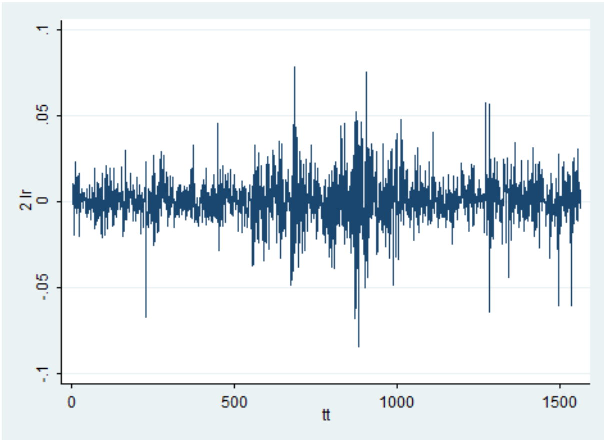

Figure 4.1: Log return for GB/ABF

The Box-Luing's serial correlation test on the absolute returns shows that absolute returns are not independently distributed, but decay geometrically with lag (Figure 4.2).

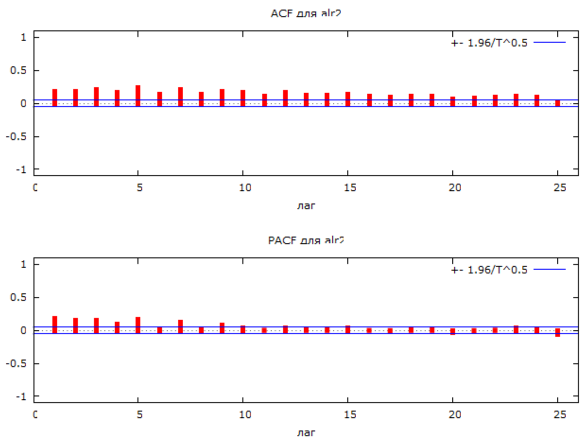

Figure 4.2: The sample ACF for daily absolute returns for GB/ABF stock price for the period July 2006 - December 2010

The results of the quasi-maximum likelihood parameter estimate can be found in Table 4.1.

Table 4.1: Parameter estimates for basic SV model for GB/ABF

y	Coef.	Std. Err.	z	$Prob > \|z\|$	$95\%Conf.$	Interval
h						
h_{t-1}	.9692545	.0118645	81.69	0.000	.9460005	.9925086
$cons$	-.0012459	.0100107	-0.12	0.901	-.0208665	.0183746
σ_h^2	.1381055	.0560022	2.47	0.014	.0283433	.2478677
σ_y^2	3.208062	.1290949	24.85	0.000	2.955041	3.461083

Estimate of ϕ is equal to 0.969. It indicates that the volatility process is highly persistent. This evidence is consistent with stylized facts on stock return. Figure 4.4 shows the predicted implied volatility. Figures 4.1 show that the estimated volatility has similar movement as $|y_t|$.

Similar results were obtained for most of the analyzed time series of stock returns (see Table C.1 in Appendix). Only for a few companies low values of persistence were obtained. For example, for $GB/AU.$ company the estimated value of parameter ϕ is equal to 0.6739. Perhaps this is due to the fact that the upward trend for stock prices was typical for that company.

4.2 Empirical Results for SV model with exogenous control process of news

Consider the extended SV model:

$$y_t = exp(h_{t-1}/2)\epsilon_t, \tag{4.1}$$

$$h_t = \omega + \phi h_{t-1} + \alpha_1 D_t^+ + \alpha_2 D_t^- + \sigma_\eta \eta_t, \tag{4.2}$$

where variables D_t^+, D_t^- denote the dummy variables for days with abnormal numbers of positive and negative news items at day t respectively.

Some companies has have much greater news coverage than the others. Therefore, the rule of labelling the days with abnormal news intensity depends on the company. For companies with small news intensity it can be

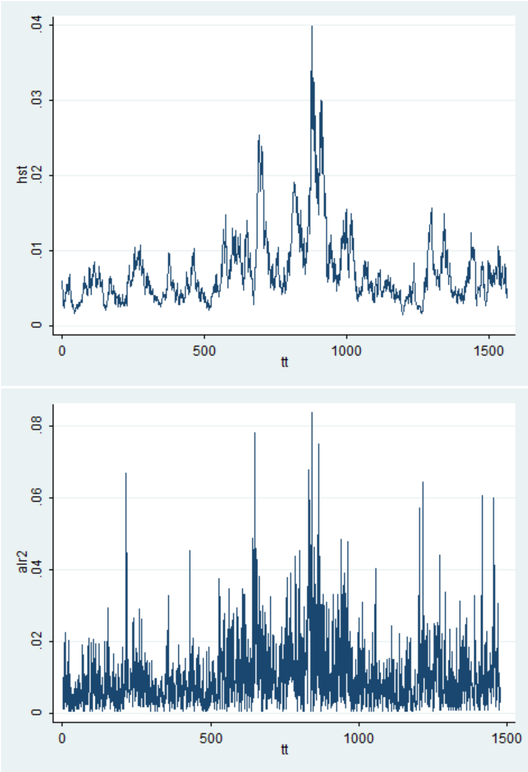

Figure 4.3: SV model. The esimated volatility and abs(return) for GB/ABF

days with only one piece of news. For companies with high news intensity (e.g. HSBC, BT, BP) we labeled day if the number of news in this day was two times higher then average news intensity level.

For GB/ABF company the news intensity is small. So we use a simple rule: a day is labelled if at least one piece of positive (negative) news came. The number of days, when at least one piece of positive news was recorded for GB/ABF, is equal to 223. The number of days with at least one negative news item is equal to 95.

The results of the quasi-maximum likelihood parameter estimation can be found in Table 4.2.

It is interesting to compare the results obtained if dummy variables are in-

Table 4.2: Parameter estimates for extended SV model with dummy variable in state equation for GB/ABF

	Coef.	Std. Err.	z	$Prob > \|z\|$	$95\% Conf.$	Interval
h						
h_{t-1}	0.966	0.012	78.14	0.000	0.941	0.990
D^{+}	0.113	0.110	1.03	0.305	-0.103	0.329
D^{-}	0.328	0.163	2.00	0.045	0.006	0.649
$cons$	-0.041	0.02	-1.88	0.060	-0.084	0.001
σ_h^2	0.116	0.046	2.48	0.013	0.0243	0.207
σ_y^2	2.764	0.113	24.34	0.000	2.541	2.987

Table 4.3: Parameter estimates for extended SV model with dummy variable in observation equation for GB/ABF

	Coef.	Std. Err.	z	$Prob > \|z\|$	$95\% Conf.$	Interval
h						
h_{t-1}	0.976	0.010	98.81	0.000	0.957	0.996
$cons$	-0.005	0.008	-0.59	0.557	-0.022	0.012
y						
D^{+}	0.379	0.108	3.52	0.000	0.168	0.590
D^{-}	0.255	0.202	1.26	0.207	-0.141	0.651
σ_h^2	0.092	0.038	2.42	0.016	0.017	0.167
σ_y^2	2.742	0.112	24.51	0.000	2.523	2.961

cluded in the observed equation (see Table 4.3 and Table C.2 Appendix). Direct inclusion of the news in the state equation does not significantly improve the quality of the model. The hypothesis that their coefficients are zero is rejected for more then half of the FTSE100 companies. However, if we include the news in the observation equation, then the hypothesis of equality of the coefficients to zero is rejected for most of FTSE100 companies.

Instead of dummy variables we also can include the number of arriving news in the SV model :

$$y_t = exp(h_{t-1}/2)\epsilon_t, \tag{4.3}$$

Table 4.4: Parameter estimates for extended SV model with logarithm of number positive (negative) news items in state equation for GB/ABF

	Coef.	Std. Err.	z	$Prob > \|z\|$	$95\% Conf.$	Interval
h						
h_{t-1}	0.965	0.012	81.34	0.000	0.942	0.988
N^+	0.139	0.096	1.44	0.149	-0.050	0.327
N^-	0.337	0.172	1.96	0.050	0.000	0.675
$cons$	-0.046	0.019	-2.46	0.014	-0.083	-0.009
σ_h^2	0.111	0.044	2.53	0.012	0.025	0.197
σ_y^2	2.766	0.113	24.42	0.000	2.544	2.988

$$h_t = \omega + \phi h_{t-1} + \beta_1 N_t^+ + \beta_2 N_t^- + \sigma_\eta \eta_t, \tag{4.4}$$

where variables N_t^+, N_t^- denote the logarithm of numbers of positive and negative news items at day t respectively.

In Table 4.4 and Table C.3 (in Appendix) we report the estimates of parameters for the model (4.3), (4.4).

Estimates of predicted volatility for basic and extended models are close enough (Figure 4.5). Note that the direct incorporation of the news in the equation of state does not significantly improve the accuracy of the model.

In our opinion, the small impact of news intensity on stock volatility might be connected with the fact that we considered only the company-specific news. It is possible that their impact is short-term. Notice that specifications of models (4.1), (4.1) or (4.3), (4.4) imply that the impact of news intensity on stock volatility is long-term, i.e. the impact holds not only for the current day but also for several days after that. We consider the possible modification of stochastic volatility model with an exogenous flow of news.

