Stock price reactions to wire news from the European Central Bank: evidence from changes in the sentiment tone and international market indexes

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Abstract

This paper examines the link between changes in the sentiment tone with respect to the European Central Bank's (ECB) announcements and stock returns. The analysis constructs a new index that describes the tone of the sentiment derived from these announcements, spanning the period January 2002 to June 2016. The novelty of this work relies on the development of a unique sentiment index associated with the messages conveyed by the ECB's activities and the effect of this index on both the mean and the volatility of certain major international stock markets. In this context, the sentiment index is present in both the conditional mean and the volatility equations. The findings indicate a significant impact on both the mean and the volatility of returns, whereas the news sentiment/stock returns association increases in strength during the crisis period. The findings survive a robustness check based on the characteristics of the ECB governor's personality.

Keywords: changes in the tone of sentiment wire news; ECB announcements; stock prices; international stock markets

JEL Numbers: G01; E58

1. Introduction

Public news provides early warnings of the current situation of the stock market, whereas media reports influence the beliefs of market participants and induce investors either to enter or to withdraw their funds from investment instruments. The ability to exploit such public information comes with the growth of big data, which crunches data sets so large that they cannot be speedily analysed by traditional database software tools. Analytics is emerging with innovative software products purposely designed for large amounts of data in all forms, including textual information, numbers and images. In fact, sentiment analysis of natural language texts is a large and growing field, especially for financial economists. This allows the human brain to discover hidden correlations in a more rapid way and, therefore, to extract a hypothesis from an incomplete data set using intuition and logical deduction. In addition, differences of opinion seem to be a source of agent heterogeneity, while they may facilitate trading in financial markets. The release of public information, which has important implications for asset prices, could substantially widen the disparity of opinion and offer an information processing advantage to some traders, perhaps leading to information asymmetries and affecting the provision of market liquidity, damaging market functionality, and harming the news transmission process. Mullainathan and Spiess (2017) argue that machine learning is a new quantitative approach that can discover complex structures and fits very functional forms that can be used to generate superior predictions, especially in the field of finance, while Moritz and Zimmermann (2016) make use of machine learning-generated information to highlight that past stock returns from US firms can have substantial predictive power over their future stock returns.

With respect to monetary policy, central bankers place great importance on the transparency and predictability of their activities and, consequently, on their associated impact on financial markets. Blinder et al. (2008) argue that communication helps central banks achieve their objectives and that it can move markets. Fawley and Neely (2014) report that the Fed has modified its procedures over time to become more transparent. By contrast, Wynne (2013) argues that policy statements may unsettle financial markets if they are too difficult to comprehend, whereas Bulíř et al. (2013) highlight that the clarity of central bank communication varies throughout the business cycle. The lengthier statements that have accompanied policy announcements in the modern era of unconventional monetary policy are more difficult to understand (Hernandez-Murrillo and Shell, 2014), which leads to higher market volatility (Jansen, 2011) and makes it more difficult for central bankers to gauge the impact of their policy decisions.

The goal of this paper is to consider, for the first time, the association between changes in the tone of the sentiment of news originating from the European Central Bank's (ECB) activities and the mean and the volatility of stock returns relevant to major global stock markets. The following key question is explored: how are stock returns influenced by these changes in the sentiment tone associated with monetary authorities' activities? Understanding how stock markets respond to changes regarding sentiment tone news significant to monetary policy is expected to aid market participants in determining improved investment/portfolio choices. The literature has not focused on how the information coming from textual analysis is relevant to central banks or whether it has any informational content for stock returns. Only a handful of empirical research attempts have explored the impact of central banks' announcement news on stock markets. Particularly, D'Amico and Farka

(2001) provide evidence in favour of the impact of monetary policy on movements of asset prices, with a tightening of interest rates driven by monetary policy having a negative effect on stock prices. Moreover, Bernoth and von Hagen (2004) highlight the importance of the Fed's announcement news for market participants, whereas Hoeberichts et al. (2009) support that ambiguous messages from central banks have only temporary effects on the increasing volatility of certain economic variables. Schmidt and Nautz (2012) claim that financial market participants have systematically misunderstood the ECB's monetary policy, which is related to the adopted interest rate rule, whereas the understanding of the monetary policy that pertains to inflation has become more accurate. Finally, Kurihara (2014) explores the role of ECB's announcements on European stock markets and finds there is an absence of any statistically significant effect on stock prices. Furthermore, given that the release of a monetary policy decision conveys information to stock markets (Funke and Matsuda, 2006), the Eurozone financial markets should react to ECB monetary policy announcements. However, the ECB also seeks credibility as part of its strategy, while financial markets aim to understand any signals about the directions of interest rate developments. The Eurozone financial markets extract information from the ECB announcements and, therefore, consider the information in subsequent investment decisions to evaluate empirically whether market participants learn how to evaluate ECB's monetary policy, as it seems to be highly important to learn from such announcements, not only with respect to the European but also the global financial markets. This learning process can be substantially enhanced by decoding the words and phrases coming from the textual analysis of those announcements, thus offering improved explanations of monetary policy decisions that are expected to enhance the

quality of communications between monetary policy decisions and financial markets and defining better transmission channels for the effectiveness of the monetary policy.

The novelty of this work relies on the development of a unique sentiment index associated with the messages conveyed by the ECB's activities and the effect of this index on both the mean and the volatility of certain stock markets. In this context, the sentiment index is present in both the conditional mean and the volatility equations. To foreshadow the key findings, the analysis documents that the constructed sentiment index associated with ECB activities exerts a strong and statistically significant effect on both the mean and the volatility of important stock market indexes. Such findings add to the discussion on whether stock returns correctly incorporate (monetary policy) news sentiments into their own pricing processes.

2. Related literature

This paper is relevant to four fundamental strands of the literature. First, it touches the literature that explores the role of news in predicting stock prices. Given that investors are not fully rational, their investment behaviours are influenced by various market news, which consequently influence stock prices. Web sites, e.g., Google Finance and Yahoo Finance, and newspapers, e.g., the Financial Times and Wall Street Journal, are two typical types of sources that provide financial news. As these news sources provide a great number of news articles daily, investors are not able to manage all updates. To separate useless news, which reduces noise signals, and useful news, which retrieves market signals, substantial human efforts are required. With the advancement of financial methodologies and computer technologies, those previously required human efforts have been replaced by computers that can manage the abundance of financial news. Although the efficient market hypothesis assumes that

the market is efficient and can absorb the news impact quickly, researchers from behavioural finance challenge that market participants are not fully rational and there are many cases indicating that investors' irrational behaviours will likely lead to mispricing, a situation that requires substantial time for the market to correct (Andersen et al., 2007; Savor and Wilson, 2013; Kurov et al., 2016; Hu et al., 2017). By contrast, in the case of the ECB announcements, Kurihara (2014) examines whether and how ECB communications influence stock returns in the Euro area. His results emphasize that the impact of such announcements on stock returns has not been significant.