Assume that at the time moment t we have $N_t^+ \neq 0, N_t^- = 0, N_{t+1}^+, N_{t+1}^- = 0$. It follows from (4.4) that the value of the state variable at the time moment $t+1$ is equal to

$$\begin{aligned} h_{t+1} =& \omega + \phi h_t + \sigma_\eta \eta_{t+1} = \\ & \omega + \phi(\omega + \phi h_t + \beta_1 N_t^+ + \sigma_\eta \eta_t) + \sigma_\eta \eta_t = \\ & (1+\phi)\omega + \phi\beta_1 N_t^+ + \phi\sigma_\eta \eta_t + \sigma_\eta \eta_{t+1} = \end{aligned} \tag{4.5}$$

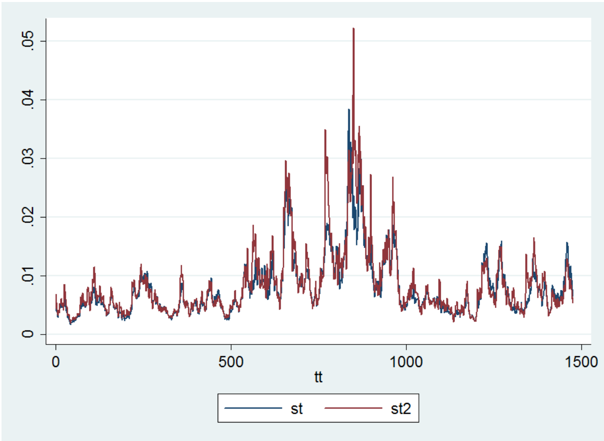

Figure 4.4: The estimated volatility for SV model and SV model with news in state equation for GB/ABF

Thus, the impact of news shock on stock volatility decays exponentially. It may be possible to derive the time of the decay of shocks, τ, from the inequality:

$$\beta_1 \phi^{\tau} < c,$$

where level c is a given as a real positive number.

In chapter 2.3 we found that news is more likely to lead to short-term jump in returns than to long-term change of volatility. We can suggest the following way of testing this hypothesis. Let us include additional variables N^+_{t-1}, N^-_{t-1} to the model.

$$y_t = exp(h_{t-1}/2)\epsilon_t, \tag{4.6}$$

$$h_t = \omega + \phi h_{t-1} + \beta_1 N^+_t + \beta_2 N^-_t + \gamma_1 N^+_{t-1} + \gamma_2 N^-_{t-1} + \sigma_\eta \eta_t, \tag{4.7}$$

If the impact of news is short-term, then the jump of volatility in the previous day would be amortized in the current day. Thus, the parameter γ_1 should be equal to $-\phi * \beta_1$. The hypothesis of short-term impact of positive and negative news on stock volatility can be written as

$$H_0 : \begin{cases} \beta_1 = -\phi\gamma_1, \\ \beta_2 = -\phi\gamma_2. \end{cases} \tag{4.8}$$

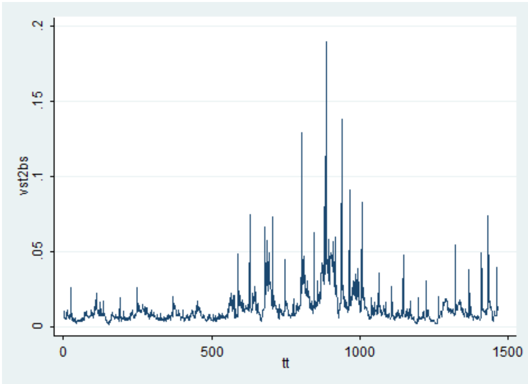

Figure 4.5: The estimated volatility for SV model with news in state equation for GB/ABF

Empirical results can be found in Table C.3 in Appendix. It is interesting that estimates of parameters β_1,β_2(the current day) are positive, while estimates of parameters γ_1,γ_2 (the prevoious day) are negative. Moreover they are significant.

It is worth noting that hypothesis 4.8 is not rejected for almost all FTSE100 companies. We use the Wald test for linear restriction on coefficients (see column χ^2 in Table C.4 of Appendix). As example, the results indicate that we cannot reject the null hypothesis for GB/ABF company:

$$H_0 : \begin{cases} \beta_1 + \gamma_1 = 0 \\ \beta_2 + \gamma_2 = 0 \end{cases} , \chi^2_{obs}] = 3.00 < \chi^2(0.05, 2) = 5.99 \quad (4.9)$$

Persistence of the extended SV model is slightly less than persistence of the basic SV model. For most of the companies estimates of the regression coefficients for negative news are statistically significant, while the same estimates of positive news are mainly insignificant. To be precise, coefficients for positive news are insignificant for companies. More than that, absolute value of the negative news coefficients is generally greater than that for positive news coefficients. We interpret this as an empirical rule: in general, negative news have more impact on jump sizes. Figure 4.5 shows the estimated volatility based on SV model with news intensity. The estimated volatility has some number of jumps.

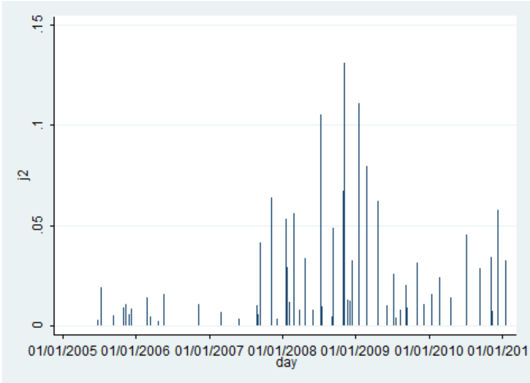

Figure 4.6: SV model with news in state equation for GB/ABF. Estimated jump size.

Figure 4.6 presents days and size of jumps. Average jump size of the days t seems be proportional to current volatilities at the day t.

4.3 Back Testing

In this section, some validation method will be discussed.

Fist of all we calculate a Value at Risk (VaR) in day t. To obtain the VaR_t we can do standard transformation:

$$VaR_t(\alpha) = \alpha\sigma_t P_0,$$

where α reflect the selected confidence level, σ_t the standard deviation of the asset return in the day t, P_0 - initial asset value.

Backtesting is a procedure where actual profit and losses are systematically compared to corresponding VaR estimates. Many standard bactests of VaR models compare the actual asset or portfolio losses for a given horizon with the estimated VaR numbers. In this section we compare the back testing result for the cases when σ_t is estimated by canonical and extended SV models.

The most widely known test based of failure rates has been suggested by Kupiec (1995). The Kupiec's test, also known as POF-test (proportion of failures), measures whether the exceed returns occurs. The backtest consist of counting the number of exception (losses larger than estimated VaR) for a given period and comparing the excepion number for chosen confidence interval. Each trading outcome either produce VaR violation or not. Under the null hypothesis that model is correct, the number of exceptions x follows a binomial probability distribution:

$$f(x) = (\begin{matrix} T \\ x \end{matrix}) p^x (1-p)^{T-x} \tag{4.10}$$

With confidence level α, the number of exceptions should be in interval around $T(1-a)$. For instance, the expected number of exception with the VaR confidence level $\alpha = 0.95$ is about $250 * (1 - 0.95)$ every year.

The Kupiec tests focus only on the frequency of exceptions and assume that exceptions should be independently distributed over time. Conditional Coverage of Frequency and Independence Test (Cristoffersen test) is introduced to test the distribution of exception.

We test the hypothesis that in day of high-intensity news flow exceptions occoured more frequently.

Suppose we have the data of asset returns of T days. Set indicator values:

$$I_t = \begin{cases} 1, & \text{if it does not exceed VaR ;} \\ = 0, & \text{otherwise;} \end{cases}$$

$$J_t = \begin{cases} 1, & \text{if the number of news exceed a threshold value;} \\ 0, & \text{otherwise.} \end{cases}$$

The threshold value for a given company is defined as 95 percent quantile of the empirical distribution of company news number in a selected day. As an example, the threshold value for BP company is equal to 28, since the news flow for this company is intensive, while for ARM the is equal 3 because for the period of 5 years it held only 647 news items.

Those we have a sequences $\{I_t\}_{t=1}^T$, $\{J_t\}_{t=1}^T$.

Table 4.5: Conditional Coverage Model

Conditional News number			
	Under threshold	Upper threshold	Total
Return Exception No Exeption	 T_{00} T_{01}	 T_{10} T_{11}	
Total	$T_0 = T_{00} + T_{01}$	$T_1 = T_{10} + T_{11}$	$T = T_0 + T_1$

Next define $T_{i,j}$ the number of of days that i, j occurs. Let π_0 is the conditional probability of $I_t = 0, J_=1$ and π_1 be the conditional probability of $I_t = 1, J_=1$:

$$\pi_0 = T_{01}/(T_{00} + T_{01}),$$

$$\pi_1 = T_{10}/(T_{10} + T_{11}).$$

Likelihood test of independence can be calculated as follows:

$$LR_{ind} = -2T_0 ln(1-c) - 2T_1 ln(c) + 2T_{00} ln(1-\pi_0) + 2T_1 1ln(\pi_0 + 2T_{10} ln(\pi_1)).$$

LR_{ind} is asymptotically distributed as $\chi^2(1)$. At 95 percent confidence interval, we will rejected the model if $LR_{ind} > 3.84$.

If volatility is predicted by canonical SV-model, then exceed returns and news flow jumps are correlated for 55 companies of 89. Table 4.6 presents the results of Cristoffersen-type test for the GB/ABF for canonical SV model.

Now let us present results of Cristoffersen-type test for SV-news model. Table 4.7 presents number of exceptions for days with number of news under and upper of threshold value for SV-news model for GB/ABF company.

Table 4.6: The number of exception for canonical SV model (GB/ABF, 6/6/2009-6/6/2011)

Conditional News number			
	Under threshold	Upper threshold	Total
Return			
Exception	16	7	23
No Exception	419	68	487
Total	435	75	510
LR=3.877			

Table 4.7: The number of exception for SV-news model (GB/ABF, 6/6/2009-6/6/2011)

Conditional News number			
	Under threshold	Upper threshold	Total
Return			
Exception	18	4	22
No Exception	417	71	488
Total	435	75	510
LR=0.209			

Results for other companies can be found in Appendix C.5. It worth nothing that the correlation between exceed returns and news flow jumps hold for 32 company only.

Thus inclusion of the news flow intensity in SV-news model leads to a better prediction power of volatility for the days with high news intensity. Nevertheless, for some companies SV-news model do not explain exceed returns better than canonical SV model. For this reason we think that it is necessary to develop different ways of news intensity to volatility models.

Chapter 5

Summary and future work

5.1 Summary and contributions

This work demonstrates evidence that news information has predictive power for stock returns and jump probabilities that leads to volatility forecast improvements on event days. We present an alternative approach to analyze the impact of news intensity on the volatility of stock market returns. Based on a stochastic volatility (SV) model with explanatory variables, we model the response of conditional volatility to news flow intensity.

We give empirical frameworks for incorporating news flow intensity in SV model. The modified SV model provides a description of dynamics of daily return volatility once the dynamics of news flow is specified. Our analysis suggests that it would be interesting to consider a more general specification of the modified SV model which require all price changes to be accompanied by news intensity.

Conditional volatility of returns consists of two factors: one related to a standard diffusive component parameterized as a SV process, and the other related to a pure jump component.

Overall, these empirical findings indicate the significance of incorporating heterogeneous news events to explain different volatility patterns. In the work we have examined SV model with news intensity as an exogenous variable. Moreover, we have included in our analysis news intensity of both positive and negative news.

We propose the different modifications of SV model:

- the first one suggests that there is a long-term impact of news intensity on stock volatility. It is the model with contemporary news intensity.
- the second model includes lagged news intensity. We proposed a way to test the hypothesis of a short-term impact of news intensity on volatility.

To estimate parameters of the models we used the QML method. The results shows that:

- news analytics data improves the quality of prediction of volatility of the SV model;
- for almost all FTSE100 companies, the hypothesis of a short-term impact of news on stock volatility is accepted;
- The proposed model allows to estimate the mean and standard deviation of volatility jumps;
- Negative news increase short-term stock volatility more likely than positive news.

Future work:

- We can try to use some alternative approach for the estimation of the extended SV model, e.g. MCMC and Particle Filter.
- to extend the SV model with jumps in volatility, provided that probability of jumps in a current day depends on the number of negative and positive news.

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Appendix

Table A.1. Summary Statistics for Daily Returns

Company	Company code	Mean	Std. dev.	Skewness	Kurtosis
Anglo American PLC	GB/AAL	0.00050	0.032	-0.179	9.306
Associated British Foods PLC	GB/ABF	0.00020	0.014	-0.165	7.795
Admiral Group PLC	GB/ADM	0.00096	0.022	0.202	19.745
Aggreko PLC	GB/AGK	0.00148	0.023	0.262	6.021
AMEC PLC	GB/AMEC	0.00075	0.022	-0.250	10.478
Antofagasta PLC	GB/ANTO	0.00107	0.032	0.041	7.331
ARM Holdings PLC	GB/ARM	0.00108	0.025	0.063	11.059
Autonomy Corp. PLC	GB/AU.	0.00145	0.027	0.258	11.021
Aviva PLC	GB/AV.	-0.00023	0.031	-1.269	27.393
AstraZeneca PLC	GB/AZN	0.00020	0.016	-0.222	8.996
BAE Systems PLC	GB/BA.	0.00010	0.018	-0.244	6.744
Barclays PLC	GB/BARC	-0.00042	0.038	1.633	39.720
British American Tobacco PLC	GB/BATS	0.00059	0.015	0.174	12.017
BG Group PLC	GB/BG.	0.00074	0.022	0.001	6.433
British Land Co. PLC	GB/BLND	-0.00014	0.023	-0.130	6.409
BHP Billiton PLC	GB/BLT	0.00078	0.028	0.000	7.904
BP PLC	GB/BP.	-0.00014	0.019	-0.071	9.626
Burberry Group PLC	GB/BRBY	0.00075	0.024	-0.220	8.350
British Sky Broadcasting Group PLC	GB/BSY	0.00029	0.017	0.522	14.116
BT Group PLC	GB/BT.A	-0.00005	0.021	-0.957	15.449
Carnival PLC	GB/CCL	-0.00015	0.022	-0.079	8.463
Centrica PLC	GB/CNA	0.00028	0.017	0.172	10.487
Cairn Energy PLC	GB/CNE	0.00077	0.026	0.009	8.795
Compass Group PLC	GB/CPG	0.00063	0.019	-0.182	8.179
Capita Group PLC	GB/CPI	0.00041	0.015	0.004	6.949
Capital Shopping Centres Group PLC	GB/CSCG	-0.00040	0.023	-0.168	8.479
Diageo PLC	GB/DGE	0.00032	0.013	0.161	9.629
Man Group PLC	GB/EMG	0.00006	0.032	-1.519	22.304
Experian PLC	GB/EXPN	0.00028	0.021	0.046	7.493
G4S PLC	GB/GFS	0.00044	0.016	0.076	6.798
GKN PLC	GB/GKN	0.00015	0.030	-0.012	7.940
GlaxoSmithKline PLC	GB/GSK	-0.00003	0.014	0.094	7.743
Hammerson PLC	GB/HMSO	-0.00016	0.023	-0.206	6.329
HSBC Holdings PLC	GB/HSBA	-0.00012	0.020	-0.342	18.966
ICAP PLC	GB/IAP	0.00030	0.029	-0.099	14.812
InterContinental Hotels Group PLC	GB/IHG	0.00036	0.021	0.118	5.338
3i Group PLC	GB/III	-0.00027	0.026	-0.304	13.168
IMI PLC	GB/IMI	0.00059	0.023	0.050	7.901
Imperial Tobacco Group PLC	GB/IMT	0.00032	0.015	0.006	8.587
Investec PLC	GB/INVP	0.00027	0.030	0.108	9.535
International Power PLC	GB/IPR	0.00031	0.021	-1.164	18.123
Inmarsat PLC	GB/ISAT	0.00058	0.021	0.192	11.480
Intertek Group PLC	GB/ITRK	0.00062	0.018	-0.340	8.280
ITV PLC	GB/ITV	-0.00033	0.028	0.730	11.704
Johnson Matthey PLC	GB/JMAT	0.00044	0.021	-0.050	7.719
Kazakhmys PLC	GB/KAZ	0.00058	0.041	-0.222	10.903
Kingfisher PLC	GB/KGF	0.00005	0.023	0.073	5.358
Land Securities Group PLC	GB/LAND	-0.00028	0.022	-0.107	7.897
Legal & General Group PLC	GB/LGEN	0.00002	0.031	-0.340	20.280

Company	Company code	Mean	Std. dev.	Skewness	Kurtosis
Lloyds Banking Group PLC	GB/LLOY	-0.00100	0.040	-1.039	33.394
Lonmin PLC	GB/LMI	0.00030	0.034	0.646	18.597
Marks & Spencer Group PLC	GB/MKS	0.00008	0.021	-1.851	28.816
Wm. Morrison Supermarkets PLC	GB/MRW	0.00030	0.016	0.158	6.347
National Grid PLC	GB/NG.	0.00012	0.015	0.003	15.636
Next PLC	GB/NXT	0.00028	0.022	0.194	6.781
Old Mutual PLC	GB/OML	0.00007	0.032	-0.111	13.800
Petrofac Ltd.	GB/PFC	0.00139	0.027	0.100	6.289
Prudential PLC	GB/PRU	0.00025	0.032	0.261	14.102
Pearson PLC	GB/PSON	0.00035	0.015	0.470	6.963
Reckitt Benckiser Group PLC	GB/RB.	0.00045	0.015	0.268	7.969
Royal Bank of Scotland Group PLC	GB/RBS	-0.00153	0.048	-8.131	187.347
Royal Dutch Shell PLC	GB/RDSA	0.00015	0.018	0.339	9.824
Reed Elsevier PLC	GB/REL	0.00002	0.016	-0.301	10.267
Rexam PLC	GB/REX	-0.00006	0.019	-0.713	11.913
Rio Tinto PLC	GB/RIO	0.00071	0.034	-1.408	27.468
Rolls-Royce Group PLC	GB/RR.	0.00062	0.021	0.000	6.874
Randgold Resources Ltd.	GB/RRS	0.00124	0.030	0.223	6.917
RSA Insurance Group PLC	GB/RSA	0.00037	0.019	0.338	7.827
J Sainsbury PLC	GB/SBRY	0.00011	0.018	-1.423	26.560
Scottish & Newcastle PLC	GB/SCTN	0.00021	0.015	-0.238	13.646
Schroders PLC	GB/SDR	0.00047	0.026	-0.121	23.702
Sage Group PLC	GB/SGE	0.00018	0.018	0.227	6.133
Shire PLC	GB/SHP	0.00076	0.018	0.329	7.943
Standard Life PLC	GB/SL	-0.00010	0.027	0.678	10.562
Smiths Group PLC	GB/SMIN	0.00018	0.018	-0.419	11.851
Smith & Nephew PLC	GB/SN.	0.00013	0.018	-0.070	9.525
Serco Group PLC	GB/SRP	0.00053	0.016	-0.138	5.544
Standard Chartered PLC	GB/STAN	0.00040	0.028	0.469	14.073
Severn Trent PLC	GB/SVT	0.00021	0.015	0.374	12.168
Tullow Oil PLC	GB/TLW	0.00130	0.027	0.447	9.499
Tesco PLC	GB/TSCO	0.00018	0.016	0.245	8.362
TUI Travel PLC	GB/TT.	0.00014	0.025	-0.455	15.424
Unilever PLC	GB/ULVR	0.00032	0.015	0.002	7.479
United Utilities Group PLC	GB/UU.	-0.00007	0.014	-0.066	9.700
Vedanta Resources PLC	GB/VED	0.00092	0.036	-0.280	7.075
Vodafone Group PLC	GB/VOD	0.00012	0.019	-0.340	9.073
Weir Group PLC	GB/WEIR	0.00118	0.027	-0.225	9.722
John Wood Group PLC	GB/WG.	0.00091	0.027	-0.122	7.741
Wolseley PLC	GB/WOS	-0.00057	0.031	-0.950	18.305
WPP PLC	GB/WPP	0.00015	0.019	-0.234	7.344
Whitbread PLC	GB/WTB	0.00033	0.020	0.091	9.050
Name	GB/XTA	0.00062	0.037	-0.249	8.283

Table A.2. Variance Comparison Tests Results. Rule for selection in marked group: Number of News Item in current day > 3 * Mean of Number of News Item