The second strand relates to the literature that focuses on providing evidence of the effect of textual information processing on asset prices through machine learning algorithms (Baker et al., 2012). Tetlock's pioneering studies (Tetlock, 2007; Tetlock et al., 2008) illustrate that news stories contain information relevant to predicting both earnings and stock returns. Subsequent studies have applied similar techniques based on a variety of news sources (Groß-Klußman and Hautsch, 2011; Dougal et al., 2012; Ro, 2012; Boudoukh et al., 2013; Chen et al., 2014; Sinha, 2016). However, the main disadvantage of the above attempts is that they are limited to a comparatively narrow event window and have not shown significant predictability beyond two days after a news release. Beetsma et al. (2013) employ Eurointelligence, which contains major newspaper articles pertaining to economic news across Europe. Their study highlights that increases in the amount of news intensifies the sovereign bond spreads in the peripheral countries. Gidofalvi (2001) obtains over 5,000 financial news articles concerning twelve specific stocks and identifies a 20-minute period before and 20-minute period after a financial news article is released. Within this period of time, he demonstrates that there exists weak ability to predict the direction

of stock returns before the market corrects itself to equilibrium. Huang et al. (2005) use support vector machines to predict weekly movements of the Japanese NIKKEI 225 index. Their approach achieved 73% using a combined modelling strategy. Lutz (2010) accepts the impact of three different sentiment measures on the future performance of stock returns, i.e., the Baker and Wurgler's Sentiment Index (Baker and Wurgler, 2006, 2007), the smoothed earnings-price ratio, and the VIX (volatility) index. His findings illustrate that such sentiment measures have very little out-of-sample predictive power. Barone-Adesi et al. (2012) is one of the very few studies that investigates the role of sentiment during the August 2007 crisis. Their results provide evidence that sentiment decreased dramatically as the systemic risk escalated during that period. Bai (2014) differentiates investor sentiment only confined within the market from sentiment across international markets. Particularly, he explores different aspects of investor sentiment impact by differentiating the scope of the influence of the sentiment. His results document that developed and emerging EU stock market regional sentiments have a significant impact on market excess returns and volatility. Moreover, his findings provide evidence that regional sentiments are transmitted across borders via specific transmission mechanisms, such as interbank lending networks. As a result, sentiments are contagious according to the strong evidence of causality across sentiment indexes.

The third strand of the literature is associated with how sentiment affects financial markets. This literature investigates the role of professional news on electronic social media (Tetlock, 2007; Tirunillai and Tellis, 2012; Karabulut, 2013) in predicting stock returns, whereas Loughran and McDonald (2011) and Jegadeesh and Wu (2013) find more rapid responses for individual stocks within a multi-day

event window and Hillert et al. (2014) suggest that media overreaction motivates stock momentum.

Finally, the fourth strand of the literature is associated with the textual analysis of the information content of central banks' communications (Bholat et al., 2015, review many applications of text mining techniques relevant to central banks). Hansen and McMahon (2016) find that FOMC communications regarding current economic conditions and shocks to forward guidance have no strong effects on real economic variables. These studies make use of dictionary-based methods to quantify the content of central banks' announcements. The dictionary used is a context-specific list developed by Apel and Grimaldi (2012), especially designed to measure the tone of central bank communications by making use of combinations of words. We contribute to this literature by developing a more detailed word list that allows for word combinations, as in Apel and Grimaldi (2012). More details regarding our newly developed word list are presented both in the data section and in Appendices 2 and 3.

3. Data and methodology

3.1. Data

To investigate the effect of textual news with respect to announcements coming from the ECB on stock markets, we employ intraday (London, Frankfurt, Paris markets) and opening (NY and Tokyo markets) price data from a number of stock market indexes, spanning the period January 1, 2002 to June 30, 2016. The analysis reports the results of the major international stock price indexes, i.e., S&P500, FTS100, CAC40, DAX, and Nikkei225. Returns (r_t) are calculated as the logged differences of stock prices, $r_t = \ln P_t - \ln P_{t-1}$, with P standing from the price of the market index.

Intraday data are obtained from the Thomson Reuters Tick History database, and current and opening price data are obtained from the Datastream database.

The employed dataset has a measure of the 'tone' or sentiment of each news story. The story-specific sentiment measure allows us to distinguish the effect of favourable vs unfavourable news. The information conveyed in the ECB's announcements may draw attention to stock returns, thereby inducing both rational and irrational trading, which may affect the liquidity of the stock market and, consequently, impact change stock returns. With respect to the empirical analysis, this study collects all ECB announcements around the main refinancing operations (MRO) during the ECB Council of Governors meetings from January 2002 to June 2016 using the event dates listed on the ECB website. The sample covers 167 statements, and the dates associated with the ECB statements are provided in the Appendix.

The analysis focuses on the MRO since it is the main instrument under control, whereas a monetary policy announcement is defined as the release of this rate by the governing council of the ECB. More specifically, the ECB governor's introductory statements at the press conference of the governing council are used for our content analysis, i.e., 4,788 different words are used in all introductory statements over the relevant period). We do not rely on raw word counts because, in many cases, this can be misleading. We, therefore, make use of a combination of words, a concept word and a tone modifier word. To develop the exhaustive central bank phrase list, we select concept words closely related to the state of the economy, with the selection of the words based exclusively on economic theory. More specifically, states of the economy-related word examples include words such as economic, unemployment, demand, income, and prices. We then programmatically extract from the text corpus all phrases that include at least one of these words. Examples include economic

activity, the unemployment rate, aggregate demand, domestic demand, and disposable income. By carefully examining all related phrases, we explicitly consider any inflections or different forms of the words of interest. Examples are wage and wages, inflationary pressure and inflationary pressures, and prices and inflation.

We then assign to each word, as well as to its similar terms, a tone modifier. The tone modifier can be either positive or negative. In doing so, we use collocation and identify the adjectives, adverbs or verbs that surround these words. As above, we again consider any inflections or different forms of the words of interest, i.e., decelerate, decelerates, decelerating, decelerated. For the tone modifier list to be as exhaustive as possible, the methodology uses the relevant word lists from WordNet. In other words, it extracts from our corpus all tokens that were included in the lists of verbs, adverbs and adjectives on WordNet. It then automatically identifies each extracted token to be positive or negative. After removing stop words from our corpus, we search for a tone modifier in a span of four words before or ahead of our concept phrase/word, selecting the tone modifier that is closest to the concept phrase/ word. The tone modifiers identify, in each case, whether the tone is positive or negative as it relates to the state of the economy. For instance, decreasing economic activity describes a downturn in the state of the economy, whereas an expanding production typically describes an upturn in the state of the economy.

Our newly created phrase list contains 112 concept phrases/words and 316 tone modifiers. The word list of Apel and Grimaldi (2012) (AG list, hereafter), which is the only one related to central banks' communications, contains 11 concepts and ten tone modifiers; as eight out of ten used tone modifiers are denoted as wild cards, the actual number of tone modifiers is greater than ten. The concepts used are inflation, price, wage, oil price, cyclical position, growth, development, employment,

unemployment, recovery and cost. The main difference between our list and that of Apel and Grimaldi (2012) is that we use, for the most part, a combination of words as key concepts, rather than just nouns. Examples include the word growth, in which case we use the phrases global growth, productivity growth, growth outlook, growth prospects, income growth, and output growth. Our phrase list also contains phrases based on words that are not included in the AG list, i.e., demand, output, income, consumption, credit, and loans. These words are determinants in describing the economic environment. We do not include the phrase cyclical position, which is included on the AG list, as it is not used in the vocabulary of the ECB and, instead, we use the phrase cyclical recovery. As a final remark regarding the AG list, we note that the separate inclusion of the word price and oil price may lead to the over or under estimation of the communication index as the token price is counted twice.

Moreover, there are substantial differences between our tone modifier list and the AG list. More specifically, the AG list contains only a limited number of adjectives, i.e., high, strong, increasing, increase, fast, low, weak, decreasing, decrease and slow, whereas our list contains the aforementioned words, plus many others. For example, our list includes foster, improve, reduce, decelerate, boost, elevate, and enhance. The inclusion of the new tone modifier words contributes to a more accurate quantification of the tone of the ECB's announcements. We automatically search for these word combinations and then insert their occurrences in a matrix for each of the announcements. Each row in the matrix represents an announcement, and each column represents the number of total occurrences of the word combinations that contribute to a positive or a negative tone. Following Apel and Grimaldi (2012), we determine the net effect of the announcements by calculating the following net sentiment index:

Net Sentiment Index=[((#positive comb.) / (#positive comb.+#negative comb.))-((#negative comb.)/(#positive comb.+#negative comb))]

where #positive comb and #negative comb denote the number of occurrences of positive and negative word combinations, respectively. The index applies values between 0 and 2, with 2 indicating a strong positive evaluation of the economic situation in the Eurozone and 0 indicating a strong negative evaluation. In addition, we calculate a sentiment index as:

Sentiment index=(#positive words-#negative words)/(#words)

where #positive and #negative words denote the number of positive and negative words in each announcement, respectively, and #words denotes the number of all words in the text. The number of positive and negative words is calculated by counting the number of words in each combination. For example, *global demand increases* counts as three positive words. The denominator, #words, represents the total number of words in each announcement. The sentiment index assumes either positive or negative values. A positive value denotes that the Eurozone expands, and a negative value denotes a pessimistic economic outlook. Sentiment and net sentiment indexes are highly correlated (0.92). A detailed example of the construction of the index is offered in the Appendix, and the detailed lists of the combinations of words that denote positive and negative outlooks for the economy are presented in the Appendix. Table 1 provides descriptive statistics for both sentiment indexes and for the corresponding ECB announcements of time stock index prices.

[Insert Table 1 about here]

3.2. Methodology

The analysis makes use of the mean-variance modelling approach, i.e., the EGARCH-X methodology (Hansen and Lunde, 2011), which retains the properties of the EGARCH model recommended by Nelson (1991) in capturing asymmetries in volatility clustering and the leverage effect observed across asset markets, while also extending the model to include any other factors in the X vector of control variables.

$$r_t = \alpha_0 + \beta\, \Delta SENT_{t-1} + \sum_{i=1}^{T} b_i\, r_{t-i} + \delta\, DUM2008 + \varepsilon_t \qquad (1)$$

$$h_t = \omega + \alpha\, \varepsilon_{t-1} + \gamma\, (|\varepsilon_{t-1}| - E|\varepsilon_{t-1}|) + \theta\, h_{t-1} + \varphi\, \Delta SENT_{t-1} \qquad (2)$$

where Δ denotes first differences, r_{it} proxies stock returns, and $SENT_{t-1}$ proxies the evaluation of sentiment news in accordance with the ECB's monetary policy activities (later defined as the baseline sentiment index-SI and the net sentiment index-NSI). It comes with a lag since it precedes the stock price reaction. A dummy variable is also included that explicitly captures the role of the 2008 crisis on returns (Blajer-Gołębiewska, 2012). The dummy variable takes the value of zero from January 2002 to July 2007 and from January 2010 to June 2016, and it takes the value of one from August 2007 to December 2009. The mean equation (1) is well described as an autoregressive-X (AR-X) model, i.e., an AR model augmented by any control variables X_t. The conditional volatility equation (2) describes a type of EGARCH-X modelling approach. In both equations, the sentiment index is allowed to play an explicit role in influencing both the mean and the volatility of stock returns.

4. Empirical analysis

4.1. Unit root tests

The variables in the mean equation should be stationary. To this end, the DF-GLS unit root test, proposed by Elliott et al. (1996), has been considered. The Akaike Information Criterion (AIC) selects the appropriate lag length to remove any serial correlation in the residuals. The DF-GLS test detrends the data to maximize power, and its null hypothesis is the non-stationarity of the series under investigation. The results, reported in Table 2, indicate that all variables considered are integrated of order one.