Company code	Std. dev. for control group	Std. dev. for marked group	Df1	Df2	F	Lower one-sided p-value	
GB/AAL	0.031	0.037	1451	112	0.723	0.0064	***
GB/ABF	0.013	0.022	1485	78	0.359	0.0000	***
GB/ADM	0.020	0.040	1489	74	0.253	0.0000	***
GB/AGK	0.022	0.042	1494	69	0.268	0.0000	***
GB/AMEC	0.021	0.030	1428	135	0.505	0.0000	***
GB/ANTO	0.032	0.036	1466	97	0.796	0.0508	
GB/ARM	0.023	0.048	1463	100	0.220	0.0000	***
GB/AU.	0.024	0.046	1420	143	0.279	0.0000	***
GB/AV.	0.029	0.051	1447	116	0.321	0.0000	***
GB/AZN	0.014	0.029	1453	110	0.230	0.0000	***
GB/BA.	0.018	0.022	1444	119	0.659	0.0005	***
GB/BARC	0.033	0.082	1475	88	0.168	0.0000	***
GB/BATS	0.014	0.024	1472	91	0.356	0.0000	***
GB/BG.	0.021	0.030	1446	117	0.492	0.0000	***
GB/BLND	0.023	0.029	1461	102	0.618	0.0002	***
GB/BLT	0.028	0.036	1444	119	0.606	0.0000	***
GB/BP.	0.017	0.033	1453	110	0.270	0.0000	***
GB/BRBY	0.023	0.050	1496	67	0.207	0.0000	***
GB/BSY	0.016	0.027	1450	113	0.350	0.0000	***
GB/BT.A	0.019	0.041	1454	109	0.199	0.0000	***
GB/CCL	0.021	0.036	1474	89	0.327	0.0000	***
GB/CNA	0.016	0.022	1442	121	0.573	0.0000	***
GB/CNE	0.026	0.032	1449	114	0.645	0.0003	***
GB/CPG	0.018	0.037	1491	72	0.233	0.0000	***
GB/CPI	0.014	0.022	1454	109	0.403	0.0000	***
GB/CSCG	0.023	0.030	1527	36	0.591	0.0066	***
GB/DGE	0.013	0.017	1455	108	0.565	0.0000	***
GB/EMG	0.029	0.066	1486	77	0.195	0.0000	***
GB/EXPN	0.020	0.029	1115	99	0.481	0.0000	***
GB/GFS	0.015	0.022	1443	120	0.502	0.0000	***
GB/GKN	0.029	0.046	1483	80	0.390	0.0000	***
GB/GSK	0.014	0.019	1459	104	0.499	0.0000	***
GB/HMSO	0.023	0.029	1479	84	0.627	0.0007	***
GB/HSBA	0.018	0.050	1521	42	0.138	0.0000	***
GB/IAP	0.028	0.071	1538	25	0.157	0.0000	***
GB/IHG	0.021	0.028	1477	86	0.561	0.0000	***
GB/III	0.025	0.033	1446	117	0.593	0.0000	***
GB/IMI	0.022	0.038	1487	76	0.328	0.0000	***
GB/IMT	0.015	0.022	1459	104	0.444	0.0000	***
GB/INVP	0.030	0.040	1469	94	0.547	0.0000	***
GB/IPR	0.020	0.028	1482	81	0.513	0.0000	***
GB/ISAT	0.020	0.035	1463	92	0.334	0.0000	***
GB/ITRK	0.018	0.026	1466	97	0.452	0.0000	***
GB/ITV	0.027	0.034	1433	130	0.650	0.0002	***
GB/JMAT	0.021	0.034	1525	38	0.375	0.0000	***
GB/KAZ	0.040	0.046	1371	104	0.774	0.0298	***
GB/KGF	0.022	0.029	1482	81	0.581	0.0001	***
GB/LAND	0.021	0.029	1453	110	0.527	0.0000	***
GB/LGEN	0.029	0.050	1466	97	0.337	0.0000	***
GB/LLOY	0.033	0.085	1443	120	0.154	0.0000	***

Company code	Std. dev. for control group	Std. dev. for marked group	Df1	Df2	F	Lower one-sided p-value	
GB/LMI	0.031	0.069	1466	97	0.196	0.0000	***
GB/MKS	0.018	0.048	1468	95	0.146	0.0000	***
GB/MRW	0.015	0.028	1477	86	0.280	0.0000	***
GB/NG.	0.015	0.019	1440	123	0.594	0.0000	***
GB/NXT	0.021	0.034	1464	99	0.379	0.0000	***
GB/OML	0.032	0.035	1459	104	0.827	0.0803	
GB/PFC	0.025	0.037	1352	126	0.466	0.0000	***
GB/PRU	0.031	0.046	1474	89	0.445	0.0000	***
GB/PSON	0.015	0.023	1468	95	0.393	0.0000	***
GB/RB.	0.014	0.023	1488	75	0.376	0.0000	***
GB/RBS	0.036	0.132	1466	97	0.073	0.0000	***
GB/RDSA	0.017	0.021	1494	69	0.710	0.0169	***
GB/REL	0.015	0.031	1491	72	0.240	0.0000	***
GB/REX	0.017	0.040	1478	85	0.188	0.0000	***
GB/RIO	0.031	0.063	1442	121	0.237	0.0000	***
GB/RR.	0.020	0.027	1418	145	0.548	0.0000	***
GB/RRS	0.029	0.032	1461	102	0.859	0.1327	
GB/RSA	0.018	0.029	1473	90	0.397	0.0000	***
GB/SBRY	0.016	0.040	1465	98	0.163	0.0000	***
GB/SCTN	0.015	0.015	1482	81	0.985	0.4440	
GB/SDR	0.025	0.033	1457	106	0.607	0.0001	***
GB/SGE	0.017	0.029	1482	81	0.337	0.0000	***
GB/SHP	0.016	0.028	1420	143	0.344	0.0000	***
GB/SL	0.027	0.031	1190	89	0.723	0.0130	***
GB/SMIN	0.017	0.028	1462	101	0.352	0.0000	***
GB/SN.	0.016	0.034	1465	98	0.219	0.0000	***
GB/SRP	0.016	0.020	1439	124	0.621	0.0000	***
GB/STAN	0.028	0.041	1483	80	0.467	0.0000	***
GB/SVT	0.015	0.021	1451	112	0.497	0.0000	***
GB/TLW	0.027	0.028	1479	84	0.905	0.2466	
GB/TSCO	0.015	0.025	1472	91	0.345	0.0000	***
GB/TT.	0.022	0.059	1504	59	0.142	0.0000	***
GB/ULVR	0.014	0.026	1468	95	0.290	0.0000	***
GB/UU.	0.014	0.017	1460	103	0.631	0.0003	***
GB/VED	0.036	0.042	1442	121	0.733	0.0069	***
GB/VOD	0.017	0.031	1454	109	0.308	0.0000	***
GB/WEIR	0.025	0.042	1480	83	0.357	0.0000	***
GB/WG.	0.026	0.035	1473	90	0.554	0.0000	***
GB/WOS	0.028	0.064	1483	80	0.192	0.0000	***
GB/WPP	0.018	0.030	1459	104	0.353	0.0000	***
GB/WTB	0.019	0.032	1469	94	0.352	0.0000	***
GB/XTA	0.037	0.034	1452	111	1.211	0.9029	

Table C.1. Estimation Results of Parameters of Canonical SV Model for FTSE100, QML Method

$$log(y_t^*) = \mu + \frac{h_t}{2} + \xi_t,$$
$$h_t = \omega + \phi h_{t-1} + \eta_t$$

N	Company	ϕ	ω	σ_η^2	σ_ξ^2
1	GB/AAL	0.9878	-0.0025	0.0747	3.0962
2	GB/ABF	0.9695	-0.0015	0.1385	3.2101
3	GB/ADM	0.9803	-0.0003	0.0816	3.4328
4	GB/AGK	0.9812	-0.0007	0.0651	3.3996
5	GB/AMEC	0.9742	-0.0009	0.1439	3.1774
6	GB/ANTO	0.9864	-0.0019	0.0680	3.2151
7	GB/ARM	0.9222	-0.0035	0.3161	3.1049
8	GB/AU.	0.6739	0.0238	2.1743	2.7936
9	GB/AV.	0.9880	-0.0022	0.1309	2.5866
10	GB/AZN	0.9717	0.0006	0.1255	3.1544
11	GB/BA.	0.9741	-0.0008	0.0853	3.3290
12	GB/BARC	0.9866	-0.0016	0.1476	2.5217
13	GB/BATS	0.9824	-0.0008	0.0614	3.2579
14	GB/BG.	0.9844	-0.0006	0.0703	3.1847
15	GB/BLND	0.9948	-0.0017	0.0320	3.1865
16	GB/BLT	0.9882	-0.0010	0.0527	3.1587
17	GB/BP.	0.9809	-0.0006	0.0768	3.1271
18	GB/BRBY	0.9737	-0.0018	0.1980	3.0617
19	GB/BSY	0.9835	0.0019	0.1368	3.0930
20	GB/BT.A	0.9870	-0.0004	0.0450	3.1854
21	GB/CCL	0.9945	-0.0015	0.0281	3.2847
22	GB/CNA	0.9808	0.0001	0.0595	3.2631
23	GB/CNE	0.9913	-0.0009	0.0251	3.3299
24	GB/CPG	0.9803	0.0008	0.0818	3.2786
25	GB/CPI	0.8946	-0.0002	0.5010	3.0516
26	GB/CSCG	0.9953	-0.0019	0.0343	3.0194
27	GB/DGE	0.9781	-0.0016	0.1211	3.0172
28	GB/EMG	0.9875	-0.0016	0.0863	2.8150
29	GB/EXPN	0.9961	-0.0028	0.0829	2.4542
30	GB/GFS	0.9562	0.0020	0.2025	3.2409
31	GB/GKN	0.9944	-0.0017	0.0382	3.1338
32	GB/GSK	0.9675	0.0003	0.0926	3.3000
33	GB/HMSO	0.9954	-0.0013	0.0283	3.2460
34	GB/HSBA	0.9886	-0.0021	0.1135	2.7492
35	GB/IAP	0.9714	0.0006	0.1807	3.0837
36	GB/IHG	0.9894	-0.0017	0.0523	3.4659
37	GB/III	0.9900	-0.0013	0.0712	2.9890
38	GB/IMI	0.9864	-0.0025	0.0668	3.4945
39	GB/IMT	0.9869	-0.0011	0.0597	3.2235
40	GB/INVP	0.9925	-0.0017	0.0567	3.1525
41	GB/IPR	0.9719	-0.0007	0.1245	3.0081
42	GB/ISAT	0.9247	0.0050	0.3662	3.2346
43	GB/ITRK	0.9686	-0.0006	0.1198	3.3385
44	GB/ITV	0.9895	-0.0020	0.0735	2.9812