[Insert Table 2 about here]

4.2. Baseline estimates

In the next step of the analysis, Table 3 reports the formal estimates of equations (1) and (2) in which changes in the sentiment index simultaneously affect stock returns and their associated (conditional) volatility. It is further noted that on the day of a Governing Council meeting, the ECB announces its decision on interest rates with a press release at 13:45 (CET). As the Tokyo market is closed at the time of this conference, any effect is not observed until the opening price of the next day. However, with respect to the Frankfurt and Paris stock markets, the 13:49 index price is used (after having determined that over the first four minutes, the impact was statistically insignificant but that in the fifth minute statistically significant results are observed). Additionally, for the London market, the 12:49 (local London time) stock index price is made available (the same explanation as above regarding statistically significant results). Finally, for the NY market we also use opening index prices.

The findings well document the statistical significance of the fact that changes in the sentiment index have a positive effect on stock returns and a negative effect on the associated (conditional) volatility, with both effects being statistically significant

at 1%. The findings also indicate that there exists a strong persistence in stock returns, while the crisis dummy exerts a negative effect on those returns. In addition, the gamma coefficient, i.e., the indicator for asymmetric volatility, is negative and statistically significant at the 1% level, implying that the estimates suggest that the coefficient for the asymmetric volatility is negative, i.e., negative shocks imply a higher next period conditional variance than positive shocks of the same sign. The results remain robust with respect to the case of the net sentiment index as well (Table 4), albeit they are of lower size. These findings illustrate the need for studying in a future research venue the potential asymmetries of reaction.

[Insert Tables 3 and 4 about here]

4.3. Robustness check: the role of the Governor of the ECB

This part of the empirical analysis investigates how the idiosyncratic characteristics of the ECB's governors have influenced the way monetary policy decision-making throughout the study period has impacted stock returns. Blinder (2009) discusses the specific features of the people who make monetary policy decisions, while Harris et al. (2011) investigate whether the characteristics of the members of the Bank of England's Monetary Policy Committee can affect the decision to dissent from the majority decision and whether differences in career backgrounds impact the manner in which the monetary policy manages inflation and unemployment. Their empirical results suggest that the institutional constraints associated with the UK monetary policy, rather than the career background and other characteristics of the members, is what influences voting behaviours. Similarly, Smales (2013) suggests that the decision-making behaviour of the Reserve Bank of Australia is related to the inflation-targeting framework within which the bank operates.

A separate part of this literature focuses on the strategic and psychological factors affecting the behaviour of monetary policy committee members. Rülke and Tillmann (2011) study the extent of herding behaviour in FOMC member forecasts regarding growth, inflation and unemployment and find no evidence of herding behaviour. These findings support the view that forecasts signal FOMC members' policy preferences. Claussen et al. (2012) emphasize the role of psychological factors, such as overconfidence, in monetary policy making. These are the factors used to explain disagreements among committee members, the provision of decision power to those members, and the fact that the governors of monetary policy committees rarely find themselves on the losing side of the committee vote. Finally, Weise (2012) suggests that political considerations contributed to delays in tackling the rise in U.S. inflation in the 1970s.

The sample period covers the tenures of Wim Duisenberg (2001 to 10/31/2003), Jean-Claude Trichet (11/1/2003 to 10/31/2011), and Mario Draghi (11/1/2011 to present) as governors of the ECB. This time frame is of particular importance considering the changing dynamics of the European economy, which has evolved through states of high inflation, low growth at the start of the Duisenberg era, high growth during the Trichet era, and the sovereign debt crisis and unconventional monetary policy during both the Trichet and Draghi eras. The new results are expected to be of significant importance to a variety of economic agents. A greater understanding of the potential role of the governor's characteristics may allow economic agents to revise their expectations more efficiently and rebalance their portfolios appropriately. In addition, economic agents can anticipate the future nature of the monetary policy, which has implications for long-term output and inflation

performance, through improved forecasting of interest rates and asset prices that could lead to the reduction in the volatility of asset prices.

With respect to the empirical analysis, the first period contains 21 announcement events, the second period has 93 such events, and the last period includes 53 announcement events. The new empirical findings, reported in Tables 5 and 6, illustrate that both sentiment indexes exert a positive impact on the means and a negative impact on the volatility of returns across all three governor eras. The insignificance of the effect during the Duisenberg era could be potentially attributed to the low number of observations or to the fact that it coincides with the first period of the Eurozone, a period when the role of the ECB had not been fully assessed. However, the impact of both sentiment indexes on stock returns during the Trichet era is either very low or statistically insignificant (especially in the non-European markets), while turns strong during the Draghi era. Regarding the remaining control variables, the decomposed results lend consistent support to the estimates across all three periods and are relevant to the overall results previously reported.

Focusing on the Trichet and Draghi eras, several conclusions are drawn. First, both governors were asked to manage the efficiency of the monetary policy in the Eurozone in light of the debt sovereign crisis period that followed the 2007 to 2009 international financial crisis. The significance of this role seems to link with Friedman's (1962) hypothesis that accidents of personality can have substantial consequences for rule-based institutions. However, Blinder (2009) favours the fact that central banks should be independent, rule-based institutions focused on the maintenance of price stability, while signifying the disappearance of strong, leading personalities. Siklos (2002) investigates how the personalities of Paul Volcker and Alan Greenspan influenced the monetary policy of the Fed, and Lebaron (2008)

develops an analytical framework or sociology of central bankers to assess how the personality characteristics of leading central bankers influence a central bank's behaviour. This line of research accepts the possibility of varying strategies regarding monetary policies, even if all central bankers share neo-liberal economic beliefs.

Nevertheless, despite the constraints posed by the treaty, the governors of the ECB are allowed significant room to manoeuvre. Accordingly, consistent with personality theories, we can accept the possibility of different policy makers choosing different monetary policy strategies. Thus, the empirical findings presented in Tables 5 and 6 document that there have been some differentiations in policy decisions between Trichet and Draghi. The reason for such differentiations in policy decisions is founded upon the different personal developments of these two decision makers. For instance, Trichet was fundamentally more constrained by the institutional framework and, therefore, less flexible than Draghi. Institutionally, although both governors were equally constrained legally, Trichet's deep involvement in the institution building process prevented any significant departure in policymaking. In contrast, Draghi, who was not institutionally bound to the ECB and whose personal development was that of an outsider, initiates changes and has adopted a flexible interpretation of the institutional mandate. For instance, Trichet and Draghi differed regarding non-standard policy measures as well as the use of long-term refinancing operations (LTROs) and the Securities Markets Programme (SMP). Although both Trichet and Draghi made use of LTROs, Trichet increased the maturity from three months to one year, whereas Draghi increased it to three years. Furthermore, Draghi decided on two large-scale refinancing operations that amounted to €1 trillion in December 2011 and February 2012, which contrasted with Trichet's hesitant use of refinancing operations (Fawley and Neely, 2014). Similarly, although both governors sought to restore

monetary policy transmissions through the SMP, Draghi progressively reduced the use of the SMP and eventually announced its replacement with Outright Monetary Transactions (OMTs). The effectiveness of OMTs was made credible because of Draghi's previous decision regarding interest rates and liquidity provisions (Bibow, 2013).