N	Company	ϕ	ω	σ_η^2	σ_ξ^2
45	GB/JMAT	0.9902	-0.0015	0.0498	3.2514
46	GB/KAZ	0.9931	-0.0041	0.0877	2.8147
47	GB/KGF	0.9959	-0.0014	0.0234	3.2869
48	GB/LAND	0.9803	-0.0002	0.1240	3.1811
49	GB/LGEN	0.9915	-0.0017	0.0695	2.8800
50	GB/LLOY	0.9956	-0.0017	0.0510	2.6020
51	GB/LMI	0.9819	-0.0006	0.0929	3.1505
52	GB/MKS	0.9923	-0.0015	0.0427	3.1412
53	GB/MRW	0.9736	0.0007	0.1168	3.2405
54	GB/NG.	0.9683	0.0007	0.1106	3.2003
55	GB/NXT	0.9968	-0.0016	0.0197	3.2992
56	GB/OML	0.9929	-0.0022	0.0669	2.9230
57	GB/PFC	0.9871	-0.0039	0.1380	3.0235
58	GB/PRU	0.9857	-0.0030	0.1255	2.7992
59	GB/PSON	0.9923	-0.0013	0.0250	3.3846
60	GB/RB.	0.9619	-0.0002	0.1432	3.3430
61	GB/RBS	0.9959	-0.0016	0.0435	2.3747
62	GB/RDSA	0.9894	-0.0009	0.0399	3.1147
63	GB/REL	0.9798	0.0004	0.0976	3.1867
64	GB/REX	0.9898	-0.0013	0.0626	3.1110
65	GB/RIO	0.9936	-0.0017	0.0332	3.1419
66	GB/RR.	0.9846	-0.0004	0.0707	3.3162
67	GB/RRS	0.9932	-0.0004	0.0146	3.4777
68	GB/RSA	0.9897	-0.0002	0.0450	3.3405
69	GB/SBRY	0.9843	-0.0013	0.1039	2.9204
70	GB/SCTN	0.9898	-0.0005	0.0309	3.3627
71	GB/SDR	0.9779	-0.0002	0.1449	3.0832
72	GB/SGE	0.9516	-0.0012	0.2257	3.2604
73	GB/SHP	0.9034	0.0041	0.3723	3.2485
74	GB/SL	0.9948	-0.0040	0.1069	2.3493
75	GB/SMIN	0.9595	-0.0011	0.1774	3.1037
76	GB/SN.	0.9509	0.0018	0.2331	3.2466
77	GB/SRP	0.9803	0.0005	0.0565	3.3576
78	GB/STAN	0.9816	-0.0009	0.1344	2.8859
79	GB/SVT	0.9731	0.0007	0.0872	3.3245
80	GB/TLW	0.9826	-0.0001	0.0593	3.3876
81	GB/TSCO	0.9826	-0.0002	0.0702	3.1311
82	GB/TT.	0.9931	-0.0009	0.0211	3.4778
83	GB/ULVR	0.9875	-0.0011	0.0585	3.2044
84	GB/UU.	0.9927	-0.0014	0.0302	3.2243
85	GB/VED	0.9882	-0.0018	0.0572	3.3201
86	GB/VOD	0.9799	-0.0010	0.0880	3.2150
87	GB/WEIR	0.9891	-0.0021	0.0738	3.0117
88	GB/WG.	0.9835	-0.0004	0.0713	3.2444
89	GB/WOS	0.9871	-0.0014	0.1124	2.9730
90	GB/WPP	0.9934	-0.0013	0.0317	3.2046
91	GB/WTB	0.9759	-0.0008	0.1637	3.0896
92	GB/XTA	0.9881	-0.0009	0.0773	2.9549

Table C.2. Estimation Results of Parameters of SV Model with News in Observations Equation, QML Method

$$log(y_t^*) = \mu + \frac{h_t}{2} + a_1 D_t^+ + a_2 D_t^- + \xi_t,$$

$$h_t = \omega + \phi h_{t-1} + \eta_t$$

Company	ϕ	ω	a_1	a_2	σ_η^2	σ_ξ^2
GB/AAL	0.9881	-0.0034	0.1537	0.1400	0.0717	3.0944
GB/ABF	0.9719	-0.0072	0.4332	0.5675	0.1179	3.1795
GB/ADM	0.9820	-0.0030	0.6969	0.9013	0.0704	3.3849
GB/AGK	0.9822	-0.0035	0.7429	1.0596	0.0605	3.3232
GB/AMEC	0.9749	-0.0064	0.4057	0.6705	0.1355	3.1291
GB/ANTO	0.9858	-0.0032	0.0703	0.4471	0.0686	3.1982
GB/ARM	0.9776	-0.0082	0.3918	0.9061	0.0622	3.1888
GB/AU.	0.6879	-0.0632	0.8691	0.5638	1.7264	2.8188
GB/AV.	0.9895	-0.0042	0.4159	0.4595	0.1110	2.5573
GB/AZN	0.9749	-0.0064	0.2616	0.8398	0.1056	3.0871
GB/BA.	0.9767	-0.0076	0.6068	0.3900	0.0777	3.2625
GB/BARC	0.9877	-0.0040	0.1640	0.5109	0.1250	2.5059
GB/BATS	0.9868	-0.0032	0.3522	0.6008	0.0417	3.2421
GB/BG.	0.9859	-0.0031	0.3142	0.4485	0.0607	3.1616
GB/BLND	0.9948	-0.0027	0.7203	0.5451	0.0313	3.1205
GB/BLT	0.9881	-0.0021	0.2825	0.0642	0.0505	3.1535
GB/BP.	0.9833	-0.0043	0.3946	0.4026	0.0583	3.1129
GB/BRBY	0.9789	-0.0057	0.5214	0.7028	0.1507	3.0394
GB/BSY	0.9868	-0.0030	0.5912	0.5729	0.1048	3.0316
GB/BT.A	0.9892	-0.0033	0.4250	0.3891	0.0362	3.1468
GB/CCL	0.9944	-0.0028	0.4124	0.4224	0.0284	3.2385
GB/CNA	0.9853	-0.0042	0.4245	0.4363	0.0413	3.2313
GB/CNE	0.9920	-0.0027	0.6146	0.3950	0.0227	3.2735
GB/CPG	0.9870	-0.0037	0.8146	1.4221	0.0485	3.1190
GB/CPI	0.9056	-0.0197	0.3323	0.6947	0.4142	3.0424
GB/CSCG	0.9957	-0.0021	-0.0594	1.1573	0.0314	3.0173
GB/DGE	0.9805	-0.0060	0.5729	0.2854	0.1081	2.9766
GB/EMG	0.9881	-0.0054	0.5970	0.4532	0.0784	2.7442
GB/EXPN	0.9962	-0.0032	0.2292	0.6183	0.0780	2.4347
GB/GFS	0.9634	-0.0032	0.4027	0.4686	0.1592	3.2451
GB/GKN	0.9945	-0.0025	0.6099	0.8433	0.0357	3.0620
GB/GSK	0.9731	-0.0058	0.3407	0.3919	0.0720	3.2816
GB/HMSO	0.9953	-0.0020	0.4132	0.4466	0.0276	3.2131
GB/HSBA	0.9900	-0.0036	0.3883	0.1902	0.0961	2.7461
GB/IAP	0.9713	-0.0044	0.4486	0.3720	0.1854	3.0530
GB/IHG	0.9896	-0.0030	0.4371	0.3608	0.0508	3.4394
GB/III	0.9907	-0.0024	0.1575	0.5275	0.0654	2.9716
GB/IMI	0.9870	-0.0042	0.5489	0.8017	0.0655	3.4439
GB/IMT	0.9882	-0.0030	0.3271	0.4958	0.0525	3.1920
GB/INVP	0.9928	-0.0025	0.4317	0.3720	0.0534	3.1341
GB/IPR	0.9797	-0.0048	0.7629	0.7342	0.0814	2.9745
GB/ISAT	0.9310	-0.0078	0.4842	0.6592	0.3121	3.2122
GB/ITRK	0.9746	-0.0053	0.6374	0.5147	0.0902	3.3097
GB/ITV	0.9918	-0.0049	0.5835	0.6037	0.0562	2.8894
GB/JMAT	0.9915	-0.0026	0.3353	0.6456	0.0426	3.2279
GB/KAZ	0.9932	-0.0051	0.3422	0.3711	0.0822	2.7913
GB/KGF	0.9959	-0.0024	0.4594	0.5089	0.0233	3.2218