[Insert Tables 5 and 6 about here]

4.4. Robustness check: the role of the 2007 to 2009 financial crisis

During the financial crisis that struck the global financial system between 2007 and 2009, many central banks aggressively eased the monetary policy to alleviate financial market distress, boost output and stabilize inflation. Overall, the monetary policy was largely successful in mitigating financial market distress, but output growth remained lower than expected in many advanced economies (Pain et al., 2014).

The financial crisis is characterized by a high degree of financial market distress, substantial balance-sheet adjustments of financial institutions, private households and firms, and a high degree of uncertainty and low confidence of firms, consumers and market participants (Reinhart and Rogoff, 2008; Bloom, 2009; Dées and Brinca, 2013). These characteristics may potentially impair the transmission of the monetary policy (Bouis et al., 2013; Bloom, 2014). It is also possible that the effects of the monetary policy could be amplified during financial crises if central banks can mitigate some of the adverse characteristics of financial crises and prevent adverse feedback loops between the financial sector and the real economy (Bernanke et al., 1999; Mishkin, 2009). Furthermore, there is ample evidence that the financial crisis disrupted not only the regular transmission mechanisms of the monetary policy

but that it also called into question whether the monetary policy could effectively steer short-term money market rates in such an environment (Eisenschmidt and Tapking, 2009; Taylor and Williams, 2009; Brunnermeier, 2009; Brunnermeier and Pedersen, 2009; Schwarz, 2010; Christensen et al., 2014), which in return may have a strong impact on the prices of financial assets and, thus, on the real economy.

Given the above discussion, this part of the empirical analysis explores the impact of the financial crisis on the uncertainty associated with the ECB's monetary policy announcements by re-estimating the impact of both sentiment indexes on both the mean and the volatility of international stock index returns only during the crisis period. This period extends from August 2007 to December 2009 and consists of 30 ECB announcement statements. The new results, which are reported in Tables 7 and 8, provide strong support that changes in both sentiment indexes exert a negative effect on stock returns and a positive impact on volatility, clearly indicating the dominance of contraction effects.

[Insert Tables 7 and 8 about here]

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5. Conclusion

This paper explored the relationship between changes in the tone of sentiment news originating from ECB's activities and stock returns. Using data from the major global stock market indexes and new sentiment news indexes and spanning the period from January 1, 2002 to June 30, 2016, the empirical evidence suggested that such changes

in the tone of sentiment news stories were substantially important for both the mean and the volatility of stock returns. More specifically, the impact on the mean of stock returns was found to be positive, whereas that on the volatility of those returns was negative. The results remained robust across all stock markets considered in this study, and they survived a robustness check with respect to the personality of the ECB governors. In this latter case, the findings were differentiated with respect to the era when governor Draghi assumed the position of the ECB governor. Finally, the role of the changes in sentiment news received stronger empirical support for estimates during the financial crisis period.

Based on these findings, we propose that market participants could use the information obtained from such sentiment news to interpret ECB's future activities and to design effective investment/portfolio strategies. Our results are important for policymakers, as they contribute to the understanding of the transmission mechanism of the monetary policy. Central bankers should be aware that because their statements may create unintentional uncertainty in financial markets, they should use language that is relatively easy to understand to ensure that the intent of policy is appropriately conveyed. Particularly, central bankers may be able to reduce the announcement effect on uncertainty by increasing guidance in advance, thus reducing the surprise factor, and by issuing statements with more familiar words and less complex reasoning. Future research could also explore the above underpinnings with respect to more stock markets and more central banks.

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Table 1. Descriptive statistics

Variables	Mean	SD	Min	Max	Jarque-Bera
SI	0.035	0.030	-0.045	0.116	3.16
NSI	1.321	0.274	0.642	1.935	4.07
S&P500	0.337	0.898	-0.933	0.337	809.52
CAC40	0.958	1.928	0.958	3.684	748.10
FTSE100	1.701	1.785	-0.824	1.701	1003.27
DAX	1.592	0.007	1.583	1.592	977.19
NIKKEI	0.704	0.913	0.704	1.996	866.53

The table provides a number of descriptive statistics. SI is the sentiment index and NSI is the net sentiment index. With respect to the stock indexes, the statistics refers to returns. The Jarque-Bera statistic is asymptotically distributed as a Chi-square with 2 degrees of freedom; its critical value at the 5% significance level is 5.99. Data are obtained from Thomson Reuters History Tick and Thomson Reuters Datastream databases.

Table 2. Unit root testing: the DF-GLS test

Country	US	France	UK	Germany	Japan
Variables					
stock prices	-1.28(3)	-1.25(3)	-1.28(3)	-1.35(3)	-1.37(4)
Δstock prices (r)	-5.33(2)***	-5.68(1)***	-6.42(2)***	-6.37(1)***	-6.21(2)***
SI	-1.35(3)				
ΔSI	-5.24(3)***				
NSI	-1.39(3)				
ΔNSI	-5.69(3)***				

The table reports the unit root test results based on the DF-GLS testing method. SI denotes the sentiment index, while NSI the net sentiment index. Returns variables are in logarithms. Δ indicates first differences. Numbers in parentheses denote the optimal number of lags used in the augmentation of the test regression and were obtained through the Akaike criterion. ***: p≤0.01. Data are obtained from Thomson Reuters History Tick and Thomson Reuters Datastream databases.