Company	ϕ	ω	a_1	a_2	σ_η^2	σ_ξ^2
GB/LAND	0.9812	-0.0028	0.2139	0.3553	0.1131	3.1778
GB/LGEN	0.9922	-0.0027	0.4177	0.4656	0.0616	2.8604
GB/LLOY	0.9961	-0.0025	0.4447	0.4585	0.0409	2.5696
GB/LMI	0.9817	-0.0041	0.4496	0.5056	0.0853	3.1076
GB/MKS	0.9937	-0.0035	0.4959	0.8552	0.0309	3.0395
GB/MRW	0.9810	-0.0043	0.8457	0.5563	0.0781	3.1916
GB/NG.	0.9708	-0.0028	0.0949	0.2230	0.1029	3.1963
GB/NXT	0.9969	-0.0020	0.8252	1.1280	0.0203	3.2452
GB/OML	0.9931	-0.0033	0.8085	0.0368	0.0666	2.8691
GB/PFC	0.9869	-0.0062	0.6927	0.2623	0.1346	2.9775
GB/PRU	0.9884	-0.0048	0.4121	0.5018	0.0983	2.7843
GB/PSON	0.9938	-0.0024	0.4700	0.4316	0.0201	3.3497
GB/RB.	0.9790	-0.0048	0.6703	0.9598	0.0636	3.3385
GB/RBS	0.9966	-0.0026	0.4512	0.5191	0.0365	2.3212
GB/RDSA	0.9894	-0.0020	0.1900	0.2223	0.0401	3.1028
GB/REL	0.9814	-0.0032	0.1985	0.7086	0.0853	3.1501
GB/REX	0.9911	-0.0035	0.5424	1.1089	0.0510	3.0155
GB/RIO	0.9933	-0.0024	0.1360	0.3540	0.0318	3.1279
GB/RR.	0.9869	-0.0032	0.3875	0.4900	0.0586	3.2921
GB/RRS	0.9933	-0.0010	0.3752	0.2405	0.0149	3.4601
GB/RSA	0.9913	-0.0014	0.1897	0.6159	0.0364	3.3262
GB/SBRY	0.9862	-0.0049	0.6213	0.3777	0.0887	2.8684
GB/SCTN	0.9906	-0.0015	0.2462	0.4349	0.0292	3.3503
GB/SDR	0.9786	-0.0046	0.2745	0.3694	0.1392	3.0595
GB/SGE	0.9593	-0.0142	0.5120	1.0196	0.1695	3.1937
GB/SHP	0.9375	-0.0162	0.7107	0.5972	0.2081	3.2199
GB/SL	0.9952	-0.0043	0.3277	0.4226	0.0968	2.3441
GB/SMIN	0.9700	-0.0082	0.4882	0.6448	0.1252	3.0786
GB/SN.	0.9490	-0.0128	0.8654	0.4929	0.2277	3.1488
GB/SRP	0.9817	-0.0020	0.4675	0.6916	0.0509	3.3219
GB/STAN	0.9822	-0.0043	0.4051	0.1206	0.1223	2.8742
GB/SVT	0.9738	-0.0053	0.5106	0.3689	0.0852	3.2745
GB/TLW	0.9845	-0.0017	0.3589	0.6307	0.0547	3.3673
GB/TSCO	0.9825	-0.0036	0.4289	0.3475	0.0660	3.0960
GB/TT.	0.9929	-0.0017	0.3316	0.6033	0.0194	3.4500
GB/ULVR	0.9886	-0.0044	0.8172	0.4344	0.0509	3.1129
GB/UU.	0.9934	-0.0018	0.5721	-0.1331	0.0266	3.2116
GB/VED	0.9884	-0.0028	0.4886	0.0384	0.0553	3.3059
GB/VOD	0.9861	-0.0057	0.4098	0.5770	0.0578	3.1729
GB/WEIR	0.9904	-0.0033	0.4978	0.8922	0.0633	2.9713
GB/WG.	0.9835	-0.0018	0.2115	1.0591	0.0699	3.2185
GB/WOS	0.9915	-0.0044	0.5355	0.7575	0.0703	2.9225
GB/WPP	0.9943	-0.0029	0.5084	0.5334	0.0259	3.1477
GB/WTB	0.9767	-0.0043	0.7174	0.3778	0.1554	3.0435
GB/XTA	0.9877	-0.0014	0.2683	0.0169	0.0793	2.9482

Table C.3. Estimation Results of Parameters of SV Model with Lagged News in State Equation, QML Method

$$log(y_t^*) = \mu + \frac{h_t}{2} + \xi_t,$$

$$h_t = \omega + \phi h_{t-1} + \beta_1 logN_t^+ + \beta_2 logN_t^- + \eta_t$$

Company	ϕ	β_1	β_2	ω	σ_η^2	σ_ξ^2
GB/AAL	0.9881	0.0572	-0.0721	-0.0163	0.0677	3.1009
GB/ABF	0.9519	0.2104	0.4575	-0.0632	0.1643	3.1820
GB/ADM	0.9623	0.1543	0.4226	-0.0212	0.1532	3.3702
GB/AGK	0.9636	-0.0682	1.2999	-0.0182	0.1041	3.3561
GB/AMEC	0.9605	0.2074	0.1156	-0.0496	0.2068	3.1289
GB/ANTO	0.9846	0.1506	0.0270	-0.0308	0.0611	3.2219
GB/ARM	0.2781	1.0057	1.2924	-0.3046	7.0327	1.5768
GB/AU.	0.6101	1.1405	0.7539	-0.3042	2.0313	2.7278
GB/AV.	0.9868	0.0203	0.0613	-0.0190	0.1384	2.5792
GB/AZN	0.9630	-0.0348	0.1031	0.0003	0.1538	3.1358
GB/BA.	0.9735	0.0684	-0.0033	-0.0452	0.0940	3.3110
GB/BARC	0.9678	-0.0607	0.2453	-0.0603	0.1796	2.5021
GB/BATS	0.9508	0.1065	0.2680	-0.0535	0.1700	3.1601
GB/BG.	0.9818	0.1143	0.0917	-0.0591	0.0564	3.1955
GB/BLND	0.9944	0.0036	0.0161	-0.0035	0.0328	3.1853
GB/BLT	0.9845	-0.0087	0.0294	-0.0056	0.0593	3.1543
GB/BP.	0.9725	-0.0295	0.0658	-0.0123	0.0986	3.1061
GB/BRBY	0.9642	0.1204	0.3164	-0.0337	0.2525	3.0173
GB/BSY	0.9804	-0.0686	0.1629	-0.0060	0.1392	3.0906
GB/BT.A	0.9757	-0.0291	0.1190	-0.0073	0.0770	3.1495
GB/CCL	0.9942	0.0094	0.1287	-0.0136	0.0247	3.2890
GB/CNA	0.9540	0.1789	0.0583	-0.0781	0.1239	3.1957
GB/CNE	0.9890	0.0644	-0.1377	-0.0044	0.0314	3.3143
GB/CPG	0.9680	0.1340	0.1416	-0.0402	0.1229	3.2352
GB/CPI	0.8073	0.2070	0.7894	-0.0783	0.9963	2.9047
GB/CSCG	0.9954	0.0377	-0.2381	-0.0009	0.0331	3.0196
GB/DGE	0.9749	0.0750	0.0778	-0.0380	0.1371	2.9979
GB/EMG	0.9705	-0.0135	0.4756	-0.0644	0.1061	2.7802
GB/EXPN	0.9919	0.0113	0.3670	-0.0243	0.0950	2.4362
GB/GFS	0.9216	0.2942	0.1059	-0.0384	0.3817	3.1449
GB/GKN	0.9911	0.0142	0.1516	-0.0117	0.0458	3.1225
GB/GSK	0.9515	-0.0354	0.1419	-0.0142	0.1423	3.2600
GB/HMSO	0.9942	-0.0096	0.0582	-0.0030	0.0307	3.2428
GB/HSBA	0.9833	-0.0446	0.1103	-0.0575	0.1086	2.7539
GB/IAP	0.9333	-0.1341	0.4947	0.2167	0.2714	3.0315
GB/IHG	0.9864	-0.0365	0.1301	-0.0028	0.0587	3.4596
GB/III	0.9877	0.0701	0.1657	-0.0318	0.0802	2.9736
GB/IMI	0.9861	0.2363	0.0942	-0.0243	0.0780	3.4604
GB/IMT	0.9887	0.0628	0.0753	-0.0242	0.0507	3.2298
GB/INVP	0.9957	0.0297	-0.1813	-0.0027	0.0420	3.1697
GB/IPR	0.9156	0.2248	1.0409	-0.0889	0.3652	2.8549
GB/ISAT	0.7850	0.7164	0.7850	-0.1111	1.1505	2.9747
GB/ITRK	0.9379	0.2379	0.3600	-0.0410	0.2440	3.2581
GB/ITV	0.9880	-0.1122	0.0928	0.0073	0.0620	2.9973
GB/JMAT	0.9851	-0.0088	0.2342	-0.0064	0.0639	3.2301
GB/KAZ	0.9851	0.1633	0.1549	-0.0453	0.1037	2.7983

Company	ϕ	β_1	β_2	ω	σ_η^2	σ_ξ^2
GB/KGF	0.9960	0.0736	0.1162	-0.0287	0.0152	3.3018
GB/LAND	0.9688	0.2337	0.4988	-0.0766	0.1139	3.1681
GB/LGEN	0.9901	0.0851	0.0059	-0.0227	0.0737	2.8695
GB/LLOY	0.9911	0.0424	0.0215	-0.0244	0.0732	2.5721
GB/LMI	0.9651	0.0672	0.3373	-0.0557	0.0961	3.1467
GB/MKS	0.9648	0.0575	0.3415	-0.0636	0.1403	3.0253
GB/MRW	0.9534	0.1946	0.0933	-0.0518	0.2073	3.1658
GB/NG.	0.9694	0.0359	-0.0366	0.0048	0.1042	3.2057
GB/NXT	0.9971	0.0615	0.5114	-0.0096	0.0186	3.2934
GB/OML	0.9931	0.0033	-0.0211	-0.0025	0.0666	2.9225
GB/PFC	0.9842	0.0591	0.1929	-0.0170	0.1532	3.0102
GB/PRU	0.9838	-0.0044	0.1018	-0.0103	0.1326	2.7933
GB/PSON	0.9940	0.0566	-0.0017	-0.0165	0.0214	3.3867
GB/RB.	0.7261	0.5010	1.2659	-0.1633	1.4688	2.9048
GB/RBS	0.9982	-0.0335	0.0594	-0.0044	0.0147	2.4322
GB/RDSA	0.9906	0.0458	-0.0335	-0.0211	0.0284	3.1324
GB/REL	0.9648	0.1457	0.2090	-0.0673	0.1526	3.1378
GB/REX	0.9800	-0.0758	0.5258	-0.0209	0.0872	3.0703
GB/RIO	0.9675	-0.0091	0.1606	-0.0616	0.0650	3.1203
GB/RR.	0.9795	-0.0598	0.1609	0.0205	0.0797	3.3095
GB/RRS	0.9937	-0.0307	-0.0397	0.0054	0.0113	3.4874
GB/RSA	0.9916	0.0415	-0.1031	-0.0045	0.0368	3.3514
GB/SBRY	0.9807	-0.0360	0.2186	-0.0212	0.1074	2.9116
GB/SCTN	0.9908	-0.0150	0.1155	-0.0025	0.0287	3.3637
GB/SDR	0.9770	0.0398	0.0142	-0.0108	0.1488	3.0797
GB/SGE	0.8923	0.4181	0.6707	-0.1133	0.4790	3.1301
GB/SHP	0.6662	0.2100	0.8357	-0.1693	1.7176	2.8917
GB/SL	0.9915	0.0989	-0.0306	-0.0239	0.1187	2.3393
GB/SMIN	0.9421	0.2323	0.1128	-0.0466	0.2621	3.0428
GB/SN.	0.8937	0.2067	0.2284	-0.0790	0.5245	3.1243
GB/SRP	0.9721	0.0196	0.3525	-0.0128	0.0794	3.3309
GB/STAN	0.9496	0.0625	0.2041	-0.1252	0.2238	2.8437
GB/SVT	0.9744	0.1183	0.0362	-0.0177	0.0810	3.3261
GB/TLW	0.9822	-0.0554	0.0491	0.0039	0.0587	3.3873
GB/TSCO	0.9609	0.0852	0.1850	-0.0647	0.1263	3.0843
GB/TT.	0.9616	0.0360	0.2149	-0.0164	0.1201	3.3667
GB/ULVR	0.9826	0.0800	0.0963	-0.0362	0.0727	3.1848
GB/UU.	0.9918	0.0295	-0.0627	-0.0034	0.0306	3.2251
GB/VED	0.9839	0.0302	0.0498	-0.0113	0.0680	3.3086
GB/VOD	0.9745	0.0084	0.0529	-0.0246	0.1083	3.1961
GB/WEIR	0.9890	0.0513	0.0003	-0.0074	0.0730	3.0123
GB/WG.	0.9810	0.0593	0.1137	-0.0093	0.0790	3.2365
GB/WOS	0.9772	-0.1263	0.3318	-0.0158	0.1269	2.9578
GB/WPP	0.9934	0.0612	0.0765	-0.0405	0.0207	3.2179
GB/WTB	0.9735	0.0917	-0.0292	-0.0186	0.1751	3.0797
GB/XTA	0.9898	-0.0677	0.2589	0.0019	0.0668	2.9625

Table C.4. Estimation Results of Parameters of SV Model with News in State Equation, QML Method

$$log(y_t^*) = \mu + \phi \frac{h_t}{2} + \xi_t,$$

$$h_t = \omega + \phi h_{t-1} + \beta_1 logN_{t-1}^+ + \beta_2 logN_{t-1}^- + \gamma_1 logN_{t-2}^+ + \gamma_2 logN_{t-2}^- + \eta_t \,.$$

Chi-square (χ^2_{obs}) for hypothesis $H_0: \begin{cases} \beta_1 = \gamma_1 \\ \beta_2 = \gamma_2 \end{cases}$ are given in the lust column

Company	ϕ	β_1	β_2	γ_1	γ_2	ω	σ_η^2	σ_ξ^2	χ^2_{obs}
GB/AAL	0.9888	0.0504	-0.3868	-0.0093	0.3069	-0.0076	0.0660	3.1009	0.96
GB/ABF	0.9651	0.2541	0.4178	-0.2706	-0.1115	-0.0168	0.1291	3.2160	5.47
GB/ADM	0.9873	0.4958	0.8192	-0.6334	-0.8240	0.0115	0.0547	3.4405	0.79
GB/AGK	0.9748	0.1936	-0.0902	-0.4876	0.8417	0.0150	0.0746	3.3700	5.90
GB/AMEC	0.9767	0.0123	0.8470	-0.0300	-1.1332	0.0171	0.1291	3.1687	2.53
GB/ANTO	0.9864	0.2109	0.5338	-0.0827	-0.6435	-0.0153	0.0617	3.2064	5.10
GB/ARM	0.9283	0.1862	-0.3067	-0.2632	0.1081	0.0257	0.3055	3.0870	0.05
GB/AU.	0.6549	0.6198	0.1081	0.0134	-0.0345	-0.1353	1.8278	2.8866	23.87
GB/AV.	0.9896	-0.0729	0.2734	0.0251	-0.3993	0.0348	0.1210	2.5834	0.20
GB/AZN	0.9775	0.1214	-0.1988	-0.2039	0.0900	0.0830	0.1095	3.1323	3.31
GB/BA.	0.9781	0.1375	0.2604	-0.1148	-0.3787	0.0007	0.0731	3.3283	0.21
GB/BARC	0.9854	0.0986	0.2224	-0.1892	-0.1135	0.0370	0.1187	2.5384	1.61
GB/BATS	0.9800	0.1564	0.3026	-0.1032	-0.3120	-0.0168	0.0622	3.2512	2.15
GB/BG.	0.9859	0.2811	-0.1079	-0.2234	0.1206	-0.0264	0.0501	3.2067	2.05
GB/BLND	0.9950	-0.1791	0.5751	0.0972	-0.6679	0.0239	0.0355	3.1621	0.00
GB/BLT	0.9844	0.1969	-0.3469	-0.2147	0.3826	-0.0017	0.0613	3.1398	0.07
GB/BP.	0.9823	-0.0959	0.4215	0.0888	-0.4060	-0.0032	0.0643	3.1208	1.07
GB/BRBY	0.9742	0.0365	0.3886	-0.1074	-0.3117	0.0044	0.1886	3.0671	1.73
GB/BSY	0.9817	0.1146	0.3436	-0.3326	-0.2440	0.0478	0.1249	3.0773	1.97
GB/BT.A	0.9837	0.2001	0.1925	-0.2664	-0.2137	0.0387	0.0528	3.1550	0.65
GB/CCL	0.9910	0.6145	-0.5211	-0.7043	0.6223	0.0072	0.0363	3.2504	1.01
GB/CNA	0.9928	0.2901	0.3141	-0.1793	-0.5142	-0.0160	0.0052	3.3416	12.44
GB/CNE	0.9884	0.1102	0.1111	-0.1277	-0.3284	0.0137	0.0310	3.3077	1.78
GB/CPG	0.9820	0.3963	0.0945	-0.4598	-0.1122	0.0172	0.0780	3.2622	1.85
GB/CPI	0.9126	0.0003	-0.4993	-0.2839	0.7430	0.0429	0.3985	3.0673	2.43
GB/CSCG	0.9955	0.5399	1.1111	-0.4435	-1.5968	0.0000	0.0317	3.0079	1.09
GB/DGE	0.9786	0.3695	-0.1719	-0.3790	0.1544	0.0041	0.1187	2.9982	0.67
GB/EMG	0.9768	-0.0324	0.4012	-0.1051	-0.1137	0.0074	0.0916	2.8015	11.04
GB/EXPN	0.9952	0.2080	-0.1114	-0.2325	0.2825	-0.0068	0.0826	2.4560	4.74
GB/GFS	0.9678	0.2073	0.6792	-0.1519	-0.9905	0.0057	0.1365	3.2655	1.66
GB/GKN	0.9941	0.7494	-0.6573	-0.9871	0.7150	0.0137	0.0368	3.1107	3.74
GB/GSK	0.9655	0.0965	0.3266	-0.1785	-0.3163	0.0705	0.0972	3.2673	0.20
GB/HMSO	0.9968	0.2167	0.3809	-0.3042	-0.4220	0.0126	0.0229	3.2424	0.00
GB/HSBA	0.9866	0.1280	0.2998	-0.2114	-0.2215	0.0330	0.0842	2.7673	7.44
GB/IAP	0.9366	0.4593	0.1594	-0.6291	0.1118	0.3258	0.2697	3.0374	14.77
GB/IHG	0.9833	0.5297	-0.3535	-0.6600	0.3862	0.0254	0.0727	3.4162	1.86
GB/III	0.9919	-0.0616	0.5413	0.0933	-0.5902	-0.0058	0.0642	2.9893	0.72
GB/IMI	0.9890	0.8672	0.3339	-0.7761	-0.4992	-0.0028	0.0571	3.4772	1.17
GB/IMT	0.9868	0.4423	0.0306	-0.4481	-0.0411	0.0016	0.0608	3.2069	0.03
GB/INVP	0.9989	0.3085	-0.5049	-0.2990	0.2034	0.0086	0.0289	3.1784	0.59
GB/IPR	0.9704	0.0815	1.2675	-0.1858	-0.8554	0.0088	0.1192	2.9947	5.83
GB/ISAT	0.9343	0.4199	0.4659	-0.3959	-0.4541	0.0014	0.2887	3.2638	3.39
GB/ITRK	0.9746	-0.0174	-0.1645	-0.1263	0.3315	0.0123	0.0971	3.3487	2.00
GB/ITV	0.9840	0.0560	0.2593	-0.2303	-0.2800	0.0500	0.0852	2.9430	3.37