Table 3. EGARCH-X estimates: Sentiment Index (baseline results)

Variables/	S&P500		CAC40		FTSE100		DAX		NIKKEI	
Equations	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
	0.026[b]	-0.027[b]	0.041[a]	-0.042[a]	0.034[b]	-0.036[a]	0.104[a]	-0.077[a]	0.083[a]	-0.058[a]
ΔSI										
	[0.05[	[0.04]	[0.00]	[0.00]	[0.04]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	0.679[a]		0.607[a]		0.619[a]		0.562[a]		0.502[a]	
r(-1)		-		-		-		-		-
	[0.00]		[0.00]		[0.00]		[0.00]		[0.00]	
	0.194[a]		0.142[a]		0.180[a]		0.155[a]		0.122[a]	
r(-2)		-		-		-		-		-
	[0.00]		[0.00]		[0.00]		[0.00]		[0.00]	
	-0.173[a]		-0.141[a]		-0.151[a]		-0.143[a]		-0.153[a]	
DUM2008		-		-		-		-		-
	[0.00]		[0.00]		[0.00]		[0.00]		[0.00]	
		0.049[a]		0.063[a]		0.057[a]		0.048[a]		0.037[a]
ω	-		-		-		-		-	
		[0.00]		[0.00]		[0.00]		[0.00]		[0.01]
		0.216[a]		0.235[a]		0.209[a]		0.216[a]		0.194[a]
α	-		-		-		-		-	
		[0.00]		[0.00]		[0.00]		[0.00]		[0.00]
		-0.075[b]		-0.083[a]		-0.079[a]		-0.088[a]		-0.052[a]
Γ	-		-		-		-		-	
		[0.03]		[0.00]		[0.00]		[0.00]		[0.00]
		0.714[a]		0.798[a]		0.765[a]		0.791[a]		0.742[a]
θ	-		-		-		-		-	
		[0.00]		[0.00]		[0.00]		[0.00]		[0.00]
LL	-	2680.9	-	2851.7	-	2906.9	-	3178.4	-	2890.6
	0.0046	-	0.0034		0.0029		0.0018		0.0015	
Constant				-		-		-		-
	[0.39]		[0.45]		[0.46]		[0.57]		[0.73]	
No. of obs.	167		167		167		167		167	

The table reports the baseline estimates of the equations (1) and (2) for the case of the SI index. LL denotes the log likelihood. Figures in brackets denote p-values. (1) indicates the estimates in relevance to Equation (1) in the EGARCH-X model and (2) indicates the estimates in relevance to Equation (2). a: $p \leq 0.01$, b:$p \leq 0.05$.

Table 4. EGARCH-X estimates: Net Sentiment Index (baseline results)

Variables/	S&P500		CAC40		FTSE100		DAX		NIKKEI	
Equations	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
	0.019[c]	-0.029[b]	0.038[a]	-0.047[a]	0.032[b]	-0.040[a]	0.075[a]	-0.082[a]	0.078[a]	-0.062[a]
ΔNSI										
	[0.06]	[0.04]	[0.00]	[0.00]	[0.03]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	0.636[a]		0.589[a]		0.590[a]		0.532[a]		0.469[a]	
r(-1)		-		-		-		-		-
	[0.00]		[0.00]		[0.00]		[0.00]		[0.00]	
	0.181[a]		0.126[a]		0.163[a]		0.139[a]		0.118[b]	
r(-2)		-		-		-		-		-
	[0.00]		[0.00]		[0.00]		[0.00]		[0.02]	
r(-3)	-	-	-	-	0.059[b]	-	-	-	-	-

					[0.02]					
	-0.166[a]		-0.141[a]		-0.148[a]		-0.143[a]		-0.153[a]	
DUM2008		-		-		-		-		-
	[0.00]		[0.00]		[0.00]		[0.00]		[0.00]	
		0.043[a]		0.057[a]		0.052[a]		0.041[a]		0.033[a]
ω	-		-		-		-		-	
		[0.00]		[0.00]		[0.00]		[0.00]		[0.01]
		0.224[a]		0.239[a]		0.219[a]		0.224[a]		0.199[a]
α	-		-		-		-		-	
		[0.00]		[0.00]		[0.00]		[0.00]		[0.00]
		-0.078[b]		-0.086[a]		-0.084[a]		-0.093[a]		-0.057[a]
γ	-		-		-		-		-	
		[0.03]		[0.00]		[0.00]		[0.00]		[0.00]
		0.719[a]		0.804[a]		0.770[a]		0.796[a]		0.747[a]
θ	-		-		-		-		-	
		[0.00]		[0.00]		[0.00]		[0.00]		[0.00]
LL	-	2877.4	-	2925.6	-	2959.2	-	3328.5	-	2937.1
	0.0015		0.0027		0.0016		0.0012		0.0011	
Constant		-		-		-		-		-
	[0.39]		[0.48]		[0.57]		[0.60]		[0.68]	
No. of obs.	167		167		167		167		167	

This table reports the baseline estimates of the equations (1) and (2) for the case of the NSI index. LL denotes the log likelihood. Figures in brackets denote p-values. (1) indicates the estimates in relevance to Equation (1) in the EGARCH-X model and (2) indicates the estimates in relevance to Equation (2) in the EGARCH-X model. a: $p \leq 0.01$, b:$p \leq 0.05$.

Table 5. EGARCH-X estimates: Sentiment Index (the role of the ECB governor)-equations (1) and (2)

Variables	The Duisenberg Era					The Trichet Era					The Draghi Era				
	S&P500	CAC40	FTSE100	DAX	NIKEI	S&P500	CAC40	FTSE100	DAX	NIKEI	S&P500	CAC40	FTSE100	DAX	NIKEI
ΔSI	0.008	0.019	0.011	0.018	0.007	0.028[c]	0.037[c]	0.033[c]	0.036[b]	0.025	0.061[b]	0.079[a]	0.088[a]	0.112[a]	0.078[b]
	[0.49]	[0.23]	[0.42]	[0.25]	[0.51]	[0.10]	[0.07]	[0.08]	[0.05]	[0.11]	[0.05]	[0.01]	[0.01]	[0.00]	[0.02]
r(-1)	0.668[a]	0.597[a]	0.602[a]	0.566[a]	0.518[a]	0.613[a]	0.556[a]	0.578[a]	0.528[a]	0.486[a]	0.632[a]	0.564[a]	0.582[a]	0.541[a]	0.494[a]
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
r(-2)	0.135[a]	0.124[a]	0.149[a]	0.114[a]	0.096[a]	0.109[a]	0.104[a]	0.114[a]	0.101[a]	0.090[a]	0.112[a]	0.119[a]	0.123[a]	0.129[a]	0.105[a]
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
DUM2008	-	-	-	-	-	-0.173[a]	-0.132[a]	-0.137[a]	-0.139[a]	-0.140[a]	-0.158[a]	-0.139[a]	-0.145[a]	-	-
						[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	0.148[a]	0.146[a]
														[0.00]	[0.00]
Constant	0.0032	0.0024	0.0021	0.0008	0.0005	0.0039	0.0038	0.0032	0.0023	0.0019	0.0034	0.0032	0.0035	0.0015	0.0013
	[0.51]	[0.55]	[0.52]	[0.67]	[0.70]	[0.47]	[0.50]	[0.46]	[0.59]	[0.64]	[0.49]	[0.43]	[0.50]	[0.62]	[0.68]
Obs	21	21	21	21	21	93	93	93	93	93	53	53	53	53	53