Company	ϕ	β_1	β_2	γ_1	γ_2	ω	σ_η^2	σ_ξ^2	χ^2_{obs}
GB/JMAT	0.9898	0.0621	0.3111	-0.0817	-0.2772	0.0205	0.0486	3.2504	5.91
GB/KAZ	0.9908	0.1815	0.1827	-0.1124	-0.1529	-0.0188	0.0881	2.8194	2.43
GB/KGF	0.9960	-0.0900	0.5010	0.0833	-0.4894	-0.0019	0.0217	3.2764	8.19
GB/LAND	0.9713	0.2407	0.4718	-0.0736	-0.0102	-0.0601	0.1026	3.1922	14.52
GB/LGEN	0.9936	-0.2952	0.0401	0.3476	-0.1994	-0.0032	0.0640	2.8695	0.86
GB/LLOY	0.9975	0.2691	0.2233	-0.2582	-0.2498	0.0014	0.0380	2.6086	1.33
GB/LMI	0.9769	0.0339	0.4888	-0.0717	-0.2669	-0.0185	0.0716	3.1795	9.83
GB/MKS	0.9922	0.1572	0.4956	-0.1841	-0.4557	0.0028	0.0397	3.1249	1.06
GB/MRW	0.9741	0.2998	0.2975	-0.3517	-0.3534	0.0185	0.1212	3.2109	0.27
GB/NG.	0.9687	0.1368	0.1502	-0.1111	-0.2484	0.0281	0.0983	3.2040	0.08
GB/NXT	0.9964	0.3054	0.7312	-0.3663	-0.4383	-0.0030	0.0190	3.2996	1.90
GB/OML	0.9915	0.1630	0.2190	-0.1919	-0.2772	0.0125	0.0744	2.9061	4.56
GB/PFC	0.9882	-0.3301	0.0137	0.2576	0.0591	0.0040	0.1371	3.0196	0.46
GB/PRU	0.9865	-0.0011	0.4652	-0.0820	-0.4217	0.0250	0.1185	2.7935	3.25
GB/PSON	0.9925	0.4610	-0.0257	-0.4733	-0.0146	0.0059	0.0248	3.3636	0.01
GB/RB.	0.9842	0.5029	0.7124	-0.4335	-1.1595	-0.0005	0.0506	3.3901	1.30
GB/RBS	0.9986	0.1887	0.3505	-0.2377	-0.2923	0.0078	0.0131	2.4191	0.26
GB/RDSA	0.9895	0.2613	0.2134	-0.2286	-0.2541	-0.0071	0.0324	3.1046	3.90
GB/REL	0.9820	0.0545	0.1131	-0.0669	-0.1673	0.0096	0.0894	3.1899	0.22
GB/REX	0.9868	-0.0271	0.6789	-0.1761	-0.4812	0.0162	0.0686	3.0901	3.48
GB/RIO	0.9809	0.0725	0.1786	-0.0828	-0.0930	-0.0285	0.0450	3.1370	0.32
GB/RR.	0.9821	-0.0064	0.6390	-0.0804	-0.5727	0.0395	0.0682	3.3077	2.80
GB/RRS	0.9929	-0.3141	0.5200	0.2632	-0.5904	0.0096	0.0118	3.4730	2.12
GB/RSA	0.9921	0.0592	-0.0610	-0.0447	-0.1740	0.0113	0.0380	3.3355	2.85
GB/SBRY	0.9817	-0.2477	0.0074	0.1511	0.1740	0.0046	0.1024	2.9173	3.43
GB/SCTN	0.9903	0.0530	0.6944	-0.0659	-0.6362	-0.0005	0.0294	3.3591	0.70
GB/SDR	0.9752	-0.2731	0.5886	0.2549	-0.8082	0.0237	0.1698	3.0448	0.87
GB/SGE	0.9570	0.5829	-0.2956	-0.5675	0.3810	-0.0086	0.1867	3.2685	5.57
GB/SHP	0.9825	0.1951	0.3721	-0.3127	-0.2698	0.0325	0.0202	3.4827	8.19
GB/SL	0.9989	0.3238	0.2447	-0.3291	-0.5460	0.0127	0.0841	2.3594	1.53
GB/SMIN	0.9690	0.3065	0.4035	-0.2286	-0.6896	0.0040	0.1247	3.1260	1.02
GB/SN.	0.9584	0.3504	-0.4308	-0.4362	0.3290	0.0374	0.2139	3.2298	0.49
GB/SRP	0.9811	0.1484	0.5587	-0.3075	-0.4926	0.0168	0.0528	3.3408	2.46
GB/STAN	0.9748	0.3439	-0.1088	-0.4317	0.2455	0.0085	0.1171	2.8862	7.81
GB/SVT	0.9710	-0.0011	-0.3210	0.0568	0.2861	0.0022	0.0953	3.3079	1.59
GB/TLW	0.9790	0.0260	-0.5942	-0.0922	0.5920	0.0075	0.0684	3.3691	1.80
GB/TSCO	0.9840	0.0116	0.2533	-0.0282	-0.2684	0.0091	0.0660	3.1305	2.01
GB/TT.	0.9989	-0.0570	0.6738	0.0550	-0.7617	0.0062	0.0075	3.4964	0.70
GB/ULVR	0.9898	0.0964	0.0355	-0.2143	-0.0566	0.0343	0.0548	3.1933	1.30
GB/UU.	0.9921	0.2369	-0.3010	-0.2929	0.2742	0.0118	0.0363	3.2026	0.53
GB/VED	0.9868	0.1800	0.1143	-0.1722	-0.0806	-0.0058	0.0589	3.3161	1.49
GB/VOD	0.9862	0.1076	0.2446	-0.1036	-0.3072	0.0178	0.0610	3.2284	0.19
GB/WEIR	0.9906	0.0941	0.5138	-0.1554	-0.8478	0.0141	0.0678	3.0058	0.86
GB/WG.	0.9860	0.6161	-0.3081	-0.7013	0.1177	0.0127	0.0643	3.2259	0.34
GB/WOS	0.9853	-0.1311	0.5560	-0.0836	-0.4896	0.0298	0.0924	2.9754	4.38
GB/WPP	0.9949	0.1036	0.2352	-0.0630	-0.2164	-0.0232	0.0188	3.2287	3.57
GB/WTB	0.9769	0.0621	0.6894	-0.1181	-0.9363	0.0232	0.1631	3.0679	0.96
GB/XTA	0.9900	-0.6297	0.6072	0.5622	-0.3623	0.0025	0.0673	2.9472	1.36

Table C.5. Cristoffersen-type Test Result for Canonical SV Model and SV-news Model, Likelihood Ratio Values.

Company	Canonical SV Model	SV-news Model
GB/AAL	1.35	1.35
GB/ABF	4.18***	2.21
GB/ADM	4.62***	1
GB/AGK	43.63***	34.63***
GB/AMEC	10.33***	5.95***
GB/ANTO	0.03	0.72
GB/ARM	9.08***	2.9
GB/AU.	9.56***	0.18
GB/AV.	5.4***	3.45
GB/AZN	2.1	2.15
GB/BA.	11.99***	5.29***
GB/BARC	2.52	0.39
GB/BATS	1.11	0.22
GB/BG.	6.21***	1.37
GB/BLND	0.12	0.3
GB/BLT	0.02	0.02
GB/BP.	0.06	0.02
GB/BRBY	4.6***	0.14
GB/BSY	22.81***	21.77***
GB/BT.A	18.52***	0.08
GB/CCL	15.08***	12.14***
GB/CNA	9.71***	0.25
GB/CNE	20.57***	17.7***
GB/CPG	35.15***	9.31***
GB/CPI	6.98***	0.43
GB/CSCG	0.61	2.94
GB/DGE	7.95***	1.9
GB/EMG	25.79***	17.63***
GB/EXPN	3.66	3.29
GB/GFS	6.9***	1.63
GB/GKN	5.98***	2.37
GB/GSK	0	0.02
GB/HMSO	8.21***	9.09***
GB/HSBA	0.01	0.11
GB/IAP	12.92***	18.08***
GB/IHG	2.17	1.21
GB/III	7.5***	5.08***
GB/IMI	19.61***	10.61***
GB/IMT	7.59***	7.92***
GB/INVP	2.65	2.16
GB/IPR	1.94	1.67
GB/ISAT	15.06***	2
GB/ITRK	7.72***	4.79***
GB/ITV	8.16***	8.66***
GB/JMAT	2.25	1.35
GB/KAZ	0.01	0.41

Company	Canonical SV Model	SV-news Model
GB/KGF	13.61***	9.48***
GB/LAND	5.86***	0.69
GB/LGEN	0.19	0.34
GB/LLOY	0.57	0.39
GB/LMI	8.04***	4.63***
GB/MKS	5.93***	0.49
GB/MRW	19.46***	11.9***
GB/NG.	5.08***	1.57
GB/NXT	7.15***	5.02***
GB/OML	13.18***	10.65***
GB/PFC	10.67***	9.75***
GB/PRU	10.67***	8.73***
GB/PSON	25.16***	20.87***
GB/RB.	2.58	2.99
GB/RBS	0.89	0.37
GB/RDSA	0.9	0.17
GB/REL	8.41***	2.86
GB/REX	0.7	1.27
GB/RIO	0.67	2.02
GB/RR.	13.18***	19.25***
GB/RRS	1.11	1.59
GB/RSA	4.12***	3.13
GB/SBRY	10.08***	4.4***
GB/SCTN	0.01	0.53
GB/SDR	3.61	3.88***
GB/SGE	6.97***	0.04
GB/SHP	21.08***	0.26
GB/SL	0.05	0.1
GB/SMIN	5.83***	1.63
GB/SN.	9.08***	2.99
GB/SRP	16.76***	10.47***
GB/STAN	2.26	0.31
GB/SVT	5.19***	6.52***
GB/TLW	2.08	0.04
GB/TSCO	2.31	0.32
GB/TT.	0.01	0.01
GB/ULVR	31.67***	15.23***
GB/UU.	6.24***	6.24***
GB/VED	0.49	0.05
GB/VOD	2.72	1.46
GB/WEIR	9.76***	9.42***
GB/WG.	2.39	1.38
GB/WOS	5.19***	9.48***
GB/WPP	1.59	0.05
GB/WTB	4.17***	4.52***
GB/XTA	1.11	0.22