Table 5. Continued

Variables	The Duisenberg Era	The Trichet Era	The Draghi Era

	S&P500	CAC40	FTSE100	DAX	NIKEI	S&P500	CAC40	FTSE100	DAX	NIKEI	S&P500	CAC40	FTSE100	DAX	NIKEI
ΔSI	-0.013	-0.019	-0.011	-0.021	-0.010	-0.014[c]	-0.022[c]	-0.019[c]	-0.032[c]	-0.014[c]	-0.044[b]	-0.069[a]	-0.063[a]	-0.079[a]	-0.070[a]
	[0.14]	[0.12]	[0.16]	[0.11]	[0.17]	[0.09]	[0.08]	[0.08]	[0.06]	[0.09]	[0.03]	[0.02]	(0.01)	[0.00]	[0.00]
ω	0.046[a]	0.059[a]	0.056[a]	0.045[a]	0.037[a]	0.053[a]	0.066[a]	0.063[a]	0.057[a]	0.049[a]	0.041[b]	0.060[a]	0.054[a]	0.050[a]	0.043[b]
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.02]	[0.00]	[0.01]	[0.01]	[0.02]
α	0.232[a]	0.247[a]	0.224[a]	0.226[a]	0.206[a]	0.240[a]	0.252[a]	0.233[a]	0.237[a]	0.218[a]	0.249[a]	0.260[a]	0.241[a]	0.239[a]	0.227[a]
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
γ	-0.083[b]	-0.092[a]	-0.089[a]	-0.098[a]	-0.062[a]	-0.095[a]	-0.099[a]	-0.103[a]	-0.110[a]	-0.077[a]	-0.102[a]	-0.108[a]	-0.117[a]	-0.119[a]	-0.086[a]
	[0.02]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
θ	0.735[a]	0.799[a]	0.785[a]	0.784[a]	0.772[a]	0.742[a]	0.784[a]	0.763[a]	0.795[a]	0.788[a]	0.751[a]	0.787[a]	0.770[a]	0.801[a]	0.794[a]
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
LL	2348.4	2864.1	3052.7	3082.6	2733.9	2492.5	2945.6	3236.5	3211.3	2805.6	2171.9	2533.6	3075.6	3019.5	2536.1
No. of obs	21	21	21	21	21	93	93	93	93	93	53	53	53	53	53

This table reports the estimates of the equations (1) and (2) for the case of the SI index per ECB governors' eras. LL stands for log likelihood. Figures in brackets denote p-values. a: p≤0.01, b:p≤0.05, c:p≤0.10.

Table 6. EGARCH-X estimates: Net Sentiment Index (the role of the ECB governor)-equations (1) and (2)

Variables	The Duisenberg Era					The Trichet Era					The Draghi Era				
	S&P500	CAC40	FTSE100	DAX	NIKEI	S&P500	CAC40	FTSE100	DAX	NIKEI	S&P500	CAC40	FTSE100	DAX	NIKEI
ΔNSI	0.005	0.014	0.007	0.013	0.004	0.023	0.032[c]	0.029	0.040[c]	0.029	0.058[b]	0.073[b]	0.083[a]	0.103[a]	0.072[b]
	[0.58]	[0.31]	[0.49]	[0.38]	[0.57]	[0.15]	[0.10]	[0.11]	[0.08]	[0.11]	[0.05]	[0.03]	[0.01]	[0.00]	[0.02]

r(-1)	0.655[a]	0.572[a]	0.585[a]	0.543[a]	0.501[a]	0.589[a]	0.542[a]	0.566[a]	0.513[a]	0.469[a]	0.624[a]	0.558[a]	0.571[a]	0.532[a]	0.480[a]
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
r(-2)	0.128[a]	0.120[a]	0.138[a]	0.102[a]	0.082[a]	0.091[a]	0.094[a]	0.102[a]	0.087[a]	0.078[b]	0.104[a]	0.112[a]	0.115[a]	0.121[a]	0.096[a]
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.02]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
DUM2008	-0.158[a]	-0.139[a]	-0.145[a]	-0.148[a]	-0.146[a]	-0.136[a]	-0.124[a]	-0.130[a]	-0.131[a]	-0.133[a]	-0.152[a]	-0.134[a]	-0.140[a]	-0.142[a]	-0.139[a]
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Constant	0.0037	0.0022	0.0026	0.0014	0.0018	0.0032	0.0035	0.0039	0.0014	0.0024	0.0030	0.0037	0.0028	0.0019	0.0018
	[0.50]	[0.57]	[0.49]	[0.63]	[0.62]	[0.52]	[0.53]	[0.42]	[0.68]	[0.60]	[0.55]	[0.41]	[0.56]	[0.59]	[0.64]
No. of obs	21	21	21	21	21	93	93	93	93	93	53	53	53	53	53

Table 6. Continued

Variables	The Duisenberg Era					The Trichet Era					The Draghi Era				
	S&P500	CAC40	FTSE100	DAX	NIKEI	S&P500	CAC40	FTSE100	DAX	NIKEI	S&P500	CAC40	FTSE100	DAX	NIKEI
ΔNSI	-0.018	-0.023	-0.025[c]	-0.032[c]	-0.012	-0.021[c]	-0.026[c]	-0.013	-0.029[c]	-0.010	-0.041[b]	-0.056[b]	-0.040[b]	-0.075[a]	-0.066[a]
	[0.11]	[0.11]	[0.10]	[0.09]	[0.14]	[0.08]	(0.07)	[0.11]	[0.08]	[0.13]	[0.03]	[0.02]	[0.03]	[0.00]	[0.01]
ω	0.042[a]	0.055[a]	0.051[a]	0.040[a]	0.032[b]	0.051[a]	0.062[a]	0.060[a]	0.054[a]	0.045[a]	0.035[b]	0.055[b]	0.046[b]	0.045[b]	0.038[b]
	[0.00]	[0.00]	[0.00]	[0.00]	[0.02]	[0.00]	[0.00	[0.00]	[0.00]	[0.00]	[0.03]	[0.02]	[0.02]	[0.02]	[0.04]
α	0.226[a]	0.242[a]	0.218[a]	0.220[a]	0.198[a]	0.234[a]	0.247[a]	0.228[a]	0.231[a]	0.212[a]	0.240[a]	0.252[a]	0.234[a]	0.233[a]	0.219[a]
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
γ	-0.079[b]	-0.088[a]	-0.085[a]	-0.093[a]	-0.056[b]	-0.091[a]	-0.092[a]	-0.095[a]	-0.102[a]	-0.071[b]	-0.091[a]	-0.094[a]	-0.108[a]	-0.110[a]	-0.081[b]
	[0.02]	[0.00]	[0.00]	[0.00]	[0.03]	[0.01]	[0.00]	[0.00]	[0.00]	[0.02]	[0.01]	[0.01]	[0.00]	[0.00]	[0.02]
θ	0.719[a]	0.778[a]	0.770[a]	0.768[a]	0.754[a]	0.733[a]	0.775[a]	0.756[a]	0.788[a]	0.779[a]	0.739[a]	0.779[a]	0.763[a]	0.790[a]	0.778[a]
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
LL	2286.0	2652.4	2928.5	2926.2	2359.8	2328.6	2854.1	3165.2	3109.5	2658.9	2095.4	2362.1	2558.3	2981.4	2352.8
No. of obs	21	21	21	21	21	93	93	93	93	93	53	53	53	53	53

This table reports the estimates of the equations (1) and (2) for the case of the NSI index per ECB governors' eras. LL stands for log likelihood. Figures in brackets denote p-values. a: p≤0.01, b:p≤0.05, c:p≤0.10.

Table 7. EGARCH-X estimates: Sentiment Index (crisis period: 2007 - 2009)

Variables/	S&P500		CAC40		FTSE100		DAX		NIKKEI	
Equations	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
	-0.032[b]	0.036[b]	-0.053[a]	0.049[a]	-0.040[b]	0.044[a]	-0.137[a]	0.085[a]	-0.089[a]	0.069[a]
ΔSI										
	[0.03]	[0.03]	[0.00]	[0.00]	[0.02]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	0.655[a]		0.619[a]		0.612[a]		0.586[a]		0.535[a]	
r(-1)		-		-		-		-		-
	[0.00]		[0.00]		[0.00]		[0.00]		[0.00]	
	0.177[a]		0.149[a]		0.188[a]		0.163[a]		0.130[a]	
r(-2)		-		-		-		-		-
	[0.00]		[0.00]		[0.00]		[0.00]		[0.00]	
		0.043[a]		0.059[a]		0.051[a]		0.040[a]		0.032[b]
Ω	-		-		-		-		-	
		[0.00]		[0.00]		[0.00]		[0.00]		[0.02]
		0.189[a]		0.216[a]		0.193[a]		0.201[a]		0.178[a]
A	-		-		-		-		-	
		[0.00]		[0.00]		[0.00]		[0.00]		[0.00]
		-0.071[b]		-0.087[a]		-0.082[a]		-0.080[a]		-0.059[a]
Γ	-		-		-		-		-	
		[0.03]		[0.00]		[0.00]		[0.00]		[0.00]
		0.725[a]		0.774[a]		0.752[a]		0.774[a]		0.731[a]
Θ	-		-		-		-		-	
		[0.00]		[0.00]		[0.00]		[0.00]		[0.00]
LL	-	2045.2	-	2178.3	-	2368.2	-	2907.9	-	2255.8
	0.0038		0.0030		0.0024		0.0007		0.0011	
Constant		-		-		-		-		-
	[0.46]		[0.47]		[0.49]		[0.68]		[0.76]	
No. of obs.	30		30		30		30		30	

This table reports the estimates of the equations (1) and (2) for the case of the SI index and during the financial crisis period. LL stands for log likelihood. Figures in brackets denote p-values. a: p≤0.01, b:p≤0.05, c:p≤0.10.

Table 8. EGARCH-X estimates: Net Sentiment Index (crisis period: 2007 - 2009)

Variables/	S&P500		CAC40		FTSE100		DAX		NIKKEI	
Equations	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
	-0.027[b]	0.035[b]	-0.044[a]	0.050[a]	-0.039[b]	0.046[a]	-0.081[a]	0.088[a]	-0.080[a]	0.067[a]
ΔNSI										
	[0.05]	[0.03]	[0.00]	[0.00]	[0.02]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	0.614[a]		0.569[a]		0.577[a]		0.521[a]		0.445[a]	
r(-1)		-		-		-		-		-
	[0.00]		[0.00]		[0.00]		[0.00]		[0.00]	
	0.139[a]		0.108[a]		0.142[a]		0.125[a]		0.126[a]	
r(-2)		-		-		-		-		-
	[0.00]		[0.00]		[0.00]		[0.00]		[0.01]	
		0.036[a]		0.051[a]		0.045[a]		0.036[a]		0.028[b]
ω	-		-		-		-		-	
		[0.00]		[0.00]		[0.00]		[0.00]		[0.01]

		0.215[a]		0.232[a]		0.206[a]		0.212[a]		0.178[a]
α	-		-		-		-		-	
		[0.00]		[0.00]		[0.00]		[0.00]		[0.00]
		-0.072[b]		-0.080[a]		-0.075[a]		-0.084[a]		-0.051[a]
γ	-		-		-		-		-	
		[0.03]		[0.00]		[0.00]		[0.00]		[0.00]
		0.693[a]		0.788[a]		0.761[a]		0.785[a]		0.740[a]
θ	-		-		-		-		-	
		[0.00]		[0.00]		[0.00]		[0.00]		[0.00]
LL	-	2321.0	-	2531.4	-	2185.6	-	2809.3	-	2350.4
	0.0012		0.0021		0.0011		0.0006		0.0003	
Constant		-		-		-		-		-
	[0.49]		[0.53]		[0.62]		[0.65]		[0.75]	
No. of obs.	30		30		30		30		30	

This table reports the estimates of the equations (1) and (2) for the case of the NSI index and during the financial crisis period. LL stands for log likelihood. Figures in brackets denote p-values. a: $p \leq 0.01$, b:$p \leq 0.05$, c:$p \leq 0.10$.